# Raising Bond Capital in Segmented Markets*

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**Abstract**

The difference between corporate bond yields at issuance and in secondary markets, the "issuance premium", spikes in bad times, increasing firms' costs of capital. Leveraging new bond-level data, I estimate a model of primary markets with imperfectly elastic investors and endogenous firms' supply of bonds that explains the impact of issuance premium on bond issuance. Using high-frequency variation in bond supply as an instrument, I find that investors are more sensitive to issuance premiums than the remainder of credit spreads. As issuance premiums rise in bad times, a more price-elastic primary market supports bond volumes.

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# 1 Introduction

Firms raise over $1 trillion in corporate bonds every year.[1] The cost of bond capital to firms is determined in the primary market – where firms sell new bonds via underwriters to investors – and often exceeds yields traded in secondary markets. The difference in primary and secondary market yields, the "issuance premium", rises in market downturns, amplifying the well-known countercyclical pattern of secondary market credit spreads (over risk-free rates).[2] During the COVID-19 crisis, average issuance premiums went from 8 to 30 basis points; during the 2008-2009 financial crisis, they reached 55 basis points. Such fluctuations in external financing costs can have material impacts on firms' real activities.[3]

In this paper, I quantify how negative demand shocks in primary markets affect firm borrowing. I start with the observation that primary and secondary markets are to some extent segmented. Firms only sell into primary markets, which are run by broker-dealers who are known to favor some investors and exclude others.[4] Because this segmentation leads to limited investor capacity to absorb shocks, shocks to firms' supply of bonds and primary market investors' demand for bonds can impact firms' costs of capital.

To quantify how much these forces affect firms, I estimate an equilibrium model of primary markets using a new industry dataset and high-frequency identification. Following the recent literature on demand-based asset pricing (e.g., Koijen and Yogo [2019]), I model investors as imperfectly elastic. Importantly, I deviate from the common assumption that the supply of assets is fixed by endogenizing the firm's issuance decision. I show that on the supply side, firms' lower sensitivity to prices in bad times exacerbates the impact of negative demand shocks on issuance premiums. On the demand side, higher issuance premiums attract more primary market investors and a larger proportion of more price-elastic investors who "flip" the bond, dampening the spike in issuance premiums and accommodating more issuance. Firms can thus access more capital in bad times due to higher issuance premiums attracting more investors.

An illustrative example of primary market dynamics is the spring 2020 bond issuance by the luxury retailer Nordstrom. Amidst the closing of all stores due to the COVID-19 pandemic, the company sought to raise $600 million of bonds in April 2020. The bond received $6 billion in

[1]Source: SIFMA Capital Markets Fact Book, 2021.

[2]See Gilchrist and Zakrajšek (2012).

[3]See *inter alia* Bolton et al. (2013) and Campello et al. (2011).

[4]See *inter alia* Benveniste and Spindt (1989) and Cornelli and Goldreich (2001).

investor orders at the issuance price, thus was oversubscribed (i.e., demand exceeded supply). Short-term investors purchased 40% of the bond, double the average share. Within the first day, the credit spread dropped over 100 basis points, suggesting that underwriters priced the bond at a higher yield (or lower price) than market clearing. Large order books along with a first day drop in credit spreads indicate restricted access to primary markets, consistent with market segmentation.

To understand how this segmentation affects firm issuance, I develop and estimate an equilibrium model of corporate bond issuance. The model incorporates demand from two types of primary market investors (short-term and long-term), supply from issuing firms, and underwriters who split surplus between firms and investors via pricing. I allow primary market investors to have different preferences over the two components of new issue credit spread: the issuance premium and the remainder of credit spreads. Decomposing the parameters in this way helps inform time-series variation in demand elasticities, which would be difficult to estimate directly. I then estimate the demand elasticities of the two types of primary market investors and firm supply elasticities.[5] Importantly, the model produces simulated counterfactual equilibria which allow me to quantify how changes in policy, fundamentals, and investor composition impact bond prices and volumes.

New micro-data on corporate bond issuance from Credit Flow Research (CFR) and Informa Global Markets (IGM) provides high-frequency variation in bond-level issuance information that allows me to identify supply-side parameters. Specifically, this dataset includes order books at issuance and changes in credit spreads and bond sizes throughout the issuance process. I combine this with a comprehensive dataset of trading, fund holdings, and bond and firm characteristics for an estimation sample from September 2010 to June 2020.

To estimate the supply side, I exploit within-day variation in proposed issuance prices and quantities for the same bond. Within the issuance day, during which firm fundamentals are presumably constant, firms adjust quantity supplied upwards when credit spreads are lower than expected. By observing multiple price–quantity pairs from the same day, I can pin down the firm's supply elasticity based on within-bond variation. I find that on average, firms respond to a 10 basis point increase in credit spreads by decreasing issuance by 1.5%;[6] during the global financial crisis (GFC), when they are more desperate for cash, they decrease issuance by half as much.[7]

[5]To be precise, I estimate semi-elasticities with respect to credit spread: that is, the percentage change in quantities given a level change in credit spreads. For ease of exposition, I will use the term "elasticities".

[6]This corresponds to a price elasticity of supply of roughly 1.5.

[7]In principle, firms can substitute to bank lending (Darmouni and Siani [2022]) or, increasingly, shadow banks (Buchak et al. [2018]); this margin is outside the scope of this paper.

Next, I estimate how investors respond to credit spreads. I take as a primitive of the model that investors are far from perfectly elastic, owing to realistic frictions such as slow-moving capital and heterogeneous institutional needs (Becker and Ivashina [2015]; Duffie [2010]; Gabaix and Koijen [2020]; Koijen and Yogo [2019]; Shleifer [1986]). Indeed, the data confirms an upward-sloping demand curve for primary market bond investors: credit spreads rise when other firms issue more bonds on the same day – a positive supply shock. The same-day issuance volume of comparable securities thus becomes a supply shifter in corporate bond issuance markets that helps identify demand elasticities. While low-frequency shifts in supply could correlate with firm and macro fundamentals as firms may endogenously choose a time window (e.g., which week) to issue bonds, the specific *day* of the week is quasi-random with respect to unobserved firm characteristics when absorbing week fixed effects. I find that a one-basis-point increase in issuance premiums corresponds to a 7% increase in short-term investor demand, but only a 3% increase in long-term investor demand, while a comparable increase in the remainder of credit spreads leads to a negligible increase in demand.[8]

I compare investor demand in primary markets with secondary markets by using cross-sectional variation in institutional holdings data, adapting Koijen and Yogo (2019) and Bretscher et al. (2020) and exploiting the investment universe of other funds as an exogenous price shifter. I find that for a one-basis-point increase in credit spreads, secondary market investors increase holdings by around 0.1%, corresponding to a price demand elasticity attributable to credit spreads of around one between 2003-2021. Higher elasticities in primary markets help explain why firms can issue very large bonds in the span of hours without significant price impacts.

Because new bonds are often oversubscribed,[9] the usual equilibrium notion of demand equals supply is insufficient. Thus, to close the model, I introduce underwriters who select an equilibrium credit spread that splits surplus between firms and investors, subject to market clearing. My estimation reveals that underwriters systematically favor investors, contributing to issuance premiums being positive on average. This is consistent with underwriter market power, which arises from high barriers to entry in the underwriting business.[10] These barriers have been documented

[8]These correspond to a primary market price elasticity of demand attributable to credit spreads of between 1.9 - 3.5 for primary market investors.

[9]See *inter alia* Aggarwal et al. (2002); Benveniste and Spindt (1989); Loughran and Ritter (2002); Nikolova et al. (2020).

[10]Moreover, the syndicate nature of underwriting could encourage collusion even if there were low barriers to entry, as broker-dealers could credibly punish any undercutting underwriter by refusing to join its syndicate; see Hatfield et al. (2020).

as search costs and relationship-building for investors,[11] and certification costs and relationship-building for firms.[12]

I use the model and parameter estimates to simulate counterfactual equilibria that inform the drivers and effects of issuance premiums and volume changes across the cycle. Changes in firms' willingness to pay drive a significant portion of the cyclicality of issuance premiums, as does investor participation and underwriter behavior. Investor heterogeneity plays an important role: without short-term investors endogenously entering when issuance premiums are high, the countercyclicality of issuance premiums would be over 48% more pronounced. Reductions in investor demand in bad times contribute 20% of the magnitude of the cyclicality, while underwriters' favoring of investors contributes another 29%.

To explore investor heterogeneity further, I simulate counterfactual equilibria in which (1) firms face a cash shortfall and demand more capital, and (2) investors face a range of fund outflows. As firms increase their willingness to pay for capital and investors retrench, issuance premiums rise and the composition of investors shifts towards more price elastic investors, leading to smaller drops in overall issuance. However, the presence of short-term investors increases average issuance premiums by 4 basis points ($2.1 million on the median bond) relative to a counterfactual economy with only buy-and-hold investors. The dark side of short-term investor participation is an increase in issuance premiums on average, while the bright side is that their presence helps primary markets absorb large supply shocks.

Finally, I quantify the price impact from large exogenous bond purchases in secondary markets versus primary markets, holding fundamentals fixed. I find that a 5% purchase of a median bond in secondary markets, where investors are relatively inelastic, leads to a drop of over 50 basis points in new issue credit spreads and 3-7% increase in the firm's issuance volumes. However, a purchase of the same size in primary markets, where investors are quite elastic over issuance premiums, has a negligible impact on issuance volumes. These findings could inform the design of Federal Reserve corporate bond purchase programs, such as the Corporate Credit Facilities of spring 2020. My model suggests that targeting the less price-elastic secondary market would have a larger effect on new issuance prices and volumes.

This paper primarily contributes to three strands of literature. First, I add to the body of work

[11] See Duffie et al. (2005) and Henderson and Tookes (2012) for search costs, and Hendershott et al. (2020) for relationships in dealer networks.

[12] See Duarte-Silva (2010); Rajan (1992); and Yasuda (2007). In the equity issuance literature, underwriters may also favor investors to gain valuable pricing information (Benveniste and Spindt [1989]).

on institutional frictions in financial markets by incorporating the firm's perspective. Constraints on participation in primary markets mean firms' costs of capital are sensitive to preferences of a subset of investors (Duffie [2010], Greenwood et al. [2018]).[13] Recent papers have developed tools to estimate investor demand systems for securities given institutional frictions (Bretscher et al. [2020], Gabaix and Koijen [2020], Koijen and Yogo [2019],Koijen et al. [2021]). I build on this work by estimating investor demand at *issuance* while endogenizing firm supply of corporate bonds and incorporating investor heterogeneity (Chodorow-Reich et al. [2021] , Coppola [2021], Greenwood and Vayanos [2010], Greenwood and Vayanos [2014], Li and Yu [2021], Vayanos and Vila [2021]).[14]

Second, I contribute to a vast literature on securities issuance pricing in both corporate bonds and equities.[15] My paper adds to papers on corporate bond underpricing, including Bessembinder et al. [2021], Cai et al. [2007], Goldstein et al. [2019],Goldstein et al. [2021], Nikolova et al. [2020], and Wang [2021], (see Cai et al. [2007] for a survey), by documenting the countercyclical pattern of issuance premiums.[16] In addition, I add to both this corporate bond issuance literature and the body of work studying underpricing in equity issuance (e.g.,Aggarwal et al. (2002), Benveniste and Spindt [1989],Cornelli and Goldreich [2003],Henderson and Tookes [2012], Rock [1986]; see Ljungqvist [2007] for a survey) by developing a framework to quantify the effects of the security underpricing on investor demand and issuance.

Third, my findings complement a broad literature that documents frictions in secondary markets for corporate bonds by relating them to primary markets. Corporate bonds are traded over-the-counter and are subject to search costs and dealer holding costs (Bao et al. [2011], Duffie et al. [2005], Duffie et al. [2007],Gavazza [2016],Goldstein and Hotchkiss [2020], Lagos and Rocheteau [2009]) that decrease liquidity, increase the costs of shorting (Asquith et al. [2013]), and increase

[13]This could exacerbate the effects of limited risk-bearing capacity on asset prices (Adrian and Shin [2014], Adrian et al. [2017], He and Krishnamurthy [2013], Manconi et al. [2012]).

[14]I build on work by Massa et al. (2013) and Zhu (2021), which document that a firm's bondholders can affect issuance decisions, by studying the equilibrium effects. My estimation of demand elasticities for different investor types contributes to the literature assessing central bank policies, particularly policies regarding corporate bond purchases (Boyarchenko et al. [2020], Falato et al. [2020], Flanagan and Purnanandam [2020], Gilchrist et al. [2020], Halling et al. [2020], Haddad et al. [2021], Haddad et al. [2022]).

[15]Agency issues between underwriters and firms have been documented in many papers including Jenkinson et al. (2018), Loughran and Ritter (2002), Ritter and Welch (2002) for equity markets, and Flanagan et al. (2019) and Nikolova et al. (2020) for corporate bond markets.

[16]U.S. Treasury bonds are known to have an on-the-run liquidity premium (Krishnamurthy [2002], Vayanos and Weill [2008]); the issuance premium I document is in the opposite direction.

expected returns (Amihud and Mendelson [1986]).[17] Moreover, dealers have relationship networks (Hendershott et al. [2020]) that benefit repeat investors (Di Maggio et al. [2017], O'Hara et al. [2018]). I quantify how the combination of these phenomena, when present in primary markets, further impact firms' costs of capital.[18]

The rest of the paper is organized as follows. Section 2 describes the data and institutional background of corporate bond issuance. Section 3 describes empirical facts characterizing the corporate bond market. Section 4 introduces the model, and Section 5 presents the estimation strategy and the parameter estimates. Section 6 discusses results and counterfactual analyses. Section 7 concludes.

# 2 Data and background

## 2.1 Data

For the empirical analysis, I compile a novel and comprehensive dataset on corporate bond issuance. New data comes from Informa Global Markets (IGM) and Credit Flow Research (CFR). These industry data providers survey broker-dealers daily to collect bond issuance information including order book size, the range of credit spreads announced during the issuance process, and adjustments to bond issuance size and credit spreads. I merge this data with Mergent FISD to get bond-level data including ratings, tenor, maturity, and seniority.[19] I further merge with NAIC bond-investor purchase data to identify insurance investors; with Enhanced TRACE data to track trading in the first days post-issuance; and with holdings data from Thomson Reuters eMaxx to estimate secondary market demand.[20]

Using the Enhanced TRACE data, I compute issuance premiums as the difference between the new issuance credit spread and the trade-weighted average of sell-side trades completed by the

[17] Moreover, because of post-crisis shifts in regulation, liquidity provision in corporate bond markets has become costlier (Dick-Nielsen and Rossi [2019]) and has moved away from bank-affiliated dealer capital ( Bessembinder et al. [2018], Bao et al. [2018], Choi and Huh [2019], Duffie [2012]), increasing the importance of non-bank dealers such as primary market investors.

[18] While models of corporate debt typically abstract away from changes in issuance costs (He and Milbradt [2014], Leland and Toft [1996]), my paper quantifies how bond issuance yields vary across the cycle beyond secondary market fluctuations (Gilchrist and Zakrajšek [2012]).

[19] Because IGM/CFR data does not have bond- or issuer-level identifiers that are common to Mergent FISD, I do a combination of fuzzy string matches and hand-matching to merge the bond-level datasets.

[20] I include only fund-years that hold at least 100 unique bonds. For the bonds in my sample, the eMAXX data covers about 50% of holdings at quarter end.

end of the first day post-issuance.[21] Because bonds are issued close to par, this measure represents firms' incremental annual cost of capital. Issuance premiums are 8 basis points on average on a yield basis, and in aggregate, cost the real sector \$3.5 billion per year.[22]

I use the order book variable from IGM/CFR as the metric for primary market investor demand. This measures the total quantity demanded by all investors at the new issue yield for each bond. For the share of short-term investors in each bond issue, I compute the ratio of total sell orders in the secondary market in the first week following issuance (as reported by Enhanced TRACE) to the original issuance size of the bond (as reported by FISD). The share of long-term investors is one minus the short-term share.

I merge issuer-level data with Compustat to get firm characteristics, with CRSP to get issuance day stock returns, and with WRDS Bond Returns for monthly average bid–ask spreads. From Mergent FISD, I include all USD corporate bonds issued by firms with at least one credit rating that are over \$100 million at issuance, are not issued in exchange, and report tenor, credit spread and size at issuance.[23] For the core analysis, I include only those bonds issued between September 2010 - June 2020 because the data on order books is most comprehensive then.[24] For my primary demand estimation analysis, I include the 3,433 primarily investment grade US dollar corporate bonds for which I have issuance premium, underwriter and order book information. See Table 1 for summary statistics of the full sample of FISD bonds and issuers versus the estimation sample.

## 2.2 Background: corporate bond underwriting process

Corporate bonds are priced as a credit spread to the risk-free rate, where the risk-free rate is that of the on-the-run U.S. Treasury bond whose duration matches the duration of the bond. A group of broker-dealers leading the underwriting process conducts a price discovery process over the span of one day. The underwriters are compensated with a fee that is a flat percentage of the total

[21] I omit extreme values with changes of greater than 300 basis points.

[22] Aggregate costs to the real sector are computed as the sum across bonds of non-discounted incremental coupon cost. The first-day excess price-based return relative to the Bloomberg Aggregate Bond Index as proposed in Cai et al. (2007) averages 52 basis points in my sample, significantly larger than the average bid-ask spread of 36 basis points. I report alternative metrics in Internet Appendix A.3.

[23] I exclude financial, utility, and sovereign issuers, and convertible bonds, capital impact bonds, community investment bonds, and PIK securities.

[24] IGM/CFR has recorded order book information for 93% of the investment grade bonds and 19% of the high yield bonds in this sample.

Table 1: Primary market bonds: sample summary statistics

| | Count | Mean | Std Dev | Percentile 1 | Median | Percentile 99 |
|---|---|---|---|---|---|---|
| Full sample | | | | | | |
| Credit spread (bps) | 4426 | 171 | 115 | 32 | 140 | 582 |
| Coupon | 4426 | 3.68% | 1.39% | 0.88% | 3.62% | 7.62% |
| Yield to maturity | 4424 | 3.72% | 1.39% | 0.91% | 3.67% | 7.75% |
| Amount ($MM) | 4426 | 798 | 666 | 250 | 600 | 3000 |
| Tenor (years) | 4426 | 12.3 | 9.7 | 2.0 | 10.0 | 40.0 |
| Credit rating | 4426 | 14.8 | 2.8 | 7.0 | 15.0 | 22.0 |
| Crowdedness ($Bn) | 4403 | 3.0 | 3.6 | 0.0 | 1.9 | 17.0 |
| Order book ($Bn) | 3699 | 3.0 | 2.2 | 0.5 | 2.4 | 11.0 |
| Issuance premium (bps) | 4389 | 6.4 | 9.0 | -9.3 | 4.5 | 43.7 |
| Pct sold first week | 4426 | 0.22 | 0.15 | 0.02 | 0.19 | 1.00 |
| Estimation sample | | | | | | |
| Credit spread (bps) | 3433 | 146 | 80 | 32 | 133 | 425 |
| Coupon | 3433 | 3.42% | 1.13% | 0.88% | 3.45% | 5.95% |
| Yield to maturity | 3433 | 3.46% | 1.12% | 0.91% | 3.48% | 5.98% |
| Amount ($MM) | 3433 | 821 | 636 | 250 | 600 | 3000 |
| Tenor (years) | 3433 | 12.6 | 9.5 | 2.0 | 10.0 | 31.0 |
| Credit rating | 3433 | 15.4 | 2.2 | 12.0 | 15.0 | 22.0 |
| Crowdedness ($Bn) | 3433 | 3.3 | 3.7 | 0.0 | 2.1 | 17.5 |
| Order book ($Bn) | 3433 | 3.0 | 2.1 | 0.5 | 2.4 | 10.8 |
| Issuance premium (bps) | 3433 | 5.5 | 7.9 | -9.3 | 4.2 | 37.0 |
| Pct sold first week | 3433 | 0.21 | 0.15 | 0.02 | 0.18 | 1.00 |

*Source:* Mergent FISD, IGM, CFR, eMaxx, and Enhanced TRACE.
*Note:* This table reports summary statistics for (1) the full sample of bonds, and (2) the estimation sample. "Credit rating" is numerically coded as per Table IA.11 in the Internet Appendix. "Crowdedness" is computed as the total volume of bonds issued by other firms, underwritten by other broker-dealers on the same day. "Issuance premium" is computed as the difference between the new issuance credit spread and the trade-weighted average of sell-side trades completed by the end of the first day post-issuance. I omit extreme values with changes of greater than 300 basis points. "Pct sold first week" is the ratio of total sell orders in the secondary market in the first week following issuance (as reported by Enhanced TRACE) to the size of the bond at issuance (as reported by FISD).

amount issued.[25] In each of four rounds, the underwriters announce a potential credit spread at

[25]The total percentage fee firms pay for bond issuance to the underwriting group varies very little in the cross section and over time. See Figure IA.1 in the Internet Appendix for bond issuance fees over time.

which the new bond could be priced, and observe the quantity demanded from investors at that credit spread.[26] While these quantities are not transacted or legally binding, investors have an incentive to report true demand because issuance is a repeated game. Once the final credit spread is set, the underwriters allocate bonds to investors who can then trade.[27]

Underwriters have the final say in the new issuance credit spread. At this final credit spread, order books as reported to IGM/CFR typically exceed the bond volume supplied by the firm. This leads to oversubscription (where the ratio of quantity demanded to quantity supplied is greater than one). As reported in Table 1, order books are regularly over 2–3 times oversubscribed.[28] This suggests that issuance credit spreads are commonly set above a competitive equilibrium, where supply would equal demand.

Indeed, I find suggestive evidence that broker dealers are subject to agency issues in underwriting bonds. Specifically, underwriters have smaller order books when they are both the underwriter and the issuer and thus internalize the costs of capital, versus when they are underwriting a comparable bond for a different issuer (see Figure IA.3 in the Internet Appendix). I interpret this as the underwriter using discretion in setting credit spreads higher than competitive equilibrium (where order books would equal quantity supplied) in order to extract rents from issuers to give to investors.[29] This is consistent with papers that show evidence that broker-dealers have discretion in underwriting (Benveniste and Spindt [1989], Nikolova et al. [2020]). I will come back to this institutional detail when modeling the underwriter's problem.

# 3 Stylized facts

In this section, I present stylized facts about the primary market for corporate bonds. First, I describe the motivating fact that issuance premiums are countercyclical. Next, I show evidence

[26]In equity markets, underwriters may sell up to 15% more shares than initially agreed upon in a "greenshoe option", or "over-allotment option". Fewer than 0.3% of the bond issuance sample have an official over-allotment option reported; however, Bessembinder et al. (2021) report that bond issues in which underwriters do over-allocate bonds have a median of $20 million over-allocated, amounting to roughly 3% of the median issuance size.

[27]While U.S. Treasury bonds are known to trade in on a "when-issued" basis between announcement and issuance, in this paper I focus on trading after issuance. Indeed, fewer than 0.02% of trades for bonds in my sample are traded on a "when-issued" basis.

[28]Figure IA.2 in the Internet Appendix shows the distribution of oversubscription for newly issued bonds in my sample.

[29]An alternative story is that underwriters have more information about self-led bond issuances; I check if this is the case by comparing a proxy for price uncertainty, the relative range of credit spreads announced throughout the span of a bond issuance, for self-led versus comparable deals in Table IA.2 in the Internet Appendix. I find no significant difference in price uncertainty between self-led and comparable deals.

of differences both between primary and secondary market investors, and within primary market investors. Taken together, these facts suggest that corporate bond issuance markets are to some extent segmented from secondary markets, making firms' costs of bond capital subject to shifts in supply and demand in primary markets.

### 3.1 Issuance premiums rise in bad times

I find that issuance premiums are countercyclical. The time-series plot in Figure 1 shows that during the GFC of 2008 and the COVID-19 crisis of 2020, there was a spike in weekly average issuance premiums. This further increases firms' costs of capital in bad times beyond the well-documented rise in credit spreads reflected in secondary markets (Gilchrist and Zakrajšek [2012]). Higher yields (lower prices) at issuance are often attributed to information asymmetries or price uncertainty (Beatty and Ritter [1986], Rock [1986]), both of which may increase in bad times. However, issuance premiums are similarly distributed across all ratings for investment-grade issuers, suggesting that uncertainty around bond value (which decreases with credit rating) is unlikely to be the only driver for investment grade bonds.[30]

To more formally test the impact of issuer and bond characteristics on issuance premiums, I regress the issuance premium on a proxy for economic activity, the Chicago Fed National Activity Index (CFNAI)[31] as follows:

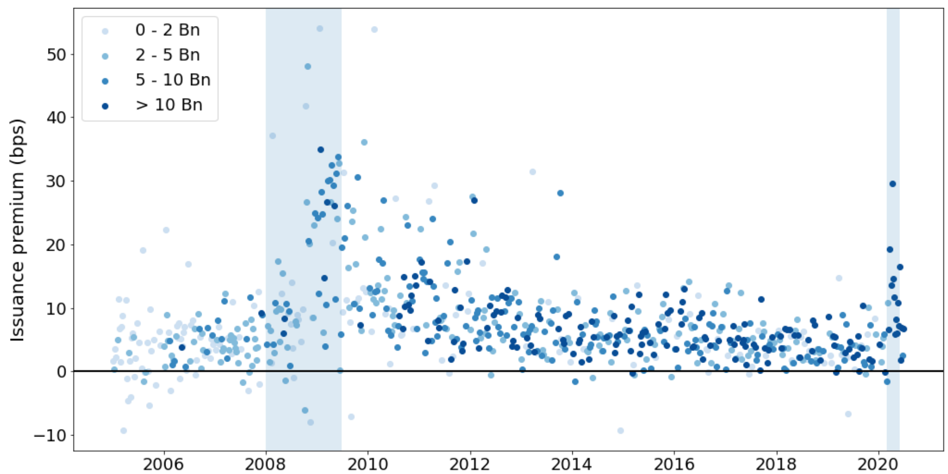
$$IssPrem_{ubft} = \beta EconActivity_t + X_{bft}\gamma + \epsilon_{ubft}, \tag{1}$$

where $b$ indicates bond, $f$ is for each firm, $u$ is for underwriter, and $t$ is for day. See Table 2 for the results. The first column is an OLS regression of issuance premium on the CFNAI index, controlling for issuer credit rating, bond size, and bond tenor. The coefficient indicates a one standard deviation deterioration in macroeconomic conditions corresponds to one basis point increase in issuance premiums. This represents 12% of the magnitude of fluctuations in the Gilchrist-Zakrajšek

[30]See Figure IA.4 in the Internet Appendix. Moreover, equity IPOs, which are considered to have greater information sensitivity (Myers and Majluf [1984]), do not exhibit a similar cyclical pattern in underpricing. Equity IPO underpricing instead rises in hot markets: Figure IA.5 in the Internet Appendix reports a time series plot of IPO underpricing. See Loughran and Ritter (2004) for a discussion. Underpricing of seasoned offerings of equities (SEOs) is positively related to IPO underpricing; see Corwin (2003) for a discussion on why SEO underpricing has increased over time, including changes to regulation and to the underwriter business model.

[31]The measure is based on 85 existing indicators that use data on variables such as production, income, employment, consumption, and sales. It is constructed to be mean zero with a standard deviation of one, where positive values indicate growth rates above trend.

Figure 1: First-day credit spread changes




*Source:* Enhanced TRACE and Mergent FISD.
*Note:* I plot the time series of weekly averages in issuance premium for newly-issued bonds. The issuance premium is defined as the credit spread difference, in basis points, between new issue credit spread and the volume-weighted average credit spread on sell trades reported in TRACE completed by end of the first day following issuance. Shaded regions are January 2008–June 2009 and March–May 2020. Darker dots indicate weeks with greater issuance volumes.

(GZ) credit spread as measured in Gilchrist and Zakrajšek (2012), estimated over the same sample period in the last column.[32]

In the column (2), I add issuer characteristics – prior quarter leverage, cash to assets, and profitability – as issuer quality is known to vary across the credit cycle (Greenwood and Hanson [2013]). In Regression (3), I test how much issuance premiums can be explained by an increase in information asymmetry in bad times. As a proxy for information asymmetry between underwriters and investors (Benveniste and Spindt [1989]), I use the range of credit spreads provided for each bond issuance as a percentage of the final credit spread.[33] I also include underwriter fixed effects to absorb any time-invariant variation in underwriter sophistication. Regression (4) tests if the pattern

[32]The GZ credit spread is calculated monthly as the arithmetic average of credit spreads on outstanding bonds in any given month. Given the correlation between GZ and CFNAI is typically higher, this coefficient illuminates how the regression that is conditional on issuance generally understates the cyclicality of the cost of capital.

[33]Wang (2021) interpret the range of credit spreads at issuance as informative about uncertainty around price.

Table 2: Issuance premiums are higher in bad times

| | (1) Baseline | (2) Issuer controls | (3) UW Info | (4) Firm FE | (5) GZ spread (bps) |
|---|---|---|---|---|---|
| Economic activity | -1.023*** | -1.069*** | -1.070*** | -1.036*** | -8.656*** |
| | (0.0929) | (0.0945) | (0.0964) | (0.0656) | (0.205) |
| Issuance range / spread | | | -0.167 | -0.297* | |
| | | | (0.142) | (0.151) | |
| Credit rating (log) | -14.35*** | -16.02*** | -16.07*** | -14.41*** | |
| | (0.446) | (0.468) | (0.478) | (1.759) | |
| Bond size (log) | 0.771*** | 0.831*** | 0.860*** | 1.162*** | |
| | (0.102) | (0.109) | (0.105) | (0.146) | |
| Tenor (years) | -0.0926*** | -0.0933*** | -0.0928*** | -0.0722*** | |
| | (0.00605) | (0.00617) | (0.00632) | (0.00445) | |
| Debt / assets | | -2.791*** | -2.739*** | -4.568*** | |
| | | (0.550) | (0.577) | (1.418) | |
| Cash / assets | | 1.196 | 0.907 | 7.230*** | |
| | | (0.785) | (0.771) | (2.569) | |
| Operating profit / assets | | 32.66*** | 31.91*** | 23.15*** | |
| | | (6.338) | (6.403) | (6.459) | |
| Firm FE | | | | ✓ | |
| Underwriter FE | | | ✓ | ✓ | |
| Observations | 17134 | 17134 | 17113 | 17074 | 24598 |
| R-squared | 0.136 | 0.141 | 0.149 | 0.479 | 0.0673 |

*Notes:* Dependent variable in regressions (1) through (4) is issuance premium, measured in basis points. Dependent variable in regression (5) is the GZ spread, as defined on a monthly basis in Gilchrist and Zakrajšek (2012). Independent variable of interest is economic activity as measured by the CFNAI monthly index, collected from the Chicago Federal Reserve, which is designed to be mean zero with a standard deviation of one. Bond controls include issuer credit rating (log), size of bond (log), and tenor in years. Firm controls in regressions (2) through (4) include the prior quarter cash to total assets ratio, total debt to total assets ratio, and operating profit to total assets ratio. Regressions (3) and (4) control for bond-level issuance range as a proportion of the final issuance credit spread. Regressions (3) and (4) include underwriter fixed effects. Regression (4) includes firm fixed effects. Observations are at the bond-underwriter level. Standard errors clustered at the underwriter level.

is driven by changes in the composition of issuers by adding firm fixed effects.[34] None of these

[34] Adding firm fixed effects can also test the possibility that firms have more information than investors and thus

specifications changes the countercyclical pattern significantly.

In summary, I find that issuance premiums are countercyclical, and that this pattern is unlikely to be driven entirely by changes in fundamentals or information asymmetries.[35] The finding is also robust to various specifications with different proxies for the cycle, including the GFC and COVID-19 periods or the VIX (see Table IA.3 in the Internet Appendix).[36] Moreover, this specification underestimates the magnitude of the pattern because of selection bias: by conditioning on issuance, I omit firms that opt out when spreads are too high. I will address this selection problem when modeling the firm's supply of bonds in Section 4.

Variation in secondary market credit spreads thus underestimate the countercyclicality of firms' costs of capital. Higher borrowing costs in bad times can deter issuance, dampening investment or reducing corporate liquidity. Indeed, after issuance premiums are realized in the day following a capital raise, higher issuance premiums correspond to lower cumulative abnormal returns on the issuing firm's stock price.[37] Moreover, this suggests some segmentation between primary and secondary markets, leaving firms subject to supply and demand shocks above and beyond fluctuations in secondary market prices. I discuss further evidence of partial segmentation below.

## 3.2 Primary market investors are different and trade in larger size

Next, I find that participants in primary and secondary markets are not the same along observable characteristics. Primary market investors buy in bigger sizes and tend to be larger funds. In Figure 2a, I plot the distribution of trade sizes in the primary and secondary markets in the first 100 days following issuance, as reported by Enhanced TRACE. The distribution of purchase sizes in primary markets is larger than that in secondary markets.

Moreover, I show a size discrepancy between primary and secondary market insurance in-

use underpricing as a signal of their type (Ibbotson [1975]).

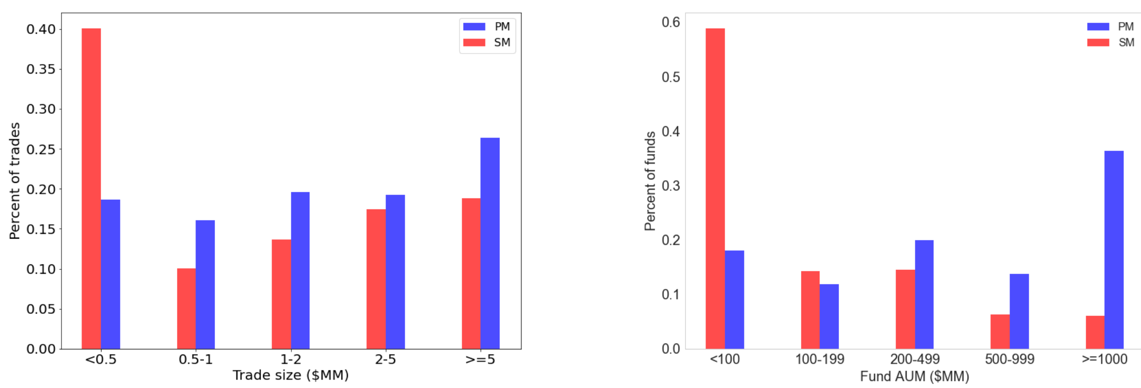
[35]Note that I am not ruling out information asymmetries as a potential driver of fluctuations in issuance premiums; but I am leaving the exercise of empirically disentangling how much information affects issuance premiums for further research.

[36]A potential alternative story is that the issuance premium is a constant percentage of total credit spreads, and the result here is simply a mechanical consequence of the well-known countercyclicality of credit spreads. However, I find in Table IA.4 that the same pattern of countercyclicality applies to the ratio of issuance premium to total credit spread. Another alternative story is that there is higher trading volatility in bad times. In unreported results, I add the standard deviation of prices within the first week following issuance as a control in the baseline regression, and the pattern still persists.

[37]Abnormal returns are computed as the cumulative return in the day of issuance and the day following issuance relative to the cumulative return of the S&P Index over the same time period. See Table IA.5 in the Internet Appendix for details.

vestors. I use the NAIC regulatory data and follow Nikolova et al. (2020) to identify primary market investments by insurers as any purchases on the offering date from an underwriter at the offering price. In Figure 2b I plot the distribution of assets under management for insurance funds that purchase in the primary market versus those that purchase only in the secondary market, and find the former tend to be larger.

Figure 2: Size differences between primary and secondary market investors




(a) Trade size comparison (TRACE)

(b) Insurer size comparison (NAIC)

*Source:* Enhanced TRACE and NAIC.
*Note:* The first panel shows the distribution of volumes for primary market versus secondary market "buy" trades (in the first 100 days), as reported by Enhanced TRACE for corporate bonds issued since 2000, cleaned by the Dick-Nielson filter (Dick-Nielsen [2014]). The second panel shows the distribution of the total assets under management for insurance investors (from NAIC) that participate in only (1) primary markets for corporate bonds in my sample (in blue) and (2) secondary markets for corporate bonds in my sample (in red).

I expand the scope to include all insurance, mutual, and pension funds using eMAXX quarterly holdings data in the first quarter of a bond's life in Table 3.[38] I proxy for primary market purchases by considering the subset of bonds issued within the last seven days of quarter end.[39] I find that

[38]Insurance investors, mutual funds, and pension funds make up about 50% of bond holdings. Other investors include ETFs, hedge funds, banks, finance companies, and the rest of the world. Figure IA.6 in the Internet Appendix shows the holders of corporate bonds based on the Federal Reserve Flow of Funds data. U.S. hedge funds are incorporated in "households", and non-U.S. hedge funds are incorporated in "rest of the world". In Q4 2020, all hedge funds held $1.9 trillion of corporate and foreign bonds; 23% of the holdings are domestic hedge funds. See `https://www.federalreserve.gov/releases/efa/efa-hedge-funds.htm` for more information.

[39]To see if this subset of bonds is significantly different from bonds issued on other days within quarter, I report

indeed, across these three fund types, only a subset of investors participate in primary markets, and this subset of funds is significantly larger in assets under management than their counterparts that participate in only secondary markets.[40]

Table 3: Primary market participants are larger than secondary market participants

| | Num unique funds | Average AUM (bn) | Median AUM (bn) |
|---|---|---|---|
| PM mutual funds | 2781 | 1.48 | 0.20 |
| SM mutual funds, not in PM (46%) | 2398 | 0.65 | 0.08 |
| PM insurance funds | 1937 | 2.15 | 0.21 |
| SM insurance funds, not in PM (52%) | 2056 | 0.26 | 0.03 |
| PM pension funds | 259 | 1.18 | 0.25 |
| SM pension funds, not in PM (63%) | 450 | 0.58 | 0.14 |

*Source:* eMAXX.
*Note:* This table reports the mean and median of most recent reported assets under management (in billions) for mutual funds, insurers, and pension funds that hold bonds in my sample in the first quarter end following issuance (at FUNDID level). I classify a fund as a primary market investor if they report holding the bond within seven days of issuance. I classify a fund as a secondary market investor if they hold the bonds in my sample but are not classified as a primary market investor. The percentage in parentheses reports the share of individual funds that hold bonds in the secondary market but not in the primary market.

Why might primary and secondary market investors differ? In the presence of search costs and potential information asymmetries (Benveniste and Spindt [1989], Cornelli and Goldreich [2001]), underwriters benefit from having repeat relationships with investors, and tend to allocate to investors with whom they have profitable trading relationships (Nikolova et al. [2020]). A finite number of investor relationships would suggest that primary market participants are a subset of all investors and are more likely to be larger funds. I find both of these to be the case.

## 3.3 Two types of primary market investors

Trading activity is concentrated in the days immediately following issuance, after which bonds trade rarely.[41] This separates primary market investors into two types. Most primary market in-

in Table IA.6 in the Internet Appendix the distributions of various issuer and bond characteristics in the full sample versus those for bonds issued in the last seven days of the quarter.

[40]This finding is robust to defining the primary market as the subset of bonds issued within the last 1, 3, or 5 days of quarter end.

[41]This is consistent with work by Bessembinder et al. (2021), Cai et al. (2007), Goldstein and Hotchkiss (2020), and Nikolova and Wang (2022), who also find that most trading activity occurs within the first few weeks after issuance.

vestors are "buy-and-hold" types that rarely, if ever, participate in secondary markets. However, a small proportion of investors (around 20%) "flip" bonds within the first few days following issuance. These investors earn the short-term profit of the issuance premium. While there is some uncertainty in the level of the issuance premium, this proves to be a profitable investment strategy for short-term investors with a Sharpe Ratio consistently above 2.[42]

To illustrate this point, in Figure 3 I plot the timing of the share of all sell orders for a set of 10-year bonds issued in 2010. There is a spike in the share of sell trades in the first day following issuance (the "flippers"), followed by comparatively small trading volumes for the remaining life of the bond.[43]

Indeed, following the initial flurry of activity, corporate bond investors tend to hold the same bond over time. By the second quarter end following issuance, 84% of holdings are by investors that held the bond in the previous quarter; for every quarter thereafter, the proportion is well over 90%.[44] This dichotomy in post-issuance behavior suggests a difference in preferences among investors, likely arising from heterogeneous funding structures and institutional needs.

I find that the share of short-term investors varies across bond issuances. I compute the share of short-term investors as the ratio of total secondary market sales reported in the first week following issuance in Enhanced TRACE to the total size of the bond. For bonds issued when economic activity is one standard deviation below average, the share of short-term investors is over 21% on average, versus 16% when economic activity is at least one standard deviation above average.[45] In

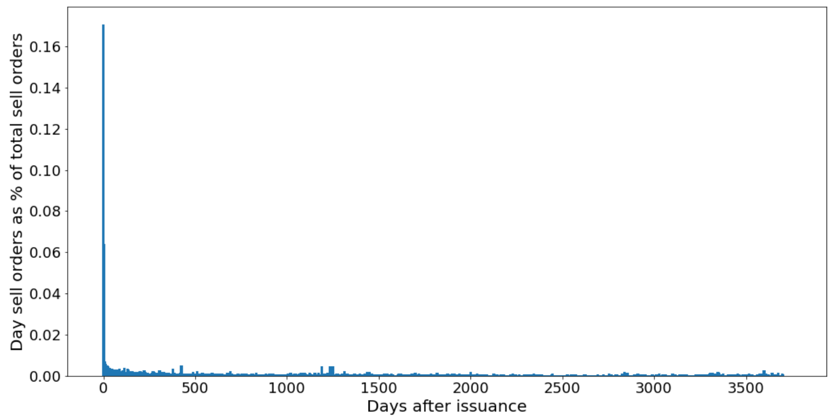
[42]To capture how attractive investing in primary markets is, I compute the Sharpe Ratio as follows. First, I construct a fund that begins the year with one dollar and invests the full amount of the fund every day into the primary market for corporate bonds and then sells the full amount the next day. If there are multiple bonds issued in a given day, then the funds are split equally among all issued bonds. If there are no bonds issued in a given trading day, then the funds are invested at the daily risk free rate. I compute the daily risk free rate using the 1-month US T-bill rate for each day. I compute excess returns by subtracting the daily risk free rate. I find an average annualized Sharpe Ratio of 4.8 for this investment strategy for the period 2005-2020. In annualizing the daily Sharpe Ratio, I account for up to 20% in serial correlation of excess returns as per Lo (2002).

[43]This behavior is consistent across ratings categories; see Figure IA.7 in the Internet Appendix.

[44]I compute the percentage of investors with reported holdings that also held that bond in the previous quarter and report the median across all bonds over the life of the bond in Figure IA.8 in the Internet Appendix. There is some variation across fund types: insurance funds on average hold bonds for over 8 quarters, while the average holding period for mutual funds and pension funds is 4–5 quarters. See Table IA.7 in the Internet Appendix for a summary of the investment behavior of the three fund classes. While the holdings data does not include all hedge fund holdings, aggregate data from the Flow of Funds shows a positive correlation between the share of short-term investors in primary markets and the share of overall corporate bond holdings attributable to hedge funds, suggesting that hedge funds are more likely to be short-term investors (see Figure IA.9 in the Internet Appendix). This is consistent with interviews with industry participants.

[45]A similar comparison holds if I consider bonds issued on days when the VIX is below the 25th percentile versus

Figure 3: Evolution of sell trades for all 10-year bonds issued in 2010




*Source:* Enhanced TRACE.
*Note:* This figure reports the volume share of "sell" trades for each day in event time since issuance. It includes secondary market trades for USD non-financial corporate bonds issued in 2010 with initial tenor of 9–11 years. The $y$-axis shows the average across all bonds of the share of each day's sell orders as a percentage of total volume of sell orders over the life of the bond (defined as trades between 0 and 4000 days following issuance).

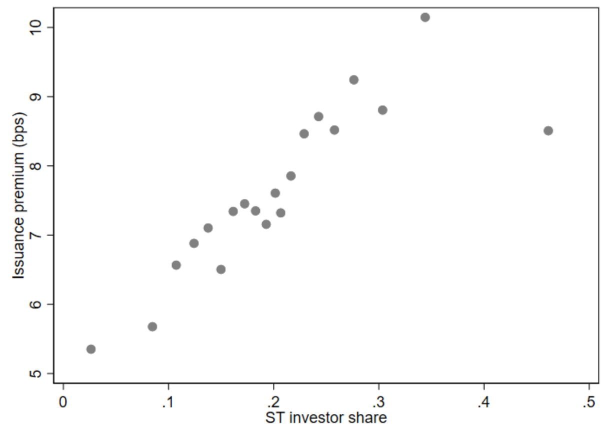
addition, in Figure 4 I observe a positive correlation between issuance premiums and the share of short-term investors. This correlation holds even when controlling for firm, underwriter, and year fixed effects. Intuitively, short-term investors directly profit from the issuance premium, so they participate more when issuance premiums are higher.[46] Higher short-term investor participation also correlates with holdings by more and smaller funds at the first quarter end after issuance, suggesting these investors perform a search and intermediation function in this market (see Figure 5).

In summary, this section highlights key features of corporate bond issuance that suggest some segmentation between primary and secondary markets: issuance premiums are positive and vary over the cycle, different investors participate in primary and secondary markets, and the majority of primary market investors buy and hold and thus do not participate in secondary markets. Moreover, I find that fewer buy-and-hold investors participate in bad times. Together, these facts suggest that

above the 75th percentile. See Appendix B for further discussion.

[46]This relationship is similar to the well-documented correlation between IPO underpricing and flipping activity. See, for example, Aggarwal (2003).

Figure 4: Higher issuance premiums $\iff$ more short-term investors




*Source:* eMAXX, Enhanced TRACE, and Mergent FISD.
*Note:* The figure shows a binned scatter plot of the share of the bond sold within the first week on issuance premium, conditional on the short-term share being between 0 and 1. It includes controls for issuer credit rating, bond tenor, bond size (log), and U.S. Treasury yields, as well as year, firm, and underwriter fixed effects.

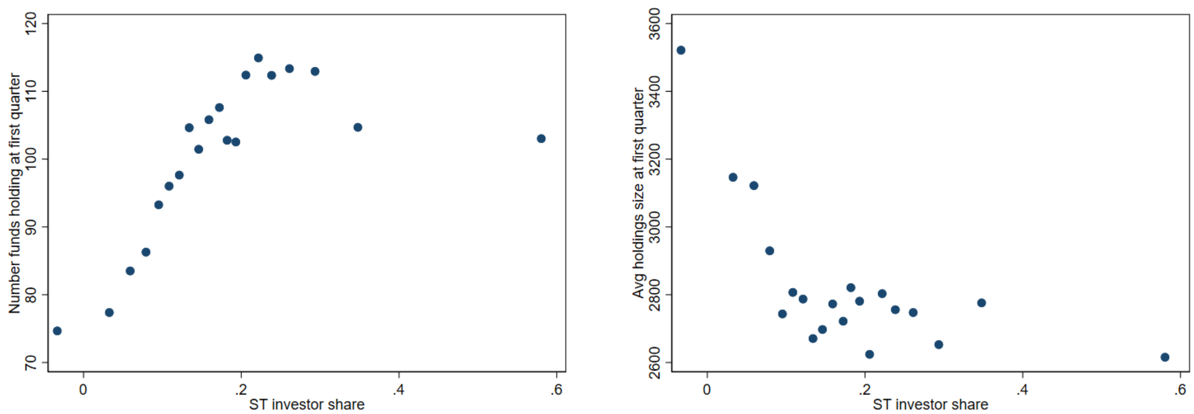
the preferences and decisions of agents in primary markets may have important implications for issuance outcomes across the cycle. In the next section, I present the model that I will use to evaluate the magnitudes of these effects.

# 4 Model

In this section, I develop a structural model of the corporate bond issuance market that predicts equilibrium firm supply of new bonds, investor demand for bonds in the primary market, and underwriter issuance decisions.

The institutional details in Section 2 and stylized facts in Section 3 motivate the model's assumptions. In particular, (1) there are two components of credit spreads that make up firms' costs of capital; (2) there is some segmentation between primary and secondary markets; (3) primary market investors exhibit two mutually exclusive behaviors: selling immediately into the secondary market, or buying and holding; and (4) underwriters choose final credit spreads by sharing rents between investors and issuers.

Figure 5: Short-term investors correlate with more and smaller fund holdings




(a) Number of distinct holdings at Q1 end

(b) Size of holdings at Q1 end

*Source*: eMAXX and Enhanced TRACE .
*Note:* The figures show a binned scatter plot with the share of the bond sold within the first week on issuance premium, winsorized at the 1% level on the x-axis. The left hand side figure plots on the y-axis the number of unique funds that hold the bond at the end of the quarter of issuance. The right hand side figure plots on the y-axis the average size of each investor's holding of the bond at the end of the quarter of issuance. Both plots residualize issuer and year fixed effects, and include only bonds issued more than eight days prior to quarter end.

## 4.1 Model setup

There are four types of agents in my model: firms $f$, two types of investors $h \in \{ST, LT\}$ (where $ST$ stands for "short-term" and $LT$ stands for "long-term"), and an underwriter $u$. Firms choose how much to raise in bond markets, investors choose how much to demand in the primary market, and an underwriter (dealer) chooses the final credit spread on new securities to split rents between issuers and investors.

The timing of events is as follows. First, firms choose a quantity $Q^S$ to issue of a bond $b$ in market $t$ based on an underlying supply curve. Second, primary market investors (indexed by $i$) optimally choose an amount $z_{ib}$ to purchase based on credit spreads and bond characteristics $X_b$. In aggregate, primary market investors have demand $Q^D$ for bond $b$. Finally, the underwriter chooses the credit spread $r_b$ relative to the risk-free rate at which to price the new bond, subject to sufficient investor demand and firm participation. Uppercase $Q$ denotes dollar amounts of bonds, in millions, and lowercase $q$ indicates the corresponding logged amounts. All proofs are in the

Internet Appendices.

### 4.1.1 Firms' supply of bonds

Each firm has an underlying supply of bonds that depends on the firm's characteristics, macro fundamentals, and the cost of capital it expects to receive in the market. A firm's cost of capital for a given bond $b$ is the risk-free rate plus the credit spread. The credit spread has two components:

$$r_b = r_b^{PM} + r_b^{SM}, \tag{2}$$

where $r_b^{PM}$ is the issuance premium and $r_b^{SM}$ is the expected credit spread for the bond once it begins trading in secondary markets.

The firm's latent supply of bonds is given by

$$q^* = \gamma_r r_b + \gamma_Z Z + e, \tag{3}$$

where $\gamma_r$ is the firm's sensitivity to credit spread $r_b$, $\gamma_Z$ is the vector of loadings for each of the firm and macro characteristics $Z$, and $e$ is a normally distributed random shock to its supply of bonds.

The firm faces fixed costs to issue securities (see, for example, Bolton et al. [2013]). Thus, it will only issue if its latent demand for capital $q^*$ is above a threshold $C$; that is,

$$q^S = \begin{cases} q^* & \text{if } q^* > c, \\ 0 & \text{otherwise,} \end{cases} \tag{4}$$

where $c = \ln C$.

Based on a standard tobit, the expected bond issuance supply for firm $f$ is

$$E[q^S|Z, q^* > c] = \gamma_r r + \gamma_Z Z + \sigma\Big[\frac{\phi((\gamma_r r + \gamma_Z Z - c)/\sigma_e)}{\Phi((\gamma_r r_f + \gamma_Z Z - c)/\sigma_e)}\Big]. \tag{5}$$

The expected amount issued conditional on issuing is a linear combination of credit spreads, firm characteristics, and an additional term that accounts for selection bias into issuing. See Appendix B for details.

Finally, I derive from (3) an expression for $\bar{r}_b$, the highest credit spread at which a firm will issue amount $q^S$:

$$\bar{r}_b = \frac{1}{\gamma_r}\big[q^* - \gamma_Z Z - e\big]. \tag{6}$$

This will be useful when simulating counterfactual equilibria.

If firms prefer lower credit spreads ($\gamma_r < 0$), then they will have a higher reservation credit spread when they have a greater propensity to issue: that is, when $e$ (shock to supply of capital) is higher or when the realization of $\gamma_Z Z$ is greater (worse fundamentals).

#### 4.1.2 Investors' demand for bonds

Investors $i$ of type $h \in \{ST, LT\}$ choose to allocate each dollar to the bond $b$ in market $t$ that maximizes expected CARA utility. For investor $i$, the problem is

$$\max_{b \in \{0,1,\dots,B+1\}} U_{ibt} = E\Big[-\exp\Big(-\frac{1}{k_h} R_{hbt}\Big)\Big], \tag{7}$$

where investors have absolute risk aversion $1/k_h$, so higher $k_h$ corresponds to lower risk aversion, and bond $b$ has stochastic returns

$$R_{hb} \sim N(\mu_{ihbt}, \sigma_t^2) \tag{8}$$

in excess of the risk-free rate. Note that I assume that $\sigma_t^2$ is constant for all bonds within a market $t$. I parameterize the mean return $\mu_{ihbt}$ as follows:

$$\mu_{ihbt} = \alpha_h r_{bt}^{PM} + \alpha_{h,SM} r_{bt}^{SM} + \beta_h X_{bt} + \xi_{hbt} + \epsilon_{ihbt} =: \delta_{hbt} + \epsilon_{ihbt}, \tag{9}$$

where $\alpha_h$ is the loading on $r_{bt}^{PM}$, $\alpha_{h,SM}$ is the loading on $r_{bt}^{SM}$, and $\beta_h$ represents the loadings on the vector $X_b$ of bond and firm characteristics. To allow for components of bond-specific demand that are unobserved by the econometrician, such as perceived risk tolerance of firm management or brand recognition, I include the term $\xi_b$, which is common to all investors. Finally, I include any unobserved investor-bond-specific characteristics in $\epsilon_{ihb}$. For example, $\epsilon_{ihbt}$ may include the covariance of bond $b$ with the rest of investor $i$'s portfolio (from classic portfolio theory), investor-specific beliefs about a firm's performance, or the liquidity and performance of the investor's portfolio.[47] I make the assumption that the investor-bond error, $\epsilon_{ihbt}$, has a Type 1 extreme value distribution.

[47] Chen et al. (2010) show empirically that funds with illiquid investments are sensitive to larger outflows based on past poor performance. This is an investor-specific shock that would impact demand for a given bond.

This is a standard assumption in the discrete choice demand estimation literature (Berry [1994], Berry et al. [1995]).

Investors allocate a dollar towards bond $b$ if their utility for bond $b$ exceeds the utility of all other bonds $m \neq b$ in the same market: $U_{ibt} > U_{imt} \; \forall m \neq b$. In addition to choosing among the bonds in each market, investors can also choose the risk-free asset, which returns zero. Exploiting the property of the extreme-value distribution, the choice probability for investor $i$ of type $h$ to invest a dollar in bond $b$ is given by the following expression:

$$s_{hbt} = \frac{\exp\left(\alpha_h r_{bt}^{PM} + \alpha_{h,SM} r_{bt}^{SM} + \beta_h X_{bt} + \xi_{hbt}\right)}{\exp\left(\frac{\sigma_t^2}{2k_h}\right) + \sum_m \exp(\alpha_h r_{mt}^{PM} + \alpha_{h,SM} r_{mt}^{SM} + \beta_h X_{mt} + \xi_{hmt})}, \tag{10}$$

where the denominator is the sum of the exponential utilities from investing in (i) the risk-free asset and (ii) all other bonds issued in the same market. Intuitively, more dollars are allocated to the risk-free rate if volatility of bonds is higher.

The demand for bond $b$ is the sum of choice probabilities over investor types:

$$Q_{bt}^D = \sum_h s_{hbt} M_{ht}, \tag{11}$$

where $M_{ht}$ is the total volume of type-$h$ investor dollars in market $t$.

### 4.1.3 Underwriters

The usual equilibrium notion of setting quantity supplied equal to quantity demanded is insufficient in primary markets, given the empirical observation that bonds are often oversubscribed. Thus, to close the model, I introduce underwriters who select an equilibrium credit spread subject to market clearing.

Underwriters are risk-neutral profit-maximizing agents. They serve two clients: corporate issuers, who pay an ex-ante fixed commission to the underwriter, and investors, who buy primary market securities and engage in secondary market trading with the underwriter as a dealer. It is well-documented that underwriters may extract rents from issuers to favor investor clients.[48]

[48] For example, underwriters may prefer regular investors that participate frequently in underwriting markets and provide valuation information and stability (Benveniste and Spindt [1989]); they may also favor large investors that provide additional revenue from trading or other services (Flanagan et al. [2019], Henderson and Tookes [2012], Nikolova et al. [2020]). Recent findings by Goldstein and Hotchkiss (2020) show that underwriters have market power

However, since underwriting is a repeat business, the underwriter cannot extract too much from issuers. Thus, underwriters choose credit spreads to split gains from trade between issuing firms and primary market investors.

The investors' gains from trade are $Q(r_{bt} - r^*_{bt})$, where $r_{bt}$ is the actual issuance credit spread and $r^*_{bt}$ is the counterfactual competitive equilibrium credit spread, taking $Q^S$ as given. The firm's gains from trade are $Q(\bar{r}_{bt} - r_{bt})$, where $\bar{r}_{bt}$ is the highest credit spread at which the firm would still be willing to issue $Q$.

The underwriter favors investors to the extent $\eta$, and thus solves the following maximization problem, where $Q$ drops out because it is a constant:

$$\max_{r_{bt}} \; \pi = (r_{bt} - r^*_{bt})^{\eta} (\bar{r}_{bt} - r_{bt})^{1-\eta}. \tag{12}$$

Differentiating (12) and applying the first-order condition yields

$$r_{bt} = \eta \underbrace{\bar{r}_{bt}}_{\text{Firm's reservation}} + (1-\eta) \underbrace{r^*_{bt}(Q_D, Q_S)}_{\text{Investors' reservation}} . \tag{13}$$

That is, underwriters select a credit spread that is between the firm's reservation credit spread and the investors' reservation credit spread. The more the underwriter favors the investors (the closer $\eta$ is to 1), the closer the new issue credit spread is to the firm's reservation credit spread. If the underwriter favors firms fully ($\eta = 0$), then the new issue credit spread is the value of $r^*$ for which demand is equal to supply.

This expression shows that new issue credit spreads are proximately a function of the firm's reservation credit spread (6), quantity supplied, and quantity demanded. Quantity demanded, as shown in the solution to the investors' problem (11), is a function of bond characteristics, risk aversion, and demand parameters. Quantity supplied and reservation credit spreads, from the firm's problem, are functions of firm characteristics. Exactly how these characteristics enter into the new issue credit spreads depends on parameter values, which I will estimate in the next section.

in secondary markets given information advantage from participating in primary markets.

# 5 Estimation

## 5.1 Estimating the firm's supply parameters

In this section, I describe the estimation and identification for the firm's supply curve for bonds. For firm controls $Z$, I include the following: (i) the volume of bonds coming due in the following three months, logged, given that firms may issue when there are upcoming maturities (Leland and Toft [1996]); (ii) firm characteristics—credit rating, previous-quarter cash-to-assets ratio, leverage, and profitability—given that these may impact issuance decisions; and (iii) the risk-free rate and a proxy for macroeconomic conditions (the CFNAI), given that market conditions may influence bond issuance decisions (e.g., Erel et al. [2012]). For firms that did not issue in a given quarter, I use the most recent issuer rating and an average tenor of 10 years (the median bond term). I also include issuer fixed effects to ensure that I am capturing how each firm makes its own decisions over time. I allow for left-censoring at $C = \$100$ million, and $c = \ln C$, given fixed costs of issuance and the empirical observation that issuance is lumpy: firms will issue zero in most quarters and a large amount in a few quarters.

The primary empirical challenge in identifying how firms respond to changes in credit spreads is endogeneity. On one hand, a reduction in credit spreads may increase the amount that firms wish to issue (e.g., Bolton et al. [2013] and Baker and Wurgler [2002] for general external financing, and Ma [2019] and Mota [2020] for bonds). However, a coefficient estimated from regressing quantity supplied on credit spreads could be biased by reverse causality. If firms decide to lever up, this could drive credit spreads upwards as investors' perceptions of firm fundamentals deteriorate. Quantifying the causal impact of credit spread changes on firm issuance decisions thus requires investor perceptions of firm fundamentals, which are inherently unobservable, to be held fixed.

To overcome this issue, I use a unique feature of the new dataset to show that firms respond to changes in credit spreads. In a subset of bond issuances (16% of the sample), firms change the size of the bond ("upsize") within the span of a day based on revised expectations of investors' demand curves.[49] Because bond issuances are completed in one day, investor perceptions of firm fundamentals (and fundamentals themselves) are unlikely to change. Thus, I can exploit the firms' within-day quantity change in response to unexpectedly low credit spreads to pin down the firm's

[49] In contemporaneous work, Zhao et al. (2021) also look at "upsized" bond issuances for to understand how firms deploy the incremental cash raised under improved credit conditions.

short-term supply elasticity.[50] The subsample of bonds that are upsized is not significantly different from the full sample of bonds (Table IA.8 compares the distributions of firm and bond characteristics in the subsample to those in the full sample).

While I can observe the initial quantity of bonds that firms intend to issue, I do not directly observe the firms' initial expectations of credit spreads. Instead, I impute each firm's initial expectation of credit spreads from the initial *announced* credit spread in round $k = 0$, which I find is a good predictor of the final credit spread for round $k = 4$ for issuances that are not upsized. To show this, I run a regression of the final credit spread on the initial credit spread with controls for bond size, credit rating, and tenor and year fixed effects,

$$r_{bt,k=4} = mr_{bt,k=0} + \beta X_{bt} + \alpha_y + \epsilon_{bkt}, \tag{14}$$

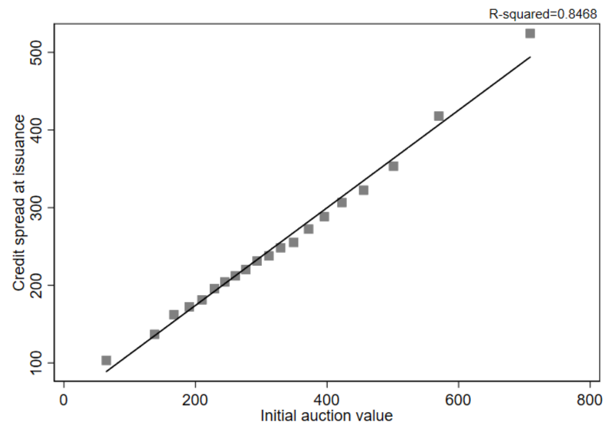
where $X_{bt}$ is a vector of controls that include amount issued (log), issuer credit rating, and tenor, and $\alpha_y$ is a year fixed-effects term to absorb any long-term trends in bond issuance practices. The regression shows that initial spreads are a good predictor of final spreads, with an R-squared of over 0.83 and a tight-fitting binscatter plot shown in Figure 6. For upsized bonds, I compute the predicted $E[r_{bt,k=4}|\text{no upsize}]$, that is, the firm's initial expectation of the final credit spread on the new bond.

As expected, for upsized bonds, initial expectations of credit spreads exceed the final issuance credit spreads by a mean (median) of 10 (7) basis points. For bond issuances that are not upsized, the mean (median) difference between expected credit spread and final issuance credit spread is 0 (2) basis points. Firms respond to these positive surprises in credit spreads by increasing the quantity supplied of bonds: I show in Figure IA.10 in the Internet Appendix that bigger declines in credit spreads correspond to larger increases in quantity supplied.[51]

[50] Note that I will identify this elasticity entirely off of "upsized" bonds. I make the assumption that firm supply elasticities are locally symmetric when interpreting the results. Fewer than 1% of bond issuances in my sample result in "downsizing," where the firm decides to decrease the size of the bond within the span of the issuance day.

[51] A potential concern is that during market downturns, greater volatility may lead underwriters and firms to be more uncertain about the price of a bond issuance, thereby beginning the issuance process with a conservatively high credit spread. I residualize the firm's initial expectation of the initial credit spread using year fixed effects in equation 14 to address low-frequency variation in this behavior and issuer credit rating to address cross-sectional variation in this behavior. Even if there is still variation in starting credit spread that persists given these controls, the firm still must be willing to sell bonds at this price, given the high reputational cost of cancelling a bond. Indeed, very few bond issuances are announced and then canceled. CFR reports that in 2018 and 2019, only 7 (2) bond issuances were canceled (or postponed) after announcement. Thus, increased uncertainty is unlikely to significantly bias the supply elasticity estimate.

Figure 6: Correlation of initial price talk with final treasury spreads




*Source*: IGM, CFR, and Mergent FISD.
*Note:* The $y$-axis shows the initial announced credit spread for a given bond. The $x$-axis shows the credit spread for a given bond. The model includes year fixed effects and controls for issuer credit rating, bond size (log), and bond tenor.

With the reasonable assumption that firm fundamentals are fixed over the course of one day, bond fixed effects absorb all endogenous firm-level variation and pin down an unbiased estimate of firm elasticities.[52] I estimate the within-bond tobit that identifies $\gamma_r$ simultaneously with a within-firm regression that estimates coefficients on time-varying firm characteristics that I take as exogenous. I do this for the whole sample of firm-quarters, and then for subsamples based on credit rating and time period (normal versus crisis) in order to estimate how elasticities change when firms have lower financial slack.

## 5.2 Estimating investor demand

In this section, I describe the estimation and identification for investor demand. For bond controls $X_{bt}$, I include (i) the prevailing risk-free rate, given that demand for bonds may be impacted by the supply and price of U.S. Treasury bonds (Krishnamurthy and Vissing-Jorgensen [2012]); (ii) bond duration, given that investors have heterogeneous preferences across the term structure

[52]It is plausible that firms learn about their own fundamentals from the market, and the change in quantity supplied reflects this learning. However, this is not a threat to identification; rather, it expands the interpretation of the estimated firm's supply elasticity to more closely resemble the firm's *long-term* supply elasticity. That is, how do firms adjust the quantity of bonds supplied in response to changes in prices, including any corresponding adjustments to real activity.

(Greenwood et al. [2010], Vayanos and Vila [2021]); (iii) issuer credit rating, given that certain investors may have preferences or mandates for higher credit ratings (Becker and Ivashina [2015], Donaldson and Piacentino [2018], Kisgen and Strahan [2010]); (iv) bond size, given that investors may also prefer larger bond sizes due to liquidity and index eligibility (Calomiris et al. [2021]); and (v) the monthly weighted average bid–ask spread for the bond to proxy for liquidity, given that investors may prefer more liquid assets.

Note that equation (10) for $s_{hbt}$, the choice probability of bond $b$, has unobservable demand characteristics entering nonlinearly. I take the traditional approach as proposed by Berry (1994) to invert the choice probability into a linear function of the unobserved demand component $\xi_{hbt}$:

$$\ln(s_{hbt}) - \ln(s_{h0t}) = \alpha_h r_{bt}^{PM} + \alpha_{h,SM} r_{bt}^{SM} + \beta_h X_{bt} + \xi_{hbt}. \tag{15}$$

Because $s_{hbt} = Q_{hbt}/M_{ht}$ by definition, I can rewrite the linear expression as

$$q_{hbt} = \alpha_h r_{bt}^{PM} + \alpha_{h,SM} r_{bt}^{SM} + \beta_h X_{bt} + \xi_{hbt} + \ln(s_{h0t}) + \ln(M_{ht}). \tag{16}$$

I assume the last two terms in (16) are common within a market, so I can absorb them with a market fixed effect (see Diamond et al. [2020]). Empirically, I use week fixed effects. I am assuming then that the set of bonds from which an investor chooses is fixed within each week. I estimate equation (16) across the two types of investors: $h \in \{ST, LT\}$.[53] To be able to compare the elasticities of the two investor types, I assume that the variance of unobservables for LT and ST investor demand is the same (Train [2009]). The $\alpha$s are the demand elasticities over credit spread that are the key parameters of interest.[54]

I cannot directly estimate equation (16) with OLS, because there is potential endogeneity between the unobserved characteristics of the bond, $\xi$, and the yield $r$. Estimating demand properly generally requires addressing two fundamental challenges: first, price is likely correlated with unobservables that affect demand, and second, demand for one good depends on prices and characteristics of other related goods (Berry and Haile [2021]).

[53]Note that this modeling choice assumes quantity demanded for each investor type depends solely on size of market and the mean utilities for each investor type.

[54]While I do not explicitly microfound the elasticities in the model, in principle, the elasticities estimated can be informative about the compensation investors demand for potential information asymmetries or the restrictions arising from constraints in the risk-bearing capacity of intermediaries. Further disentangling the sources of the elasticities theoretically and empirically is outside the scope of this paper, but is a promising avenue for future research.

To overcome this, I use an exogenous supply shifter: the within-week variation in daily supply of new bonds issued by *other* firms in the same market, underwritten by other broker-dealers. I call this metric "crowdedness." I make two assumptions. First, I assume that newly issued corporate bonds are imperfect substitutes. This is reasonable, since bonds issued by large corporations have similarly stable, predictable cash flows, and default rates are historically very low. Second, I assume that the day of week on which each firm chooses to issue is reasonably random, and thus is orthogonal to the unobservables of other firms issuing on the same day.[55] This assumption is based on industry interviews: a firm's specific issuance day may be influenced by the maturity date of existing debt, the progress of a liability management program, an acquisition, or even the management's ability to finish documentation necessary for issuance. To account for slow-moving economy-wide trends in demand for capital, I include week fixed effects so the focus is on within-week variation.[56] Moreover, while one firm's underwriter may be able to advise the firm on the timing of other firms' issuance, that underwriter will not necessarily know the exact timing of bonds underwritten by other broker-dealers. With these assumptions, the random variation in other firms' bond supply acts as an exogenous supply shifter.

Indeed, I find that more crowded markets have higher credit spreads, controlling for firm characteristics. More sophisticated firms may find ways to issue on less crowded days; to deal with this potential concern, I include firm fixed effects. Finally, bigger broker-dealers may know about a larger proportion of issuance on any given day, so I include underwriter fixed effects. Specifically, I regress issuance premiums and credit spreads on crowdedness as follows:

$$IssPrem_{ufbt} = \beta_1 \ln(Crowded)_{uft} + \beta_2 \ln(Crowded)^2_{uft} + \alpha_w + \alpha_f + \alpha_u + X_{fbt}\gamma + \epsilon_{ufbt}, \quad (17)$$

where the subscript $b$ represents the bond, $f$ the firm, $t$ the day, $w$ the week, and $u$ the underwriting bank. I compute crowdedness as the total bond issuance volume on the same day by other non-financial firms with no overlapping active underwriters. I include both the log and the squared log terms to allow for nonlinearities. For bond controls $X$, I include the same set of controls used in the demand estimation.

First stage estimates are reported in Table 4. The coefficient on the log of crowdedness is

[55] While there is some evidence of a "week-end" effect in stock markets, for example Jaffe and Westerfield (1985), I find zero correlation between the day of week and issuance premiums.

[56] As a robustness check, I try using the number of other firms that are issuing on the same day (with other underwriters) as an alternative instrument to the crowdedness metric, and get similar results.

statistically significant and positive: the more crowded a market, the higher the issuance premium and credit spread. The effect is nonlinear: as markets become more crowded, the effect becomes smaller. At a crowdedness of $2.5 billion, the effect becomes negative; however, only 4% of bonds are subject to such high levels of other issuance. Thus, an increase in supply of other firms issuing will generally increase a firm's cost of capital, consistent with an upward-sloping demand curve for bonds.

Table 4: Price impacts of supply shocks in primary markets

| | (1)<br>Issuance premium (bps) | (2)<br>SM credit spread (bps) |
|---|---|---|
| Amount issued by other firms (log) | 1.101*** | 5.391*** |
| | (0.214) | (1.857) |
| Amount firm f issues day t (log sq) | -0.605*** | -2.722*** |
| | (0.0902) | (0.717) |
| U.S. Treasury yield | -0.280*** | -6.485*** |
| | (0.104) | (0.876) |
| Bond size (log) | 1.116*** | 15.63*** |
| | (0.143) | (1.118) |
| Credit rating (log) | -17.19*** | -334.4*** |
| | (2.923) | (16.07) |
| Tenor (log) | -0.381*** | 35.64*** |
| | (0.0872) | (0.866) |
| Bid–ask spread | -0.407 | 2.015 |
| | (0.361) | (1.956) |
| Bank FE | ✓ | ✓ |
| Week FE | ✓ | ✓ |
| Issuer FE | ✓ | ✓ |
| Observations | 12613 | 12613 |
| R-squared | 0.591 | 0.869 |

*Note:* Dependent variable in the first regression is the issuance premium, measured in basis points. Dependent variable in the second regression is the secondary market credit spread on the newly issued bond, measured in basis points. Independent variables of interest is the amount issued by other firms, underwritten by other banks, in the same day (both logged and logged squared). Controls include U.S. Treasury yield for the duration of the bond, size of bond (log), issuer credit rating (log), tenor in years (log), and the monthly weighted average bid–ask spread. The model includes underwriter, issuer, and week fixed effects. Observations are at the bond-underwriter level. Standard errors clustered at the underwriter level.

As additional instruments, I follow the standard IO literature (see Berry [1994], Berry et al. [1995],) and use the characteristics of other issuers (credit rating and previous-quarter cash ratios) in the same market. These characteristics are relevant because they affect the prices of other bonds, while satisfying the exclusion restriction because they do not directly enter into investors' utilities over bond $b$. I aggregate the instruments into vector $Z_{bt}$ and estimate

$$E[\xi_{bt} Z_{bt}] = 0. \tag{18}$$

I can use the same framework to compute aggregate demand elasticities for each bond. The aggregate demand expression is

$$\begin{aligned} Q_{bt}^D = W_t \theta_t & \frac{\exp\left(\alpha_{ST} r_{bt}^{PM} + \alpha_{ST,SM} r_{bt}^{SM} + \beta_{ST} X_{bt} + \xi_{ST,b}\right)}{\exp\left(\frac{\sigma_t^2}{2k_{ST}}\right) + \sum_{mt} \exp(\alpha_{ST} r_{mt}^{PM} + \alpha_{ST,SM} r_{mt}^{SM} + \beta_{ST} X_{mt} + \xi_{ST,m})} \\ + W_t(1-\theta_t) & \frac{\exp\left(\alpha_{LT} r_{bt}^{PM} + \alpha_{LT,SM} r_{bt}^{SM} + \gamma_{LT} X_{bt} + \xi_{LTb}\right)}{\exp\left(\frac{\sigma_t^2}{2k_{LT}}\right) + \sum_{mt} \exp(\alpha_{LT} r_{mt}^{PM} + \alpha_{LT,SM} r_{mt}^{SM} + \gamma_{LT} X_{mt} + \xi_{LT,m})}, \end{aligned} \tag{19}$$

which I then log-linearize to

$$q_{bt}^D \approx q_t^D + \big(\theta_t \alpha_{ST} + (1-\theta_t)\alpha_{LT}\big) r_{bt}^{PM} + \big(\theta_t \alpha_{ST,SM} + (1-\theta_t)\alpha_{LT,SM}\big) r_{bt}^{SM} + \big(\theta_t \beta_{ST} + (1-\theta_t)\beta_{LT}\big) X_{bt} + \xi_{bt} + \zeta_t, \tag{20}$$

where $\theta_t$ is the market-wide share of the demand coming from short-term investors and $W_t$ is the total wealth to be invested in period $t$. I include week fixed effects to absorb $\zeta_b$. Empirically, I proxy for $\theta_t$ using the share of short-term investors in the primary market at the weekly level.

### 5.2.1 Comparison to secondary market investors

Next, I compare preferences of primary and secondary market investors. To estimate demand elasticities for secondary market investors, I adapt the method of using cross-sectional variation in institutional investment mandates from Koijen and Yogo (2019). I relegate the details of this method to Appendix B.1. I deviate from existing papers (e.g., Bretscher et al. [2020] and Koijen et al. [2021]) in an important way: I define each investor's investment universe, and thus the instrument, using *classes* of bonds, rather than individual securities. The reason for this is that there are many more unique bonds than equities. Empirically, I define each class as a triplet of tenor, rating, and issuer sector. This classification is motivated by existing papers that document clientele effects among bond investors by rating category (Becker and Ivashina [2015], Gomes et al. [2020]) and by tenor ( Greenwood and Vayanos [2014], Guibaud et al. [2013], Vayanos and Vila [2021]). There are 391 classes of bonds in my sample. I find empirical evidence that holders of corporate bonds tend to continue holding the same class of bond over time (see Table IA.9). I exploit the cross-sectional variation in investment universes as an instrument for credit spreads to estimates how secondary market investors adjust quantities in response to changes in credit spreads.

### 5.3 Estimating the underwriter's solution

In this section, I describe how I estimate $\eta$, which represents how much underwriters favor investors relative to firms. First, I derive an expression for $r^*$ (the counterfactual competitive equilibrium holding $Q$ fixed) that is a function of estimated parameters and the data. I proxy for $\bar{r}$, the firm's outside option, using the initial credit spread announced in each issuance process. I plug these into the underwriter's solution (13), and solve for the value of $\eta$ that minimizes the distance between the model-implied $r_b$ and observed credit spreads.

I first write an expression for the counterfactual credit spread $r^*$ that is dependent on observables, parameters, and the recovered latent demand:

$$r^* \equiv \{r : Q^D(r, X, \xi; \hat{\alpha}, \hat{\beta}) = Q^S\}. \tag{21}$$

I do not directly observe latent demand $\xi$, so I recover it from the observed quantity demanded at the observed credit spread for each bond, $q^D(r_b^o)$, using equation (20). This gives me an expression $\xi_b(q(r_b^o), X, \hat{\alpha}, \hat{\beta})$. I plug this into (21) and get

$$r_b^o - r_b^* = \frac{q^D(r_b^o) - q^S}{\alpha_1\theta_t + \alpha_2(1-\theta_t)}. \tag{22}$$

This expression has an intuitive interpretation: the amount by which the observed new issue credit spread exceeds counterfactual competitive equilibrium credit spreads is a function of how much observed demand exceeds supply, scaled by the weighted-average demand elasticities of investors.

I can then write the empirical analogue of the underwriter's solution (13):

$$r_b = \eta \bar{r} + (1-\eta)\Big(\frac{q^S - q^D(r_b^o)}{\alpha_1 \theta_t + \alpha_2(1-\theta_t)} + r_b^o\Big). \tag{23}$$

Using the estimated parameters from the demand side, I solve for the value of $\eta$ that minimizes the distance between model-implied credit spreads and observed credit spreads.

## 5.4 Estimated investor demand

Table 5 presents my estimates of demand-side parameters for primary market investors. The first column reports estimates for short-term primary market investors, and the second column reports estimates for long-term primary market investors. Both investor types have a stronger loading on issuance premium than the remainder of credit spreads. A one-basis-point increase in issuance premiums will increase short-term investor demand by $7\%$ and long-term investor demand by $3\%$. However, a one-basis-point increase in the remainder of credit spreads reflected in secondary markets does not have a significant impact on demand from either investor type. The higher elasticity over issuance premium may reflect that this incremental spread more closely resembles a pure expected return, while the remainder of credit spreads represents the financial health of the firm plus compensation to investors for secondary market illiquidity or exposure to default risk (e.g., Gilchrist and Zakrajšek [2012]).[57] Both investor types have higher demand for larger bonds and more liquid bonds (as proxied by lower bid–ask spreads).

Short-term investors are more elastic to issuance premiums than long-term investors. To see the significance of the difference, I compare elasticities of short- and long-term investors in the last column of Table 5. Positive coefficients reflect a higher loading for short-term investors than for long-term investors. The difference between short-term and long-term elasticities over issuance premiums is positive and significant, and helps to explain the positive correlation between short-term share and issuance premiums, which I discuss further in the next section. In addition, short-term investors are more likely to purchase more liquid bonds, likely because this improves their ability to exit their positions. Consistent with the reduced form evidence in 3, short-term investors also participate more when macro fundamentals are weak. Surprisingly, they are more likely to purchase longer-duration bonds, potentially reflecting the relative ease of flipping these bonds,

[57] A frictionless benchmark would suggest an infinite elasticity over a pure expected return as unconstrained arbitrageurs pile in. However, the finite estimated elasticities are consistent with well-known and realistic limits to arbitrage, such as slow-moving capital (Duffie [2010]).

Table 5: Primary market estimates: full sample

| | (1) Qd short-term (log) | (2) Qd long-term (log) | (3) Qd(ST) / Qd(LT) |
|---|---|---|---|
| Issuance premium (bps) | 0.0694*** | 0.0341*** | 0.0353*** |
| | (0.0114) | (0.00743) | (0.00982) |
| SM credit spread (bps) | -0.000956 | 0.00149 | -0.00244 |
| | (0.00249) | (0.00131) | (0.00214) |
| U.S. Treasury yield | 0.0000978 | -0.0000851 | 0.000183 |
| | (0.000243) | (0.000114) | (0.000228) |
| Bond size (log) | 0.507*** | 0.608*** | -0.101** |
| | (0.0524) | (0.0275) | (0.0453) |
| Credit rating (log) | -0.186 | 0.847* | -1.033 |
| | (0.843) | (0.501) | (0.694) |
| Tenor (log) | 0.422*** | -0.0541 | 0.476*** |
| | (0.0888) | (0.0423) | (0.0783) |
| Bid–ask spread | -0.381*** | -0.0672*** | -0.314*** |
| | (0.0308) | (0.0178) | (0.0310) |
| Underwriter FE | ✓ | ✓ | ✓ |
| Week FE | ✓ | ✓ | ✓ |
| Issuer FE | ✓ | ✓ | ✓ |
| Observations | 11182 | 11182 | 11182 |

*Note:* This table covers sample bonds issued 2010–2020 with the share of short-term investors between 0 and 1. Observations are at the bond-underwriter level. Controls include issuance amount (log), issuer credit rating (log), tenor in years (log), and the monthly weighted average bid–ask spread. Instruments include amount of bonds issued on the same day by other firms and underwritten by other broker-dealers (log), and average rating and cash balances of same-day bond issuers. The model includes bank fixed effects to account for cross-sectional variation in underwriter balance sheets and variation in expected rationing; week fixed effects to absorb trends in demand for capital; and firm fixed effects to account for cross-sectional variation in unobserved firm characteristics. Standard errors are clustered by bank. Observations are weighted by size of bond.

which tend to be more liquid. Finally, long-term investors prefer better-rated bonds than short-term investors, likely reflecting institutional mandates to buy higher-rated securities (e.g., Becker and Ivashina (2015)).

Next, I compute aggregate primary market demand elasticities over time. Because issuance is sporadic, primary markets lack sufficient observations to directly estimate time-varying elasticities. However, I argue that variation in primary market demand's sensitivity to credit spreads is driven primarily by (1) changes in the share of issuance premium to total credit spread and (2) changes in investor compositions. Thus, the estimated semi-elasticities discussed above are sufficient to understand time series variation in demand elasticities.

Concretely, I first compute the semi-elasticity for each type of investor based on the average proportion of issuance premium to credit spreads in each period. Then, I compute the weighted average of semi-elasticities across the two types of investors using the average proportion of investors in each period. For easier comparison to the extant literature on demand elasticities for assets, I convert the semi-elasticities to price elasticities of demand. With the caveat that I am only considering variation in credit spreads and holding fixed the risk free rate, I find a range for primary market price elasticities of demand attributable to changes in credit spreads of 1.8 (in 2019) to 3.5 (in 2009). See Table 8 in the Appendix for a summary.

Point estimates for secondary market investor demand are summarized in Table 9. Converting these estimates to demand elasticities, I find that the long term holders of corporate bonds are more inelastic than primary market investors, with price elasticities of demand arising from changes in credit spreads ranging from 0.96 to 1.1 in the period 2003 - 2020.[58] The elasticity is thus close to one with little time series variation, indicating the total dollar volume held in secondary markets does not change significantly with prices.[59]

[58]To convert estimates to demand elasticities, I adapt the method from Koijen and Yogo (2019) and Bretscher et al. (2020), and note that $-\frac{\partial q_{bt}}{\partial p_{bt}} = 1 + \frac{\hat{\beta}_t}{n_{bt}}(1 - w_{bt})$, where $n_{bt}$ is the years to maturity. These estimates are in line with Bretscher et al. (2020), who estimate elasticities for the corporate bond market incorporating changes in both credit spreads and the underlying benchmark security.

[59]See Bretscher et al. (2020) for a discussion of demand heterogeneity across investors.

## 5.5 Estimated firm supply

Table 6 presents my tobit estimates of supply-side parameters.[60] I translate these estimates into supply elasticities unconditional on issuance using the average value of covariates. The average issuer responds to a ten-basis-point increase in credit spreads with a 1.5% decrease in issuance volumes, corresponding to a supply elasticity of 1.5. Firms have greater loadings on other covariates, such as the risk-free rate and macro and firm fundamentals, when deciding issuance volumes. The coefficients on other covariates are as expected: firms that are higher-rated, with more cash on their balance sheets and less leverage in the previous quarter, issue more. IG firms with higher profitability and more debt coming due in the next three months also issue more bonds. All firms issue more when U.S. Treasury yields are lower and macro fundamentals (as proxied by CFNAI) are weaker.

To test how supply elasticities change when firms have less financial slack, I estimate for the following subsets of bonds: bonds issued by A-rated firms or BBB-rated firms, and bonds issued during the GFC period (2008–2009), the COVID-19 period (2020H1), and the period between (2010–2019). I report results in Table IA.10. Lower-rated firms are less responsive to changes in credit spreads; high-yield (investment grade) firms have an unconditional supply elasticity at average value of covariates of 1.1 (1.6). Firms issuing during the GFC are similarly less elastic. These results are consistent with firms becoming less price sensitive when they are lower in financial slack. Firms issuing in the first half of 2020 have higher elasticities than on average, but since this period overlaps with the Federal Reserve's announcement that it would intervene in bond markets, I cannot distinguish between issuance to improve financial slack and opportunistic issuance (e.g., Baker and Wurgler [2002], Ma [2019]), the latter of which would bias supply elasticities to be higher in absolute magnitude.

## 5.6 Estimated underwriter behavior

For the underwriter's problem, I get an estimate of $\hat{\eta} = 0.634$, with bootstrapped standard errors equal to $0.0076$. Underwriters thus systematically favor investors over firms. This is consistent with

[60] To interpret these estimates as the quantity response to a change in credit spread, I follow Wooldridge (2002):

$$\frac{\partial E[q|Z,r]}{\partial r} = \hat{\gamma}_r \Phi\left(\frac{\hat{\gamma}_r r + Z\hat{\gamma}_Z - c}{\hat{\sigma}_e}\right), \tag{24}$$

where $\Phi(\frac{\hat{\gamma}_r r + Z\hat{\gamma}_Z - c}{\hat{\sigma}_e})$ is the probability of issuance.

Table 6: Firm supply estimates (standard tobit)

| | (1)<br>All issuance | (2)<br>Amount issued by IG firms (log) | (3)<br>Amount issued by HY firms (log) |
|---|---|---|---|
| PM Credit spread (bps) | -0.00221*** | -0.00431 *** | -0.00203 *** |
| | (0.0002) | (0.0002) | (0.0004) |
| US Treasury Yield | -1.434*** | -1.479*** | -2.010*** |
| | (0.343) | (0.477) | (0.762) |
| Credit rating | -4.237** | -5.312 | -3.808 |
| | (1.812) | (3.291) | (2.909) |
| Cash/Assets last qtr | -6.612*** | -10.13*** | 1.727 |
| | (1.606) | (3.397) | (4.170) |
| CFNAI | -0.253** | -0.258*** | -0.255 |
| | (0.101) | (0.0625) | (0.200) |
| Leverage last qtr | -2.092** | -3.702** | -2.233 |
| | (0.858) | (1.513) | (2.023) |
| ROA last qtr | 8.551 | 22.97* | -5.922 |
| | (5.805) | (12.85) | (7.200) |
| Amount due in 3 months | 0.0227 | 0.0360** | -0.0408 |
| | (0.0141) | (0.0167) | (0.0635) |
| Undrawn credit line (t-1) | -0.0000870* | -0.000111* | -0.0000780 |
| | (0.0000503) | (0.0000656) | (0.000160) |
| Market to book (t-1) | 0.00137*** | 0.00152*** | 0.00214 |
| | (0.000511) | (0.000574) | (0.00243) |
| / | | | |
| var(e.logamt) | 25.19* | 30.45 | 34.85 |
| | (14.00) | (19.93) | (29.46) |
| Observations | 16038 | 11347 | 4691 |

*Note:* This table covers sample bonds issued 2000–2020. Observations are at the firm-quarter level. Standard errors are clustered at the firm level. Standard tobit estimation is left-censored at log of $100 million. First regressor is estimated in a simultaneous within-bond estimation. Dependent variable is logged quarterly issuance volume plus one.

the literature that finds that underwriters value relationships with investors(Benveniste and Spindt [1989], Henderson and Tookes [2012], Nagler and Ottonello [2020]), who are more frequent participants in the corporate bond market than firms. The largest institutional investors[61] participate

[61] Examples include Allstate and Pacific Life Insurance.

in primary markets every other day, while the largest corporate issuers[62] issue at most one out of every 140 active market days. Many underwriting banks also act as dealers in the secondary market, and thus have relationships with bond investors that help them place bonds in primary markets (Goldstein and Hotchkiss [2012], Hendershott et al. [2020], Nikolova et al. [2020]). This may manifest in underwriters helping investors profit at the expense of issuers.[63] While underwriters earn revenue from firms through mergers and acquisitions advisory and underwriting, aggregate revenues from trading with investors are typically higher.[64]

# 6 Discussion

In this section, I discuss economic implications of the parameter estimates and describe counterfactuals that help inform drivers of countercyclical issuance premiums.

Estimated demand elasticities can inform relative price impacts of different markets. A higher demand elasticity corresponds to a lower price impact for a given supply shock, all else equal. Intuitively, attracting an incremental investor dollar requires a smaller increase in credit spreads when the demand elasticity is high. The inverse relationship between demand elasticities and price impacts yields two useful implications. First, higher price elasticities in primary markets suggest a given supply shock has a smaller price impact in primary markets than it would in secondary markets. The comparison helps explain why primary markets can absorb large bond issuances without a significant increase in yields.

Second, the estimates can inform time-series variation in price impacts in bond issuance. As documented in Section 3, downturns coincide with higher issuance premiums (as a share of overall credit spreads) and higher shares of short-term investors. Because demand elasticities over issuance premiums are higher than those for the remainder of credit spreads, and even higher for short-term investors, this indicates overall PM price elasticities increase in downturns. This pattern means the market is better able to absorb large supply shocks in bad times, contributing to the

[62]Examples include Verizon, AT&T, and Apple.

[63]This behavior has been documented in many papers, both in equity markets (Benveniste and Spindt [1989], Cornelli and Goldreich [2001], Cornelli and Goldreich [2003], Jenkinson et al. [2018]) and in corporate bond markets (Nikolova et al. [2020], Goldstein and Hotchkiss [2020]).

[64]In Q1 2021, the twelve largest broker-dealers reported $29 billion in revenue from trading (including fixed income, commodities, and currencies) and $17 billion from investment banking. Source: "Global investment banks post highest H1 revenue in decade—Coalition Greenwich", September 17, 2021, `https://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/global-investment-banks-post-highest-h1-revenue-in-decade-8211-coalition-greenwich-666326`

resilience of the corporate bond issuance market.[65]

## 6.1 Counterfactuals

I return now to the motivating fact that issuance premiums spike in bad times: what drives this pattern? Because issuance markets are segmented from secondary markets, issuance prices are subject to shifts in supply and demand. In bad times, there are investor outflows (Falato et al. [2020]) and reductions in intermediary risk-bearing capacity (Gilchrist and Zakrajšek [2012]) that reduce investor demand for bonds. This naturally increases issuance premiums (decreases prices), just as a reduction in demand for any normal good will reduce prices. At the same time, firms' willingness to pay increases during downturns as they become more desperate for liquidity (Acharya and Steffen [2020]). How much does each of these factors matter?

To answer this question, I first use the model, estimated parameters, and exogenous characteristics (economic activity, U.S. Treasury yields, and firm fundamentals) described in the previous sections to simulate a series of issuance premiums, endogenizing quantities and investor shares.[66] Note that as with all analyses of this nature, results should be interpreted with caution; the Lucas (1976) critique applies if the estimated coefficients vary in the counterfactual equilibria.

First, I allow firms to be less price-sensitive in bad times by assigning them the elasticity estimated from the GFC when economic activity is at least one standard deviation below average. I then run regressions of the simulated issuance premium on economic activity, controlling for bond characteristics (credit rating, amount, and tenor) and firm characteristics (prior-quarter leverage, cash-to-assets ratio, and profitability). I report results in Table 7. The first column shows that regressions in the model fit the regressions from the data (in Table 2) well. Next, I impose the same supply elasticity on firms throughout the cycle to see how changes in firms' price elasticity affect the cyclicality of issuance premiums. The pattern is tempered by about 6%, indicating that the reduction in firms' sensitivity to credit spreads contributes somewhat to the cyclicality of issuance premiums.

To test the shifts in investor demand that are unrelated to observable bond and firm characteristics, I run a counterfactual that shuts down fluctuations in latent demand by setting the total investor volume in the market to the average across periods. I report results in the third column of Table

[65] See Becker and Benmelech (2021) for a discussion on other factors contributing to resilience of the corporate bond market.

[66] See Figure IA.11 in the Internet Appendix for a visual of model fit, comparing the distribution of the short-term investor share in each bond issuance as simulated in the model to that of the underlying data.

7. This counterfactual reduces the cyclical pattern by about 20%, highlighting the importance of investor demand to the cyclicality of firms' funding costs. A reduction in non-fundamentals-driven investor demand in bad times increases primary-market-specific credit spreads. This is similar to the finding of Gilchrist and Zakrajšek (2012) that constraints on intermediaries increase the excess bond premium in bad times. Next, I shut down time-series variation in each firm's willingness to pay by assigning all firm fundamentals the average value within-firm. This takes away the cyclical pattern altogether, suggesting that despite frequent oversubscription, firms are price-takers in issuance markets.

How do institutions impact the transmission of shocks? To answer this question, I run two additional counterfactuals on market structure. In the fifth column of Table 7, I shut down investor heterogeneity, assigning all investors the demand elasticities of long-term investors. This amplifies the countercyclical pattern significantly, by over 48%. I will discuss the importance of investor heterogeneity further in the next section.

Finally, I run the counterfactual where underwriters favor firms and investors equally (this corresponds to setting $\eta = 0.5$ in the model). Many papers document that broker-dealers favor investors in the underwriting process, either to gather information (Benveniste and Spindt [1989]) or to maximize trading profits (Nikolova et al. [2020]). This well-known favoritism has led the SEC to open investigations into the underwriting practices of prominent broker-dealers.[67] Eliminating this favoritism in the simulation reduces the countercyclical pattern by nearly 30%, suggesting that underwriters' extraction of rents from firms amplifies the cyclicality of cost of credit. Because underwriters favor investors, when firms' willingness to pay increases, this is reflected more so in higher issuance premiums than the counterfactual where underwriters favored investors less so. Moreover, in the counterfactual where underwriters favor firms and investors equally, issuance premiums are on average 5 basis points lower.[68] This highlights the importance of incorporating underwriter incentives into our understanding of primary markets.

[67]"SEC probes Goldman and Citi bond allocations", February 28, 2014, https://www.ft.com/content/977f4dc2-a0b7-11e3-8557-00144feab7de.

[68]Note that I do not make statements about efficiency in this analysis. While underwriters favoring investors may cost firms in individual bond issuances, I cannot rule out the possibility that the expectation of higher issuance premiums helps attract and maintain investor demand in primary markets in the long run. How much underwriter behavior leads to investor entry, that is, the macro-elasticity of corporate bond issuance markets (Gabaix and Koijen [2020]), is a fruitful avenue for future research.

Table 7: Counterfactual magnitudes of issuance premium cyclicality

| | (1)<br>Baseline | (2)<br>Same firm elasticity | (3)<br>Investor demand shocks | (4)<br>Firm propensity to issue | (5)<br>Homogeneous investors | (6)<br>UW even split |
|---|---|---|---|---|---|---|
| Economic activity | -1.000*** | -0.943*** | -0.803*** | 0.0609 | -1.486*** | -0.710*** |
| | (0.0404) | (0.0402) | (0.0387) | (0.193) | (0.0532) | (0.0305) |
| Firm controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Bond controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Underwriter FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 8262 | 8262 | 8262 | 8262 | 8262 | 8262 |

*Note:* Outcome variable is issuance premium, measured in basis points. Dependent variable is the monthly CFNAI index from the Chicago Federal Reserve. The model includes industry (NAICS2) and underwriter fixed effects. Controls include prior-quarter leverage, cash-to-assets ratio, and profitability as measured by operating income over total assets. Bond controls include tenor (log), rating (log), and bond size (log). Standard errors are clustered at the underwriter level.

## 6.2 Effects of investor heterogeneity

How do fluctuations in issuance premiums impact firm issuance? I find that this depends on what kinds of investors are participating in primary markets. In this section, I examine the impact of investor heterogeneity on bond prices and volumes.

The demand parameter estimates detailed in the previous section confirm the heterogeneity across investors: short-term investors have a much higher loading on issuance premiums than long-term investors, and both types of primary market investors are more elastic than secondary market investors. Short-term investors' stronger preference for issuance premiums reflects the difference in investment strategy: they have a shorter time horizon within which to make profits, so they care less about the remainder of the credit spread and the riskiness of the issuer. These comparisons imply two ways in which investor composition affects the cost of capital and access to credit. On the dark side, because short-term investors have a high loading on issuance premiums, a higher share of short-term investors means higher issuance premiums, all else being equal. On the bright side, the endogenous shift to a higher share of short-term investors in bad times allows a higher level of equilibrium quantities than a counterfactual of only long-term investors. Below, I describe the counterfactual simulations I run to make these findings more concrete.

To show the impact of investor heterogeneity on average issuance premiums, I simulate an equilibrium that shuts down investor heterogeneity by assigning all primary market investors the elasticities of long-term investors. This reduces issuance premiums on average by 4 basis points, which corresponds to a \$2.1-million reduction in the firm's cost of capital on a median 10-year, \$650 million bond.[69] This means that the participation of short-term investors in primary markets represents a cost to firms on average.

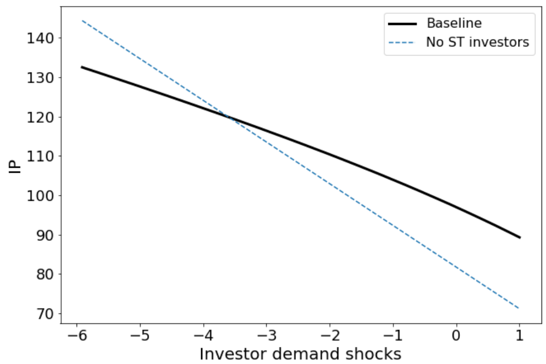
Next, I consider how investor heterogeneity impacts the transmission of shocks to firms. I simulate a series of counterfactual equilibria in which firms face a negative shock to their cash-to-assets ratios equal to one standard deviation in the cross-section of Compustat firms, which is $3\%$. I add on a range of negative investor latent demand shocks from zero to the levels seen during the COVID-19 pandemic, representing, for example, large fund outflows. In Figure 7 I plot the equilibrium outcomes for a baseline economy that allows for endogenous changes in investor composition (in solid lines), and compare it to an economy where all primary market investors have long-term elasticities (in dashed lines). As firms supply more bonds, the increase in supply and their higher willingness to pay pushes issuance premiums up (Panel 7a). This encourages an increase in the share of short-term investors participating in primary markets (Panel 7b). As short-term investors endogenously enter, the issuance premium actually increases *less* than in the counterfactual without short-term investors. Moreover, as all primary market investors experience larger negative demand shocks, equilibrium quantities decrease less than in the counterfactual economy with only long-term investors (Panel 7c).

This mechanism sheds light on why I observe higher participation by short-term investors and high issuance premiums in periods of market distress. Firms' higher willingness to pay drives up issuance premiums as underwriters continue to favor investors in splitting the surplus between firms and investors. This increases the share of short-term investors. Because short-term investor dollars are more price-elastic, they enter in larger quantities for a given rise in issuance premium, pushing up quantity demanded. In the example of Nordstrom, discussed in the introduction, the firm's bond issue garnered significant demand despite deteriorating firm fundamentals. The large order book of \$6 billion reflected high demand from short-term investors chasing issuance premiums.[70] The presence of short-term investors allowed Nordstrom to raise sufficient capital at a time when it badly needed cash. This reflects the bright side of endogenously changing investor composition in primary markets: right when firms need capital the most, more price-elastic investors are attracted

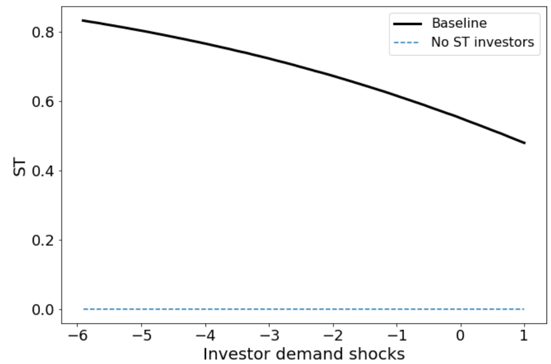
[69]Assuming an 8-year duration on the 10-year bond, $\$2.1\text{MM} = 0.04\% \times \$650\text{MM} \times 8$.

[70]Note that the day after Nordstrom's bond issuance was April 9, when the Federal Reserve announced important updates to the corporate bond purchase facilities, including its intention to purchase high-yield corporate bonds. Even after accounting for the one-day change in the BBB U.S. Corporate Index credit spread, the Nordstrom bond still had an issuance premium of well over 100 basis points.

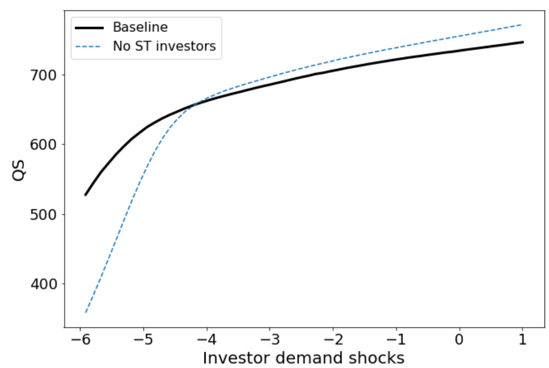
Figure 7: Counterfactuals: positive supply and negative demand shocks




(a) Issuance premiums




(b) Short-term share




(c) Quantity issued

*Note*: The plots show counterfactual issuance outcomes in which firms face a negative shock to their cash-to-assets ratios equal to one standard deviation in the cross-section of Compustat firms, which is 3%. On the $x$-axis is a range of shocks to investor latent demand. The solid line represents counterfactual outcomes that allow for endogenous changes in the share of short-term investors. The dashed line represents counterfactual outcomes where all primary market investors have long-term elasticities.

by higher issuance premiums and keep bond issuance volumes up.

### 6.3 Policy implications

My results could inform the design of corporate bond purchase programs targeting primary or secondary markets. For example, in spring 2020, the Federal Reserve announced the creation of two credit facilities to purchase corporate bonds in primary and secondary markets. While the announcement of this program decreased yields, increased issuance volumes (Boyarchenko et al. [2020], Gilchrist et al. [2020]) and helped to stem large fund outflows (Falato et al. [2020]), likely due to the implicit promise to bailout bond markets in the worst states of the world (Haddad et al. [2022]), the actual purchases were small and conducted exclusively in the secondary market.

Suppose the only consideration for selecting between primary and secondary market intervention was the impact on new issue prices and volumes, holding fixed announcement effects and political considerations. My estimated model makes it possible to quantify and compare the effects of purchases in primary versus secondary markets. Using average secondary market estimates, a purchase of 5% of a bond in secondary markets would cause a 50-basis-point decrease in secondary market credit spreads, all else being equal, and an additional drop of 3 basis points in issuance premiums. This would lead to a 3-7% increase in the firm's issuance volumes in equilibrium. A similarly sized purchase in primary markets, however, would have a relatively small effect of -2 basis points, with no significant increase in issuance. In other words, an increase in purchases in the primary market alone would not impact secondary market credit spreads; the only price impact would be via issuance premiums, and this would be very small, given how elastic primary market investors are to issuance premiums. The effect is even smaller if the share of short-term investors in primary markets increases, which is the case in bad times. Thus, when targeting corporate bond markets and aiming to maximize price effects, central banks should consider the relative elasticities between the primary and secondary markets, as well as the variation in primary market elasticities as short-term investors endogenously enter.

# 7 Conclusion

I present several new facts about the primary market for corporate bonds. I find model-free evidence that primary markets are subject to shocks distinct from those of secondary markets: in particular, the difference between primary and secondary market yields is greater in bad times, and this difference cannot be explained by issuer composition or firm fundamentals. The variation reflects segmentation between primary and secondary markets: firms cannot participate in secondary markets, while investors without underwriter relationships cannot participate in primary markets. Thus, the preferences of primary market agents are directly relevant to the transmission of investor demand shocks to firms' costs of bond capital and access to credit.

To quantify the impact of shocks on cost of capital and issuance volumes, I propose and estimate an equilibrium model of corporate bond issuance using new micro-data on bond issuance and novel high-frequency identification. I find primary market investors value highly issuance premiums and thus become more price-elastic in bad times, allowing for smaller drops in issuance precisely when firms are least sensitive to credit spreads. These results have important policy implications both for regulation of broker-dealers and for future central bank interventions in corporate bond markets.

As capital markets become a greater share of financing of the real economy, the framework in this paper can serve as a starting point for many important questions that arise, including if and how regulators or monetary policy authorities should intervene.

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# A Appendix

# B Short-term share of investors

To study how short-term investor behavior varies over the cycle, I regress this share of short-term investors on a proxy for economic conditions (the CFNAI):

$$STshare_{bft} = \beta_1 EconActivity_t + \alpha_y + \alpha_u + \alpha_f + X_{bft}\gamma + \epsilon_{bft}, \tag{25}$$

where $X_{bft}$ includes bond controls (tenor, rating, and size) to absorb any clientele effects along those dimensions, $\alpha_u$ represents underwriter fixed effects to absorb underwriter-specific bias towards short-term investors, $\alpha_y$ represents year fixed effects to absorb slow moving macro trends in investor participation, and $\alpha_f$ represents firm fixed effects. I report the results in Table 10. I find that worse macro fundamentals correspond to higher shares of short-term investors.

Why is there a shift towards short-term investors in downturns? I test whether short-term investors are participating more due to worsening firm fundamentals, by including issuer fixed effects and characteristics, including default probabilities and lagged cash and leverage ratios in the second column. The coefficient on economic activity is smaller but still significant, suggesting that some of the variation is driven by changing fundamentals.

Next, I test a demand-driven story: in bad times, institutional investors as intermediaries are more capital-constrained (He and Krishnamurthy (2013)), and short-term investors may be less constrained than long-term investors. In the last column of Table 10, I include (1) the TED spread (the difference between LIBOR and the U.S. Treasury bill rate) to proxy for dealer funding costs (Friewald and Nagler (2019)), and (2) a proxy for dealer balance sheet capacity [71]. The inclusion of these controls somewhat reduces the magnitude of the coefficient on economic activity, suggesting that some of the pattern is demand-driven. Higher short-term shares are correlated with measures of aggregate balance sheet constraints, suggesting that short-term investors are less capital-constrained than the average investors in bad times. When long-term investors are more constrained, short-term investors act as a stopgap.

## B.1 Secondary market demand estimation

I adapt the characteristics-based demand derived in Koijen and Yogo (2019) for equities to corporate bonds, similar to Bretscher et al. (2020) and Koijen et al. (2021). Demand for individual bond $b$ by investor $i$ at time $t$ can be written as

$$\frac{w_{itb}^{SM}}{w_{it0}^{SM}} = exp\{\alpha_i r_{bt} + \beta_i X_{bt}\}\epsilon_{itb}^{SM}, \tag{26}$$

where characteristics in $X$ include duration-matched U.S. Treasury yield, ratings category (log), amount issued (log), remaining years of bond (log), original tenor (log), and bid–ask spreads as reported by WRDS. The term $\epsilon_{itb}$ is investor $i$'s latent demand; it captures each investor's demand for unobserved characteristics of asset $b$. Investors choose optimal portfolio weights based on asset characteristics. The coefficient $\alpha$ captures investor preference for higher interest rates (Becker and Ivashina (2015)).

Because credit spreads and quantities can be jointly determined, I need an instrument for credit

[71] Specifically, I use the dealer intermediated volume ratio, computed as the ratio of weekly buy volume from customers to weekly buy volume from dealers (Boyarchenko et al. (2021)).

spreads. Following the literature, I use the investment universes of other investors in a given quarter. I make the assumption that (1) wealth distribution across other investors and (2) the investment universes of other investors are exogenous to demand shocks impacting investor $i$. Empirically, bond investors tend to hold the same kind of bond over time. I categorize bonds into classes based on three characteristics: tenor, rating, and industry (two-digit NAIC code). In Table IA.9, I report how persistent the holdings are by bond class. Investors of all sizes continue to hold the same class of securities over time, indicating investment universes are plausibly orthogonal to shocks to other investors or to bond characteristics.

Thus, I construct the following instrument:

$$z_{it}(b) = \ln\left(\sum_{j\neq i} A_{jt} \frac{\mathbf{1}_{jt}(n)}{1+\sum_{m=1}^{N}\mathbf{1}_{jt}(m)}\right), \tag{27}$$

where $\mathbf{1}_j(n)$ indicates that investor $j$ includes class $n$ in its investment universe at that point in time, where bond $b$ is a in class $n$. The investment universe of an investor includes outstanding bonds of all classes that the investor has held at any point in the past 12 quarters.[72] The more (and larger) investors have bonds like $b$ in their investment universe, the greater the portion of outside demand for the bond. Figure IA.12 in the Internet Appendix shows that the instrument is relevant: that is, the t-statistic magnitude is consistently above the Stock and Yogo (2005) critical value of 4.05.

I can then write the following moment condition, wherein log of latent demand is 0 given other investors' exogenous latent demand and observable characteristics:

$$E[ln(\epsilon_{itb}^{SM})|\hat{z}_{itb}, \mathbf{X}_{bt}] = 0 \tag{28}$$

For the dependent variable, I use the market value of holdings, conditional on a non-negative value, to compute $w_{itb}$, and the par value invested in other fixed income securities outside of my sample to compute the investor's weight in the outside option $w_{it0}$.[73] To avoid dropping zero holdings for bonds that are within each fund's investment universe, I compute the log of one plus the left hand side variable in equation (26). I run the estimation separately by year, weighting by fund AUM and including fund-quarter fixed effects to absorb any fund-specific shocks. Estimates

[72]To ensure the instrument is robust, I include in its calculation only those funds that hold at least 95% of their respective investment universe.

[73]For holdings that do not have a price reported in a given quarter, I use the par value.

are reported in Table 9.

# C Additional Tables

Table 8: Summary of primary market demand estimates

| Year | Short-term share | Issuance premium | Credit spread | Duration | Elasticity |
|---|---|---|---|---|---|
| 2002 | 0.05 | 4.02 | 182.72 | 9.13 | 2.31 |
| 2003 | 0.18 | 4.28 | 159.69 | 8.53 | 2.44 |
| 2004 | 0.14 | 3.40 | 135.75 | 6.43 | 3.23 |
| 2005 | 0.05 | 2.62 | 112.77 | 6.19 | 3.48 |
| 2006 | 0.12 | 3.94 | 143.59 | 6.22 | 3.52 |
| 2007 | 0.12 | 5.04 | 150.60 | 8.24 | 2.91 |
| 2008 | 0.14 | 10.51 | 274.12 | 8.02 | 3.18 |
| 2009 | 0.17 | 19.57 | 335.55 | 9.21 | 3.50 |
| 2010 | 0.22 | 12.36 | 269.54 | 9.99 | 2.75 |
| 2011 | 0.20 | 10.59 | 239.71 | 9.55 | 2.82 |
| 2012 | 0.22 | 8.30 | 196.67 | 10.83 | 2.41 |
| 2013 | 0.19 | 6.10 | 149.40 | 10.38 | 2.49 |
| 2014 | 0.18 | 4.95 | 144.91 | 10.66 | 2.21 |
| 2015 | 0.19 | 5.63 | 158.11 | 11.24 | 2.13 |
| 2016 | 0.19 | 5.89 | 160.94 | 10.32 | 2.36 |
| 2017 | 0.17 | 4.13 | 128.05 | 10.13 | 2.27 |
| 2018 | 0.18 | 3.85 | 128.93 | 10.52 | 2.09 |
| 2019 | 0.19 | 3.80 | 144.86 | 11.11 | 1.84 |
| 2020 | 0.15 | 9.79 | 233.14 | 11.64 | 2.29 |

*Source:* Mergent FISD and author computations.

*Notes:* Reports annual primary market demand elasticities and inputs for computation. Annual means of share of short-term investors, credit spreads, and issuance premiums are computed on the observations in each sample period, winsorized at the 1% and 99%.

Table 9: Summary of secondary market holdings demand estimates

| Year | Credit spread | Credit rating | Bond size (log) | Years remaining (log) | Bid ask | UST |
|---|---|---|---|---|---|---|
| 2003 | 0.1669 | 0.0059 | 0.0001 | 0.0001 | -0.0193 | 0.0823 |
| | (0.003) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) |
| 2004 | 0.2510 | 0.0057 | 0.0000 | 0.0000 | -0.0580 | 0.0441 |
| | (0.004) | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) |
| 2005 | 0.3560 | 0.0094 | -0.0001 | -0.0000 | -0.1713 | 0.1264 |
| | (0.009) | (0.000) | (0.000) | (0.000) | (0.004) | (0.003) |
| 2006 | 0.4826 | 0.0126 | -0.0002 | -0.0001 | -0.2350 | 0.3108 |
| | (0.018) | (0.000) | (0.000) | (0.000) | (0.009) | (0.012) |
| 2007 | 0.0337 | 0.0009 | 0.0003 | 0.0000 | -0.0136 | 0.0253 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| 2008 | 0.0103 | 0.0008 | 0.0003 | 0.0000 | -0.0105 | 0.0135 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| 2009 | 0.0107 | 0.0008 | 0.0003 | 0.0000 | -0.0142 | 0.0068 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| 2010 | 0.0215 | 0.0009 | 0.0002 | 0.0000 | -0.0140 | 0.0028 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| 2011 | 0.0336 | 0.0014 | 0.0002 | 0.0000 | -0.0177 | 0.0004 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| 2012 | 0.0789 | 0.0034 | 0.0002 | 0.0000 | -0.0475 | -0.0068 |
| | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| 2013 | 0.6790 | 0.0206 | -0.0002 | 0.0002 | -0.4548 | -0.1124 |
| | (0.025) | (0.001) | (0.000) | (0.000) | (0.017) | (0.004) |
| 2014 | 0.4361 | 0.0115 | 0.0001 | 0.0000 | -0.2453 | -0.0482 |
| | (0.011) | (0.000) | (0.000) | (0.000) | (0.006) | (0.001) |
| 2015 | -0.0292 | -0.0013 | 0.0002 | -0.0000 | 0.0161 | 0.0055 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| 2016 | -0.0225 | -0.0010 | 0.0002 | -0.0000 | 0.0267 | -0.0011 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| 2017 | -0.1242 | -0.0031 | 0.0002 | -0.0000 | 0.0802 | 0.0288 |
| | (0.001) | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) |
| 2018 | -0.2587 | -0.0074 | 0.0004 | 0.0000 | 0.2594 | 0.0186 |
| | (0.005) | (0.000) | (0.000) | (0.000) | (0.005) | (0.000) |
| 2019 | -0.0268 | -0.0009 | 0.0002 | 0.0000 | 0.0355 | -0.0313 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| 2020 | -0.0424 | -0.0023 | 0.0001 | -0.0001 | 0.0319 | 0.0841 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) |

*Source:* Thomson Reuters eMAXX

*Note:* The table summarizes the coefficient estimates on characteristics for each year, controlling for fund-quarter fixed effects. Observations are at the investor-bond-quarter level, where zero holdings are included if the bond is within the investment universe of the investor that quarter. Estimation sample is from 2003Q1 to 2021Q4, and includes all investors that hold at least 100 unique bonds that year. A negative coefficient on credit spread indicates that an increase in credit spreads decreases the market value of fund's holdings, resulting from a combination of a mechanical decline in the price per security and any change in number of securities held. Standard errors, in parentheses, are clustered at the fund level.

Table 10: Increased short-term investor participation in bad times

| | (1) Short-term share | (2) Firm fundamentals | (3) Demand-side effects |
|---|---|---|---|
| Economic activity | -0.00200*** | -0.00138*** | -0.00118*** |
| | (0.000378) | (0.000385) | (0.000411) |
| Probability of default | | 1.203*** | 1.158*** |
| | | (0.122) | (0.129) |
| Bond size (log) | -0.0105*** | -0.0129*** | -0.0135*** |
| | (0.00281) | (0.00282) | (0.00283) |
| Tenor (years) | 0.00246*** | 0.00252*** | 0.00254*** |
| | (0.000136) | (0.000140) | (0.000139) |
| Credit rating (log) | -0.0789*** | -0.00721 | -0.00541 |
| | (0.0170) | (0.0224) | (0.0224) |
| Cash / assets | | 0.0651*** | 0.0623*** |
| | | (0.0203) | (0.0222) |
| Debt / assets | | -0.0315 | -0.0234 |
| | | (0.0242) | (0.0250) |
| TED spread | | | 0.0112** |
| | | | (0.00446) |
| Intermediated volume (dealer capacity) | | | -0.00950*** |
| | | | (0.00166) |
| Year FE | ✓ | ✓ | ✓ |
| Firm FE | ✓ | ✓ | ✓ |
| Underwriter FE | ✓ | ✓ | ✓ |
| Observations | 14001 | 14001 | 14001 |
| R-squared | 0.309 | 0.313 | 0.314 |

*Note:* Dependent variable is the share of short-term investors for each bond, measured as the selling activity in the first week following issuance divided by the size of the bond issuance. Independent variable of interest is the CFNAI monthly index, a proxy for economic activity. Bond controls include size of bond (log), tenor in years, and issuer credit rating (log). Regression (2) adds the following firm controls: probability of default as computed using CDS trading, the prior quarter cash to total assets ratio, and the prior quarter total debt to total assets ratio. Regression (3) adds the following market level controls: the TED spread (the difference between LIBOR and the U.S. Treasury bill rate) and the dealer intermediated volume ratio, computed as the ratio of weekly buy volume from customers to weekly buy volume from dealers. All regressions include year, firm, and underwriter fixed effects. Observations are at the bond-underwriter level. Standard errors clustered at the underwriter.

# Internet Appendix

# A Metrics used in the paper

## A.1 Computing yields from TRACE data

Yields reported in TRACE are incomplete and inaccurate. To overcome this, I compute yields directly using the following formula:

$$P = \sum_{t=1}^{T*f} \frac{C}{(1+y/f)^t} + \frac{1}{(1+y/f)^{(T*f)}}, \tag{29}$$

where $C$ is the bond's annual coupon amount, $f$ is the frequency of coupon payments (for example, $f = 2$ for semiannual bonds), $y$ is the yield to maturity, and $T$ is the number of years to maturity of the bond (also known as the tenor). I use a Newton optimization method in Python to compute the yield to maturity $y$ given the rest of the observed bond characteristics and the price $P$ of the bond reported in TRACE.

## A.2 Computing credit spreads

To compute credit spreads for secondary market holdings, I first compute market yields on all relevant bonds as reported in TRACE data. I primarily rely on the monthly TRACE data reported by WRDS. If this dataset is missing quarter-end yields on bonds, I use Enhanced TRACE data and compute the volume-weighted average of sell-side trades on the last trading day of each quarter. To compute credit spreads, I use the interpolation method described in Gürkaynak et al. (2007). I match the remaining maturity for each bond to the corresponding interpolated risk-free rate. Credit spreads for bond $b$ with remaining term $\tau$ at date $t$ are thus

$$cs_{bt}(\tau) = yield_{bt} - r_{ft}(\tau). \tag{30}$$

## A.3 Alternative metrics for issuance premium

I employ three alternative methods for computing the first-day returns. A summary table of each metric is below.

1. **Day 1 price return**: I follow Cai et al. (2007) and take the trade-volume-weighted average

of prices on all sell trades up to one day following issuance, compute the return relative to the offering price, and then subtract the one-day return on the Bloomberg Aggregate Bond Index.

2. **New issue concession**: This is an ex-ante measure collected by IGM/CFR based on a survey of underwriting banks. This metric is the basis point difference between the yield on a newly issued bond and the market yield on a comparable existing bond.

3. **Issuance premium for first 3 (7) days**: I first compute the yield to maturity on all trades in the first day following issuance, based on TRACE-reported prices. Then I take the trade-volume-weighted average of the yields and subtract the duration-matched U.S. Treasury yield for the first 3 (7) days after issuance to compute the corresponding credit spread. Finally I subtract this computed credit spread from the new issuance credit spread.

Table IA.1: Alternative metrics and benchmarks for issuance premium

| | Mean | Std Dev | Pct 1 | Pct 25 | Median | Pct 75 | Pct 99 |
|---|---|---|---|---|---|---|---|
| Issuance premium (1 day) | 7.7 | 11.6 | -9.3 | 1.4 | 4.9 | 9.9 | 62.4 |
| Issuance premium (3 days) | 7.5 | 17.7 | -20.0 | 1.5 | 4.9 | 10.0 | 65.8 |
| Issuance premium (7 days) | 8.1 | 18.7 | -22.7 | 1.6 | 5.4 | 11.0 | 70.6 |
| New issue concession | 4.6 | 15.9 | -30.0 | -2.5 | 3.0 | 9.0 | 63.1 |
| CHW Day 1 excess return (based on price) | 51.8 | 80.6 | -94.0 | 4.9 | 35.2 | 80.1 | 352.4 |
| Bloomberg Agg 1 day return (based on price) | -1.1 | 22.9 | -55.0 | -14.5 | -2.1 | 12.2 | 56.9 |
| Bid-ask spread (based on price) | 36.2 | 36.7 | 2.0 | 17.0 | 28.0 | 44.0 | 161.0 |

*Notes:* This table reports the distribution of the issuance premium used in the baseline estimation, as well as alternative metrics described in Section A.3, all in basis points. Because the Day 1 excess return computed as per Cai et al. (2007) is based on prices, the measure is of larger magnitude. The Bloomberg Agg is the US Agg Total Return Value Unhedged USD Index, pulled from Bloomberg. This index was previously known as the Lehman U.S. Aggregate Bond Index.

# B Proofs

*Proof of equation* (22)*: outside option for investors participating in PM.* Investors take quantity supplied of bonds as given. Thus, their outside option is to purchase the corporate bond at a competitive price in the secondary market, where the quantity demanded equals the amount of the bond issued:

$$Q^{D,PM}(r_b^*) = Q^S. \tag{31}$$

The expression for $q^D(r^*) = \ln\big(Q^D * (r^*)\big)$ is derived as below. Note that I model an expectation of rationing $\omega$, allowing for the possibility that investors anticipate underwriter rationing and scale up their orders accordingly. The baseline model assumes $\omega = 0$, which does not impact the estimation results significantly.

I start with aggregate demand:

$$Q_{bt}^D = W_t\theta_t \frac{\exp\left(\delta_{ST,b}\right)}{\exp\left(\frac{\sigma_t^2}{2k_{ST}}\right) + \sum_m \exp(\delta_{ST,m})} \frac{1}{1-\omega_{ST}} + W_t(1-\theta_t)\frac{\exp\left(\delta_{LT,b}\right)}{\exp\left(\frac{\sigma^2}{2k_{LT}}\right) + \sum_m \exp(\delta_{LT,m})} \frac{1}{1-\omega_{LT}}. \tag{32}$$

For ease of exposition, I make the following substitutions:

$$d_1 = \exp\left(\frac{\sigma^2}{2k_{ST}}\right) + \sum_m \exp(\delta_{ST,m}), \tag{33}$$

$$d_2 = \exp\left(\frac{\sigma^2}{2k_{LT}}\right) + \sum_m \exp(\delta_{LT,m}). \tag{34}$$

For the baseline model, I assume $\omega_1 = \omega_2 = \omega$. Taking logarithms, I get

$$\begin{aligned}
q_{bt}^D &= \ln\big(Q_{bt}^D\big) \\
&= \ln(W_t) - \ln(1-\omega) + \ln\left[\frac{\theta\exp(\delta_{1b})}{d_1} + \frac{(1-\theta)\exp(\delta_{2b})}{d_2}\right] \\
&= \ln(W_t) + \omega + \ln\left[\exp(\delta_{2b})\frac{\theta\exp(\delta_{1b}-\delta_{2b})}{d_1} + \frac{(1-\theta)}{d_2}\right] \\
&= \ln(W_t) + \omega + \delta_{2b} + \ln\left[\frac{\theta\exp(\delta_{1b}-\delta_{2b})}{d_1} + \frac{(1-\theta)}{d_2}\right] \\
&= \ln(W_t) + \omega + \theta\delta_{1b} + (1-\theta)\delta_{2b} - \theta\ln(d_1) - (1-\theta)\ln(d_2).
\end{aligned} \tag{35}$$

For the third line, within the second term, I can factor out $\exp\left(\delta_{2b}\right)$. In the second-to-last-line, I make a first-order Taylor approximation around $\theta = 0$:

$$\begin{aligned}
f(\theta) &= \ln\Big[\frac{\theta\exp(\delta_{1b}-\delta_{2b})}{d_1} + \frac{(1-\theta)}{d_2}\Big] \\
&\approx f(0) + f'(\theta)\Big|_{\theta=0} \times \theta \\
&= -\ln\big(d_2\big) + d_2\Big(\frac{\exp(\delta_{1b}-\delta_{2b})}{d_1} - \frac{1}{d_2}\Big)\theta \\
&\approx -\ln\big(d_2\big) + \Big(\frac{d_2}{d_1}\exp(\delta_{1b}-\delta_{2b}) - 1\Big)\theta \\
&= -\ln\big(d_2\big) + \Big(\exp\Big(\delta_{1b}-\delta_{2b}+\ln\Big(\frac{d_2}{d_1}\Big)\Big) - 1\Big)\theta \\
&\approx -\ln\big(d_2\big) + \Big(\delta_{1b}-\delta_{2b}+\ln\Big(\frac{d_2}{d_1}\Big)\Big)\theta.
\end{aligned} \tag{36}$$

I then have

$$\begin{aligned}
q_{bt}^D = w_t &+ (r_b - r^{SM})\big(\alpha_1\theta_t + \alpha_2(1-\theta_t)\big) + r^{SM}\big(\alpha_{1,SM}\theta_t + \alpha_{2,SM}(1-\theta_t)\big) \\
&+ X_b\big(\beta_1\theta_t + \beta_2(1-\theta_t)\big) + \xi_b + \omega \\
&+ (\theta-1)\ln\Big(\exp\big(-k_2/\sigma^2\big) + \sum_m \exp(\alpha_2 r_m + \beta_2 X_m + \xi_m)\Big) \\
&- \theta\ln\Big(\exp\big(-k_1/\sigma^2\big) + \sum_m \exp(\alpha_1 r_m + \beta_1 X_m + \xi_m)\Big).
\end{aligned} \tag{37}$$

I substitute this last expression into (31) to get

$$\begin{aligned}
r_b^* = \frac{1}{\alpha_1\theta_t + \alpha_2(1-\theta_t)}\Big(&q^S - w_t - \omega \\
&+ r^{SM}\big((\alpha_1 - \alpha_{1,SM})\theta_t + (\alpha_2 - \alpha_{2,SM})(1-\theta_t)\big) \\
&- X_b\big(\beta_1\theta_t + \beta_2(1-\theta_t)\big) - \xi_b \\
&+ (1-\theta)\ln\Big(\exp\big(-k_2/\sigma^2\big) + \sum_m \exp(\alpha_2 r_m + \beta_2 X_m + \xi_m)\Big) \\
&+ \theta\ln\Big(\exp\big(-k_1/\sigma^2\big) + \sum_m \exp(\alpha_1 r_m + \beta_1 X_m + \xi_m)\Big)\Big).
\end{aligned} \tag{38}$$

I use the first-stage estimates to compute the implied values for $\xi_b$, the unobserved common component of investor demand for bond $b$:

$$
\begin{aligned}
\xi_b = q^D - w_t - \omega \\
&- (r_b^o - r^{SM})(\alpha_1\theta + \alpha_2(1-\theta)) - r^{SM}(\alpha_{1,SM}\theta + \alpha_{2,SM}(1-\theta)) \\
&- X_b\big(\beta_1\theta_t + \beta_2(1-\theta_t)\big) \\
&+ (1-\theta)\ln\Big(\exp\big(-k_2/\sigma^2\big) + \sum_m \exp(\alpha_2 r_m + \beta_2 X_m + \xi_m)\Big) \\
&+ \theta\ln\Big(\exp\big(-k_1/\sigma^2\big) + \sum_m \exp(\alpha_1 r_m + \beta_1 X_m + \xi_m)\Big).
\end{aligned} \tag{39}
$$

I can then rewrite $r^*$ as

$$
\begin{aligned}
r_b^* &= \frac{1}{\alpha_1\theta_t + \alpha_2(1-\theta_t)}\Big(q^S - q^D + r_b^o(\alpha_1\theta + \alpha_2(1-\theta))\Big) \\
&= \frac{1}{\alpha_1\theta_t + \alpha_2(1-\theta_t)}\Big(q^S - q^D\Big) + r_b^o.
\end{aligned} \tag{40}
$$

Rearranging, I have a straightforward way to relate observed credit spreads $(r_b^o)$ to the counterfactual credit spread $r^*$ that would result if investors took $q^S$ (the log bond size) as given, and the bond were priced competitively among investors:

$$
r_b^o - r_b^* = \frac{q^D - q^S}{\alpha_1\theta_t + \alpha_2(1-\theta_t)}. \tag{41}
$$

The issuance premium is a function of the oversubscription (logged), divided by the weighted average demand elasticity of investors.

□

*Derivation of aggregate demand $Q_{bt}$ in equation* (19). Using properties of the lognormal distribution, I rewrite the investor's objective function as

$$
\max_b - \exp\Big(-\frac{1}{k_i}\mu_{ihb} + \frac{\sigma^2}{2k_h^2}\Big) \tag{42}
$$

where

$$
\mu_{ihb} = \alpha_h r_b^{PM} + \alpha_{h,SM} r_b^{SM} + \gamma X_b + \xi_b + \epsilon_{ib},
$$

or

$$\max_b - \exp\big(-\frac{1}{k_i}U_i(b)\big) \tag{43}$$

where

$$U_i(b) = \delta_{hb} + \epsilon_{ib} - \frac{\sigma^2}{2k_h}. \tag{44}$$

Each investor dollar is allocated to the bond that provides the greatest utility:

$$U_i(b) > U_i(m) \qquad \forall m \neq b, \tag{45}$$

where $m$ is the index of all other bonds being issued on the same day.

I now derive the unconditional probability that investor $i$ chooses bond $b$ as per Train (2009). First, I write down the conditional probability that investor $i$ chooses bond $b$:

$$\begin{aligned} P(i \text{ choose } b) &= P(U_{ib} > U_{im}\ \forall m \neq b) \\ &= P(\delta_{hb} + \epsilon_{ib} - \frac{\sigma^2}{2k_h} > \delta_{hm} + \epsilon_{im} - \frac{\sigma^2}{2k_h}\ \ \forall m \neq b) \\ &= P(\epsilon_{im} < \delta_{hb} - \delta_{hm} + \frac{\sigma^2}{2k_h} - \frac{\sigma^2}{2k_h} + \epsilon_{ib}\ \ \forall m \neq b). \end{aligned} \tag{46}$$

Suppose first that $\epsilon_{ib}$ is known. Since the $\epsilon$ terms are independent, the probability of investor $i$ choosing $b$ is just the cumulative distribution function (CDF) for each potential value of $\epsilon_{im}$ for all $m \neq b$, and I can write the CDF for all bonds $m \neq b$ as the product of the CDFs for the individual bonds:

$$P(i \text{ choose } b|\epsilon_{ib}) = \prod_{m \neq b} \exp\big(-\exp\Big(-(\delta_{hb} - \delta_{hm} + \frac{\sigma^2}{2k_h} - \frac{\sigma^2}{2k_h} + \epsilon_{ib})\Big)\big). \tag{47}$$

Since I do not observe any of the $\epsilon_{ib}$ values in reality, I evaluate the unconditional probability that investor $i$ chooses bond $b$ by integrating over all potential values of $\epsilon_{ib}$. I assume the outside option has $U_{0h} = 0$ for every $h$. I then obtain the following expression for the probability that investor $i$

chooses bond $b$ out of a given market $t$:

$$\begin{aligned} P_{ib} = P(i \text{ choose } b) &= \int \prod_{m \neq b} \exp\big(-\exp\Big(-(\delta_{hb} - \delta_{hm} + \frac{\sigma^2}{2k_h} - \frac{\sigma^2}{2k_h} + \epsilon_{ib})\Big)\big) f(\epsilon_{ib}) d\epsilon_{ib} \\ &= \frac{\exp\big(\delta_{hb} - \frac{\sigma^2}{2k_h}\big)}{1 + \sum_m \exp\Big(\delta_{hm} - \frac{\sigma^2}{2k_h}\Big)} \\ &= \frac{\exp\big(\delta_{hb}\big)}{\exp\Big(\frac{\sigma^2}{2k_h}\Big) + \sum_m \exp(\delta_{hm})}. \end{aligned} \tag{48}$$

Next, I need to map the probability of investor $i$ participating in the primary market for bond $b$ to the total quantity demanded for bond $b$ as observed in the data. The aggregate demand for bond $b$ in market $t$ is just the sum over all types of investors that unconditionally choose to purchase bond $b$:

$$Q_{bt}^D = \sum_h P_{hbt} M_{ht}. \tag{49}$$

Assume there are only two types of investors: a proportion $\theta_t$ that are short-term investors, and a proportion $(1 - \theta_t)$ that are not. Market size $M_{ht}$ is defined as the proportion of type $h$ in the full amount of investor wealth in market $t$: $M_{ST,t} = W_t \theta_t$ and $M_{LT,t} = W_t(1 - \theta_t)$, where $W_t$ is the whole universe of potential investors in a given market $t$. Note that $w_t = \ln(W_t)$. The aggregate demand is then given by

$$Q_{bt}^D = W_t \theta_t \frac{\exp\big(\delta_{ST,b}\big)}{\exp\Big(\frac{\sigma^2}{2k_{ST}}\Big) + \sum_m \exp(\delta_{ST,m})} + W_t(1 - \theta_t) \frac{\exp\big(\delta_{LT,b}\big)}{\exp\Big(\frac{\sigma^2}{2k_{LT}}\Big) + \sum_m \exp(\delta_{LT,m})}. \tag{50}$$

□

*Derivation of firm's supply of bond in equation (5).* Note that given the normal error, I can write the unconditional expectation of issuance $q$ for a given firm as

$$\begin{aligned} E[q|Z] &= Pr(q > 0|Z) \times E[q|Z, q > 0] \\ &= \Phi((\gamma_r r + Z\gamma - c)/\sigma_e) \times E[q|Z, q > 0], \end{aligned} \tag{51}$$

where, following the standard censored tobit model (see Wooldridge (2002), Chapter 16),

$$E[q|Z, q > 0] = \gamma_r r + Z\gamma + E[u|u > c - \gamma_r r - Z\gamma] = \gamma_r r + Z\gamma + \sigma_e \Big[ \frac{\phi((\gamma_r r + Z\gamma - c)/\sigma_e)}{\Phi((\gamma_r r + Z\gamma - c)/\sigma_e)} \Big]. \tag{52}$$

Note further that the change in expected issuance, unconditionally, given a change in $r$, is

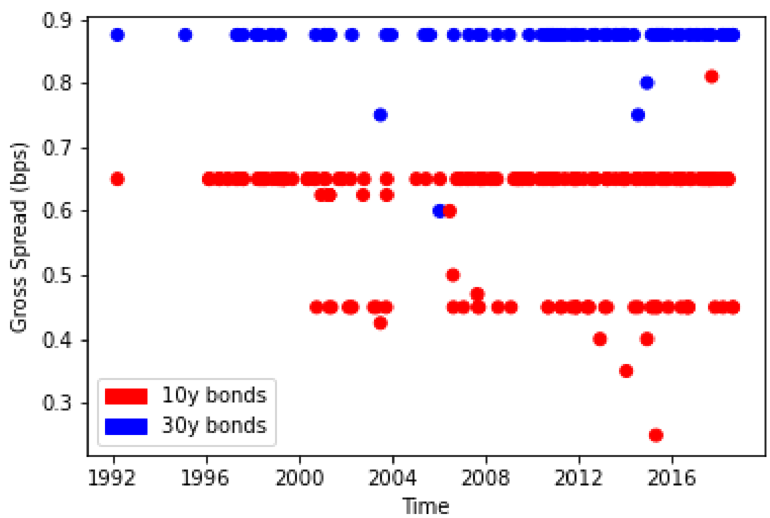
$$\frac{\partial E[q|Z, r]}{\partial r} = \gamma_r \Phi\big((\gamma_r r + Z\gamma - c)/\sigma_e\big), \tag{53}$$

where $\Phi\big((\hat{\gamma}_r r + Z\hat{\gamma} - c)/\hat{\sigma}_e\big) = Pr(q > 0|Z, r)$ is the estimated probability of issuing given $Z, r$.

□

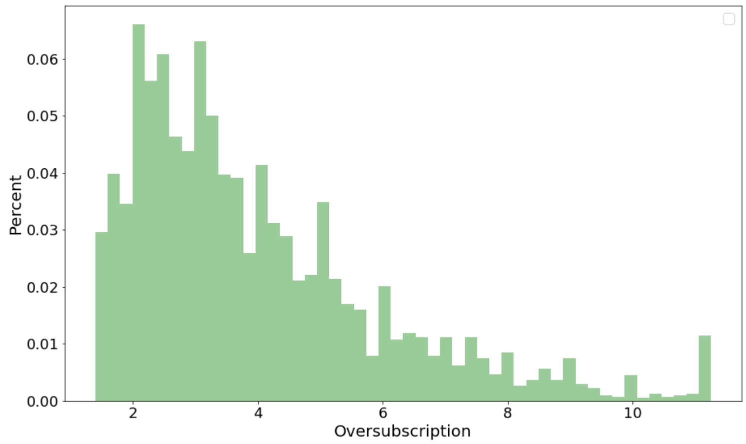
# C Additional Figures and Tables

Figure IA.1: Underwriter fees for 10- and 30-year Baa1 rated corporate bonds




*Source:* SDC Platinum.
*Note:* The figure shows underwriting fees (gross spreads) for all USD corporate bonds issued in the U.S. public market in the non-utility, non-financial sectors. I include secured, unsecured, senior, and subordinated bonds. In red are fees on 10-year bonds, and in blue are fees on 30-year bonds.

Figure IA.2: Distribution of oversubscription ratio



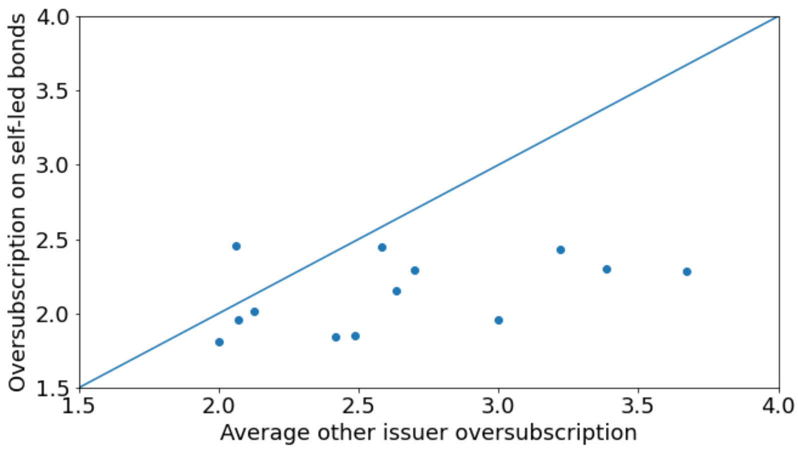

*Source:* IGM and CFR.
*Note:* Histogram of oversubscription ratios for bonds issued 2010–2020. Oversubscription is computed as the ratio of quantity demanded to quantity supplied at the final issuance price.

Table IA.2: Broker-dealers as underwriter and issuer versus as underwriter

| Broker-dealer | # self-uw bonds | # other bonds | Oversub(self) | Oversub (other) | Issuance range/spread (self) | Issuance range/spread (other) |
|---|---|---|---|---|---|---|
| 'CITICORP' | 101 | 46 | 2.01 | 2.13 | 0.11 | 0.15 |
| 'JPM' | 95 | 5 | 1.84 | 2.42 | 0.22 | 0.13 |
| 'BOA' | 84 | 20 | 2.30 | 3.39 | 0.07 | -0.13 |
| 'GS' | 79 | 18 | 2.45 | 2.58 | 0.09 | 0.14 |
| 'WFC' | 67 | 10 | 1.81 | 2.00 | 0.13 | 0.11 |
| 'HSBC' | 58 | 7 | 2.46 | 2.06 | 0.08 | 0.16 |
| 'MS' | 46 | 17 | 2.28 | 3.67 | 0.04 | 0.13 |
| 'UBS' | 33 | 15 | 1.96 | 2.07 | 0.11 | 0.13 |
| 'DB' | 32 | 13 | 1.85 | 2.49 | 0.10 | 0.15 |
| 'BARC' | 29 | 8 | 2.29 | 2.70 | 0.07 | 0.13 |
| 'CREDSUISSE' | 28 | 6 | 2.16 | 2.63 | -0.31 | 0.11 |
| 'BNPP' | 27 | 4 | 2.43 | 3.22 | 0.10 | -0.23 |
| 'RBS' | 7 | 3 | 1.96 | 3.00 | 0.00 | 0.02 |
| t-test for diff in means, p-value: | | | | 0.00294677 | | 0.77707 |

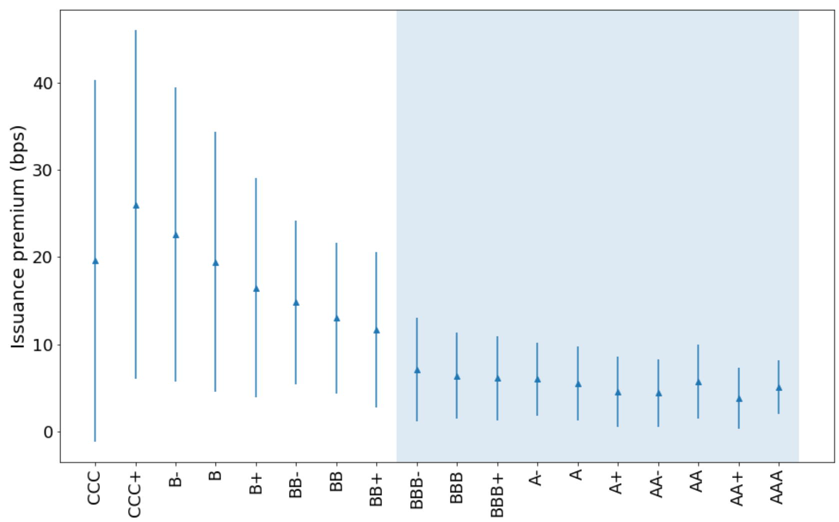
*Notes:* Reports for all broker-dealers that underwrite bonds for themselves, the average oversubscription and range of credit spreads for both self-led bond issuances and comparable underwritten bonds issued by other financial firms. To be included in the analysis, bonds issued by other financial firms must be within 2.5 years of bank $u$'s average tenor and within 250MM of bank $u$'s average bond size, rated within 1 notch of bank $u$'s most recent highest rating, and have $\leq 5$ underwriters. P-values for two-sample related t-test of difference in means between self-led and comparable bond issuances are reported for both oversubscription and the ratio of issuance credit spread range to final credit spread.

Figure IA.3: Banks have less oversubscription when they are both underwriter and issuer



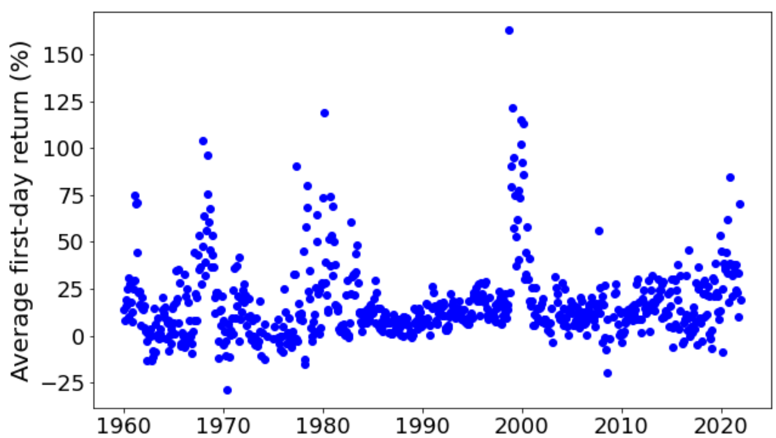

*Source:* IGM, CFR and Mergent FISD.
*Note:* Each dot represents a broker-dealer. The $y$-axis shows the average oversubscription on bonds issued and underwritten by broker-dealer $u$. The $x$-axis shows the average oversubscription on bonds underwritten by broker-dealer $u$ but issued by other financial firms. Includes bonds issued by financial firms within 2.5 years of bank $u$'s average tenor and within 250MM of bank $u$'s average bond size, rated within 1 notch of bank $u$'s most recent highest rating, and with $\leq 5$ underwriters. The line is the 45-degree line. Dots below the line indicate oversubscription is higher when the broker-dealers is underwriting bonds issued by other firms. Data is reported in Table IA.2.

Figure IA.4: Issuance premiums across ratings categories




*Source:* Enhanced TRACE and Mergent FISD.
*Note:* I aggregate credit ratings to the issuer level using Moody's, S&P, and Fitch issuer credit ratings at the time of issuance of each bond. I use the median if there are three ratings, and the minimum if there are two, as per Becker and Ivashina (2015).

Figure IA.5: Average first day return of equity IPOs




*Source:* Jay Ritter's IPO Data website, `https://site.warrington.ufl.edu/ritter/ipo-data/`.
*Note:* The figure shows the monthly average first day percentage return for all equity IPOs listed on CRSP with offer price \$5 and above, excluding closed-end funds, REITs, acquisition companies, ADRs, limited partnerships, units, banks and S&Ls.

Table IA.3: Issuance premiums higher during GFC and COVID-19

| | (1)<br>GFC / COVID Dummies | (2)<br>VIX |
|---|---|---|
| COVID period (dummy) | 12.24*** | |
| | (0.859) | |
| GFC period (dummy) | 13.11*** | |
| | (0.490) | |
| VIX | | 0.316*** |
| | | (0.0147) |
| Credit Rating (log) | -16.17*** | -15.07*** |
| | (1.702) | (1.698) |
| Bond size(log) | 1.042*** | 1.353*** |
| | (0.163) | (0.171) |
| Tenor (years) | -0.0627*** | -0.0628*** |
| | (0.00443) | (0.00468) |
| Debt / assets | -7.123*** | -6.433*** |
| | (1.312) | (1.087) |
| Cash / assets | 13.17*** | 13.77*** |
| | (1.592) | (1.685) |
| Operating profit / assets | 19.71*** | 10.46 |
| | (6.947) | (6.731) |
| Firm FE | ✓ | ✓ |
| Underwriter FE | ✓ | ✓ |
| Observations | 17074 | 17074 |
| R-squared | 0.520 | 0.526 |

*Notes:* Dependent variable is issuance premium, measured in basis points. Independent variable of interest is a dummy variable for the bond being issued in the 2020 COVID crisis or 2008 GFC in regression (1), and the VIX in regression (2). GFC period is an indicator variable for issuance between September 1, 2008, and June 1, 2009. COVID-19 period is an indicator variable for issuance between March 1, 2020, and April 8, 2020. Controls include issuer credit rating (log), size of bond (log), tenor in years, total debt to total assets ratio, prior quarter cash to total assets ratio, and operating profit to total assets ratio. Includes firm and underwriter fixed effects. Observations are at the bond-underwriter level. Standard errors clustered at the underwriter level.

Table IA.4: Countercyclicality of issuance premiums as % of credit spreads

| | (1) Baseline | (2) Issuer controls | (3) UW FE | (4) UW Info |
|---|---|---|---|---|
| Economic activity | -0.000608** | -0.00106*** | -0.00110*** | -0.00126*** |
| | (0.000270) | (0.000224) | (0.000233) | (0.000155) |
| Issuance range / spread | | | 0.125*** | 0.127*** |
| | | | (0.0123) | (0.0118) |
| Credit rating (log) | 0.0280*** | 0.0126*** | -0.00475* | -0.00962* |
| | (0.00297) | (0.00233) | (0.00281) | (0.00565) |
| Bond size (log) | 0.00241*** | 0.00294*** | 0.00136** | 0.000509 |
| | (0.000909) | (0.00103) | (0.000567) | (0.00115) |
| Tenor (years) | -0.00116*** | -0.00117*** | -0.000891*** | -0.000879*** |
| | (0.0000527) | (0.0000571) | (0.0000412) | (0.0000349) |
| Debt / assets | | -0.0233*** | -0.0257*** | -0.0690*** |
| | | (0.00423) | (0.00289) | (0.0115) |
| Cash / assets | | 0.00945 | 0.00244 | 0.0267*** |
| | | (0.00681) | (0.00568) | (0.00621) |
| Operating profit / assets | | 0.349*** | 0.225*** | 0.302*** |
| | | (0.0958) | (0.0374) | (0.0436) |
| Firm FE | | | | ✓ |
| Underwriter FE | | | ✓ | ✓ |
| Observations | 17208 | 17208 | 17187 | 17149 |
| R-squared | 0.0215 | 0.0287 | 0.507 | 0.612 |

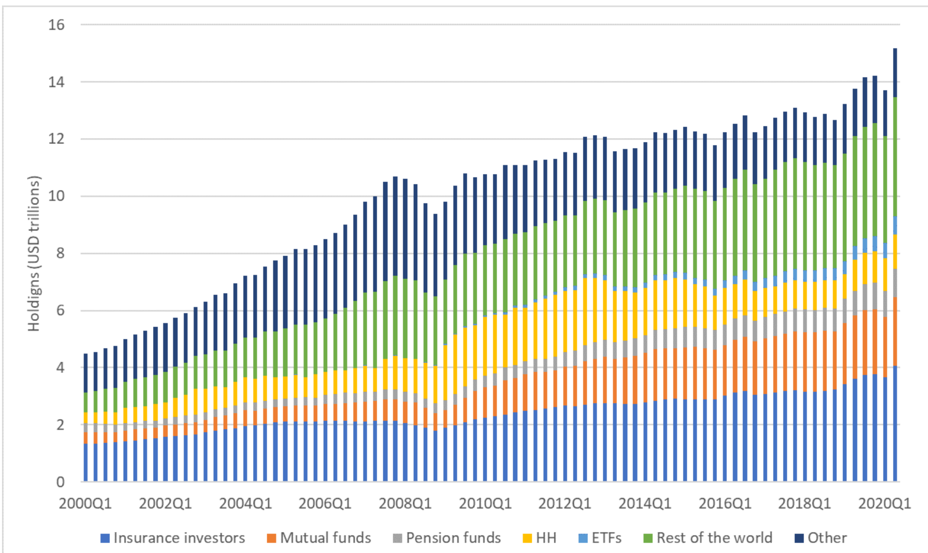
*Notes:* Dependent variable is issuance premium as a percent of total credit spreads at issuance. Independent variable of interest is economic activity as measured by the CFNAI monthly index, collected from the Chicago Federal Reserve, which is designed to be mean zero with a standard deviation of one. Bond controls include issuer credit rating (log), size of bond (log), and tenor in years. Firm controls in regressions (2) through (4) include the prior quarter cash to total assets ratio, total debt to total assets ratio, and operating profit to total assets ratio. Regressions (3) and (4) control for bond-level issuance range as a proportion of the final issuance credit spread. Regressions (3) and (4) include underwriter fixed effects. Regression (4) includes firm fixed effects. Observations are at the bond-underwriter level. Standard errors clustered at the underwriter level.

Table IA.5: Correlation between issuance premiums and cumulative abnormal stock returns

| | (1)<br>Stock return (Day 0) | (2)<br>Stock return (Day 1) | (3)<br>Stock return (Day 0) | (4)<br>Stock return (Day 1) |
|---|---|---|---|---|
| Issuance premium (bps) | 0.0000544 | -0.000142 | -0.000149 | -0.000427* |
| | (0.0000662) | (0.000108) | (0.000149) | (0.000248) |
| U.S. Treasury yield | 0.000240 | 0.000182 | 0.000487 | 0.000389 |
| | (0.000509) | (0.000926) | (0.000618) | (0.00109) |
| Bond size (log) | 0.000636 | 0.00269* | 0.00160* | 0.00263 |
| | (0.000711) | (0.00159) | (0.000932) | (0.00209) |
| Credit rating (log) | -0.00303 | -0.0214* | -0.00911 | -0.0528* |
| | (0.00598) | (0.0112) | (0.0136) | (0.0316) |
| Tenor (log) | -0.000357 | -0.0000177 | -0.000901 | -0.000605 |
| | (0.000612) | (0.00100) | (0.000737) | (0.00122) |
| Issuer FE | ✓ | ✓ | ✓ | ✓ |
| Industry-quarter FE | ✓ | ✓ | ✓ | ✓ |
| Observations | 6149 | 6147 | 3785 | 3785 |
| R-squared | 0.448 | 0.425 | 0.476 | 0.492 |

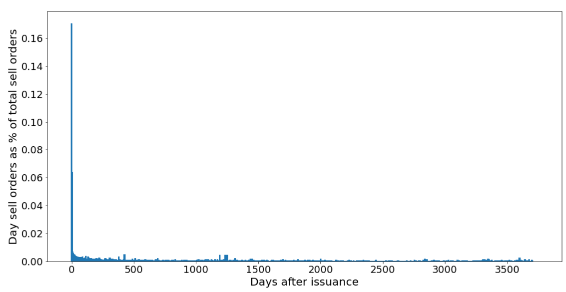
*Note:* Dependent variable is cumulative abnormal return of the issuing firm's stock price in the day of issuance (Day 0) or in the day of issuance and the first trading day following issuance (Day 1), measured as the cumulative return as reported in CRSP relative to the return on the S&P Index in the same time period. Independent variable of interest is issuance premium. Bond controls include duration-matched U.S. Treasury rate, size of bond (log), issuer credit rating (log), and tenor of bond in years (log). All regressions include firm and industry-quarter fixed effects, where industry is the 2-digit NAICS industry classification. Observations are at the bond level. Sample in the first two models include all bonds with observed issuance premium 2000-2010; sample in the last two models include all bonds included in the estimation sample, 2010-2020. Standard errors clustered at the firm level.

Figure IA.6: Corporate bond holders

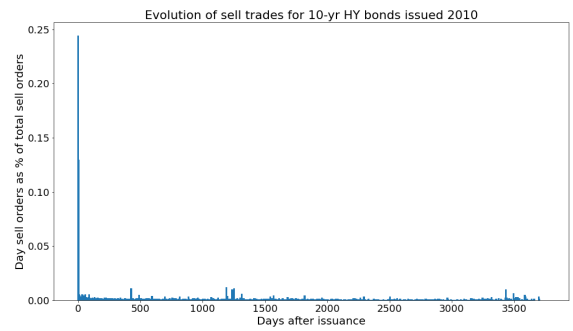



*Source:* Federal Reserve Flow of Funds.
*Note*: "HH" includes households and non-profit organizations. "Other" includes depository institutions, state and local governments, closed-end funds, finance companies, broker dealers, REITs, credit unions, GSEs, money market funds, and the federal government.

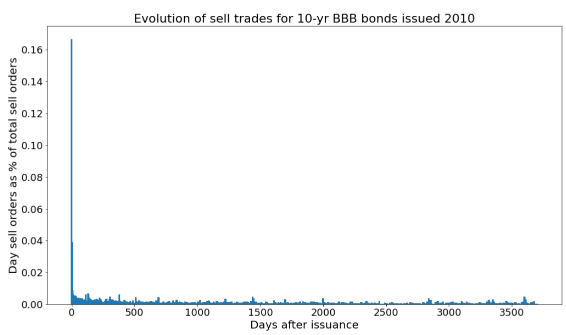
Figure IA.7: Evidence from TRACE: heterogeneous bond buyers



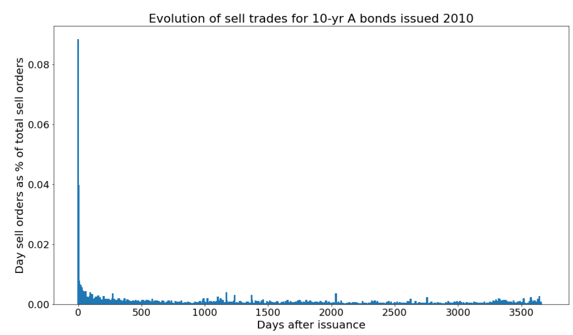

(a) All 10-year bonds issued 2010




(b) HY 10-year bonds issued 2010



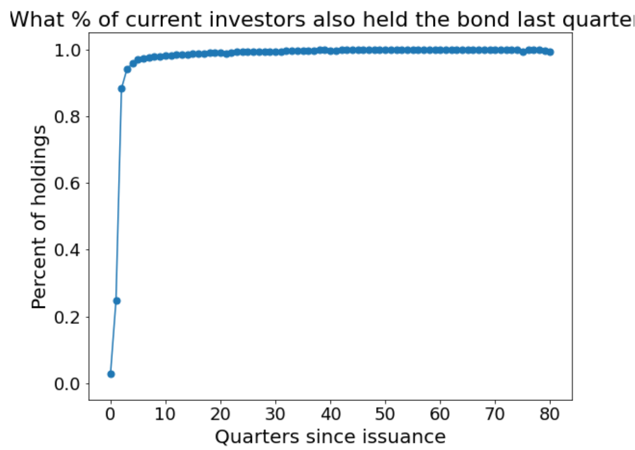

(c) BBB-rated 10-year bonds issued 2010




(d) A-rated 10-year bonds issued 2010

*Source:* Enhanced TRACE
*Note:* The figure reports the total volume of sell trades in event time since issuance. It includes only USD non-financial corporate bonds issued in 2010 with initial tenor of 9–11 years. The $y$-axis shows the average across all bonds of share of each day's sell orders as a percentage of total volume of sell orders over the life of the bond (defined as trades between 0 and 4000 days following issuance). The terms "HY bonds", "BBB-rated bonds", and "A-rated bonds" refer to bonds rated below BBB-, between BBB- and BBB+, and A- or higher, respectively.

Figure IA.8: Persistence of investor holdings




*Source:* eMAXX.
*Note:* Reports the median number of percent of investors (FUNDIDs) that also held the bond in the previous quarter.

Table IA.6: Sample summary statistics: bonds issued last 7 days of quarter

| | Full sample: Mean | Full sample: StDev | Last 7 days sample: Mean | Last 7 days sample: StDev |
|---|---|---|---|---|
| Amount ($MM) | 632.72 | 565.85 | 605.15 | 499.83 |
| Tenor (Years) | 9.60 | 8.76 | 10.52 | 8.44 |
| Credit rating | 14.35 | 4.34 | 12.77 | 3.95 |
| Credit Spread (bps) | 263.47 | 222.06 | 303.96 | 242.66 |
| Coupon | 4.88% | 2.48% | 5.76% | 2.46% |
| Probability of Default | 0.02 | 0.02 | 0.02 | 0.02 |
| First day spread decrease | 7.67 | 11.58 | 9.90 | 14.00 |
| Cash/Assets | 0.08 | 0.10 | 0.06 | 0.08 |
| Total Debt (log) | 8.52 | 1.77 | 7.90 | 1.47 |
| Assets (log) | 9.81 | 1.80 | 9.13 | 1.41 |
| Leverage | 0.32 | 0.20 | 0.35 | 0.29 |
| Number of bonds | | 16075 | | 473 |
| Number of firms | | 4736 | | 314 |

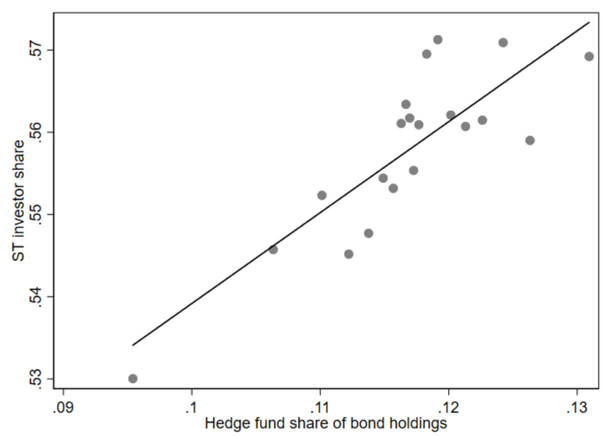
*Source:* Mergent FISD, IGM, CFR, Emaxx, TRACE, Markit
*Note*: This table compares the full sample of bonds, including all USD non-financial corporate bond issuances from 2000-2020, to the subsample of bonds that are issued within the last seven days of the quarter.

Table IA.7: Bond holders

| | Insurance funds | Mutual funds | Pension funds |
|---|---|---|---|
| Num funds | 1222.72 | 1191.03 | 128.52 |
| AUM (Bn) | 9.24 | 4.37 | 1.54 |
| Unique bonds held | 184.42 | 274.85 | 128.96 |
| Unique classes held | 52.21 | 63.89 | 41.76 |
| Pct held last qtr | 0.90 | 0.84 | 0.78 |
| Avg length of holdings (qtrs) | 8.16 | 4.41 | 4.50 |
| Avg length of holdings (pct of tenor) | 0.22 | 0.12 | 0.13 |

*Source:* Thomson Reuters eMAXX
*Note*: Includes fund holdings reported in eMAXX, 2002-2019. Values are first averaged across all funds within a fund class for each quarter, and then averaged across quarters. Insurance investors include life, health, property and casualty, and diversified insurance. Mutual funds include annuity and money market funds. Pensions include hospitals, governments, and 401K funds.

Figure IA.9: Correlation: short-term investors and hedge fund share



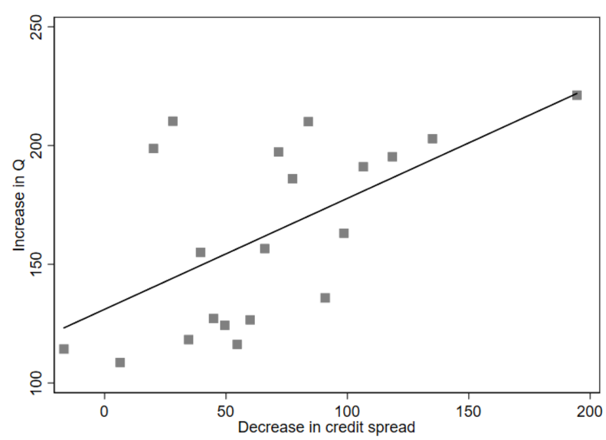

*Source:* eMAXX and Enhanced TRACE
*Note:* The figure shows a binned scatter plot of percentage of hedge funds in Flow of Funds data on percentage of bond sold in the first 7 days. The model includes firm and underwriter fixed effects.

Table IA.8: Full sample vs. upsized sample of bonds and issuers

| | Full sample: Mean | Full sample: StDev | Upsized sample: Mean | Upsized sample: StDev |
|---|---|---|---|---|
| Amount ($MM) | 632.72 | 565.85 | 614.97 | 426.92 |
| Tenor (years) | 9.60 | 8.76 | 9.97 | 7.46 |
| Credit rating | 14.35 | 4.34 | 12.00 | 3.73 |
| Credit spread (bps) | 266.63 | 255.26 | 318.46 | 217.56 |
| Coupon | 4.88% | 2.48% | 5.55% | 2.13% |
| Probability of default | 0.02 | 0.02 | 0.03 | 0.03 |
| First day spread decrease | 6.07 | 11.60 | 6.81 | 12.06 |
| Cash/assets | 0.08 | 0.10 | 0.06 | 0.09 |
| Total debt (log) | 8.52 | 1.77 | 8.12 | 1.46 |
| Assets (log) | 9.81 | 1.80 | 9.29 | 1.41 |
| Leverage | 0.32 | 0.20 | 0.36 | 0.22 |
| Number of bonds | | 16075 | | 2626 |
| Number of firms | | 4736 | | 1251 |

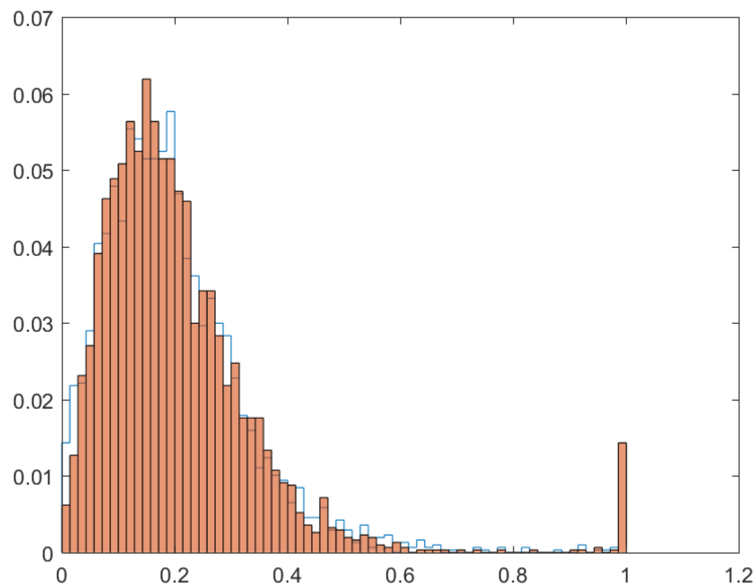
*Source:* Compustat, IGM/CFR, and Mergent FISD.
*Notes:* Full sample selection includes all USD non-financial corporate bond issuances. Upsized sample includes all bond issuances that are upsized during the day of issuance.

Figure IA.10: Greater increase in quantity supplied for upsized issuances when credit spreads lower




*Source*: IGM, CFR, and Mergent FISD.
*Note:* The $y$-axis shows the increase in amount issued for a given bond issuance. The $x$-axis shows the difference between the initial expected credit spread and the final credit spread. A positive $x$-axis value indicates that credit spreads were lower than the firm anticipated. I control for credit rating, tenor and year fixed effects.

Figure IA.11: Distribution of short-term share: model fit




*Note:* I simulate an equilibrium vector of credit spreads, quantities demanded, quantities supplied, and share of short-term investors using the estimated parameters. The shaded region is the actual distribution of the underlying data, from TRACE, and the outline is the model-predicted distribution of the short-term share.

Table IA.9: Persistence in set of corporate bonds held by investors

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AUM_0 | 0.62 | 0.79 | 0.85 | 0.89 | 0.92 | 0.94 | 0.95 | 0.95 | 0.96 | 0.97 | 0.97 |
| AUM_1 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| AUM_2 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| AUM_3 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| AUM_4 | 0.99 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| AUM_5 | 0.98 | 0.99 | 0.99 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| AUM_6 | 0.98 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 1.00 | 1.00 | 1.00 | 1.00 |
| AUM_7 | 0.98 | 0.98 | 0.98 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 |
| AUM_8 | 0.98 | 0.98 | 0.98 | 0.98 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 |
| AUM_9 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 |

*Source:* eMAXX

*Note:* The table shows the percentage of bond classes held in the current quarter that were also held in the previous 1–11 quarters; it is similar to Table 1 of Koijen and Yogo (2019). Each cell gives the median across time (2000–2017) and across all institutions in a given percentile of assets under management.

Table IA.10: Firm supply elasticities (standard tobit)

| | (1) All | (2) HY | (3) IG | (4) A-rated | (5) BBB-rated | (6) 2010-2019 | (7) 2008-2009 | (8) 2020H1 |
|---|---|---|---|---|---|---|---|---|
| Quantity (log) | | | | | | | | |
| Credit spread (bps) | -0.00221*** | -0.00203*** | -0.00431*** | -0.00579*** | -0.00397*** | -0.00251*** | -0.00152*** | -0.00357*** |
| | (0.000223) | (0.000220) | (0.000446) | (0.000520) | (0.000487) | (0.000264) | (0.000583) | (0.000693) |
| Observations | 3433 | 1744 | 1689 | 569 | 1120 | 2470 | 314 | 125 |

*Note:* The table covers sample bonds issued 2000–2020. Observation is by firm-quarter. Dependent variable for all columns is firm-quarter issuance volume, in logs. Standard errors are clustered at the firm level. Standard tobit estimation is left-censored at log of $100 million. I include within-bond fixed effects.

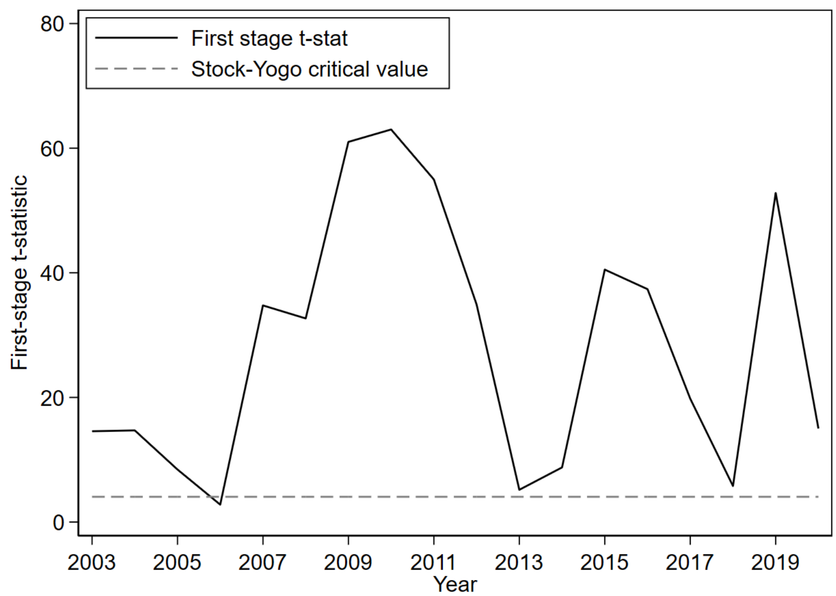



Figure IA.12: First stage test

*Note:* The figure reports the absolute value of the first stage t-statistics on the instrument for credit spreads as defined in Equation 27, and compares them to the critical value for rejecting the null of weak instruments of 4.05 (Stock and Yogo (2005)). Each estimation is on annual data with fund-quarter fixed effects, from 2003 to 2020.

Table IA.11: Credit rating legend

| **Moody's** | **S&P** | **Fitch** | **Numerical** |
|---|---|---|---|
| Aaa | AAA | AAA | 22 |
| Aa1 | AA+ | AA+ | 21 |
| Aa2 | AA | AA | 20 |
| Aa3 | AA- | AA- | 19 |
| A1 | A+ | A+ | 18 |
| A2 | A | A | 17 |
| A3 | A- | A- | 16 |
| Baa1 | BBB+ | BBB+ | 15 |
| Baa2 | BBB | BBB | 14 |
| Baa3 | BBB- | BBB- | 13 |
| Ba1 | BB+ | BB+ | 12 |
| Ba2 | BB | BB | 11 |
| Ba3 | BB- | BB- | 10 |
| B1 | B+ | B+ | 9 |
| B2 | B | B | 8 |
| B3 | B- | B- | 7 |
| Caa1 | CCC+ | CCC+ | 6 |
| Caa2 | CCC | CCC | 5 |
| Caa3 | CCC- | CCC- | 4 |
| Ca | CC | CC | 3 |
| C | C | C | 2 |
| D | D | D | 1 |