Essays in Financial Economics

Kerry Yang Siani

Submitted in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy
under the Executive Committee
of the Graduate School of Arts and Sciences

COLUMBIA UNIVERSITY

2022

Abstract

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This dissertation studies topics in financial economics. In the first chapter, *Raising Bond Capital in Segmented Markets*, I study the cost of bond capital. The cost of bond capital to firms that is determined at issuance often exceeds yields trading in secondary bond markets. I find that the difference between yields at issuance and in secondary markets, the "issuance premium", spikes in bad times, increasing firms' costs of capital. This suggests that the economics of the relatively understudied primary bond markets – where firms sell new bonds via underwriters to investors – are important for understanding firms' costs of capital and access to credit over the cycle. Leveraging new data on bond issuance, I estimate a model of primary markets that explains the issuance premium and its impact on bond issuance volume. 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, the share of more price-elastic short-term investors endogenously increases, supporting bond volumes. The preferences of primary market investors therefore directly affect the transmission of shocks to firms' costs of capital and bond issuance volume, as well as the price impacts of corporate bond purchase policies.

The second chapter, *Bond Market Stimulus: Firm-Level Evidence from 2020-21*, is co-authored with Olivier Darmouni. We use micro-data on corporate balance sheets to study firm behavior after the unprecedented policy support to corporate bond markets in 2020. We find that as bond yields

fell, firms issued bonds to accumulate large and persistent amounts of liquid assets instead of investing. Conceptually, the benefits depend on how highly bond issuers valued this liquidity at the margin. We show they generally had access to bank liquidity that they chose not to use: many issuers left their credit lines untouched, while others used bonds to repay existing loans. Moreover, equity payouts remained high: almost half of issuers still repurchased shares in Spring 2020.

In the third chapter, *Global Demand Spillovers: the Role of Underwriting Networks*, I study the role of underwriter networks in transmitting demand shocks across global jurisdictions. Using novel data and a difference-in-differences strategy, I find that central bank corporate bond purchases spill over to foreign jurisdictions through bond underwriting networks. The diff-in-diff exploits the European Central Bank's 2016 corporate sector purchase program. I compare U.S. firms connected to underwriters with more or less Eurozone clients. Firms connected with banks with more European clients had larger orderbooks and issued more at lower costs. Treated firms do not increase real investment, but rather increase equity payouts. I identify bond underwriting networks as a novel channel through which demand shocks spread across borders. These results matter for understanding the overall impact of corporate quantitative easing programs.

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Acknowledgements

I owe a huge debt of gratitude to my sponsor Olivier Darmouni, my committee chair Wei Jiang, and my committee members Charles Calomiris, Yiming Ma, Giorgia Piacentino, and Jesse Schreger. Olivier patiently guided me through years of idea exploration, giving detailed feedback on countless drafts of my paper. Wei believed in me from the beginning, providing on-point feedback and guidance along the way. Giorgia always challenged me to think more deeply about the economics of my results. Yiming gave actionable, practical advice and encouraged me in the exact moments I needed it the most. Jesse always lent a different perspective and plenty of positivity. Charlie's enthusiasm for my work helped see me through the finish line. Without the ongoing support of this set of mentors who taught me how to conduct research, I could not have continued my work through a pandemic, pregnancy, maternity leave, and a challenging job market.

I benefited greatly from many other faculty members at Columbia. Thank you in particular to Xavier Giroud, Tano Santos, Suresh Sundaresan, and Neng Wang for their excellent teaching and generosity in providing feedback. I am incredibly grateful to my friends, and in particular Lira Mota, Cristina Tessari, and Larissa de Lima, who read my dissertation in every iteration and provided invaluable feedback and support throughout.

I am eternally grateful for the unwavering encouragement and support of my husband, Ottavio Siani. He is the first filter for my ideas, lending his real-world experience to sanity check my intuition. Thank you to my family, especially my parents Ken and Liping Yang and my sister Alicia Archer for their confidence in me, and my son Enzo for his smiles and positive energy.

To Mom.

Chapter 1

Raising Bond Capital in Segmented Markets [1]

Firms raise over $1 trillion in corporate bonds every year.[2] 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 countercyclical pattern of secondary market credit spreads (over risk-free rates) documented by Gilchrist and Zakrajšek (2012). 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 segmented. Secondary markets exclude firms from participating, while primary markets are run by broker-dealers who are known to favor some investors and exclude others.[4] Indeed, I document facts consistent with investor segmentation: primary investors are larger than their counterparts in secondary markets, and on average 20% of them "flip" the bond within days, causing a sharp spike in trading post-issuance,

[1]This chapter is based on Siani (2021). For their continued patience and interest at all stages of my project, I am indebted to my committee: Olivier Darmouni, Charles Calomiris, Wei Jiang, Yiming Ma, Giorgia Piacentino, and Jesse Schreger. I benefited greatly from conversations with Simona Abis, Kim Cramer, Kent Daniel, Nina Boyarchenko, Matthieu Gomez, Yifeng Guo, Sam Hanson, Anna Kovner, Jane Li, Larissa de Lima, Harry Mamaysky, Florian Nagler, Stijn van Nieuwerburgh, Lira Mota, Tomasz Piskorski, Tano Santos, Jose Scheinkman, Or Shachar, Irene Sun, Suresh Sundaresan, Cristina Tessari, Laura Veldkamp, Neng Wang, Pierre-Olivier Weill, Daniel Wolfenzon, Kairong Xiao, and seminar participants at Columbia Business School and the Federal Reserve Bank of New York. I am also grateful to Chris Reich and the teams at Credit Flow Research and Informa Global Markets for support and access to their data. All errors are my own.

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

[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).

while the remainder rarely trade.

Because this segmentation leads to limited investor capacity to absorb shocks, shifts in supply and demand in primary markets can impact firms' costs of capital (Duffie (2010)). To quantify how much, I estimate an equilibrium model of primary markets using a new industry dataset and high-frequency identification. 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 a larger proportion of more price-elastic short-term investors who "flip" the bond, dampening the spike in issuance premiums and accommodating more issuance. Firms can thus access more bond capital in bad times due to higher issuance premiums attracting more short-term investors, relative to a counterfactual with only buy and hold investors. The preferences of primary market participants therefore directly affect the transmission of shocks to firms' costs of capital and access to credit.

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 on April 8 in order to shore up cash reserves. The bond was issued at 8.75% – their highest bond yield since prior to the 2008 financial crisis – and received \$6 billion in investor orders. Short-term investors purchased 40% of the bond, double the average share. Within the first day, the credit spread dropped over 100 basis points once trading in secondary markets began, suggesting that underwriters had "left money on the table" by pricing the bond at a higher yield (or lower price) than market clearing. The Nordstrom example aligns with facts I document about primary markets. Large order books along with a first day drop in credit spreads indicate restricted access to primary markets, consistent with market segmentation. Moreover, short-term investors generally participate more during downturns, when issuance premiums are higher.

Motivated by these facts, 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 (credit spreads). I allow primary market investors to have different preferences over the two components of new issue credit spread: the issuance premium and the secondary market credit spread. 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 firm fundamentals, investor composition, and underwriter favoritism 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, holdings, bond, and firm characteristics from the Enhanced Trade Reporting and Compliance Engine (TRACE), Thomson Reuters eMAXX, the National Association of Insurance Commissioners (NAIC), Mergent FISD, and Compustat. The combined sample for the primary estimation is from July 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 2%; during the global financial crisis (GFC), when they are more desperate for cash, they decrease issuance by half as much.[6]

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 (Duffie (2010), Koijen and Yogo (2019), Gabaix and Koijen (2020), Becker and Ivashina (2015)). Indeed, the data confirms an upward-sloping demand curve

[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] In principle, firms can substitute to bank lending (Darmouni and Siani (2020)) or, increasingly, shadow banks (Buchak et al. (2018)).

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. The resulting estimates show 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.

I compare primary market investor demand with secondary market investor demand to demonstrate the difference between these two sets of investors. I estimate secondary market demand elasticities using cross-sectional variation in institutional holdings data, following Koijen and Yogo (2019) and Bretscher et al. (2020), exploiting the investment universe of other funds as an exogenous price shifter. However, I deviate from the security-level instrument of these two papers by defining each investor's investment universe using *classes* of bonds, which are defined as bonds of the same tenor and credit rating, issued by firms in the same industry. I do this because greater demand for bonds at the investment class level generates a greater exogenous component of demand. I find that for a one-basis-point increase in credit spreads, secondary market investors increase holdings by 0.1%. The comparison of elasticities is further evidence that primary and secondary market investors are distinct groups with different preferences.

Because new bonds often attract higher quantity demanded than quantity supplied, and demand is known to be rationed,[7] 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

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

entry in the underwriting business.[8] These barriers have been documented as search costs and relationship-building for investors[9] , and certification costs and relationship-building for firms.[10]

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. I find that changes in firms' willingness to pay drive a significant portion of the cyclicality of issuance premiums, but investor participation and underwriter behavior explain the magnitudes. 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 in primary markets endogenously shifts towards short-term investors. This shift leads to smaller drops in overall issuance relative to a counterfactual with no short-term investors. The phenomenon can be seen in the Nordstrom example, where large issuance premiums increased both the share of short-term investors and the quantity demanded. On the other hand, in normal times, 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 an increase in short-term investors is an increase in issuance premiums on average, while the bright side is that an endogenous shift towards more short-term investors in bad times helps primary markets absorb large supply shocks.

Finally, I quantify the price impact from large exogenous bond purchases in secondary markets

[8] 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).

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

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

versus primary markets, allowing firms to endogenously respond to changes in issuance costs but holding fundamentals fixed. I find that a \$6.5 million purchase of a median bond in secondary markets, where investors are relatively inelastic, leads to a drop of nearly 60 basis points in new issue credit spreads and just under \$6.5 million increase in 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 secondary market intervention would have a larger effect on new issuance prices and volumes, owing to the relative elasticities and higher share of short-term participants in bad times.

Related literature: This paper primarily contributes to three strands of literature. First, I add to the body of work on the role of institutions in financial markets by taking the firm's perspective. While models of corporate debt typically abstract away from changes in issuance costs (Leland and Toft (1996), He and Milbradt (2014)), my paper quantifies how bond issuance prices and volumes may vary across the cycle beyond secondary market fluctuations (Gilchrist and Zakrajšek (2012)), due to institutional frictions in primary markets. Constraints on participation in primary markets mean firms' costs of capital are subject to supply and demand shocks; this is related to the concept of slow-moving capital (Duffie (2010), Greenwood et al. (2018)). Firms' costs of capital are therefore vulnerable to the supply constraints of a smaller set of investors, exacerbating the effects of limited risk-bearing capacity on asset prices (Gilchrist and Zakrajšek (2012), He and Krishnamurthy (2013), Manconi et al. (2012), Adrian et al. (2017), Adrian and Shin (2014)). Moreover, investor heterogeneity can arise from different funding structures or investment strategies (Chodorow-Reich et al. (2021), Greenwood and Vayanos (2014), Greenwood and Vayanos (2010), Vayanos and Vila (2021), Aragon and Strahan (2012)); I find this heterogeneity plays an important role in primary markets.

As institutional frictions lead to inelastic investors, recent papers have developed tools to estimate investor demand systems for securities (Koijen and Yogo (2019), Gabaix and Koijen (2020), Bretscher et al. (2020)). I build on this work by estimating investor demand while endogenizing firm supply of corporate bonds. Moreover, I quantify the effects of secular shifts in investor composition (Li and Yu (2021)) on firms' costs of capital. My estimation of demand elasticities for different investor types contributes to the literature assessing central bank policies, particularly policies regarding corporate bond purchases (Falato et al. (2020), Gilchrist et al. (2020), Flanagan and Purnanandam (2020), Boyarchenko et al. (2020), Halling et al. (2020b)).

Second, I contribute to a vast literature on securities issuance in both bonds and equities. My paper relates to papers on corporate bond underpricing, including Cai et al. (2007), Goldstein et al. (2021), Nikolova et al. (2020), Goldstein et al. (2019), Wang (2021), Bessembinder et al. (2021), and Nagler and Ottonello (2020) (see Cai et al. (2007) for a survey), by documenting the countercylical pattern of issuance premiums and quantifying the effects of investor heterogeneity and underwriter agency.[11] In the literature on equity underwriting and underpricing (see Ljungqvist (2007) for a survey), the dominant explanation for underpricing is information asymmetry. Corporate bonds are less information-sensitive than equities, for three reasons. First, information asymmetries between firms and investors (Myers and Majluf (1984)) are limited, because many investors are repeat investors (Zhu (2021)), and because bond outcomes lie within a narrow range, given low default rates.[12] Second, information asymmetries between underwriters and investors (Benveniste and Spindt (1989), Cornelli and Goldreich (2003), Booth and Smith (1986)) are mitigated by frequent bond issuance, which provides pricing benchmarks: in 2019, for example, there were 151 equity IPOs in the U.S. and 2,097 corporate bond offerings (SIFMA 2020). Finally, while underpricing may arise from information asymmetry among investors (Rock (1986)), particularly between institutions and the retail buyers who hold 32% of U.S. equities (Green (2007)), less than 7% of corporate bonds are held by retail investors.[13]

[11]Moreover, 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.

[12]Corporate bonds historically have low default rates: since 1981, default rates for investment-grade corporate bonds have remained well below 1%, peaking at 0.42% in 2002 and 2008, in the wakes of the dotcom crisis and the GFC, respectively. Source: "Default, Transition, and Recovery: 2019 Annual Global Corporate Default and Rating Transition Study", S&P Global, April 29, 2020.

[13]Source: Federal Reserve Flow of Funds.

The primary non-information story for equity underpricing involves agency issues between underwriters and firms (Ritter and Welch (2002), Jenkinson et al. (2018), Loughran and Ritter (2002)). This also affects bond underwriting: agency costs in securities underwriting for bonds are documented in Flanagan et al. (2019) and Nikolova et al. (2020). I contribute to this literature, as well as the literature that estimates structural methods to study the effects of imperfect competition in financial markets (Robles-Garcia (2019), Eisenschmidt et al. (2020), Wang et al. (2020), Xiao (2020b), Drechsler et al. (2017), Scharfstein and Sunderam (2016)), by explicitly modeling underwriters' surplus split between firms and investors and quantifying the effect on fluctuations in costs of capital.

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, inventory holding costs, and heterogeneous bargaining power (Duffie et al. (2005), Duffie et al. (2007), Lagos and Rocheteau (2009), Gavazza (2016)). These transaction costs decrease liquidity and increase expected returns (Amihud and Mendelson (1986)). The literature on this subject would suggest higher transaction costs in times of greater market volatility, when bonds are overall more illiquid (Bao et al. (2011)), since dealers are less willing to take riskier and more illiquid bonds into inventory (Goldstein and Hotchkiss (2020)). 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 (Duffie (2012), Bessembinder et al. (2018), Bao et al. (2018), Choi and Huh (2019)), increasing the importance of non-bank dealers such as primary market investors. Finally, dealers have relationship networks (Hendershott et al. (2020)) and exercise market power to benefit more active investors and to investors with whom they have relationships (O'Hara et al. (2018), Di Maggio et al. (2017)), just as underwriters do in the primary market setting.

The rest of the paper is organized as follows. Section 1.1 describes the data and institutional background of corporate bond issuance. Section 1.2 describes empirical facts characterizing the corporate bond market. Section 1.3 introduces the model, and Section 1.4 presents the estimation strategy and the parameter estimates. Section 1.5 discusses results and counterfactual analyses. Section 1.6 concludes.

1.1 Data and background

1.1.1 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; with NAIC bond-investor purchase data to identify insurance investors; and with Enhanced TRACE data to track trading in the first days post-issuance. I further merge with holdings data from Thomson Reuters eMaxx to estimate secondary market demand. I include only fund-years that hold at least 20 unique bonds. For the bonds in my sample, the eMAXX data covers about 50% of holdings at quarter end.

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 end of the first day post-issuance. I omit extreme values with changes of greater than 300 basis points. The metric nets out changes in U.S. Treasury yields and other market conditions. Because bonds are issued close to par, this measure represents firms' incremental annual cost of capital. On a yield basis, issuance premiums are 8 basis points on average.[14] For robustness, I compute several alternative metrics: the same computation but over the first 3- and 7- days, the underwriters' view of issuance premiums collected by IGM/CFR, and a price-based first day excess return as proposed

[14]While I use a yield-based metric in my analysis, I can more easily compare to benchmarks in the literature by computing a price-based analogue. 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.

by Cai et al. (2007). See Appendix 1.8.4 for details.

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 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, and with Markit credit default swap (CDS) quotes to compute probabilities of default. I estimate each firm's time-varying probability of default from the market spread of its CDS as per Hull (2012).[15] I collect bid–ask spreads for each bond at the monthly level from WRDS Bond Returns data. Finally, I collect historical U.S. Treasury bond yields and TED spreads (the difference between the 3-month LIBOR and the U.S. Treasury bill yield) from the St. Louis Federal Reserve and historical values of the Chicago Fed National Activity Index (CFNAI) from the Chicago Federal Reserve.

Included in the estimation are bonds that are underwritten publicly by broker-dealers and thus are included in the IGM/CFR data. These bonds tend to be larger and issued by higher-rated firms. For my primary estimation analysis, I have 4,013 US dollar corporate bonds issued by 508 non-financial, non-utility firms. See Table 1.8 for summary statistics of the full sample of FISD bonds (non-convertible, non-financial USD bonds of at least $100 million in size at issuance) and issuers, versus the sample available for estimation.

1.1.2 Background: corporate bond underwriting process

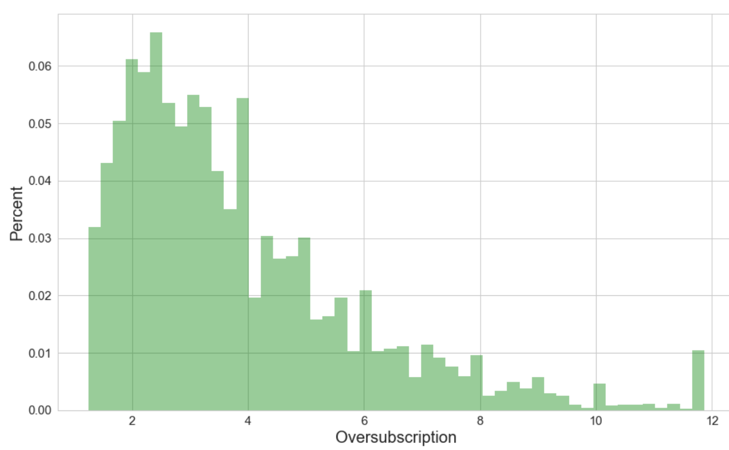
Corporate bonds are priced as a credit spread to the risk-free rate, where the risk-free rate is that of the on-the-run U.S. Treasury bond whose duration matches the duration of the bond. A group of broker-dealers leading the underwriting process conducts a price discovery process over the span

[15] See Appendix for how I compute probability of default. I am only able to match 20% of firms with CDS, which issued 40% of the bonds in my sample. Thank you to Lira Mota for help with this merge.

of one day. In each of four rounds, the underwriters announce a potential credit spread at which the new bond could be priced, and observe the quantity demanded from investors at that credit spread. While these quantities are not transacted, 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. Bonds begin trading in the secondary market almost immediately following issuance.

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). Figure 1.1 shows the magnitude of oversubscription for newly issued bonds in my sample. As can be seen in the histogram, order books are regularly over 2–3 times oversubscribed. This suggests that issuance credit spreads are commonly set above a competitive equilibrium, where supply would equal demand.

Figure 1.1: Distribution of oversubscription ratio



Source: Credit Flow Research and Informa Global Markets
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.

Indeed, I find suggestive evidence that broker dealers are subject to agency issues in underwriting bonds when they do not internalize the costs of capital. Specifically, underwriters have smaller order books when they are both the underwriter and the issuer versus when they are underwriting a comparable bond for a different issuer (see Figure 1.10). 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.[16] When this practice is more costly because the underwriter is itself the issuer, the underwriter sets a credit spread closer to the market credit spread. This is consistent with papers that show evidence that broker-dealers have discretion in underwriting (Nikolova et al. (2020), Benveniste and Spindt (1989)). I will come back to this institutional detail when modeling the underwriter's problem.

1.2 Stylized facts

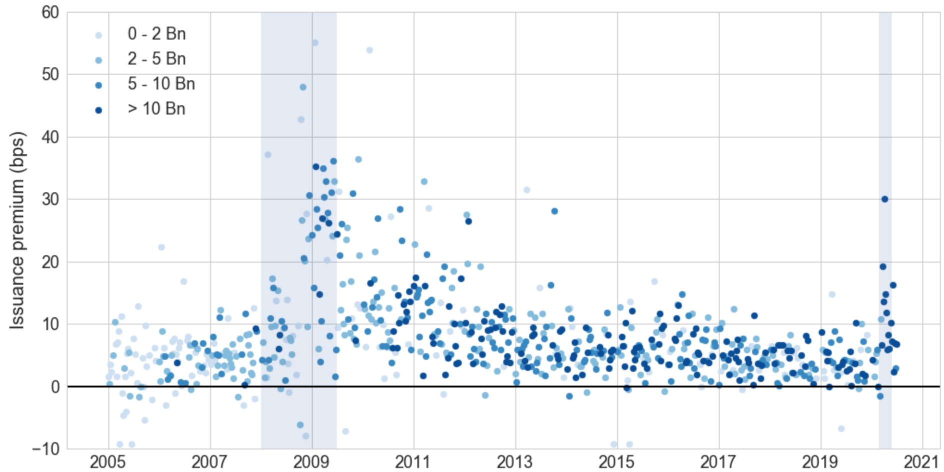
In this section, I present stylized facts about the primary market for corporate bonds. First, I describe the motivating fact that issuance premiums are countercyclical. Next, I discuss three features of primary market investors: the difference in types of investors in the two markets, primary market investor behavior, and cyclical variation in this investor behavior. These facts, taken together, suggest that primary markets are segmented from secondary markets and are thus subject to shifts in supply and demand, given limited investor capacity to absorb shocks (Duffie (2010)).

1.2.1 Issuance premiums rise in bad times

I find that issuance premiums are countercyclical. The time-series plot in Figure 1.2 shows that during the GFC of 2008 and the COVID-19 crisis of 2020, there was a spike in weekly average issuance premiums. Moreover, the distribution of issuance premiums is similar within each ratings category for investment-grade issuers, as seen in Figure 1.11, suggesting that uncertainty around bond value (Beatty and Ritter (1986), Rock (1986)), which correlates with credit rating, is unlikely

[16] 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 1.9. I find no significant difference in price uncertainty between self-led and comparable deals.

Figure 1.2: 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. A positive value indicates the bond was issued at a higher yield than post-market trading. Shaded regions are January 2008 to June 2009 and March–May 2020. Darker dots indicate weeks with greater issuance volumes.

to be the only driver.

To more formally test the impact of issuer characteristics on issuance premiums, I regress the issuance premium on a proxy for economic activity, the Chicago Fed National Activity Index (CFNAI).[17] The model is as follows:

$$IssPrem_{ubft} = \beta EconActivity_t + X_{bft}\gamma + \epsilon_{ubft}, \tag{1.1}$$

where b indicates bond, f is for each firm, u is for underwriter, and t is for day. See Table 1.1 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 is-

[17]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.

suance premiums, even when accounting for bond characteristics and credit rating. This represents 12% of the magnitude of fluctuations in the Gilchrist-Zakrajšek (GZ) credit spread as measured in Gilchrist and Zakrajšek (2012), estimated over the same sample period in the last column.[18] In the second column, 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)). Even after absorbing time-series variation in firm fundamentals, the coefficient does not change significantly.

Next, 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. The wider the range of credit spreads, the greater the ex-ante uncertainty of the price. I also include underwriter fixed effects to absorb any time-invariant cross-sectional variation in underwriter sophistication. I find that the countercyclical pattern persists. Alternatively, firms may have more information than investors and thus use underpricing as a signal of their type (Ibbotson (1975)). Moreover, the composition of issuers may change over the cycle; if certain firms are more information sensitive, this could contribute to the observed pattern. To test these hypotheses, I absorb any cross-sectional variation across firms with firm fixed effects in the next regression, and find little change in the coefficient of interest.

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. The finding is also robust to various specifications with different proxies for the business and credit cycle, including using dummy variables for the GFC and COVID-19 periods or the VIX (see Table 1.11 in the

[18]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.

Table 1.1: 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.

Appendix).[19] Moreover, this specification underestimates the countercyclical pattern because of

[19] 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 countercylicality of credit spreads. However, I find in Table 1.10 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.

selection bias: by conditioning on issuance, this analysis omits firms that did not issue in bad economic conditions because issuance premiums were too high for them. I will address this selection problem when modeling the firm's supply of capital in Section 1.3.

Increases in secondary market credit spreads in bad times, as documented in Gilchrist and Zakrajšek (2012), thus underestimate the countercyclicality of firms' costs of capital. This is important for firms because higher borrowing costs can deter issuance, dampening investment or reducing corporate liquidity. In the next section, I present observations about primary markets that will inform how to quantify the drivers and effects of issuance premiums.

1.2.2 Three facts about primary market investors

In this section, I discuss three features of primary markets. The first two are consistent with segmentation between primary and secondary markets: first, primary and secondary market investors differ from each other in trade size, fund size, and investor type; second, only a small fraction of primary market investors also participate in secondary markets. Third, in bad times, the share of investors that flips bonds from primary to secondary markets increases.

Primary market investors are different and trade in larger size

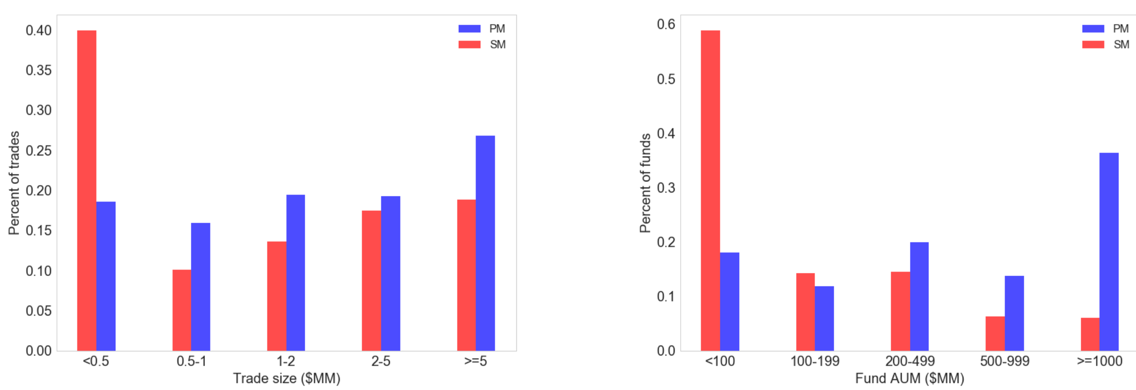
First, I find that participants in primary and secondary markets are not the same along observable characteristics. Primary market investors buy in bigger sizes and tend to be larger funds. In Figure 1.3a, I plot the distribution of trade sizes in the primary and secondary markets in the first 100 days 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 investors. 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 1.3b 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:

clearly, primary market insurers tend to be larger in fund size.

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 1.7.[20] I proxy for primary market purchases by considering the subset of bonds issued within the last seven days of quarter end.[21] I find that 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.[22]

Figure 1.3: Size differences between primary and secondary market investors



(a) Trade size comparison (TRACE)

(b) Insurer size comparison (NAIC)

Source: 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).

[20] 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 1.9 in the 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.

[21] To see if this subset of bonds is significantly different from bonds issued on other days within quarter, I report in Table 1.12 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.

[22] 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.

Why might primary and secondary market investors differ? In the presence of search costs (Henderson and Tookes (2012)) 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.

Most trading occurs right after issuance

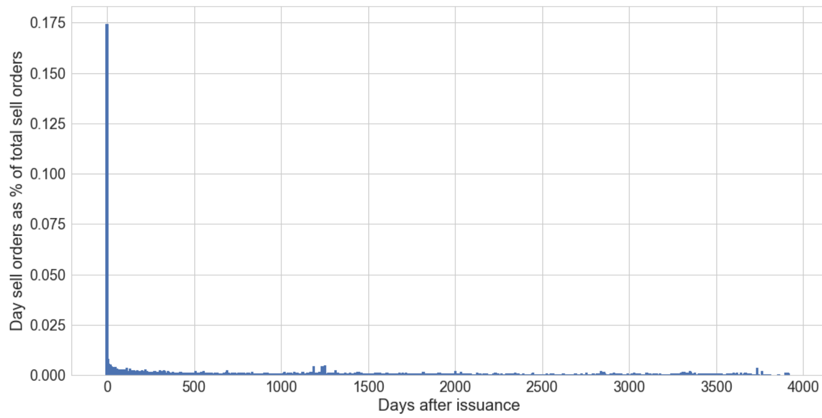
Second, trading activity is concentrated in the days immediately following issuance. This separates primary market investors into two types. Most primary market investors are "buy-and-hold" types that rarely, if ever, participate in secondary markets. However, a small proportion of investors "flip" bonds within the first few days following issuance. These investors earn the short-term profit of the issuance premium. This fact is consistent with work by Goldstein and Hotchkiss (2020), Bessembinder et al. (2021), Cai et al. (2007), who also find that most trading activity occurs within the first few weeks after issuance.

To illustrate this point, in Figure 1.4 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.[23]

Indeed, following the initial flurry of activity, corporate bond investors tend to hold the same bond over time. 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 1.12. By the end of the second quarter after issuance, 84% of holdings are by investors that held the bond in the first quarter following issuance. The percentage is well over 90% for every

[23]This behavior is consistent across ratings categories; see Figure A.1 in the Internet Appendix.

Figure 1.4: 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).

quarter thereafter.[24] This dichotomy in post-issuance behavior suggests a difference in preferences among primary market investors, likely arising from heterogeneous institutional funding needs. It also further segments primary and secondary markets: because a large proportion of primary market investors buy and hold, secondary market investors are excluded from holding a significant portion of these bonds.

More short-term investors participate in bad times

Third, I show that the share of short-term investors varies across the cycle. I run regressions of short-term investor participation in primary markets on various proxies for market downturns. I compute the share of short-term investors as the ratio of total secondary market sales reported in

[24]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 1.13 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 1.13). This is consistent with interviews with industry participants.

the first week following issuance in Enhanced TRACE to the total size of the bond. The average bond in my sample has a short-term share of 20%. I regress this share of short-term investors on the CFNAI, a proxy for economic conditions:

$$STshare_{bft} = \beta_1 EconActivity_t + \alpha_y + \alpha_u + \alpha_f + X_{bft}\gamma + \epsilon_{bft}, \tag{1.2}$$

where X_{bft} includes bond controls (tenor, rating, and size) to absorb any clientele effects along those dimensions, α_u represents underwriter fixed effects to absorb underwriter-specific bias towards short-term investors, α_y represents year fixed effects to absorb slow moving macro trends in investor participation, and α_f represents firm fixed effects. I report the results in Table 1.2. 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? In the second column, I test whether short-term investors are participating more due to worsening firm fundamentals, by including issuer fixed effects and issuer-specific time-varying characteristics: default probabilities derived from CDS trading and lagged cash and leverage ratios. The coefficient on economic activity is somewhat smaller but still significant, suggesting that some of the variation in the proportion of short-term investors 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 more or less constrained than long-term investors. In the last column of Table 1.2, I include (1) the TED spread, computed as the difference between LIBOR and the U.S. Treasury bill rate, as a proxy for dealer funding costs (Friewald and Nagler (2019)), and (2) the dealer intermediated volume ratio, computed as the ratio of weekly buy volume from customers to weekly buy volume from dealers, as a proxy for dealer balance sheet capacity (Boyarchenko et al. (2021)). The inclusion of these controls somewhat reduces the magnitude of the countercyclical pattern, suggesting that some of the pattern is demand-driven. The coefficient estimates on both metrics are consistent with the story that short-term investors are less capital-constrained than long-term investors in bad times:

higher short-term shares are correlated with higher TED spreads and higher intermediated volume. These results suggest that when long-term investors are more constrained, short-term investors act as a stopgap.

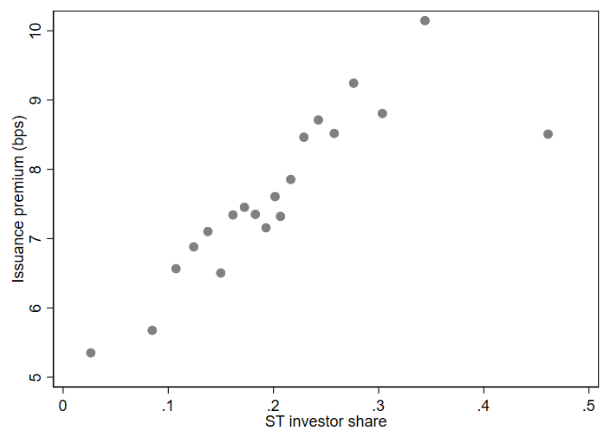
Table 1.2: Increased short-term investor participation in bad times

	(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.

Relatedly, in Figure 1.5 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 realize the profits from the issuance premium, so their increased participation in bond issues with high issuance premiums is expected.[25]

Figure 1.5: Higher issuance premiums $\Longleftrightarrow$ more short-term investors



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.

In summary, this section highlights two key features of corporate bond issuance that set primary and secondary markets apart: primary and secondary market investors are different along observable dimensions, and many primary market investors buy and hold and thus do not participate in secondary markets. Moreover, I find that these short-term investors participate more in bad times. Together, these facts suggest that 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.

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

1.3 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 1.1 and stylized facts in Section 1.2 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.

1.3.1 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 appendices.

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:

$$r_b = r_b^{PM} + r_b^{SM}, \tag{1.3}$$

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

$$q^* = \gamma_r r_b + \gamma_Z Z + e, \tag{1.4}$$

where γ_r is the firm's sensitivity to credit spread r_b, γ_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,

$$q^S = \begin{cases} q^* & \text{if } q^* > c, \\ 0 & \text{otherwise,} \end{cases} \tag{1.5}$$

where $c = \ln C$.

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

$$E[q^S|Z, q^* > c] = \gamma_r r + \gamma_Z Z + \sigma\Big[\frac{\phi((\gamma_r r + \gamma_Z Z - c)/\sigma_e)}{\Phi((\gamma_r r_f + \gamma_Z Z - c)/\sigma_e)}\Big]. \tag{1.6}$$

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 A.1 for details.

Finally, I derive from (1.4) an expression for $\bar{r}_b$, the highest credit spread at which a firm will issue amount q^S:

$$\bar{r}_b = \frac{1}{\gamma_r}\big[q^* - \gamma Z - e\big]. \tag{1.7}$$

This will be useful when simualating 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 γZ is greater (worse fundamentals).

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

$$\max_{b\in\{0,1,\ldots,B+1\}} U_{ibt} = E\Big[-\exp\Big(-\frac{1}{k_h}R_{hbt}\Big)\Big], \tag{1.8}$$

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

$$R_{hb} \sim N(\mu_{ihbt}, \sigma_t^2) \tag{1.9}$$

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

$$\mu_{ihbt} = \alpha_h r_{bt}^{PM} + \alpha_{h,SM} r_{bt}^{SM} + \beta_h X_{bt} + \xi_{hbt} + \epsilon_{ihbt} =: \delta_{hbt} + \epsilon_{ihbt}, \tag{1.10}$$

where α_h is the loading on r_{bt}^{PM}, $\alpha_{h,SM}$ is the loading on r_{bt}^{SM}, and β_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 ξ_b, which is common to all investors. Finally, I include any unobserved investor-bond-specific characteristics in ϵ_{ihb}. For example, ϵ_{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.[26] I make the assumption that the investor-bond error, ϵ_{ihbt}, has a Type 1 extreme value distribution. 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:

$$s_{hbt} = \frac{\exp\left(\alpha_h r_{bt}^{PM} + \alpha_{h,SM} r_{bt}^{SM} + \beta_h X_{bt} + \xi_{hbt}\right)}{\exp\left(\frac{\sigma_t^2}{2k_h}\right) + \sum_m \exp(\alpha_h r_{mt}^{PM} + \alpha_{h,SM} r_{mt}^{SM} + \beta_h X_{mt} + \xi_{hmt})}, \tag{1.11}$$

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:

$$Q_{bt}^D = \sum_h s_{hbt} M_{ht}, \tag{1.12}$$

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

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.

[26]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.

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.[27] 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 η, and thus solves the following maximization problem, where Q drops out because it is a constant:

$$\max_{r_{bt}} \; \pi = (r_{bt} - r^*_{bt})^{\eta}(\bar{r}_{bt} - r_{bt})^{1-\eta}. \tag{1.13}$$

Differentiating (1.13) and applying the first-order condition yields

$$r_{bt} = \eta \underbrace{\bar{r}_{bt}}_{\text{Firm's reservation}} + (1-\eta) \underbrace{r^*_{bt}(Q_D, Q_S)}_{\text{Investors' reservation}} . \tag{1.14}$$

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 η is to 1), the closer the new issue credit spread is to the firm's reservation credit spread. If the

[27] 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 (Henderson and Tookes (2012), Nikolova et al. (2020), Flanagan et al. (2019)). Recent findings by Goldstein and Hotchkiss (2020) show that underwriters have market power in secondary markets given information advantage from participating in primary markets.

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 (1.7), quantity supplied, and quantity demanded. Quantity demanded, as shown in the solution to the investors' problem (1.12), 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.

1.4 Estimation

1.4.1 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 favorable market conditions may also encourage bond issuance (Ma (2019), Mota (2020)). 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., Ma (2019) and Mota (2020) for bonds, and Bolton et al. (2013) and Baker and

Wurgler (2002) for general external financing). 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 within the span of a day based on revised expectations of investors' demand curves. Because bond issuances are completed in one day, investor perceptions of firm fundamentals (and fundamentals themselves) are unlikely to change. I find that in some bond issuances, firms respond to unexpectedly low credit spreads by "upsizing," or increasing the quantity of bonds supplied to the market. The subsample of bonds that are upsized is not significantly different from the full sample of bonds (Table 1.16 compares the distributions of firm and bond characteristics in the subsample to those in the full sample).

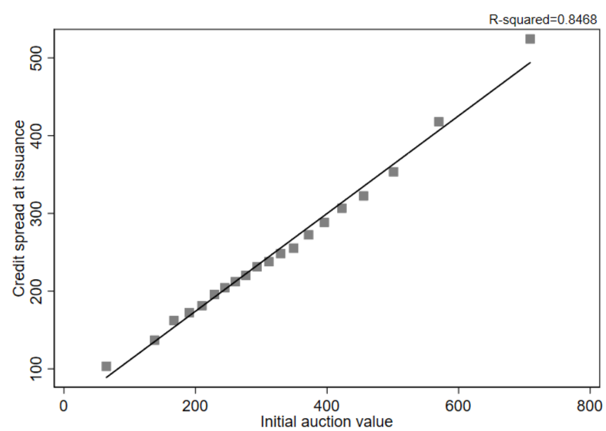
While I can observe the initial quantity of bonds that firms intend to issue, I do not directly observe the firms' initial expectations of credit spreads. Instead, I impute each firm's initial expectation of credit spreads from the initial *announced* credit spread in round $k = 0$, which I find is a 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,

$$r_{bt,k=4} = mr_{bt,k=0} + \beta X_{bt} + \alpha_y + \epsilon_{bkt}, \tag{1.15}$$

where X_{bt} is a vector of controls that include amount issued (log), issuer credit rating, and tenor, and α_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 1.6. For upsized bonds, I compute the predicted $E[r_{bt,k=4}|\text{no upsize}]$.

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 1.14 that bigger declines in credit spreads correspond to larger increases in quantity supplied.

Figure 1.6: Correlation of initial price talk with final treasury spreads



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. I estimate the within-bond tobit that identifies γ_r simultaneously with a within-firm regression that allows me to estimate 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.

1.4.2 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 (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 (Donaldson and Piacentino (2018), Becker and Ivashina (2015), 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)); (v) the monthly CFNAI to proxy for macro conditions; and (vi) 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 (1.11) 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 ξ_{hbt}:

$$\ln(s_{hbt}) - \ln(s_{h0t}) = \alpha_h r_{bt}^{PM} + \alpha_{h,SM} r_{bt}^{SM} + \beta_h X_{bt} + \xi_{hbt}. \tag{1.16}$$

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

$$q_{hbt} = \alpha_h r_{bt}^{PM} + \alpha_{h,SM} r_{bt}^{SM} + \beta_h X_{bt} + \xi_{hbt} + \ln(s_{h0t}) + \ln(M_{ht}). \tag{1.17}$$

I assume the last two terms in (1.17) 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 (1.17) across the two types of investors: $h \in \{ST, LT\}$.[28] To be able to compare

[28] 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.

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)).

I cannot directly estimate equation (1.17) with OLS, because there is potential endogeneity between the unobserved characteristics of the bond, ξ, 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)).

To overcome this, I use an exogenous supply shifter: the 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. 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. 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.

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. 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:

$$IssPrem_{ufbt} = \beta_1 \ln(Crowded)_{uft} + \beta_2 \ln(Crowded)^2_{uft} + \alpha_w + \alpha_f + \alpha_u + X_{fbt}\gamma + \epsilon_{ufbt}, \quad (1.18)$$

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.

The coefficient on the log of crowdedness is 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.

As additional instruments, I follow the standard IO literature (see Berry et al. (1995), Berry (1994)) 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

$$E[\xi_{bt} Z_{bt}] = 0. \quad (1.19)$$

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

Table 1.3: Price impacts of supply shocks in primary markets

	(1) Issuance premium (bps)	(2) 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.

gate demand expression is

$$\begin{aligned} Q_{bt}^{D} = W_t\theta_t & \frac{\exp\left(\alpha_{ST} r_{bt}^{PM} + \alpha_{ST,SM} r_{bt}^{SM} + \beta_{ST} X_{bt} + \xi_{ST,b}\right)}{\exp\left(\frac{\sigma_t^2}{2k_{ST}}\right) + \sum_{mt}\exp(\alpha_{ST} r_{mt}^{PM} + \alpha_{ST,SM} r_{mt}^{SM} + \beta_{ST} X_{mt} + \xi_{ST,m})} \\ + W_t(1-\theta_t) & \frac{\exp\left(\alpha_{LT} r_{bt}^{PM} + \alpha_{LT,SM} r_{bt}^{SM} + \gamma_{LT} X_{bt} + \xi_{LTb}\right)}{\exp\left(\frac{\sigma_t^2}{2k_{LT}}\right) + \sum_{mt}\exp(\alpha_{LT} r_{mt}^{PM} + \alpha_{LT,SM} r_{mt}^{SM} + \gamma_{LT} X_{mt} + \xi_{LT,m})}, \end{aligned} \tag{1.20}$$

which I then log-linearize to

$$q_{bt}^{D} \approx q_{t}^{D} + \big(\theta_t\alpha_{ST} + (1-\theta_t)\alpha_{LT}\big) r_{bt}^{PM} + \big(\theta_t\alpha_{ST,SM} + (1-\theta_t)\alpha_{LT,SM}\big) r_{bt}^{SM} + \big(\theta_t\beta_{ST} + (1-\theta_t)\beta_{LT}\big) X_{bt} + \xi_{bt} + \zeta_t, \tag{1.21}$$

where θ_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 ζ_b. Empirically, I proxy for θ_t using the share of short-term investors in the primary market at the weekly level.

Comparison to buy-and-hold investors in SM

In order to compare preferences of PM and SM investors, I need demand elasticities for SM bond investors. For this, 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 1.8.5. I deviate from existing papers (e.g., Koijen and Yogo (2019) and Bretscher et al. (2020)) 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 bond securities than equity securities. 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 (Vayanos and Vila (2021), Greenwood and Vayanos (2014), Guibaud et al. (2013)). 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 1.14). I can then write the following moment condition, wherein log of latent demand is 0 given other investors' exogenous latent demand and observable characteristics:

$$E[ln(\epsilon_{itb}^{SM})|\hat{z}_{itb}, \mathbf{x}_{bt}] = 0 \tag{1.22}$$

The vector of control variables includes log rating, log number of years remaining, log amount of bond at issuance, probability of default, and bid–ask spreads.

Estimating the underwriter's solution

In this section, I describe how I estimate η, 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 (1.14), and solve for the value of η 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:

$$r^* \equiv \{r : Q^D(r, X, \xi; \hat{\alpha}, \hat{\beta}) = Q^S\}. \tag{1.23}$$

I do not directly observe latent demand ξ, so I recover it from the observed quantity demanded at the observed credit spread for each bond, $q^D(r_b^o)$, using equation (1.21). This gives me an expression $\xi_b(q(r_b^o), X, \hat{\alpha}, \hat{\beta})$. I plug this into (1.23) and get

$$r_b^o - r_b^* = \frac{q^D(r_b^o) - q^S}{\alpha_1\theta_t + \alpha_2(1-\theta_t)}. \tag{1.24}$$

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 (1.14):

$$r_b = \eta\bar{r} + (1-\eta)\Big(\frac{q^S - q^D(r_b^o)}{\alpha_1\theta_t + \alpha_2(1-\theta_t)} + r_b^o\Big). \tag{1.25}$$

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

1.4.3 Parameter estimates

Table 1.4 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. Within primary markets, short-term investors are more elastic to issuance premiums than long-term investors. A one-basis-point increase in issuance premiums will increase short-term investor demand by 7% and long-term investor demand by 3%. Demand elasticities over SM credit spreads are not significantly different from zero for short-term investors. Both investor types have higher demand for larger bonds and more liquid bonds (as proxied by lower bid–ask spreads).

I compare elasticities of short- and long-term investors in the last column of Table 1.4. 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. Short-term investors are more likely to purchase more liquid bonds, as this improves their ability to exit their positions. 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 longer-duration bonds, which tend to be more liquid. Long-term investors prefer better-rated bonds than short-term investors.

Demand elasticities of secondary market investors are summarized in Table 1.15. The coefficients on credit rating, default probability, and bid–ask spreads have the expected signs: secondary market investors have positive loadings on higher-rated, less risky bonds that are more liquid. To compare PM and SM elasticities, note that the overall elasticity of each PM investor type is the average of the elasticities over issuance premium and the SM credit spread, weighted by the share of the overall credit spread that is due to the issuance premium. Short-term PM investors are more elastic to overall credit spreads than SM investors.

Table 1.4: Primary market estimates: full sample

	(1) Total order book (log)	(2) Qd short-term (log)	(3) Qd long-term (log)
Issuance premium (bps)	0.0728***	0.0335***	0.0393***
	(0.0124)	(0.00817)	(0.0107)
SM credit spread (bps)	-0.00205	0.00157	-0.00362
	(0.00269)	(0.00154)	(0.00234)
US Treasury yield	0.00401	-0.00832	0.0123
	(0.0248)	(0.0115)	(0.0238)
Bond size(log)	0.525***	0.607***	-0.0821
	(0.0552)	(0.0298)	(0.0495)
Credit Rating (log)	-0.504	0.867	-1.371*
	(0.907)	(0.555)	(0.759)
Tenor (log)	0.462***	-0.0571	0.519***
	(0.0956)	(0.0509)	(0.0853)
CFNAI	-0.0494***	-0.00808	-0.0413***
	(0.0176)	(0.0121)	(0.0121)
Bid-ask spread	-0.372***	-0.0676***	-0.305***
	(0.0327)	(0.0192)	(0.0318)
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. Controls include issuance amount (log), issuer credit rating (log), tenor in years (log), the CFNAI monthly index, 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.

Table 1.5 presents my tobit estimates of supply-side parameters.[29] At average values of co-

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

$$\frac{\partial E[q|Z,r]}{\partial r} = \hat{\gamma}_r \Phi\left(\frac{\hat{\gamma}_r r + Z\hat{\gamma}_Z - c}{\hat{\sigma}_e}\right), \tag{1.26}$$

variates, the firm responds to a ten-basis-point increase in credit spreads with a 2% decrease in issuance volumes. Firms have greater loadings on other covariates, such as the risk-free rate (see Mota (2020)) and macro and firm fundamentals (Bolton et al. (2013)), 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 1.17. Lower-rated firms are less responsive to changes in credit spreads, and firms issuing during the GFC are similarly less elastic. These results are consistent with firms becoming less price sensitive when they are low 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.

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 the literature that finds that underwriters value relationships with investors and that such relationships benefit the process of underwriting (Henderson and Tookes (2012), Benveniste and Spindt (1989), Nagler and Ottonello (2020)). Institutional investors are much more frequent participants in the corporate bond market, with the largest institutional investors[30] participating in

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

[30]Examples include Allstate and Pacific Life Insurance.

Table 1.5: Firm supply estimates (standard tobit)

	(1) All issuance	(2) Amount issued by IG firms	(3) Amount issued by HY firms
PM Credit spread (bps)	-0.00221***	-0.00431 ***	-0.00203 ***
	(0.0002)	(0.0002)	(0.0004)
US Treasury Yield	-0.669***	-0.829***	-0.692***
	(0.133)	(0.227)	(0.224)
Credit rating	-2.853**	-1.031	-3.176
	(1.188)	(1.364)	(1.953)
Cash/Assets last qtr	-7.195***	-12.05***	-0.729
	(1.452)	(3.384)	(2.101)
CFNAI	-0.225***	-0.238***	-0.260
	(0.0829)	(0.0469)	(0.179)
Leverage last qtr	-1.262*	-2.183**	-1.500
	(0.665)	(1.096)	(1.374)
ROA last qtr	8.225*	18.78**	-2.805
	(4.424)	(9.362)	(4.698)
Amount due in 3 months	0.0166	0.0293**	-0.0422
	(0.0104)	(0.0134)	(0.0472)
Observations	20711	14688	6023

Note: This table covers sample bonds issued 2000–2020. Observation is by firm-quarter. 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. Issuance volume is in logs.

primary markets every other day, while the largest corporate issuers[31] participate on 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 (Hendershott et al. (2020), Goldstein and Hotchkiss (2012), Nikolova et al. (2020)). This potential conflict of interest may manifest in underwriters helping investors profit at the expense of issuers.[32] While underwriters also earn revenue from firms through mergers and acquisitions advisory and securities underwriting, revenues from trading with investors are typically higher than

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

[32] 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)). It is consistent with recent papers on incomplete competition among brokers in financial markets (Robles-Garcia (2019), Wang et al. (2020)).

those from corporate-facing activities.[33]

1.5 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 (2020b)). 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.[34] I allow firms to be less price-sensitive in bad times by assigning them the elasticity estimated from the GFC when economic activity is 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 1.6. The first column shows that regressions in the model fit the regressions from the data (in Table 1.1) 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 somewhat, by about 6%, indicating that the reduction in firms'

[33]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-6663260`

[34]See Figure 1.15 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.

sensitivity to credit spreads contributes 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 fourth column of Table 1.6. 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. Finally, 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 1.6, I shut down investor heterogeneity, assigning all investors the demand elasticities of long-term investors. This amplifies the countercylical 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.[35] 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, the effect on issuance premiums is more pronounced. Moreover, in the counterfactual where underwriters favor firms

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

and investors equally, issuance premiums are on average 5 basis points lower. This highlights the importance of incorporating underwriter incentives into our understanding of primary markets.

Table 1.6: Counterfactual magnitudes of issuance premium cyclicality

	(1) Baseline	(2) Same firm elasticity	(3) Investor demand shocks	(4) Firm propensity to issue	(5) Homogeneous investors	(6) 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.

1.5.1 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 maintains 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.

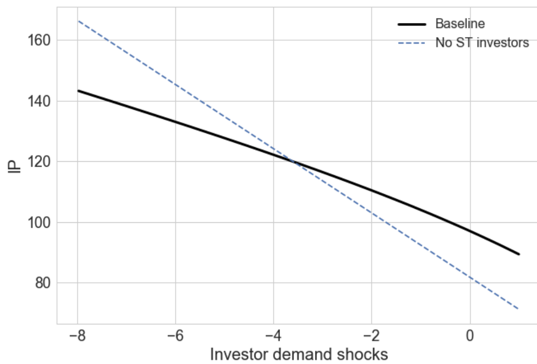
To show the impact of investor heterogeneity on average issuance premiums, I simulate an equilibrium that shuts down investor heterogeneity by assigning all primary market investors the elasticities of long-term investors. This reduces issuance premiums on average by 4 basis points, which corresponds to a \$2.1-million reduction in the firm's cost of capital on a median 10-year, \$650 million bond.[36] 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 1.7 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 1.7a). This encourages an increase in the share of short-term investors participating in primary markets (Panel 1.7b). 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 1.7c).

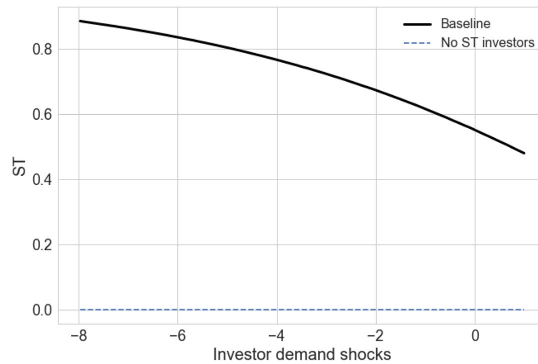
This mechanism sheds light on why I observe high participation by short-term investors and high issuance premiums in periods of market distress. Firms' higher willingness to pay drives up issuance premiums as underwriters continue to favor investors in splitting the surplus between firms and investors. This increases the share of short-term investors. Because short-term investor

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

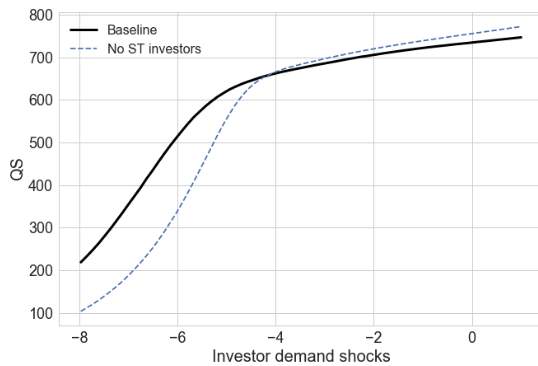
Figure 1.7: Counterfactuals: positive supply and negative demand shocks



(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.

dollars are more price-elastic, they enter in larger quantities, 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. 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 by higher issuance premiums and keep bond issuance volumes up.

1.5.2 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 and increased issuance volumes (Gilchrist et al. (2020), Boyarchenko et al. (2020)), as well as helping to stem large fund outflows (Falato et al. (2020)), 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. For example, using the elasticity estimate from 2018 in Table 1.15, a purchase of 10% of a bond in secondary markets would cause a 56-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 10% increase in 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.

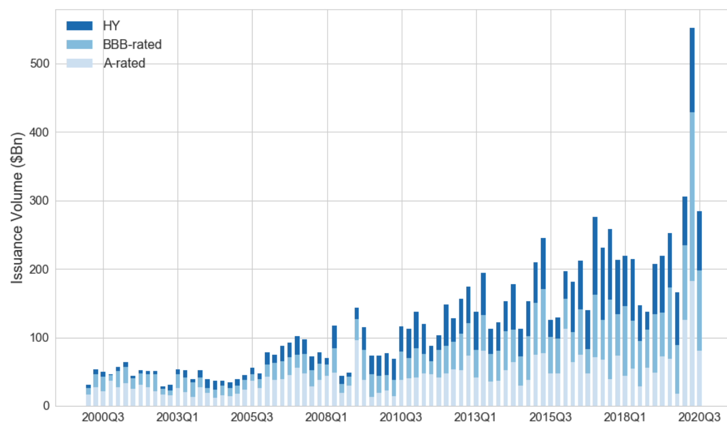
1.6 Conclusion

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 – firms, investors, and underwriters – 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. I find that short-term investors demand higher issuance premiums to participate in primary markets, but also help absorb large demand shocks and prevent credit spreads from spiking even further in bad times. This shift in investor composition highlights a self-correcting mechanism of capital markets: while issuance premiums drive costs of capital up even further in downturns, primary markets become more elastic and allow 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.

1.7 Additional Figures and Tables

Figure 1.8: Corporate bond issuance volumes



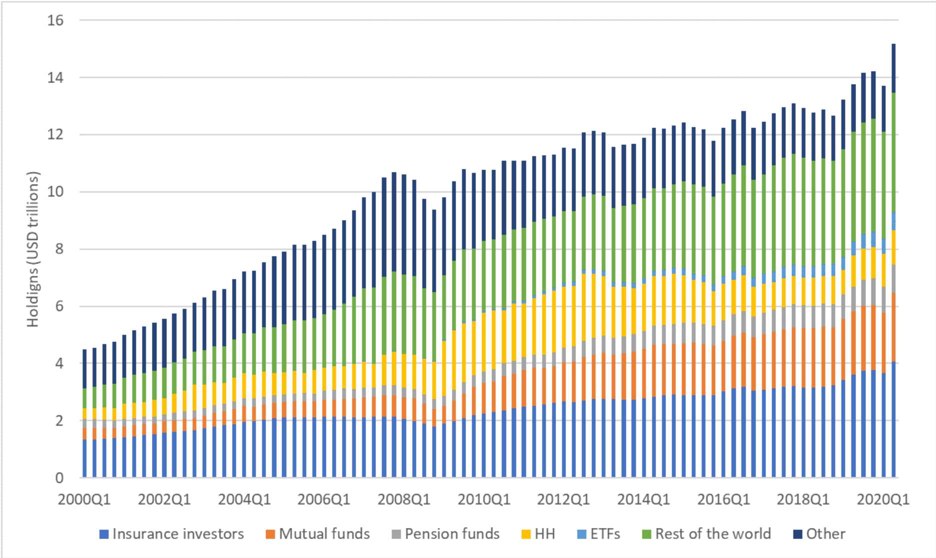
Source: Mergent FISD
Note: Includes USD corporate non-financial bonds greater than $100 million in size at issuance. Excludes convertibles, capital impact bonds, community investment bonds, PIK securities, and bonds issued by financials, sovereigns, supra-sovereigns, and utilities.

Table 1.7: 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: Thomson Reuters 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.

Figure 1.9: 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.

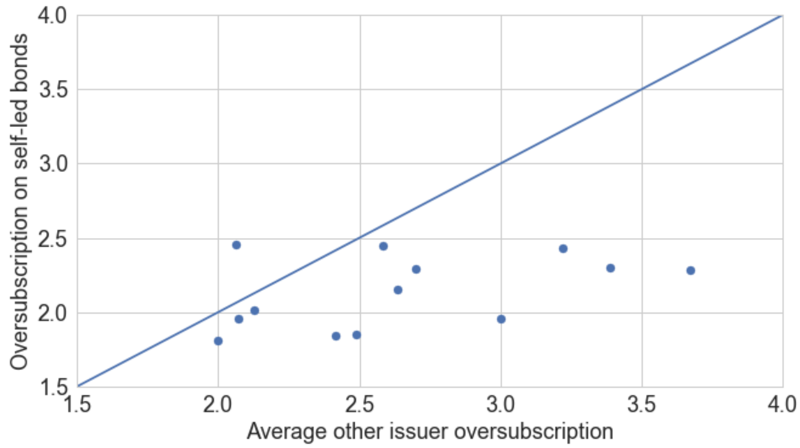
1.8 Additional

1.8.1 Computing probabilities of default

Using the CDS spreads, I can compute probabilities of default. To do this, I follow Hull (2012) and set the present value of expected CDS payments to the insurer if there is no default (the expression (1) in the following equation) plus the present value of accrued payments made to the insurer in the case of default (the expression (2)) equal to the expected present value of CDS payoffs from the insurer in the case of default (the expression (3)):

$$\underbrace{\sum_{t=1}^{5} s(1-\rho)^t e^{-r_f t}}_{(1)} + \underbrace{\sum_{t=1}^{5} \frac{s}{2}\rho(1-\rho)^{t-1} e^{-r_f(t-\frac{1}{2})}}_{(2)} = \underbrace{\sum_{t=1}^{5} \rho(1-\rho)^{t-1}(1-R)Se^{-r_f(t-\frac{1}{2})}}_{(3)}. \quad (1.27)$$

Figure 1.10: Banks have less oversubscription when they are both underwriter and issuer



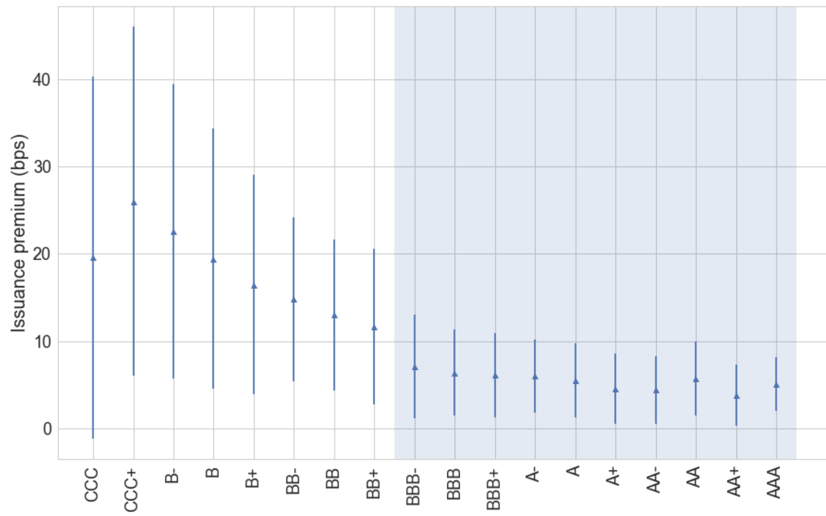
Note: Each dot represents a broker-dealer. The y-axis shows the average oversubscription on bonds issued and underwritten by broker-dealer u. The x-axis shows the average oversubscription on bonds underwritten by broker-dealer u but issued by other financial firms. To be included in the analysis, bonds 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, must be rated within 1 notch of bank u's most recent highest rating, and must have ≤ 5 underwriters. The line is the 45-degree line: any dots on this line would indicate that the broker-dealer has the same oversubscription when underwriting its own bonds as when underwriting as comparable bonds issued by other firms. Dots below the line indicate broker-dealers achieving more oversubscription when underwriting bonds issued by other firms. Data is reported in Table 1.9.

I then solve for the implied probability of default based on monthly averages of daily 5-year CDS spreads (s), given a risk-free rate of 3%, a notional amount S, and expected recovery rate R (from the Markit data).

1.8.2 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

Figure 1.11: Issuance premiums across ratings categories



Source: Mergent FISD and Enhanced TRACE
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).

spreads for bond b with remaining term τ at date t are thus

$$cs_{bt}(\tau) = yield_{bt} - r_{ft}(\tau). \tag{1.28}$$

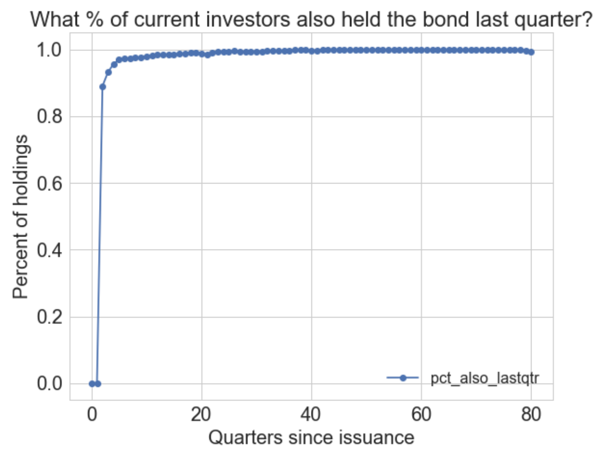
1.8.3 Computing yields from TRACE data

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

$$P = \sum_{t=1}^{T*f} \frac{C}{(1+y/f)^t} + \frac{1}{(1+y/f)^{(T*f)}}, \tag{1.29}$$

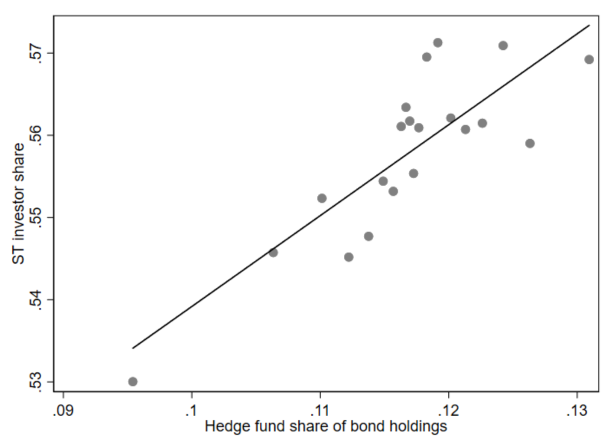
where C is the bond's annual coupon amount, f is the frequency of coupon payments (for example, $f = 2$ for semiannual bonds), y is the yield to maturity, and T is the number of years to maturity of the bond (also known as the tenor). I use a Newton optimization method in Python to compute

Figure 1.12: Persistence of investor holdings



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

Figure 1.13: 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 1.8: Primary market bonds: sample summary statistics

	Mean	Std Dev	Percentile 1	Median	Percentile 99
Full sample					
Credit Spread (bps)	263	222	29	185	1042
Coupon	4.88%	2.48%	0.00%	4.70%	12.00%
Yield to maturity	5.25%	2.84%	1.06%	4.90%	12.50%
Amount ($MM)	633	566	100	500	3000
Tenor (Years)	9.6	8.8	1.0	8.0	32.0
Credit rating	14.3	4.3	5.0	14.0	22.0
Issuance premium (bps)	7.7	11.6	-9.3	4.9	62.4
Money Left (MM)	6.0	14.8	-9.5	2.3	66.9
Pct sold first week	0.17	0.17	0.00	0.14	1.00
Issuance credit spread range (bps)	24	384	-2	10	76
Estimation sample					
Credit Spread (bps)	148	82	32	135	425
Coupon	3.44%	1.17%	0.88%	3.45%	6.24%
Yield to maturity	3.47%	1.16%	0.90%	3.49%	6.15%
Amount ($MM)	830	633	250	650	3000
Tenor (Years)	12.5	9.5	2.0	10.0	31.0
Credit rating	15.4	2.2	12.0	15.0	22.0
Crowdedness ($Bn)	3.3	3.8	0.0	2.1	17.4
Order book ($Bn)	3.0	2.2	0.5	2.4	11.1
Issuance premium (bps)	5.5	7.8	-9.3	4.2	35.2
Money Left (MM)	6.1	16.5	-10.3	2.1	79.5
Pct sold first week	0.20	0.15	0.01	0.17	1.00
Issuance credit spread range (bps)	15	14	0	15	61

Source: Mergent FISD, IGM, CFR, eMaxx, TRACE, Markit

the yield to maturity y given the rest of the observed bond characteristics and the price P of the bond reported in TRACE.

1.8.4 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

Table 1.9: 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 ≤ 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.

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 1.10: Countercyclicality of issuance premiums as % of credit spreads

	(1) Baseline	(2) Issuer controls	(3) UW Info	(4) UW FE
Economic activity	-0.00108***	-0.00108***	-0.00112***	-0.00124***
	(0.000228)	(0.000228)	(0.000234)	(0.000163)
Issuance range / spread			0.125***	0.127***
			(0.0123)	(0.0119)
Credit Rating (log)	0.0122***	0.0122***	-0.00599**	-0.0105*
	(0.00245)	(0.00245)	(0.00294)	(0.00544)
Bond size(log)	0.00338***	0.00338***	0.00182***	0.000392
	(0.000971)	(0.000971)	(0.000517)	(0.00123)
Tenor (years)	-0.00118***	-0.00118***	-0.000883***	-0.000843***
	(0.0000538)	(0.0000538)	(0.0000458)	(0.0000404)
Debt / assets	-0.0245***	-0.0245***	-0.0269***	-0.0663***
	(0.00456)	(0.00456)	(0.00308)	(0.0117)
Cash / assets	0.00698	0.00698	0.00113	0.0107
	(0.00669)	(0.00669)	(0.00553)	(0.00707)
Operating profit / assets	0.354***	0.354***	0.233***	0.297***
	(0.0967)	(0.0967)	(0.0363)	(0.0421)
Firm FE				✓
Underwriter FE	✓	✓	✓	✓
Observations	17113	17113	17113	17074
R-squared	0.0310	0.0310	0.510	0.611

Notes: Outcome variable is ratio of issuance premium to overall credit spread for the same bond. Economic activity is measured using the CFNAI monthly value, collected from the Chicago Federal Reserve, designed to be mean zero with a standard deviation of one. Observations are at the bond-underwriter level. Standard errors clustered at the underwriter.

1.8.5 Secondary market demand estimation

I adapt the characteristics-based demand derived in Koijen and Yogo (2019) for equities to corporate bonds. Demand for individual bond b by investor i at time t can then be written as

$$\frac{w_{itb}^{SM}}{w_{it0}^{SM}} = exp\{\alpha_i r_{bt} + \beta_i X_{bt} + \epsilon_{itb}^{SM}\}, \tag{1.30}$$

which I can rewrite for strictly positive holdings as

$$q_{itb} = q_{it0} + \alpha_i r_{bt} + \beta_i X_{bt} + \epsilon_{itb}^{PM}, \tag{1.31}$$

Table 1.11: Issuance premiums higher during GFC and COVID-19

	(1) GFC / COVID Dummies	(2) 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: 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. Standard errors are clustered at the underwriter level.

Table 1.12: 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 1.13: 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.

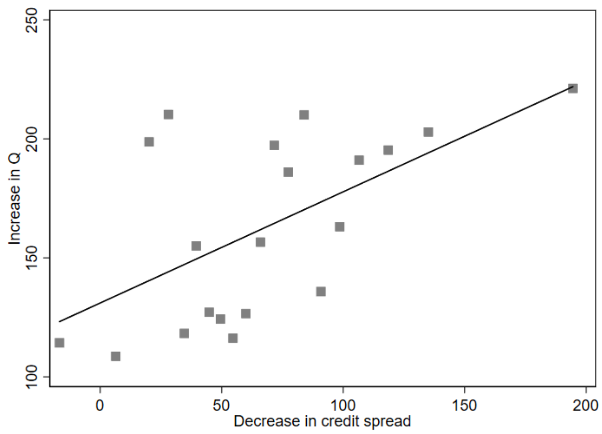
Table 1.14: Persistence in set of corporate bonds held by investors

	1	2	3	4	5	6	7	8	9	10	11
AUM_0	0.93	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
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	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00
AUM_6	0.98	0.98	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	0.98	0.98	0.99	0.99	0.99	0.99	0.99	0.99
AUM_8	0.97	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.99	0.99	0.99
AUM_9	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99

Source: Thomson Reuters 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.

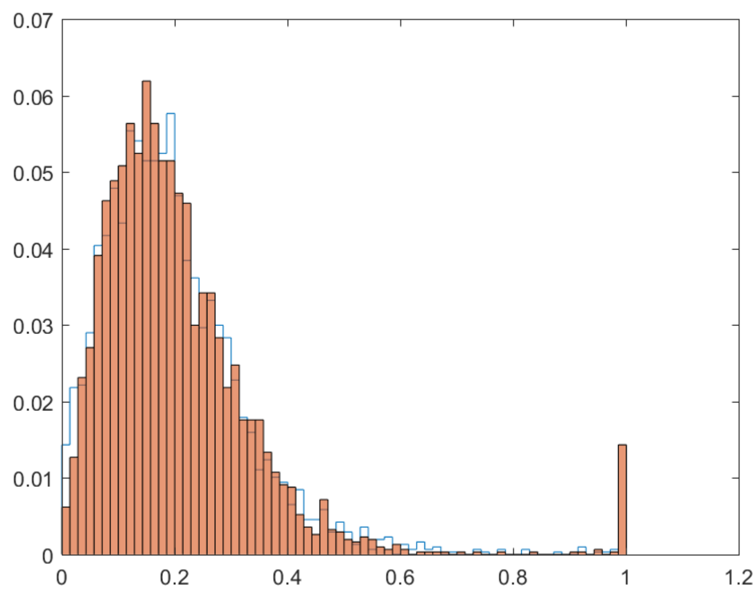
where $q_{itb} = \ln(A_{it}w_{itb})$ is the volume that investor i invests in bond b, and $q_{it0} = \ln(A_{it}w_{it0})$ is the volume invested in the outside option of investor i. Characteristics in X include ratings category (log), amount issued (log), remaining years of bond (log), probability of default of the issuer (as derived from its CDS trading), and bid–ask spreads as reported by WRDS. The term ϵ_{itb} is investor i's latent demand; it captures each investor's demand for unobserved characteristics of asset b.

Figure 1.14: Greater increase in quantity supplied for upsized bond issuances when credit spreads are lower



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 1.15: 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 1.15: Summary of secondary market holdings demand estimates

Year	Credit_Spread	Rating	Log_Amount	Years_Remaining	Bid_Ask	Probability_Default	UST
2002	0.0003	0.0054	0.0108	-0.5819	-0.0024	-1.6679	0.2893
	(0.000)	(0.013)	(0.005)	(0.718)	(0.002)	(0.355)	(0.355)
2003	0.0007	-0.0026	-0.0002	0.8168	-0.0034	-3.8330	-0.3939
	(0.000)	(0.023)	(0.005)	(0.638)	(0.007)	(1.651)	(0.320)
2004	0.0008	0.0318	0.0006	0.7083	0.0067	-3.7185	-0.3580
	(0.000)	(0.011)	(0.003)	(0.595)	(0.009)	(0.970)	(0.306)
2005	0.0007	0.0189	0.0002	-0.0332	-0.0063	-3.6565	0.0336
	(0.000)	(0.007)	(0.002)	(0.011)	(0.007)	(1.347)	(0.011)
2006	0.0013	0.0032	-0.0069	-0.0256	0.0206	-9.2777	-0.1221
	(0.000)	(0.025)	(0.008)	(0.009)	(0.011)	(4.585)	(0.079)
2007	0.0007	0.0264	-0.0043	-0.0161	-0.0068	-2.9685	-0.0331
	(0.000)	(0.023)	(0.002)	(0.022)	(0.020)	(0.942)	(0.041)
2008	0.0003	0.1854	0.0119	0.1490	0.0093	-0.7102	-0.1066
	(0.000)	(0.098)	(0.016)	(0.109)	(0.008)	(0.711)	(0.055)
2009	0.0011	0.0465	-0.0065	-0.0097	0.0266	-2.5473	0.0140
	(0.000)	(0.028)	(0.009)	(0.042)	(0.025)	(2.435)	(0.025)
2010	0.0004	0.0338	0.0007	0.0263	-0.0083	-1.8440	-0.0086
	(0.000)	(0.007)	(0.001)	(0.022)	(0.004)	(0.378)	(0.012)
2011	0.0008	0.1316	-0.0101	-0.0185	-0.0046	-2.5315	0.0093
	(0.000)	(0.034)	(0.006)	(0.052)	(0.009)	(0.914)	(0.026)
2012	0.0010	0.2033	0.0000	0.0403	-0.0005	-2.6517	-0.0473
	(0.000)	(0.072)	(0.004)	(0.059)	(0.015)	(0.787)	(0.050)
2013	0.0007	0.0293	0.0062	0.0735	0.0013	-2.1723	-0.0478
	(0.000)	(0.014)	(0.003)	(0.056)	(0.006)	(0.820)	(0.027)
2014	0.0011	0.0358	0.0084	0.1319	-0.0013	-3.5942	-0.1360
	(0.000)	(0.044)	(0.008)	(0.120)	(0.013)	(1.243)	(0.113)
2015	0.0010	0.0872	0.0037	0.2927	-0.0465	-3.2577	-0.2927
	(0.000)	(0.031)	(0.003)	(0.180)	(0.021)	(0.888)	(0.169)
2016	0.0007	0.0453	-0.0001	-0.0416	-0.0202	-2.3593	0.0421
	(0.000)	(0.013)	(0.002)	(0.061)	(0.010)	(1.218)	(0.069)
2017	0.0009	0.0623	0.0045	-0.0847	-0.0389	-2.6305	0.0752
	(0.000)	(0.026)	(0.006)	(0.121)	(0.015)	(0.802)	(0.178)
2018	0.0018	0.1490	-0.0012	-0.1471	-0.1245	-6.5650	0.3966
	(0.000)	(0.041)	(0.007)	(0.041)	(0.108)	(1.953)	(0.178)
2019	0.0009	0.0847	-0.0063	-0.0320	-0.0435	-2.1912	0.0048
	(0.000)	(0.019)	(0.003)	(0.010)	(0.018)	(0.554)	(0.046)

Source: Thomson Reuters eMAXX
Note: Coefficients on characteristics are computed for each investor (FUNDID) in each quarter in which the investor holds at least 20 bonds. Estimates here are computed as the mean across all investor-quarters. Standard errors, in parentheses, are computed from the distribution of estimates for each year. Quarterly sample period is from 2002Q1 to 2019Q4. Coefficient estimates on credit spreads are restricted to be positive.

Investors choose optimal portfolio weights based on asset characteristics. This equation is essentially a nonlinear regression model of the cross-section in asset demand on asset characteristics. The coefficient α captures investor preference for higher interest rates, or the well-documented

Table 1.16: Full sample vs. upsized sample of 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.

Table 1.17: 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.

tendency to "reach for yield" (Becker and Ivashina (2015)), and is thus restricted to be positive in the estimation.

In classic asset pricing models, investors are atomistic, so demand shocks will not impact prices significantly. Consequently, prices are considered exogenous, and the moment equation $E[\epsilon_{bit}|r_{bt}, X_{bt}] = 1$ can be used for estimation. However, in bond markets, I observe that as investors are large and concentrated, this assumption no longer holds. I therefore need an instrument for the interest rate (price of bonds).

I first make the assumption that (1) wealth distribution across other investors and (2) investment mandates of other investors are exogenous to demand shocks impacting investor i. To justify this

Table 1.18: 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 1.8.4, 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.

assumption, I show empirically that bond investors tend to purchase the same kind of bond. I categorize bonds into categories based on three characteristics: tenor, rating, and industry (two-digit NAIC code). (See Table 1.14, inspired by Table 1 in Koijen and Yogo (2019).) Using eMAXX data, I first compute the percentage of a fund's reported holdings that is invested in securities that the same fund held in the past 1–11 quarters. Each cell of the table reports the median across percent holdings across funds in the corresponding size class. Investors across the spectrum of sizes (as measured by assets under management) tend to purchase securities of the same class that they have purchased in the past. Investment mandates are plausibly orthogonal to individual bond characteristics, as they appear to change little over time. Thus, I construct the following instrument (with time subscripts suppressed):

$$z_i(b) = \ln\left(\sum_{j\neq i} A_j \frac{\mathbf{1}_j(n)}{1+\sum_{m=1}^{N}\mathbf{1}_j(m)}\right). \tag{1.32}$$

I define n as the class of bond b. The idea is that, for a given bond b, the more investors there are that have bonds like b in their investment universe, the greater the portion of latent demand for the bond. Moreover, the larger those investors (and the fewer other kinds of bonds they hold), the greater the portion of latent demand. Note that while I estimate this metric for each quarter, the primary source of variation is cross-sectional.

Chapter 2

Bond Market Stimulus: Firm-Level Evidence from 2020-21 [1]

The corporate bond market took center stage in the recent COVID crisis. In the midst of a "dash for cash" (Acharya and Steffen, 2020b), March witnessed significant market turmoil that included sudden spikes in credit spreads and outflows from bond funds, liquidity drying up, and a drop in new issuance. This turmoil triggered a spectacular change in the Federal Reserve credit policy and direct support for the corporate bond market for the first time ever through a series of announcements in March and April. There is considerable evidence that this intervention led to a remarkable "V-shaped recovery" in bond markets in a matter of weeks. Credit spreads fell abruptly, fund outflows were reversed, and liquidity was restored, ultimately leading to record bond issuance volume.[2] The Fed intervention aimed to “support market functioning”, but importantly it also targeted “employment and spending of businesses”, in the words of Chairman Powell.[3] While it is clear that the Federal Reserve revitalized *markets*, there are still some open questions regarding the net effects on *firms* and the real sector. In particular, the transmission channel of such unconventional monetary policy is not well understood.

[1]This chapter is based on Darmouni and Siani (2020). Olivier Darmouni (omd2109@columbia.edu) and Kerry Y. Siani (kfy2101@columbia.edu) are at Columbia Business School, New York, NY. For helpful comments, we thank Bo Becker, Mitchell Berlin, Simeon Djankov, Sam Hanson, Christoph Herpfer, Rustom Irani, Wei Jiang, Nobu Kiyotaki, Yiming Ma, Bill Maxwell, Patricia Mosser, Emi Nakamura, Giorgia Piacentino, Michael Schwert, Sascha Steffen, Philip Strahan, Stijn Van Nieuwerburgh, Laura Veldkamp, Neng Wang, and Nancy Xu, as well as participants at the 2021 NBER Monetary Economics Summer Institute, Boston College, the University of Wisconsin-Madison, the Federal Reserve Bank of Philadelphia, the Federal Reserve Bank of Boston, University of Bonn, Durham, Lugano, the Texas Finance Festival 2021, the Barcelona GSE Summer Forum 2021, FIRS 2021, the Midwest Finance Association 2021, and the Econometric Society Winter Meetings 2020. Jessica Goldenring provided excellent research assistance. This is a substianlly revised version of a previous draft titled "Crowding Out Bank Loans: Liquidity-Driven Bond Issuance."

[2]For detailed micro-evidence, including high-frequency analysis of the announcements effects of the bond purchasing program, see Haddad et al. (2020); Gilchrist et al. (2020); Kargar et al. (2020); Boyarchenko et al. (2020); Halling et al. (2020b); O'Hara and Zhou (2020); Falato et al. (2020); Flanagan and Purnanandam (2020).

[3]Semiannual Monetary Policy Report to the Congress, June 16th, 2020.

To this end, this paper studies firm behavior in the wake of the intervention using micro-data on corporate balance sheets. We ask a central empirical question: what did bond issuers do with the funds? We link bond issuance data with firm-level outcomes, following firms up to a year after the intervention, and document the dynamics of real investment, cash, bank credit, and equity payouts. We find that firms issued bonds to accumulate large and persistent amounts of liquid assets instead of investing. Conceptually, the benefits depend on how valuable this additional liquidity was to firms. We show that these firms generally had access to bank liquidity that they chose not to use and equity payouts remained high, raising the question of how highly many issuers valued this additional liquidity at the margin.

We first provide evidence that, unlike normal times, 2020 bond issuers used bond proceeds to accumulate liquid assets. Importantly, this accumulated cash was still largely unspent by early 2021, up to a year after issuance. On the other hand, there was virtually no increase in real assets, consistent with investment opportunities being depressed through 2020. For example, Chevron issued \$650 million in bonds on March 24th, but cut its 2020 capital spending plan by \$4 billion. Acharya and Steffen (2020b) first identified that the safest firms issued bonds to raise cash at the start of the COVID crisis. The Fed intervention allowed riskier firms to do the same.

Our finding that firms borrowed to accumulate cash is at odds with state-of-the-art macroeconomic models of monetary transmission that assume that firms borrow to finance investment (Kaplan et al., 2018; Ottonello and Winberry, 2020; Auclert et al., 2020). However, dynamic corporate finance models that stress the value of corporate liquidity can explain this behavior: firms preemptively lock-in long-term financing when it is temporarily plentiful (Bolton et al., 2013; Eisfeldt and Muir, 2016; Acharya et al., 2020). Nevertheless, in theory, the marginal value of additional liquidity declines with the total financial slack available to the firm. For this reason, it is important not to consider bond financing in isolation. The next two parts of the paper thus investigate available bank credit and equity payouts, respectively.

Using data on credit lines, we document two new facts that suggest that many bond issuers were apparently far from a binding credit limit. First, many firms left their existing credit lines untouched while instead issuing bonds. For example, CVS had over $6 billion in credit line available, yet it still issued $4 billion in BBB-rated bonds. Strikingly, both riskier high yield (HY) and safer investment grade (IG) firms often chose not to use their available "dry powder" from banks that had been arranged before the crisis. Almost 30% of HY firms that issued bonds received no new net bank funding between January and March. The pattern is even stronger for BBB-rated IG firms, which were responsible for the bulk of bond issuance in this period, with 50% not drawing on their existing credit lines. Importantly, establishing this fact requires looking at data on off-balance sheet bank credit, an important source of liquidity for firms.

Second, issuers that did borrow from their banks early in the crisis aggressively repaid these loans by issuing bonds after the intervention. Among HY issuers that received bank funds in March, nearly three quarters repaid some amount after their bond issuance, while 40% actually repaid their credit line in full by the end of June 2020. For example, Kraft Heinz, which was downgraded from IG to junk in February 2020, drew $4 billion from its credit line between February and March. In May, it issued $3.5 billion in bonds and used these funds to repay its credit line. Kraft was far from an isolated example: among HY issuers repaying bank loans, the median firm paid back 100% of its Q1 borrowing, representing 54% of its bond issuance. The pattern is similar for IG firms, although a smaller share drew on their credit lines in the first place. We estimate that at least $110 billion was repaid by bond issuers to banks between April and June alone.

These findings suggest revisiting classical theories of the choice between bonds and bank loans. The view that bond issuance in bad times is primarily driven by weak balance sheets of banks, given compelling evidence from the previous crisis (Becker and Ivashina, 2014, 2018), seems less plausible in this setting.[4] Moreover, even though bond yields fell, it is not obvious in the data that bonds became cheaper than loans for these firms in this period. Nevertheless, differences in other

[4]There was no concurrent banking crisis to depress loan supply to the same extent as in 2008-09. Banks entered the crisis with strong balance sheets, received large deposit inflows and were able to lend extensively, at least to large firms in the form of credit lines draw-downs (Acharya and Steffen, 2020b; Li et al., 2020; Greenwald et al., 2020; Chodorow-Reich et al., 2020). This is not to say that there were no disruptions in loan markets, in particular for small firms (Greenwald et al., 2020; Chodorow-Reich et al., 2020; Kapan and Minoiu, 2021; Acharya et al., 2020). The market for term loans for large firms was also disrupted (Becker and Benmelech, 2021), partly because of institutional investors (Fleckenstein et al., 2020).

contract terms, such as longer maturity, fixed interest rates, or weaker covenants for bonds could explain the substitution even if relative prices did not change much: the core logic is to lock-in funds for as long as possible. While this is intuitive, classical theories of banks' advantage in liquidity provision over capital markets tend to ignore this aspect of borrower demand.[5]

A second open question relates to the effects on equity payouts. Acharya and Plantin (2021) raise the concern that loose monetary policy can lead to leveraged payouts. In normal times, it is not uncommon for bond issuance to finance share repurchases (Farre-Mensa et al., 2018; Ma, 2019). During COVID, though, the probability of repurchasing shares following bond issuance fell by about 20 percentage points. This is consistent with some firms aiming to preserve cash on their balance sheets, as covered widely in the news media.[6] However, it is important to note that almost 50% of issuers still repurchased shares between March and June 2020, in a period of high uncertainty. At face value, this evidence questions how highly many issuers valued additional liquidity at the margin and suggests the large reduction in yields following the intervention might have unintentionally fueled opportunistic issuance.

Our findings also suggest that the 2020 Federal Reserve program had a different transmission mechanism relative to the 2016 ECB corporate bond purchase program. While both programs had similar effects on markets by reducing yields and stimulating issuance, the effect on firms' balance sheets was strikingly different: Grosse-Rueschkamp et al. [2019] find no effect on cash holdings, credit line balances, or share repurchases. At a broad level, both programs led to bond-loan substitution, but in quite distinct ways given the different settings.

Evidence from 2020-21 can thus help to draw a more complete picture of how corporate bond purchases by central banks transmit to the real economy. It highlights the value of not just looking at market data, such as yields and issuance volumes, but also at firms' balance sheets and opera-

[5]Classical corporate finance models predict that bank loans are more attractive to borrowers needing emergency liquidity, while capital markets fund investment in good times. Different theories of the advantage of bank debt have been proposed: in Holmström and Tirole (1998) credit lines committed in advance provide liquidity insurance; in Kashyap et al. (1996) and Gatev and Strahan (2006), having a deposits franchise decreases the cost of providing liquidity; in Diamond (1991) or Rajan (1992) bank have superior monitoring ability.

[6]Ford Motor Co. and Freeport-McMoRan Inc. suspended dividend payments while AT&T halted share repurchases. "Companies Race for Cash in Coronavirus Crisis", *Wall Street Journal*, 03/23/2020. Interestingly, Hotchkiss et al. (2020) shows that equity issuance was important for smaller and riskier firms that typically do not issue bonds.

tions throughout the months following the intervention. Our evidence also points to considerable heterogeneity among issuers and to the practical challenge for central banks of how to best target these unconventional policy actions, in order to help firms that need liquidity the most. The events of 2020 show that a closer integration of corporate finance and macroeconomics is an important agenda for further research.

Related literature: This paper contributes to our understanding of unconventional monetary policy, and specifically measures aimed at the corporate bond market. While there is extensive evidence that the Federal Reserve actions lowered bond yields and stimulated issuance in 2020,[7] we provide a first step towards understanding real effects by documenting the dynamics of firms' real investment, cash, bank credit, and equity payouts, up to a year after the intervention. Our evidence relates to the debate on whether asset purchase programs stimulate firm investment or only lead to capital structure changes (Stein, 2012; Giambona, Matta, Peydro, and Wang, Giambona et al.). We also show that the effect of the 2020 intervention on firm's balance sheets was different from the CSPP implemented in Europe.[8]

The goal of this paper is to provide evidence on the transmission channel in order to inform the micro-foundations of state-of-the-art macroeconomic models of monetary transmission (Ottonello and Winberry, 2020; Kaplan et al., 2018; Auclert et al., 2020). Just as the Global Financial Crisis showed that financial intermediation was more complex than previously thought and needed a proper place in macro-finance models, evidence from 2020-21 highlights the complexity and importance of bond markets and corporate finance for the macro-economy. Nevertheless, estimating the full macroeconomic effects is beyond the scope of this paper, and our reduced-form evidence is not the proper counterfactual to assess what would have happened absent the intervention.

This paper is also part of a growing literature on corporate financing during the COVID crisis.

[7]See for instance Boyarchenko et al. (2020); Haddad et al. (2020); Kargar et al. (2020); O'Hara and Zhou (2020); Gilchrist et al. (2020); Liang (2020); Flanagan and Purnanandam (2020); Vissing-Jorgensen (2020).

[8]See Grosse-Rueschkamp et al. (2019); Ertan et al. (2019); Arce et al. (2021). Other work examining the effect of conventional and unconventional monetary policy on the bond market include Kashyap et al. (1996); Crouzet (2019); Lhuissier and Szczerbowicz (2018); Todorov (2020); Pegoraro and Montagna (2021); De Santis and Zaghini (2019); Ippolito et al. (2018); Holm-Hadulla and Thürwächter (2020); Bolton and Freixas (2006); Elliott et al. (2019); Giambona, Matta, Peydro, and Wang (Giambona et al.); Siani (2019); Darmouni et al. (2019).

We build on Acharya and Steffen (2020b) who link bond ratings with credit line drawdowns and bond issuance in the early part of the COVID crisis by studying the later period after the intervention and following firms into early 2021. Moreover, Halling et al. (2020b) show that aggregate equity issuance was an order of magnitude smaller than bond issuance, but Hotchkiss et al. (2020) argues that equity was the predominant form of financing for small, young, and unrated firms, while the larger firms we focus on relied entirely on debt. While Li et al. (2020); Greenwald et al. (2020); Chodorow-Reich et al. (2020) show that only large firms benefited from the large increase in bank lending, we show that many bond issuers did not in fact use bank funding even before the intervention. Becker and Benmelech (2021) document the resilience of the corporate bond market relative to loans markets. We view these results as highly complementary, reinforcing the view that bond markets should not be considered in isolation and that sources of financing vary in the cross-section of firms.

Finally, we also contribute to the literature trying to understand the role of the bond market in corporate finance. Given compelling evidence from the Global Financial Crisis, prior work has argued that the key driver of bond issuance in bad times is weak balance sheets of banks (Becker and Ivashina, 2014; Crouzet, 2017; De Fiore and Uhlig, 2015; Schwert, 2018; Adrian et al., 2013; Erel et al., 2012). Our evidence shows that during the COVID crisis, which did not originate in the banking sector, bonds were largely revealed-preferred to loans, suggesting that this is unlikely to be the only force at play. Furthermore, the conventional view stresses that bond financing is used to fund investment, while bank credit lines are used for liquidity management (Acharya et al., 2018).[9] The fact that bond issuance was broadly used to expand liquidity buffers and competed with credit lines suggests that the bond market is more central to corporate liquidity management than previously thought. Interestingly, the economics behind bond issuance seem quite different from commercial paper, which is typically seen as the main source of market-based liquidity for firms. Lastly, we relate to prior work on bond-financed payouts (Acharya and Plantin, 2021; Ma, 2019; Farre-Mensa et al., 2018).

[9]This squares with evidence that many large firms keep sizeable credit lines with banks, even if they have access to the bond market for investment (Sufi, 2009; Acharya et al., 2018; Greenwald et al., 2020).

2.1 Background and Data

There was a significant increase in the need for corporate liquidity following the COVID shock in early 2020. Many firms faced large reductions in operating income and rising uncertainty in spring 2020 (De Vito and Gomez, 2020; OECD, 2020). A "dash for cash" ensued (Acharya and Steffen, 2020b), as cash-generating operations halted and firms resorted to a variety of measures to alleviate severe cash shortfalls.[10]

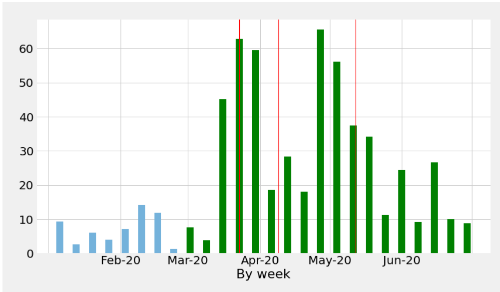
Moreover, bond markets took center stage in early 2020. First, the onset of the crisis saw significant disruptions in secondary markets. In March, we observed sudden spikes in spreads and outflows from bond funds as secondary market liquidity dried up (Haddad et al., 2020; Kargar et al., 2020; O'Hara and Zhou, 2020; Falato et al., 2020; Ma et al., 2020). Issuance in primary markets plummeted to a near stop, especially for riskier firms. This bond market turmoil triggered a spectacular response by the Federal Reserve. In addition to lowering the policy rate back to zero, providing liquidity to dealers and purchasing large quantities of Treasuries bonds, it also directly supported the market for the first time by announcing the purchases of corporate bonds.

These announcements on March 23 and April 9 had a significant effect on bond markets. High-frequency analysis using secondary market data shows that these two dates had the strongest effects and stand out even compared to the battery of other emergency measures taken during this period (Haddad et al., 2020). In turn, this market rebound spilled over to primary markets: issuance quickly reached historical heights leading to a remarkable "V-shaped recovery" in bond markets in a matter of weeks, including for riskier firms.[11]

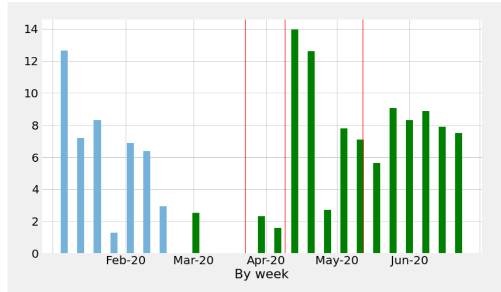
Figure 2.1 illustrates these dynamics for both the investment-grade (IG) and high-yield (HY) markets. The riskiest firms issued over $120 billion in USD high yield bonds in January-May 2020,

[10] In addition to cash-flow shocks and increased uncertainty, other factors might have contributed to increased corporate liquidity demand, such as the concern that credit lines might be withdrawn like in the 2008-09 crisis (Chodorow-Reich and Falato, 2017; Acharya et al., 2014) or the desire to reassure stakeholders and market participants that the firm would be able to survive the crisis.

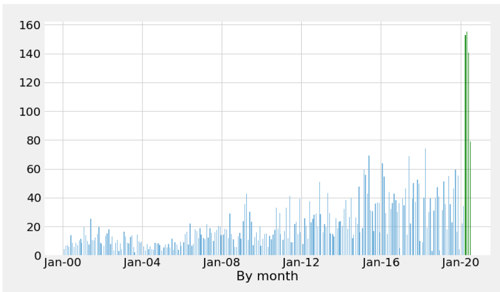
[11] Note also that it is well understood that the intervention worked mainly through an announcement effect: actual purchases did not occur until weeks later and ended up being small given the strong market recovery. For more micro-evidence on secondary and primary markets during the Spring 2020 crisis, see Halling et al. (2020b); Boyarchenko et al. (2020); Gilchrist et al. (2020); Liang (2020); Flanagan and Purnanandam (2020).



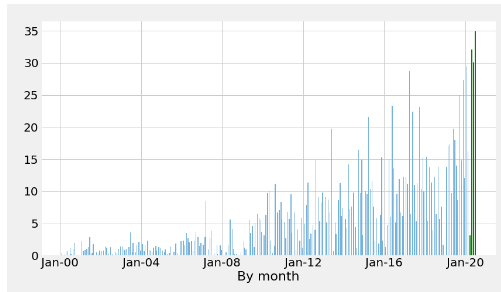
(a) IG: 2020



(b) HY: 2020



(c) IG: 2000-2020



(d) HY: 2000-2020

Figure 2.1: Comparing IG vs. HY bond issuance volumes

Source: Mergent FISD, retrieved via WRDS October 21, 2020. Denotes weekly issuance volumes for USD corporate bond issuance of over \$100 million in size issued by U.S. domiciled companies or companies that report in U.S. dollars. Note red lines correspond to March 23, 2020 (first Fed announcement to buy corporate bonds); April 9, 2020 (first Fed announcement to buy high yield corporate bonds); and May 12, 2020 (start of Fed bond buying program).

compared to over \$90 billion in the same period in 2019, despite a three-week hiatus in March 2020.[12] Similarly, IG bond issuance hit over \$500 billion in volume issued by May, compared with over \$200 billion over the same period in 2019.

While it quickly became clear that the Federal Reserve's announcements of its intent to purchase bonds revitalized markets, there are still some open questions regarding the net effects on firms and the real sector. The goal of this paper is to study firm behavior in the wake of the intervention and draw implications for monetary policy. We take the market rebound as given and ask a central empirical question: What did bond issuers do with the funds? This firm-level evidence is a key first step to better understanding the transmission mechanism. Nevertheless, we note from the outset that estimating the full macroeconomic effects is beyond the scope of this paper:

[12] Becker and Benmelech (2021) and Hotchkiss et al. (2020) find that the number of HY issuers was nevertheless below trend initially. Section 2.4 shows however that HY issuance strengthened in the second half of 2020, in line with HY yields falling more slowly relative to IG.

our reduced-form evidence is not the proper counterfactual to assess what would have happened absent the intervention.[13]

We construct a panel data set covering all U.S. non-financial bond issuers in the past two decades. Our main empirical analysis compares the behavior of bond issuers in the post-intervention "COVID" period of March 23 to June 30, 2020 with those of the "normal" period of 2010-2019. Additional tests use issuance data all the way back to 2000, as well as through December 2020. Importantly, we follow 2020 issuers' balance sheets into early 2021, up to one year after their first 2020 issuance. This is key to understanding the impact on firms beyond the immediate market rebound.

Bond issuance data comes from Mergent FISD, which includes detailed security-level data on corporate bond offerings. We restrict the sample to U.S. dollar bonds of at least $100 million face value issued by firms that report in U.S. dollars. In line with much of the empirical literature on corporate bond issuance, we exclude financial, sovereign, and utility issuers. We further exclude convertible bonds, capital impact bonds, community bonds, PIK securities, and registered bonds issued directly in exchange for an identical Rule 144A bond.[14] We merge the issuance data with quarterly balance sheet data from Compustat and quarterly debt composition from Capital IQ. The filters and merges yield a sample of 313 firms issuing 594 bonds during the COVID period, and 1,256 firms issuing 6,443 bonds in the "normal period".[15] Tables B.1 and B.2 in Internet Appendix

[13]Note that the difference-in-difference design of high-frequency studies looking at relative changes in secondary market spreads around eligibility threshold (Kargar et al., 2020; Boyarchenko et al., 2020; O'Hara and Zhou, 2020; Gilchrist et al., 2020) are difficult to replicate when studying primary markets and low-frequency firm-level outcomes. This is in part because the Fed announcements seemed to have had very broad effects on issuance, beyond specific eligibility criteria. For instance, the programs targeted especially bonds with maturities below five years, which is much shorter than the average maturity of the bonds issued in the COVID-19 period (Halling et al., 2020b).

[14]Convertible issuance was particularly strong in early 2020: "Convertible bond issues surge in coronavirus-hit market", Reuters, July 3, 2020. In our main analysis, we exclude convertible bonds, however including convertible issuance has no significant effect on our results. Bonds associated with the T-Mobile / Sprint acquisition in April 2020 are also excluded. We also do not focus on equity issuance, given that bond issuance was significantly larger during this period (USD 300 billion versus USD 16 billion) (Halling et al., 2020b). However, interestingly Hotchkiss et al. (2020) show that equity, not debt, was the predominant form of financing for small, young, and unrated firms.

[15]We are able to match 87% of bonds in our sample to firms in Compustat. 46% of unmatched bonds are foreign issuers. The rest do not have reported financials in Compustat in the quarters of issuance. For balance sheet analyses, we include only the 90% of matched issuing firms that either report financial statements in U.S. dollars or are domiciled in the U.S.

display summary statistics of our baseline sample.[16] During the peak COVID episode of March-May 2020, the median bond was $600 million with an eight-year tenor and a yield of 4.07%. In the same months of the years 2017-2019, the median bond size was $500 million with an eight year tenor and yield of 5.125%.[17]

The 2020 crisis was an unusual episode, but it is in fact particularly interesting to study in this context for two reasons. First, there was a significant increase in the need for corporate liquidity due to high uncertainty and reductions in operating income, while investment opportunities were depressed (OECD, 2020). This is useful because classical theories suggest bond demand is driven by investment rather than liquidity needs. Indeed, it is well understood that many large firms prefer bonds to loans when it comes to financing long-term investment: high-quality firms fund long-term projects with bonds, while lower-quality firms rely on banks (Diamond, 1991; Holmstrom and Tirole, 1997). On the other hand, even large firms are thought to rely on bank loans to weather cash-flows shocks, specifically in the form of credit lines draw-downs (Holmström and Tirole, 1998; Kashyap et al., 2002; Gatev and Strahan, 2006; Sufi, 2009; Acharya et al., 2018; Greenwald et al., 2020). These theories would thus predict low bond issuance and greater reliance on bank loans during the 2020 crisis.

Second, there was no concurrent banking crisis to depress loan supply to the same extent as in 2008-09. This is useful because a common concern is that liquidity shocks for firms are often correlated with bank liquidity shocks. For instance, during the 2008-09 financial crisis, weak bank balance sheets led to a drastic fall in loan supply, which led many firms to turn to the bond markets (Becker and Ivashina, 2014; Crouzet, 2017; De Fiore and Uhlig, 2015; Adrian et al., 2013). On the other hand, banks entered 2020 with strong balance sheets and received large deposit inflows. There is considerable evidence that they were able to lend extensively to large firms in the form of credit lines draw-downs (Acharya and Steffen, 2020b; Li et al., 2020; Greenwald et al., 2020;

[16]Firms that issue in bond markets are on the larger end of the distribution of all firms. In 2019, the median bond issuer had $10.7 billion in total assets and $1.2 billion in quarterly revenues at year end, compared to the median Compustat firm with $1.5 billion in assets and $195 million in quarterly revenues.

[17]Table B.11 also shows that secured bonds were more common during COVID, consistent with the long-term evidence of Benmelech et al. (2020), although they still constituted a small share of issuance.

Chodorow-Reich et al., 2020). [18] However, this is not to say that there were no disruptions in loans markets, in particular for small firms (Greenwald et al., 2020; Chodorow-Reich et al., 2020; Kapan and Minoiu, 2021; Acharya et al., 2020). The market for term loans for large firms was also disrupted (Becker and Benmelech, 2021; Fleckenstein et al., 2020). For these reasons, when analyzing firms' choices between loans and bonds, we will focus on the credit line draw-down activity of bond issuers, as this segment faced little turmoil compared to the 2008-09 crisis.

2.2 Liquid Assets vs. Real Investment

This section revisits a classical macroeconomic paradigm in the light of 2020 data. State-of-the-art macroeconomic models of monetary transmission typically assume that firms borrow to finance investment (Kaplan et al., 2018; Ottonello and Winberry, 2020; Auclert et al., 2020). According to this view, an intervention that stimulates credit should have a direct effect on investment. These models tend to abstract from corporate liquidity, assuming that cash is equivalent to negative debt. This contrasts with a long-standing focus in dynamic corporate finance to relate external financing to liquidity management (see for example Bolton et al. (2011)).

To investigate this, we examine quarterly changes in firms' balance sheets around bond issuance. We compare firms that issued between March 23 and June 30, 2020 to "normal times", defined as 2010-2019. Importantly, we trace out the effects on firms' balance sheets through early 2021, up to one year after the intervention. We run an *event study analysis* by regressing firm balance sheet quantities on dummy variables for each of the five quarters leading up to issuance and the four quarters following issuance.

$$Y_{fq} = \sum_{m=-5}^{4} \beta_m Issue_{f,q+m} + \alpha_f + \alpha_{ind \times year} + \epsilon_{fq} \tag{2.1}$$

[18] Interestingly, while banks reported tightened lending standards in 2020, they cited deterioration of fundamentals rather than conventional balance sheet constraints as the primary reason. According to the Federal Reserve Senior Loan Officer Survey April 2020 Survey, while 60% of large banks tightened lending standards, less than 10 percent of respondents said it was due to a deterioration in their current/expected capital or liquidity position. Instead, the vast majority of banks cited a less favorable economic outlook or worsening of industry-specific problems as very important reasons for tightening credit.

We run the regression separately for issuance during normal times vs. issuance during COVID. Then we plot the time dummy coefficients, β_m, to visualize the pre- and post-trends of balance sheet quantities in both periods. The analysis exploits within-firm variation by including firm fixed effects in order to account for the selection of firms into bond issuance. We also include industry-year fixed effects. To capture firm heterogeneity, our main specification is run separately for IG and HY, while additional cross-sectional tests also consider different exposure to the COVID shock and pre-shock balance sheet strength measures such as liquidity and short-term leverage.

Cash accumulation: We first find striking evidence of cash accumulation following issuance. The top panel of Figure 2.2 shows the dynamic coefficients plots for cash as a ratio of prior year assets in both periods. Issuance during COVID is followed by a large increase in cash levels that is highly persistent. Importantly, the cash accumulated was still largely unspent four quarters after issuance in early 2021. In contrast, in normal times, cash holdings rise modestly and revert within two quarters following issuance.[19]

Both the safest investment-grade firms as well as high-yield issuers exhibit this behavior. Acharya and Steffen (2020b) first identified that the safest firms issued bonds to raise cash at the start of the COVID crisis. The Federal Reserve intervention appears to have enabled riskier firms to do the same, with cash levels staying persistently high throughout the year.

Note also during COVID, cash had started to increase in the quarter prior to bond issuance. This reflects that firms sought out alternative sources of cash (such as drawing down on a bank credit line) before the intervention. We provide novel evidence on the direct link between credit lines draw-downs and bond issuance extensively in Section 2.3.

Real investment: It is also apparent that real investment did not follow a similar pattern. The second panel in Figure 2.2 shows the dynamics of non-cash assets as a proxy for investment in operating activity. Prior to COVID, bonds are typically issued in periods in which the firm is growing and investing, in line with Becker and Josephson (2016) or Darmouni and Papoutsi (2020).

[19]Figure B.1 in the Internet Appendix shows that average cash accumulation after issuance during COVID was higher relative to the Global Financial Crisis, in line with the cash-flow shocks being larger and more sudden in 2020. See Xiao (2020a) and Erel et al. (2012) for broad evidence on the GFC.

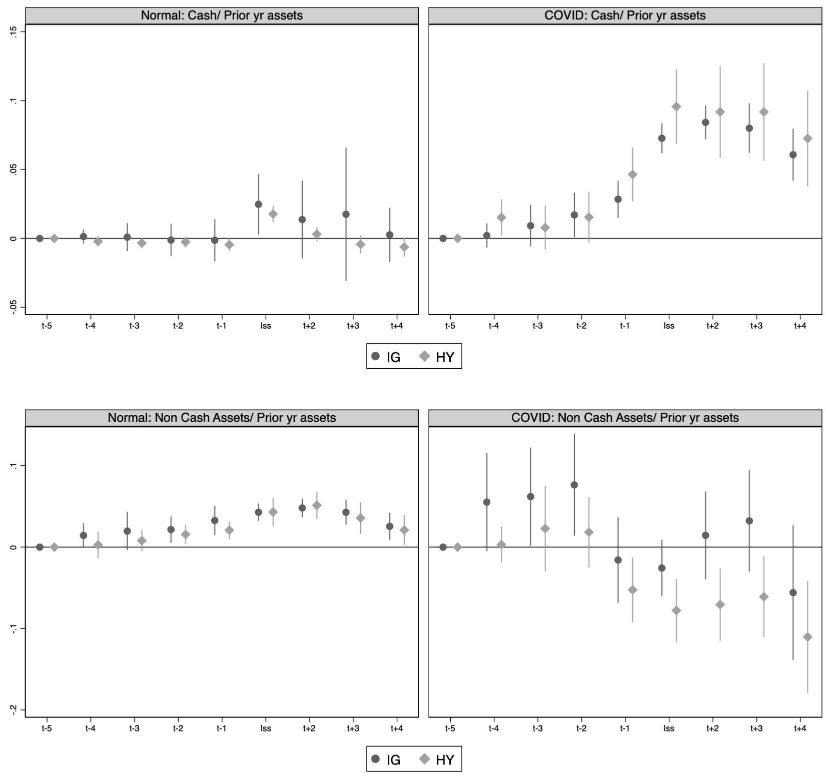


Figure 2.2: Liquid Assets vs. Real Assets: Coefficient plots

Notes: Each point is an estimate of β_{t+m} from the regression $Y_{fq} = \sum_{m=-5}^{4} \beta_m Issue_{f,t+m} + \alpha_f + \alpha_{ind \times year} + \epsilon_{fq}$, with 95% confidence intervals. "Cash" is cash and short term investments. "Non-cash assets" is total assets minus cash and short term investments. The circles are investment grade firms (rated BBB- and above), while the diamonds are high yield firms (rated below BBB-). Observations are firm-quarters up to five quarters prior to a bond issuance and four quarters following a bond issuance. "Iss" denotes the quarter ending immediately after issuance. We include firm and industry-year fixed effects. Standard errors are clustered by 2-digit industry level. All ratios are winsorized at the 1% level in the entire sample. To further limit the effects of outliers, variables are further winsorized at the 1% level for HY firms in the "Normal" times, as well as for IG firms' cash ratio in "Covid" times. "Normal" times includes bonds issued between 2010-2019, "Covid" times includes bonds issued March 23 - June 30, 2020.

However, that is not the case during COVID: bond issuance does not coincide with an increase in real investment, even at a horizon of a full year. This is particularly stark for HY issuers that experience a persistent reduction in real assets throughout 2020.

Intuitively, these results are consistent with investment opportunities being depressed after March 2020 and many firms preferring to preserve cash in the face of uncertainty. An illuminating example is Chevron, which raised $650 million in bond capital on March 24th, and explicitly said that it would not use these funds for investment. Instead, it planned to reduce its 2020 capital spending plan by $4 billion (or 20%) in response to the crisis. Chevron CEO said: "We are taking actions expected to preserve cash, support our balance sheet strength, lower short-term production, and preserve long-term value." This suggests that the fast rebound in bond issuance was disconnected from any quick rebound in real activity.

These reduced-form results are striking but should nevertheless be interpreted with care. They do not imply that the intervention crowded-out real investment. Indeed, firms such as Chevron reported a lack of desire to invest. It is at least equally plausible that the intervention instead crowded-in investment: investment might have been even lower if firms did not increase cash balances through debt issuance.

One might expect that liquidity accumulation is concentrated in issuers that are more directly exposed to the shock. However, micro data suggest the pattern is more subtle. For instance, Hotchkiss et al. (2020) document a U-shaped relationship between cash flow shocks and external financing raised. Table B.3 in the Internet Appendix delves further into this heterogeneity among bond issuers by running additional cross-sectional regressions. In our sample of COVID issuers, Column 1 of Table B.3 shows that exposure to COVID, measured with industry abnormal employment decline in 2020Q1 as in Chodorow-Reich et al. (2020), matters perhaps less than expected: more exposed firms only accumulate weakly higher cash balances. Firms with higher initial cash balances in fact tend to also increase cash relatively more. Having more debt due soon or less available undrawn credit has no predictive power.[20] In fact, dynamic corporate finance theories

[20] In fact, firms with higher COVID exposure increase real assets relatively more, possibly because of increases in working capital. Higher initial cash balances also predict higher increases in real assets.

often emphasize that direct cash-flow shocks are not the only drivers of external financing, as we discuss next.

Connection to existing theories: Importantly, firm behavior was at odds with state-of-the-art macroeconomic models of monetary transmission (Kaplan et al., 2018; Ottonello and Winberry, 2020; Auclert et al., 2020). These models assume that firms borrow to finance investment and would fail to match the striking pattern of debt issuance for the purpose of accumulating liquid assets. Because cash is equivalent to negative debt, borrowing to hoard cash has effectively no value.

However, dynamic corporate finance models have stressed the value of accumulating liquidity, even if the immediate investment response is weak. In particular, they can explain the concurrent external financing and cash accumulation observed in the data. The models of Bolton et al. (2013), Eisfeldt and Muir (2016) or Acharya et al. (2020) are among the clearest in illustrating this channel. Specifically, in the presence of time-varying financial conditions, firms have incentives to preemptively lock-in long-term financing when it is temporarily plentiful. Moreover, they use the funds to accumulate liquid assets instead of investing, as we observe in the data. This channel squares well with the fact that emergency measures by the Federal Reserve implemented in Spring 2020 significantly improved credit conditions for firms.

Conceptually, this suggests revisiting the micro-foundations of the transmission channel. Instead of the investment multiplier of classical macroeconomic models, these theories would stress *the value of corporate liquidity*: i.e. that in the presence of financial frictions, a dollar inside the firm can be worth more than a dollar outside. However, the marginal value of additional liquidity is theoretically declining in total financial slack available to the firm (Bolton et al., 2011). For this reason, it is important not to consider bond financing in isolation. Bond issuers are among the largest firms with access to other sources of financing. While directly measuring financial constraints in the data is notoriously difficult, our micro-data nevertheless contains information about other margins. As a first cut, we thus examine the dynamics of total debt on the balance sheet. The next two sections examine bank credit and equity payouts, respectively.[21]

Debt dynamics: The top panel of Figure 2.3 investigates to what extent bond proceeds were used to repay existing debt. Bond issuance in normal times is followed by a persistent increase in total debt of 10% of prior year assets. During COVID, however, changes in total debt after issuance were smaller. This is particularly striking for HY issuers: their debt level is surprisingly flat around bond issuance, in stark contrast to normal times. This suggests that these firms used a significant portion of new bond proceeds to pay back existing debt. The bottom panel of Figure 2.3 isolates the dynamics of bonds only. It is apparent that bonds grew more than total debt after the intervention. This suggests that these firms used a significant portion of bond proceeds to pay back *other* types of debt. Debt substitution was thus a key part of bond issuers' behavior after the Federal Reserve intervention. The next section explores this pattern in detail.

We make two additional observations regarding debt dynamics. First, comparing Figures 2.2 and 2.3, we see that the average net increase in bonds outstanding lines up closely with the increase in liquid assets, at about 10% of prior year's assets. This reinforces the quantitative importance of issuing bonds for cash accumulation in 2020.[22] Second, we investigate roll-over risk which was flagged as a major concern in the Spring 2020.[23] Not being able to issue a new bond could be costly for firms that have an existing bond due in 2020, especially for non-IG firms that might get cut off from the market.[24] We find evidence suggesting that immediate rollover risk, while important for some firms, was less likely to be the primary decision factor for issuance during COVID than initially thought. Table B.5 in the Appendix shows that less than a third of Spring 2020 issuers had a bond coming due later that year. Moreover, over 80% of these issuers were rated investment-grade. Overall, HY issuers with a bond maturing in 2020 made up only 5% of all issuers and 17% of HY issuance volume in Spring 2020. Additional cross-sectional tests in

[21] The corporate finance models cited above tend to model only equity financing for tractability reasons and abstract from different types of external financing. However, in 2020, large public firms like the ones that we study relied on debt financing (Halling et al., 2020b), while only smaller listed firms issued equity (Hotchkiss et al., 2020).

[22] Table B.4 in the Internet Appendix calculates aggregate flows for our sample of COVID issuers. In aggregate, they increased cash by over \$470B and outstanding bonds by \$336B in the first half of 2020.

[23] "Will the coronavirus trigger a corporate debt crisis?", *Financial Times*, 03/12/2020.

[24] Indeed, Harford et al. (2014) find that increased refinancing risk due to shorter debt maturities contributes to firms increasing cash holdings.

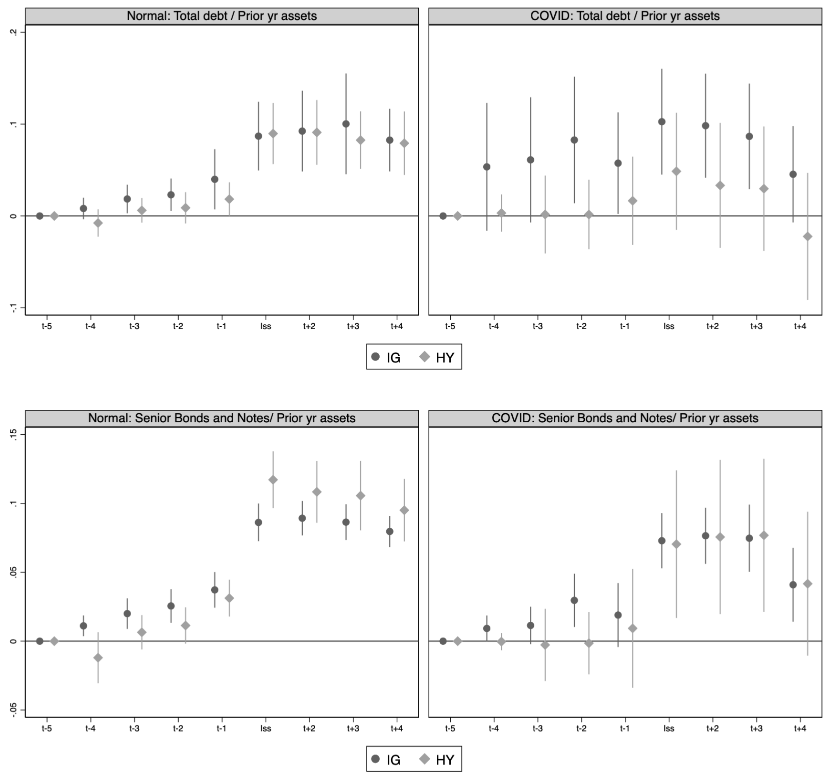


Figure 2.3: Debt dynamics: Coefficient plots

Notes: Each point is an estimate of β_{t+m} from the regression $Y_{fq} = \sum_{m=-4}^{4} \beta_m Issue_{f,t+m} + \alpha_f + \alpha_{ind \times year} + \epsilon_{fq}$, with 95% confidence intervals. Total debt is total long term debt plus debt in current liabilities. Senior bonds and notes are from Capital IQ. The circles are investment grade firms (rated BBB- and above), while the diamonds are high yield firms (rated below BBB-). Observations are firm-quarters up to five quarters prior to a bond issuance and four quarters following a bond issuance. "Iss" denotes the quarter ending immediately after issuance. We include firm and industry-year fixed effects. Standard errors are clustered by 2-digit industry level. All ratios are winsorized at the 1% level in the entire sample. To further limit the effects of outliers, senior bonds and notes are further winsorized at the 1% level for IG firms. "Normal" times includes bonds issued between 2010-2019, "Covid" times includes bonds issued between March 23 - June 30, 2020.

Table B.3 as well as below confirm that current-debt-to-assets ratios have little to no significant explanatory power in our sample.[25]

2.3 Bonds vs. Bank Loans

To understand the benefits of the liquidity accumulation documented in Section 2.2, it is important not to consider bond financing in isolation. The marginal value of additional liquidity is higher for firms that have less financial slack. Large firms have access to multiple sources of financing, including bank loans and bonds, and can substitute between the two. Indeed, even the largest bond issuers have large credit lines with banks (Sufi, 2009; Acharya et al., 2018; Greenwald et al., 2020) and in recent years, while term loans did not keep up with bond issuance, undrawn credit lines have grown significantly (Berg et al., 2020).

Classical theories in fact predict that bank debt is more attractive to borrowers facing liquidity needs.[26] Impaired loan supply would however lead firms to turn to the bond market (Becker and Ivashina, 2014). Given that the 2020 shock originated outside of the banking sector, the conventional view suggests that credit line draw-downs should dominate bond issuance in this period, in line with the evidence of extensive borrowing by large firms (Li et al., 2020; Greenwald et al., 2020; Chodorow-Reich et al., 2020).

This section sheds new light on this question by focusing directly on the revealed preference of firms choosing between bonds and bank credit using micro-data on bank loans. We match our issuance data with information on each issuer's debt composition from Capital IQ.[27] These data contain information on amount outstanding of different debt instruments, including drawn amounts on revolving credit lines and total bank debt. It also includes information on undrawn (off-balance

[25] Section 2.4 discusses the evidence on early refinancing of bonds that mature at later dates.

[26] Different (non-exclusive) channels have been proposed: in Holmström and Tirole (1998), credit lines committed in advance provide liquidity insurance; in Kashyap et al. (1996) and Gatev and Strahan (2006), having a deposits franchise decreases the cost of providing liquidity; in Diamond (1991) or Rajan (1992), banks have superior monitoring ability.

[27] For the COVID analysis, we can match 283 issuers to Capital IQ bank credit line data. Table B.6 shows that in general bond issuers matched to Capital IQ seem to have identical characteristics relative to all issuers, in 2020 as well as in earlier periods.

sheet) credit lines that were available as the COVID crisis unfolded. As debt composition data is reported only at quarter end, we approximate flows by computing differences between quarters. We break down the COVID part of the analysis into two periods: (i) the first quarter of 2020 (early part of the crisis) and (ii) the second quarter of 2020 (later part of the crisis, after the intervention).

2.3.1 Issuing Bonds when Bank Credit was Already Committed

We first show that many firms left their existing credit lines untouched in the first quarter of 2020 and issued bonds instead. To start, we lay out aggregate credit flows for all firms that issued bonds during COVID in Table 2.1. We split firms into three separate categories based on their credit ratings. Investment grade issuers with BBB credit ratings had \$340 billion in available credit committed by their banks as of end of 2019. By March 2020, these firms only drew down on \$88 billion in aggregate, roughly one quarter of the total amount available. These firms instead opted to raise capital in bond markets, issuing \$263 billion of bonds. The safest, A-rated firms exhibit a similar pattern, drawing down on 3.5% of credit available and opting to raise \$209 billion in bonds instead. While the gap between bond issuance and credit lines is smaller for high yield firms, a large majority of funds raised in the bond market could similarly have come from drawing on existing credit lines. High yield firms in our sample issued over \$104 billion in bonds in Q1 2020. These firms, in aggregate, had \$116 billion in availability in bank credit lines as of the end of 2019. Figure B.2 in the Internet Appendix illustrates this unused aggregate dry powder visually.

As an example, CVS had \$6 billion of its credit line available at the beginning of 2020, yet it still issued \$4 billion in BBB-rated bonds. We show that CVS was far from an isolated case, and strikingly, this behavior includes many riskier HY firms. Table 2.2 tracks the change in debt composition during the first quarter of 2020. The first three rows show the share of firms that, respectively, (i) maxed out their credit lines (i.e., have revolving credit outstanding larger than 90% of their available credit as of end of 2019), (ii) drew on their credit lines without maxing out, and (iii) did not draw on their credit line. Note that because the data consists of stocks of debt

Table 2.1: Debt Composition: Aggregate Flows over 2020Q1

	HY Billions of USD	IG, BBB Billions of USD	IG, A or above Billions of USD
Bond issuance	104.2	262.9	209.1
Credit line	59.1	87.7	7.68
All bank debt	66.8	117.4	22.5
Undrawn credit EOY 2019	115.7	339.4	220.6

Notes: This table classifies aggregate debt flows based on FISD bond issuance data (Row 1) as well as changes in outstanding debt for other credit instruments during 2020Q1 based on Capital IQ Capital Structure Summary table (Rows 2 and 3). Undrawn credit EOY 2019 is the outstanding available Undrawn Revolving Credit at the end of 2019. Issuers include all U.S. firms that issued a bond March 23 - June 30 2020 that we could merge with Capital IQ information.

outstanding reported quarterly, these numbers are not completely free of measurement error.[28] The fourth row reports the share of firms that did not receive bank funding, in net, in the first quarter, aggregating all forms of bank debt. The fifth row reports average draw-down rates, defined as the ratio of additional revolving credit over available credit at the end of 2019.

For the riskiest firms that issued between March 23rd and June 30th, only 27% had maxed out their credit line by end of March, and the average draw-down rate was 47%. Looking beyond credit lines and including all potential sources of bank debt does not change the picture: 28% did not receive new net bank funding in the first quarter that covers the height of the crisis. This implies that many of these riskier firms had available "dry powder" from banks, arranged ex ante, that they decided not to use early on in the crisis, even though they did not issue any bonds until later in the crisis. The pattern is even more striking when looking at IG firms, although there is still a risk gradient within this group. Among firms rated BBB (the riskiest IG issuers), 48% left their credit line untouched and 35% did not get any additional bank funds, in net, in the first quarter of 2020. For BBB firms that did draw down on their credit line, on average they only took advantage of 27% of available credit capacity. For the safest firms, rated A or above, 71% left their credit line

[28]First, our definition of "maxing out" can occasionally incorrectly include firms that signed new credit lines during the COVID crisis. In our exploration, this measurement problem seems to be more pronounced for IG firms. For instance, McDonald's signed a new credit line of $10B, of which it drew $1B. Second, we can only observe quarter-end balance. If a firm drew on its credit line on March 1st and repaid it by March 31st, our data would not capture this behavior.

Table 2.2: Bank borrowing in 2020Q1 for bond issuers

	HY Share	IG, BBB Share	IG, A or above Share
Maxed out CL	0.27	0.15	0.098
Drew some CL	0.44	0.37	0.20
Did not draw CL	0.28	0.48	0.71
No net bank funds	0.28	0.35	0.61
Av. drawdown rate	0.47	0.27	0.098

Notes: This table classifies bond issuers based on changes in outstanding debt for different credit instruments during 2020Q1, based on the Capital IQ Capital Structure Summary tables. Row 1 includes issuers that maxed out their credit lines, i.e. the increase in Revolving Credit is at least 90% of Undrawn Revolving Credit at the end of 2019. Row 2 includes issuers that drew some of their credit lines, i.e. the increase in Revolving Credit as a ratio of Undrawn Revolving Credit at the end of 2019 is between 0% and 90%. Row 3 includes issuers that did not draw, i.e. the increase in Revolving Credit is 0 or less. Row 4 includes issuers with no net bank funding, defined as the sum of Revolving Credit, Term Loans and Federal Home Loan Bank borrowings. Row 5 reports the average increase in the drawdown rate, defined as the ratio of Revolving Credit to the Undrawn Revolving Credit at the end of 2019. Bond issuers are all U.S. firms that issued a bond March 23 - June 30, 2020 that we could merge with Capital IQ.

untouched and the draw-down rate was only 10% on average.

This difference across rating categories is consistent with differences in draw-downs described in Acharya and Steffen (2020b) and predicted in Acharya and Steffen (2020a). In addition to ratings, part of the heterogeneity across firms can also be explained by different exposure to the COVID shock. Table B.7 in the Internet Appendix shows that exposure to the COVID shock predicts credit line draw-downs in our cross-section of bond issuers. Moreover, firms with larger undrawn credit lines balances from 2019 were more likely to draw but less likely to max out. Other balance sheet characteristics, such as lower initial cash balances or higher current debt ratios, do not have much predictive power once accounting for other factors.

One possibility is that undrawn credit was in fact restricted by banks, for instance because of actual or potential covenant violations. Three pieces of evidence tend to speak against this interpretation: the extensive borrowing by large firms (Li et al., 2020; Greenwald et al., 2020; Chodorow-Reich et al., 2020), the apparent lack of enforcement around covenant violations in 2020 (Acharya et al., 2021), and the observation that riskier issuers drew more.

Our evidence suggests the link between credit lines and bond issuance might not be as simple as initially thought. The simplest view is that bond issuers first drew on credit lines and then issued bonds later because markets were shut off until the Federal Reserve intervention. However, this view is incomplete: the majority of bond issuers, including many riskier firms, left their credit lines untouched throughout the crisis. While primarily large firms drew on their credit lines during this episode (Li et al., 2020; Chodorow-Reich et al., 2020; Greenwald et al., 2020), not all chose to do so, and in particular, many bond issuers chose not to draw. Importantly, while not drawing down on credit lines preserves liquidity, this is a sign that many bond issuers had a significant amount of financial slack in Spring 2020.

2.3.2 Repaying Bank Loans After Issuing Bonds

Next, we examine whether firms use proceeds from bond issuance to repay bank loans. The previous section documents significant heterogeneity among bond issuers at the outset of the crisis: a minority of bond issuers did rely heavily on bank lending at first. In this section, we investigate changes in these firms' debt composition during the second quarter of 2020.

We find that a large share of firms that did borrow from their banks early in the crisis issued bonds in Q2 2020 to aggressively repay their bank loans. For example, Kraft Heinz, a "fallen angel" which was downgraded from IG to HY in February 2020, drew \$4 billion from its credit line between February and March. In May after the intervention, it issued \$3.5 billion of bonds (up from a planned \$1.5 billion, due to strong investor demand) and used these funds to repay its credit line in its entirety. Within the span of six months, the share of Kraft Heinz's credit coming from banks went from zero to 12% and then back to zero.

Kraft Heinz is not unique. Figure 2.4 illustrates the cross-section of repayment behavior by plotting credit line draw-downs in Q1 against draw-downs in Q2 for each firm in our sample. A negative value indicates that the firm paid down a portion of the outstanding credit line. Strikingly, many firms are exactly on the negative forty-five degree line, denoting full repayment within three months, like Kraft Heinz. These firms borrowed from available bank credit lines only to pay back 100% of bank borrowings following a bond issuance. A noticeable number of firms repaid even

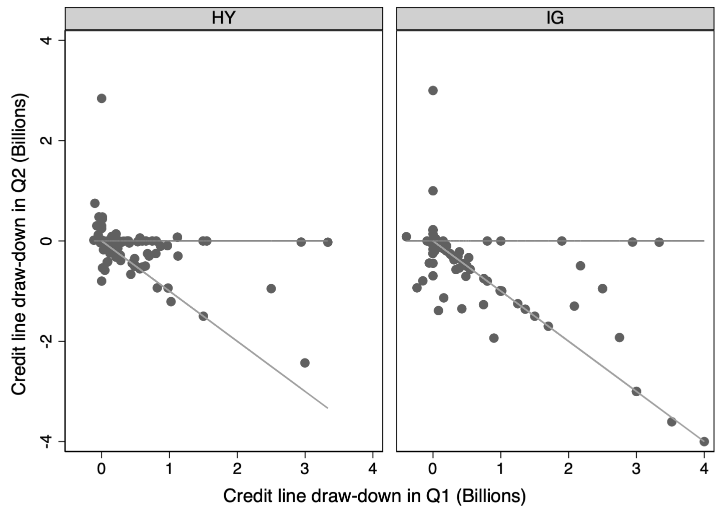


Figure 2.4: Loan-bond substitution: Credit line draw-downs in 2020Q2 vs. 2020Q1

Note: This figures plots credit line repayment in 2020Q2 against 2020Q1 credit line draw-downs, based on Capital IQ Capital Structure Summary tables, separately for high-yield and investment grade issuers. For ease of interpretation, the figure also displays the negative 45 degree line (exact repayment in Q2) and horizontal line (no change in credit line in Q2). Issuers include all U.S. firms that issued a bond March 23 - June 30 2020 that we could merge with Capital IQ information. For clarity, the plots excludes large outliers Volkswagen, Ford, and GM.

more, using bonds to pay down bank debt that preceded the COVID crisis. Many firms repaid partially, with only a few firms borrowing more in the second quarter.

Table B.8 in the Internet Appendix provides more detail on the distribution of credit line repayments. Panel A shows that among all HY issuers, 72% of these repaid some amount of credit line after their bond issuance. In fact, 40% actually repaid their credit line *in full*, and only a few borrowed additional funds from banks in the second quarter. Panel B shows the distribution of credit line repayment as a fraction of either (1) Q1 draw-down or (2) bond issuance, conditional on repaying. Among HY issuers repaying bank loans, the median firm paid back 100% of its Q1 borrowing, representing 54% of their bond issuance. These patterns are similar for IG firms, although a smaller share drew on their credit lines in the first place. 91% of BBB firms that drew down on their bank credit line in Q1 repaid their bank in Q2 following bond issuance, with the median also repaying 100%. The safest, A-rated firms exhibit a similar pattern, with the vast majority (over 77%) of firms repaying 100% of Q1 credit line borrowings in Q2 following bond issuance. Table

B.9 in the Internet Appendix provides some aggregate magnitudes. We estimate that at least $111 billion was repaid by bond issuers to banks between April and June 2020 alone.[29]

Again, while repaying credit lines does preserve liquidity, this is another sign that bond issuers had significant financial slack in Spring 2020. It is plausible that issuers expected other shocks to materialize in the future, making this additional dry powder more valuable. Nevertheless, at least conceptually, the marginal value of additional liquidity is lower if firms have access to more financial slack.

2.3.3 Mechanism

Overall, the evidence in this section suggests that the main narrative for bond-loan substitution in bad times should be revisited. Indeed, the conventional view is that the key driver of bond issuance in bad times is weak balance sheets of banks, based on compelling evidence from the GFC (Becker and Ivashina, 2014; Crouzet, 2017). In 2020, bonds appeared to be largely *revealed-preferred* to loans although banks' balance sheets were strong and access to credit lines was largely unimpeded for large firms.[30]

The simplest alternative explanation would be that bonds became cheaper relative to loans during this time. This is in fact not as obvious as it is may sound, since it is not sufficient that bond yields have fallen, which is well documented, since loan interest rates have also fallen. It is also well-known that bonds tend to be more expensive than loans.[31] Nevertheless, it is possible that the bond-loan spread shrank during this time. To gauge the potential for this simple explanation,

[29]Debt substitution occurs following bond issuance in normal times as well, but to a much smaller extent. Of course, in normal times, liquidity needs are significantly smaller and far fewer firms draw on or repay their credit lines. Figure B.3 in the Internet Appendix shows the estimates of a dynamic within-firm regression similar to Figure 2.2 but for credit line draw-downs for a two year window around issuance. Table B.10 and Figure B.4 in the Internet Appendix summarize the magnitudes of draw-downs and repayments for the first half of 2019 rather than 2020. No IG bond issuers maxed out on their credit lines, and only 1.7% of HY firms maxed out on their credit lines; 58% of the riskiest bond issuers did not draw down on their credit lines.

[30]Of course, our results should not be interpreted as bank lending being unimportant for firms' access to liquidity. In fact, many firms do not have access to bond markets and crucially rely on bank funding. For example, Halling et al. (2020a) argue that while there has been an emphasis on loan-bond substitution in recessions, bank financing still increases for the average US public firm during these times.

[31]This is in large part because bonds are junior to bank loans. Schwert (2020) uses firm-level variation to estimate the level of the loan-bond spread in a sample of U.S. firms.

we provide a back of the envelope estimate of the relative cost of bonds vs. loans during this time period. In fact, in aggregate data it is not obvious that the bond-loan spread shrank significantly, consistent with emergency measures affecting both loans and bond markets. Looking at changes between February 14 (before the crisis) to June 30, 2020 (end of our COVID issuance sample, after the market panic and Fed intervention), bond yields were not much lower. For AA rated bonds, yields on ICE BofA US Corporate Index went from 2.18% to 1.57%, an 61bps decrease. For BBB bonds, the fall was even smaller, at 24bps (2.92% to 2.68%), while for BB HY bonds yields actually increased by 159bps (3.52% to 5.11%). Figure B.5 in the Appendix confirms this pattern using micro-data on bond yields within issuer.

Estimating changes in loan rates is more challenging. One approach followed by Acharya et al. (2021) is to calculate loans spreads using loans traded in the secondary market as part of the U.S. Leveraged Loan Index. Strikingly, they find that if anything, loan spreads *fell more* than bond spreads for firms with rating BB or above in the months following the intervention. A potential limitation though is that credit lines rarely trade in secondary markets. An alternative approach is to directly look at credit line contracts and pricing. On that front, one thing to note is that the vast majority of credit lines have a floating rate that move one to one with a benchmark rate (often LIBOR or the prime rate). In Spring 2020, these benchmark rates fell by 100 to 150bps as the Federal Reserve returned to the zero lower bound. This is about two times greater than the drop in bond yields for highly rated firms. Moreover, micro-data on loan pricing at the firm-level also suggests that it is unlikely that bonds became cheaper than loans: in the sample of COVID issuers for which we were able to find loan pricing in Dealscan, the yield on their 2020 bond was on average 172bps higher than the LIBOR spread of their credit line (176bps for the median). While these different approaches all point against bonds having become obviously cheaper than loans during this time, this is however not definitive evidence and a more thorough analysis of loan vs bond spreads is warranted.[32]

Nevertheless, differences in other contract terms, such as maturity, interest rate fixation, or covenants could explain the substitution even if relative prices did not change much. Indeed, the core logic is to lock-in funds for as long as possible. Firms' preferences for bonds could thus be explained by them having significantly longer maturities than loans and/or being more likely to be fixed-rate. These differences are well documented for both bonds issued in 2020 and prior years.[33]

As a concrete example, consider again Kraft Heinz. Their May 2020 bond issuance included three tranches with maturity ranging from seven to thirty years, priced at 3.9% to 5.50%. This is a 15-60 basis point higher yield relative to their previous issuance in September 2019 (priced between 3.75% and 4.9%). While the pricing of their credit line is more complex, its maximum spread (accounting for its rating downgrade) was 1.75% over the benchmark rate, which was 1.5% in March and then fell dramatically in spring 2020. The interest expense associated with drawing down on their bank credit line was thus likely lower than issuing bonds, and declined even further in spring 2020. However, their bank loan had a time to maturity between three and four years.[34] Kraft Heinz seemed to prefer the longer-maturity source of funds (bonds) even though it did not appear to have become relatively cheaper.

Finally, it is also possible that bonds having less restrictive covenants than loans might have

[32] It is well understood that credit line pricing is complex and that the micro-data quality is imperfect. We are able to find all-in-drawn spread information for only 116 out of the 313 firms that composed our main sample of March 23-June 30 issuers. Nevertheless, the all-in-drawn spread, although widely used, is only a proxy of the marginal cost of drawing in bad times. Interest rates floors can limit the pass-through, although Roberts and Schwert (2020) estimate that LIBOR floors on loans originated after 2018 are smaller than 50bps. Performance pricing provisions or covenant violations can lead to an increase in loan spreads as borrower creditworthiness deteriorates. On the other hand, the all-in-drawn spread often includes fees that are paid irrespective of drawn amounts, and must thus be deducted to estimate the marginal cost of drawing. There is unfortunately too little data on floors, performance pricing, and fees in our matched sample to conduct a high-frequency analysis of loan pricing in spring 2020. For more details on loan pricing in the United States and data limitations, see Berg et al. (2016).

[33] While the typical loan maturity for a bond issuer is four years (Schwert, 2018), the median IG bond issued in 2020 is 10 years, and 7 years for the median HY bond. Halling et al. (2020b) argue that bond maturities did not significantly shorten during COVID, in spite of the Federal Reserve intervention incentivizing short maturity, contrary to prior evidence (Erel et al., 2012).

[34] More details are available in their annual report `https://www.sec.gov/ix?doc=/Archives/edgar/data/1637459/000163745921000009/khc-20201226.htm`. The credit line pricing is complicated by the fact that there was a floating rate multi-currency loan (and thus has multiple base rates) and that the spread depended on their rating without the formula being disclosed. A conservative estimate is 3.25%, coming from taking both the highest benchmark rate value in March 2020 and the highest spread. In reality, this is likely to be an upper bound.

played a role. While loans have covenants that give lenders discretion to reduce credit before maturity, bond covenants are less intrusive and much more rarely triggered passively (they more rarely include "maintenance" covenants, relying instead on "incurrence" covenants).[35] This implies a more nuanced perspective on the value of bank "flexibility" relative to market financing. A well understood benefit of bank debt is that it is easier to renegotiate because it tends to be held by more concentrated creditors relative to bonds (Bolton and Scharfstein, 1996). However, the flip side is that renegotiation can be detrimental to the borrower: loan contracts include non-price loan terms that grant lenders discretion after bad news. This is well understood in practice.[36] Nevertheless, how much weaker bond covenants really are is the subject of active research: incurrence covenants impose restrictions on firm behavior (Bräuning et al., 2021), and banks did not seem to strictly enforce covenants violations in 2020 (Acharya et al., 2021).

While the implication of these differences in contract terms is intuitive, they are nevertheless absent from the classical models that rationalize banks' comparative advantage in providing liquidity relative to the market (Holmström and Tirole, 1998; Kashyap et al., 2002; Gatev and Strahan, 2006; Acharya et al., 2018).[37]

[35]For more on covenants violations on bank loans, see Sufi (2009); Murfin (2012); Chodorow-Reich and Falato (2017); Lian and Ma (2018); Greenwald (2019); Acharya et al. (2014); Berlin et al. (2020). For bond covenants, see Green (2018); Becker and Ivashina (2016); Rauh and Sufi (2010). Table B.11 in the Internet Appendix confirms this difference in covenants, in line with Bradley and Roberts (2015) that use an earlier sample.

[36]" 'Companies don't want to be subject to the testing of maintenance covenants,' said Evan Friedman, head of covenant research at Moody's. 'Going to the bond market can give companies more freedom, as they don't have to demonstrate their financial fitness again until the debt matures.' " Source: "Companies Issue New Bonds to Pay Down Short-Term Debt Amid Pandemic", *Wall Street Journal*, September 2nd 2020. Note also that this could potentially explain part of the surge in convertible bond issuance witnessed in 2020, as Kahan and Yermack (1998) and Rauh and Sufi (2010) show the almost complete absence of covenants in convertible issues. Note however that this argument essentially assumes that covenants on a firm's existing loans do not apply if the loan is not drawn i.e. springing covenants (Berlin et al., 2020). More generally, this relates to the role of different types of creditors in insolvency outcomes (Djankov et al., 2008). Note finally that there can be ex-ante efficiency gains achieved by using debt covenants (Green, 2018).

[37]Interestingly, the economics behind bond issuance thus seem quite different from commercial paper, which is typically seen as the main source of market-based liquidity for firms. The very short-term nature of commercial paper makes it a poor option to lock-in funds and build liquidity buffers.

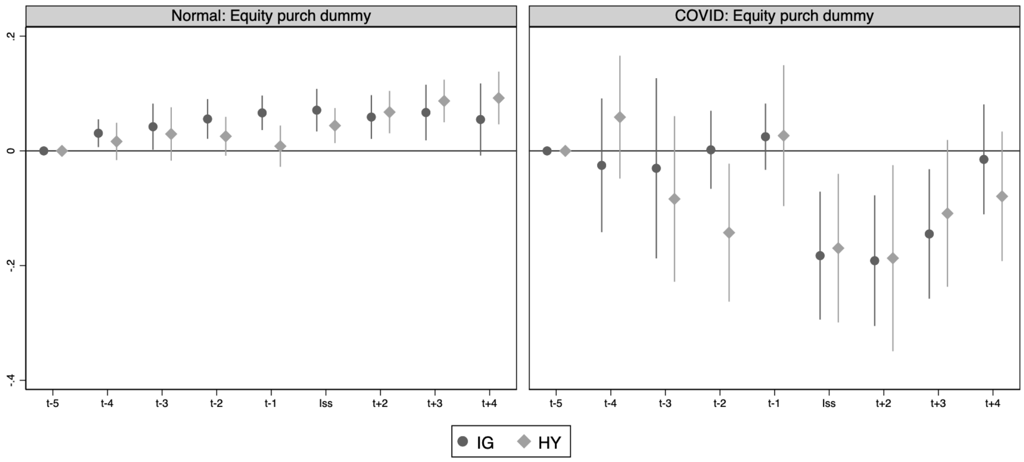


Figure 2.5: Equity repurchases: Coefficient plots

Notes: Each point is an estimate of β_{t+m} from the regression $Y_{fq} = \sum_{m=-5}^{4} \beta_m Issue_{f,t+m} + \alpha_f + \alpha_{ind \times year} + \epsilon_{fq}$, with 95% confidence intervals. "Equity purchase dummy" is an indicator for positive purchases of common or preferred shares in that quarter. The circles are investment grade firms (rated BBB- and above), while the diamonds are high yield firms (rated below BBB-). Observations are firm-quarters up to five quarters prior to a bond issuance and four quarters following a bond issuance. "Iss" denotes the quarter ending immediately after issuance. We include firm and industry-year fixed effects. Standard errors are clustered by 2-digit industry level. All ratios are winsorized at the 1% level. "Normal" times includes bonds issued between 2010-2019, "Covid" times includes bonds issued between March 23 - June 30, 2020.

2.4 Equity Repurchases

Finally, we explore whether firms use bond proceeds to pay out shareholders. Bond issuers are generally among the less financially constrained firms in the economy. There is therefore a potential concern that loose monetary policy can lead to leveraged payouts, instead of stimulating corporate investment (Acharya and Plantin, 2021). Note that in normal times, it is not uncommon for bond issuance to finance share repurchases (Farre-Mensa et al., 2018; Ma, 2019).

To shed light on this issue, we conduct an event study analysis similar to Section 2.2 looking at firms that issued bonds between March 23 and June 30, 2020. The variable of interest is a dummy for whether the firm conducted share repurchases in a given quarter.[38] Figure 2.5 shows dynamic coefficients plots around issuance. It confirms that bond issuance is often associated with share repurchases in normal times.

[38]We exclude normal dividends from this measure given firms' well-know reluctance to cut them; on the other hand, share repurchases are more discretionary in nature. See Farre-Mensa et al. (2018) for more details.

However, the dynamics during COVID are more nuanced. On the one hand, issuers were on average significantly less likely to purchase equity following bond issuance. The probability of repurchase after issuance falls by about 20 percentage points. These results are consistent with the hypothesis that many firms aim to preserve cash on their balance sheets, and both issued bonds and scaled back on equity purchases to do so. High-profile examples of reductions in shareholder payouts were widely covered in the news.[39] Nevertheless, share repurchase activity resumed normally quite rapidly, within a few quarters following issuance.

Despite the overall reduction, 47% of issuers still repurchased shares between March and June 2020. Given the general level of uncertainty, this is quite striking. This evidence points to an important group of issuers that, at face value, do not appear to highly value inside liquidity at the margin. Table B.4 estimates that over $160B was spent on share repurchases between March and December 2020 in our sample of COVID issuers.[40] For this group of firms, the large reduction in yields following the intervention might have unintentionally fueled opportunistic issuance. Table B.12 in the Internet Appendix investigates heterogeneity in the cross-section of Spring 2020 bond issuers. High cash balances from 2019Q4 are the only strong predictor of repurchases after March 2020. Credit ratings and being in a sector exposed to COVID have no significant explanatory power, confirming that payouts were pervasive.

Early bond refinancing: A related possibility is that bond issuance was used to retire existing bonds early. While this is distinct from equity payouts, it does share the feature of choosing to pay back existing investors as opposed to keeping funds inside the firm. While this happened to some degree, Becker and Benmelech (2021) argue that call activity did not exceed prior years.[41] This refinancing activity was likely concentrated towards the end of the year: Figure 2.3 shows a dip in bonds outstanding a few quarters after the intervention, in line with aggregate net debt financing turning negative at the end of 2020 (Hotchkiss et al., 2020). Moreover, some early bond

[39]For example, Ford Motor Co. and Freeport-McMoRan Inc. suspended dividend payments while AT&T halted share repurchases. "Companies Race for Cash in Coronavirus Crisis", *Wall Street Journal*, 03/23/2020.

[40]This is in line with the broad analysis of equity issuance by Hotchkiss et al. (2020) that finds that in aggregate, large companies paid out more to their equity holders than they raised.

[41]In line with their evidence, we were only able to find 21 COVID issuers that engaged in early bond refinancing using Mergent FISD data up to October 2020.

retirements might have been primarily motivated by maturity extension rather than interest savings. For example, between May and October 2020, Kraft retired over $3B of existing bonds, through a mix of tender offer and debt redemption. Interestingly, the retired bonds did not typically have higher yields, but instead much shorter maturities, with most coming due in 2021 or 2022. This is consistent with the evidence in Xu (2018) that shows that speculative-grade firms tend to refinance their corporate bonds early to extend maturity rather than to save on interest payments, particularly under accommodating credit supply conditions.[42]

Late issuers: Finally, we investigate the behavior of firms that issued bonds later in the year, specifically between July 1 and December 31, 2020. By early July, uncertainty had receded compared to the peak of March-April,[43] but the Federal Reserve continued to purchase bonds until the end of December of 2020. In the interest of understanding heterogeneity among bond issuers, we first look at the joint dynamics of issuance and yields. By revealed preference, a firm that is willing to issue earlier at a higher yield likely values liquidity more at the margin relative to a firm that waits longer.

We note that while bond yields dropped across the board in 2020, the big drop in yields occurred months earlier for safer issuers than for riskier firms. Figure B.6 in the Internet Appendix shows a time series of weekly issuance volume and bond yields, aggregated by rating categories (the yield series extend to 2021 for clarity). It is clear that IG yields quickly reached low levels: by May-June they were already below their 2019 value. On the other hand, it took until September for HY yields to be below their 2019 value. They also kept falling for the rest of the year, while IG yields flattened out. These differential yield dynamics line up with issuance dynamics: while it is clear that issuance slowed down, the drop was less pronounced for HY firms. Yield dynamics can thus potentially explain why the number of HY issuers was below trend early in the crisis (Becker and Benmelech, 2021; Hotchkiss et al., 2020) and picked up in late summer.

A natural prediction is that late issuers value liquidity less relative to early issuers. Thus, we

[42] See also Brunnermeier and Yogo (2009) for the role of maturity choice in liquidity risk management.

[43] For example, the VIX indexed fell to 28 on June 29th, which is comparable to the 2018 peak of 30 but significantly below the 2020 peak of 65.

would expect to see firms that issued bonds in July - December 2020 to accumulate less cash and exhibit more opportunistic behavior compared to firms that issued bonds in the spring of 2020, when uncertainty was higher. Figure B.7 in the Internet Appendix lends support to this view: firm-level dynamic regressions suggest that late issuers were relatively less likely to accumulate cash or cut share repurchases, and were not more likely to increase real investment.

2.5 Discussion and Implications

At a general level, evaluating the aggregate effects of the intervention requires estimating a quantitative macroeconomic model. This is necessary to run the counterfactual of what would have happened absent the intervention. The first objective of this section is thus to inform the micro-foundations of such a model in light of the firm-level evidence presented above.

The events of 2020 show that a closer integration of corporate finance and macroeconomic models is important to understand the transmission of unconventional monetary policy. For instance, state-of-the-art models of monetary transmission assume that firms borrow to finance investment (Kaplan et al., 2018; Ottonello and Winberry, 2020; Auclert et al., 2020). To rationalize the pattern of debt issuance for the purpose of accumulating liquid assets, these models must be extended to incorporate an explicit role for liquid assets and long-term financing, so that cash is not equivalent to negative debt. Nevertheless, there has been some effort to incorporate corporate liquidity in macroeconomic models (Xiao, 2020a; Arellano et al., 2019; Kiyotaki and Moore, 2019; Rocheteau et al., 2018; Jeenas, 2019; Kim, 2021).[44] Moreover, the active choice of bonds over bank loans implies modeling explicitly this margin, going beyond existing models that tend to focus on shocks to banks' balance sheets (Crouzet, 2017; De Fiore and Uhlig, 2015). Finally, given that we observe many firms issuing bonds to repurchase equity, incorporating joint debt issuance and payouts in models of unconventional monetary policy is an important avenue for future

[44]In particular, Xiao (2020a) presents a model where firms borrow to save based on evidence from the Great Recession. The mechanism stresses gradually resolving uncertainty and imperfect debt and asset adjustments, through the interaction of a *negative* credit supply shock with an increase in the volatility of idiosyncratic productivity. Interestingly, the mechanism of Bolton et al. (2013) can explain borrowing to save when financing conditions *improve*.

research (Acharya and Plantin, 2021).[45] More generally, the rising importance of corporate bond markets calls for refining the monetary policy toolbox.

Our evidence suggests that the main benefit of the intervention is linked to the value of corporate liquidity, as opposed to a direct investment multiplier. Estimating how large this value is for bond issuers is thus key for future policy analysis. Importantly, our second and third main findings highlight forces that are important to size this value. First, while not tapping credit lines preserves liquidity, bond issuers were typically far from their credit limit. Conceptually, theory suggests that the marginal value of additional liquidity is declining in total financial slack available to the firm. Moreover, equity payouts are a direct sign of a low value of funds inside the firm relative to outside. Our evidence thus makes it clear that to assess the potential real effect of the intervention it is crucial to not just look at market data, such as yields and issuance volumes, but also at firms' balance sheets and operations.

A practical challenge for central banks is thus how to target unconventional policy actions aimed at the bond market. As a group, bond issuers are the least financially constrained firms in the economy. While some issuers exhibited behavior consistent with low liquidity, such as maxing out their credit lines and cutting equity payouts, our evidence suggests that many firms did not. While a welfare analysis is beyond the scope of this paper, targeting firms with the highest value of liquidity may minimize the risk of opportunistic issuance.[46]

With that in mind, dissecting the Federal Reserve's actual corporate bond portfolio yields two interesting observations. On the one hand, while the market reaction was large, actual purchases have been small. By the end of the eight-months program in December 2020, they amounted to

[45]Note that this pattern represents a challenge to many corporate finance theories of liquidity management: firms typically raise funds when cash is low but pay out when cash is high, but do not do both at once. Acharya and Plantin (2021) present a model of corporate finance with agency frictions that predicts that loose monetary policy can lead to leveraged payouts. More generally, models of market timing such as Ma (2019) can also explain this pattern with shifts in relative valuation between debt and equity markets; see also Baker and Wurgler (2002); Baker et al. (2003); Pegoraro and Montagna (2021). For other theories of debt-financed payouts, see Farre-Mensa et al. (2018). Macroeconomic models that predict debt-financed payouts in good times include Jermann and Quadrini (2012); Begenau and Salomao (2019); Covas and Den Haan (2011).

[46]The extent to which debt-driven payouts lead to inefficiencies is an open question. In the model of Acharya and Plantin (2021), payouts inefficiently crowd out real investment, while Almeida et al. (2016) provide causal evidence of share repurchases reducing employment and investment. Nevertheless, estimating the magnitude of this crowding out in a time when investment opportunities are depressed like 2020 is an important avenue for future research.

only \$14B out of the potential \$750 billion proposed, while over \$500B was issued in March-June alone. The program was much smaller in scope relative to the ECB, which purchased bonds for over five years, accumulating a portfolio of over 300B €.[47] The amount of public dollars spent was thus limited. On the other hand, the composition of the portfolio was highly skewed towards safer firms that appear less constrained: IG bonds made up as much as 87% of the total purchased. Moreover, 11% of the firms and 20% of the volume of the Federal Reserve's portfolio issued bonds in spring 2020 and subsequently repurchased equity.[48] Nevertheless, the broad market reaction observed in the data seemed to have benefited many firms. In this paper, we take the market response as given; however, understanding what drives these announcements effects is an important avenue for future research.[49]

Interestingly, our evidence also points to the 2020 Federal Reserve program having a different transmission mechanism relative to what prior work has identified for the 2016 Corporate Sector Purchase Program in Europe (CSPP). While both programs had similar effects on markets by reducing yields and stimulating issuance, the transmission to real effects differs significantly. Grosse-Rueschkamp et al. (2019) report a strikingly different impact of the CSPP on firms' balance sheets. They find no effect on credit lines balances, cash holdings, or share repurchases. Instead, BBB-rated firms repaid term loans while highly-rated firms increased acquisitions. On the other hand, the Fed program seemed to have been more about a direct effect on issuers through increasing their available liquidity. At a broad level, both programs led to bond-loan substitution, but in

[47] As of December 31, 2021, the ECB held just under 310B € from purchases via the CSPP.

[48] Includes firms that issued bonds March 15 - June 30, 2020 and subsequently repurchased equity at some point in 2020 that were also included in the December 2020 Federal Reserve Broad Market Index. For more details on Fed early purchases, see Flanagan and Purnanandam (2020).

[49] What is the right underlying mechanism is an open question. Hanson et al. (2020) highlight the response of investors' beliefs to central bank announcements, and Haddad et al. (2021) provide high-frequency evidence that the Fed announcements shifted investor's beliefs of future intervention in bad states of the world. Another potential mechanism is the feedback loop between secondary bond market liquidity and firms' probability of default in He and Xiong (2012). Investor expectations of fiscal policy changes may also factor into the announcement effects (Xu and You, 2021).

quite different ways.[50] Our evidence is thus a key piece of drawing a complete picture of how corporate bond purchases by central banks transmit to the real economy.[51]

Overall, one might ask which lessons can generalize beyond this specific recent episode. Each crisis is indeed different and many factors determine the effects of public intervention, such as the source of the shock or the state of the banking sector. Nevertheless, our findings are rooted in trends in corporate financing for large firms that are likely here to stay. First, the paramount importance of bond financing in corporate finance: bonds have not just replaced bank loans for the purpose of funding investment in good times (Berg et al., 2020), they are also used to accumulate liquidity buffers in bad times, and in fact were preferred to bank credit lines or commercial paper. Second, the bond market should not be considered in isolation: large bond issuers have access to significant quantities of off-balance sheet credit from banks. Third, debt-financed payouts, defined as concurrent debt issuance and share repurchases, are pervasive among large firms.

2.6 Conclusion

This paper studies firm behavior in the wake of the unprecedented policy support to the corporate bond market in 2020. While bond issuance surged, real investment did not, as funds were mainly used to accumulate liquid assets, repay other loans, or repurchase shares. Moreover, most bond issuing firms had access to credit lines from banks that they chose not to use, even though the crisis did not originate in the banking sector. Interestingly, the effect of the intervention on firms' balance sheets was different from that of corporate bond purchases carried by the ECB in 2016,

[50] The ECB program helped banks relax their lending constraints, allowing them to lend to smaller firms (Grosse-Rueschkamp et al., 2019; Arce et al., 2021; Ertan et al., 2019). As of now, there is little evidence that corporate bond purchases by the Federal Reserve have benefited smaller borrowers: it seems that small firms were largely unable to borrow from banks during the spring of 2020 (Chodorow-Reich et al., 2020; Greenwald et al., 2020; Kapan and Minoiu, 2021). Grosse-Rueschkamp et al. (2019) argue that bank balance sheet constraints were key for the transmission of the CSPP. This logic thus suggests that the strength of U.S. banks at the start of 2020 can potentially explain the difference. Note however that the repayment of existing loans was not an explicit goal of the U.S. intervention, unlike for the ECB program.

[51] Note that recent work by Pegoraro and Montagna (2021) argue that European issuers timed the market after the CSPP, changing the characteristics of their bonds such that they are eligible for the program. They find little effect on investment and some effect on cash balances.

even if both programs lowered spreads and stimulated issuance.

Our evidence highlights the value of studying firms' balance sheets, beyond the market rebound, to better understand potential real effects of bond purchases and inform the micro-foundations of macroeconomic models. The rich interactions between corporate debt and the macro-economy is a promising agenda going forward (Brunnermeier and Krishnamurthy, 2020). Just as the GFC showed that financial intermediation was more complex than previously thought and needed a proper place in macro-finance models, the market turmoil in 2020 highlights the complexity and central place of bond markets and corporate finance for the macro-economy.

Chapter 3

Global Demand Spillovers: the Effect of Underwriting Networks [1]

In recent years, more central banks have adopted the unconventional policy of buying corporate bonds. The European Central Bank (ECB) announced its 2016 corporate bond purchasing program (CSPP) to "further strengthen the pass-through of the Eurosystem's asset purchases to the financing conditions of the real economy."[2] In a break from convention, the U.S. Federal Reserve announced in March 2020 that it, too, would participate in large-scale corporate bond purchases. While many papers study the direct effects of these interventions, an outstanding question is how these corporate bond demand shocks spill across to other jurisdictions. Moreover, do spillovers have impacts on real activity in other geographies?

Evaluating spillover effects of monetary policy or other demand shocks across economies that are already linked through trade and large global corporations is difficult. Significant investor demand shocks are often systemic and may coincide with other events that impact global corporate demand for capital. In this paper, I overcome this problem by tracing the spillover of the ECB's bond purchase program to U.S. firms via a bond underwriting channel. Specifically, I compare issuance outcomes and decisions at U.S. firms that are more and less exposed to the ECB's corporate bond-buying program through their bond underwriting networks. By comparing more exposed

[1]This chapter is based on Siani (2019). I am grateful for the comments and suggestions of Simona Abis, Nina Boyarchenko, Charles Calomiris, Kent Daniel, Olivier Darmouni, Xavier Giroud, Robert Hodrick, Wei Jiang, Yiming Ma, Andrew MacKinlay (discussant), Harry Mamaysky, Lira Mota, Giorgia Piacentino, Tomasz Piskorski, Tano Santos, David Scharfstein, Sergio Schmukler (discussant), Or Shachar, Suresh Sundaresan, Cristina Tessari, Kairong Xiao, Neng Wang, and seminar participants at Columbia Business School, the European Finance Association Annual Meeting 2020, Northern Finance Association Annual Conference PhD Session 2020. Thank you to the Chazen Institute and Columbia Business School for helping fund this project. Thank you to Informa Global Markets for access to and help with the data.

[2]ECB Press Release, April 21, 2016: ECB announces details of the corporate sector purchase programme (CSPP) https://www.ecb.europa.eu/press/pr/date/2016/html/pr160421_1.en.html

U.S. firms to a control group of comparable, non-exposed U.S. firms, I can attribute differential increases in bond issuance to demand spillovers from the Euro-zone, holding fixed any economy-wide effects.

To clarify the identification logic, consider the example of Barclays and Wells Fargo, two large bank underwriters active in the U.S. corporate bond market. 75% of Barclays' institutional relationship network is in the Euro-zone, while 0% of Wells Fargo's institutional relationship network is in Europe. After the implementation of the ECB's bond buying program, prices of Euro-area securities are driven up and institutional investors seek out bonds of a similar risk profile in the U.S. market. Because bank-investor relationships are persistent and primary market trades are exclusively dealt through underwriters, European investors participate in bonds underwritten by Barclays, but not by Wells Fargo. As a result, U.S. firms that work with Barclays receive a larger order book for their bonds and a lower cost of capital after the start of the ECB program. I can then track how these treated firms (Barclays' clients) change issuance decisions in response to the demand spillovers.

I construct a novel data set merging industry data with detailed characteristics on bond issuance with Compustat. The combined dataset includes information on order book size, total auction timing for 4,629 bonds issued by 833 issuers through 87 bank underwriters. I construct a firm-level exposure metric to the Euro-zone using firm-bank underwriting relationships and bank-level investor relationships.

I find that, following the start of the ECB's bond buying program, U.S. firms that have relationships with banks that are more exposed to the Euro area receive more orders for their bonds, have lower costs of capital, and issue more bonds. I show that this is *not* related to firm fundamentals or geography. Moreover, I find that riskier firms and less frequent bond issuers raised more bond capital in response to the positive credit supply shock. My estimates show that the average exposed firm saw a decrease in its annual cost of capital by 4-5 basis points and increased average quarterly issuance volume by 6.5% relative to the control group of firms not exposed to the Euro-area. A rough back of envelope calculation suggests that in aggregate, the CSPP can account for a $5 billion increase in quarterly USD bond issuance volume by U.S. non-financial firms. The magnitude of the impact on U.S. firms can be considered a lower bound for the overall spillover effect of ECB corporate bond purchases on the U.S., because any overall impact that affects all U.S. firms similarly is differenced out.

Next, I investigate the long-term consequences of the unconventional monetary policy on a firm's debt and real investment. I find evidence that firms that are more exposed to the ECB's bond buying program pay out more to equity holders in lieu of making real investments. Treated firms do not increase operational assets (using non-cash assets as a proxy) as much as they do following normal bond issuances. In addition, I find that firm leverage ratios remain elevated up to two years after bond issuance. The results suggest that underwriter networks transmit demand shocks from one jurisdiction's unconventional monetary policy to another jurisdiction. Moreover, the positive demand shock can increase bond issuance and leverage at affected firms.

My empirical methodology relies on two key assumptions: (i) banking relationships with both firms and bond investors are persistent and (ii) the cross-sectional variation in US firms' bank exposure to Europe is orthogonal to the cross-sectional variation in US firms' operational exposure to Europe. I verify that these two assumptions are true in the data. Indeed, I find that (i) firms (banks) tend to choose banks (investors) with whom they have existing relationships, and this tendency does not change in response to or in anticipation of the ECB's quantitative easing program, and (ii) firms that work with more European banks do not necessarily have more operational exposure to Europe. Hence, the channel that I identify has to do solely with bank networks, rather than direct effects of ECB policy on U.S. firms.

To check that the chain of causality is indeed from the ECB's bond buying program to firm issuance outcomes, I control for firm-specific demand by including firm fixed effects in my main specification.[3] Next, I control for potential secular changes in firm-specific real demand for bonds by running a within-firm-year regression. I want to ensure that my results reflect movement *along* the firm's demand curve for bond capital, rather than reflecting a simultaneous *shift outward* of the

[3] This is akin to the empirical strategies in Khwaja and Mian (2008), Schnabl (2012),Paravisini et al. (2015)

firm's demand curve due to changes in real investment opportunities that coincide with the ECB's policies. I find that my baseline results hold. This test supports the notion that the ECB's QE program impacted U.S. firms via the bank underwriting network, lowering their costs of capital and encouraging increased issuance.

Next, I discuss other potential mechanisms of monetary actions spilling over to U.S. firms, including the ECB's 2015 government and agency bond purchases, as well as the Federal Reserve's third round of quantitative easing (QE3). I provide evidence that the heterogeneous impacts on issuance volumes and costs of capital that I identify across U.S. firms is caused primarily by the ECB's corporate bond purchase program, rather than other government asset purchase programs that occurred around the same time.

I run a series of robustness checks to ensure that results are not being driven by endogenous firm-bank choice. Firms working with banks that are more exposed to Europe may have more operational exposure to European banks. To deal with this potential confounder, I construct a measure of the extent of Euro-zone operations that each U.S. issuer has by scraping the text in their company filings. I find that cross-sectional variation in the measure of operational exposure to Europe has no impact on firms' bond issuance decisions after the start of the ECB's QE program. Further, I find no evidence that the metric of operational exposure is correlated with a firm's exposure through its bank network. The robustness checks confirm the hypothesis that shocks can be transmitted across borders through bank underwriting networks.

Why might demand shocks transmit globally through bank underwriting networks?[4] When underwriting bonds, banks incur costs in search of buyers of securities. Because banks and investors are repeat agents in this market, banks can reduce long-term search costs by maintaining relationships with the same investors. As such, demand shocks transmit through bank underwriting networks. I conduct a series of empirical tests that show results consistent with such a mechanism. Using a novel metric of time spent on issuance to proxy for search costs, I find evidence that banks

[4]It is well established that demand shocks transmit through bank networks via a balance sheet channel; see, for example, Peek and Rosengren (1997), Kashyap and Stein (2000), Khwaja and Mian (2008), and Chodorow-Reich (2014)

do incur costs when searching beyond their typical network. This suggests that banks derive value from forming long-term relationships with investors.

My paper highlights a novel transmission mechanism for demand shocks across borders: bond underwriting networks. I thus contribute to the literature on how financial intermediaries can propagate global demand shocks.[5] A rich empirical literature uses natural experiments (Peek and Rosengren (1997), Khwaja and Mian (2008), Schnabl (2012), Gilje et al. (2016), Chava and Purnanandam (2011)) and variations in bank relationships across firms (Ivashina and Scharfstein (2010), Lin and Paravisini (2013)) or bank balance sheets (Becker and Ivashina (2018)) to identify how financial intermediaries can transmit shocks. I also show how firms respond to the transmitted shocks, contributing to papers that study how firms respond to supply frictions in capital markets (Saretto and Tookes (2013), Chakraborty and MacKinlay (2020), Massa et al. (2013), Faulkender and Petersen (2006), Almeida et al. (2012)).

My paper further contributes to the literature on indirect effects of unconventional monetary policy on the real economy.[6] Many empirical studies identify direct and indirect effects of the ECB's corporate bond buying on firms. Broadly, they find that the CSPP lowered issuance costs for eligible firms (Pegoraro and Montagna (2019), Rischen and Theissen (2017)), encouraging them to raise more bond capital (De Santis and Zaghini (2019)) and substitute away from bank loans (Grosse-Rueschkamp et al. (2019), Arce et al. (2018) and Galema and Lugo (2021)) or increase dividends rather than fund real investment (Todorov (2020)). Moreover, the benefits of lower issuance costs spilled over to ineligible Euro-area firms (Abidi and Miquel-Flores (2018) and Zaghini (2019)). Recent papers (Boyarchenko et al. (2020), Halling et al. (2020b), Gilchrist et al. (2020), Flanagan and Purnanandam (2020)) analyze the effects of the Federal Reserve's bond buying program, including higher issuance, lower yields and relaxed funding constraints. I add

[5]See Buch et al. (2019) for a recent survey. A related literature discusses how equity capital inflows affect equity issuance, using micro-data on firm-level issuance. See, for example, Calomiris et al. (2021).

[6]Chakraborty et al. (2020) document an origination channel of the mortgage-backed securities (MBS) purchase program. Further transmission mechanisms of monetary policy are documented in Drechsler et al. (2017), Rodnyansky and Darmouni (2017), Darmouni et al. (2019); see Drechsler et al. (2018) for a survey. Many empirical studies (Kashyap and Stein (2000), Bernanke and Blinder (1992), Kashyap et al. (1993),Jiménez et al. (2012)) document the bank lending channel of conventional monetary policy (Kashyap and Stein (1994)).

to this literature by studying the indirect effects of the ECB's program via spillovers to U.S. firm bond issuance.

The outline of this paper is as follows. Section 3.1 discusses the institutional background on the bond primary market, introduces facts about bank relationships, and describes the ECB monetary policy program of interest. Section 3.2 describes the data used in this study, defines key variables, and gives summary statistics. The empirical strategy is outlined in Section 3.3, and empirical results and robustness checks are presented in Section 3.4. Section 3.5 discusses results and mechanisms, and I conclude and discuss next steps in Section 3.6.

3.1 Institutional Detail

3.1.1 Corporate Bond Market

The corporate bond market is an important source of capital for corporations. Corporate bond issuance is over eight times the volume of common equity issuance.[7] In 2018, 87% of that issuance was Investment Grade (rated above BBB-), and 81% of the issuance was fixed-rate (See Figure 3.1). Unlike equity issuance and bank lending, investment grade corporate bond issuance is subject to less information asymmetry.[8] Corporate bond issuers tend to be larger, more transparent firms.[9] The median non-financial bond issuer in my sample (detailed in Section II) had $5.2 billion annual revenue and $12 billion in total assets as of 2010. By comparison, the median non-financial firm in Compustat had $31 million in annual revenue and $203 million in total assets in 2010.

Corporate bonds are often underpriced at issuance.[10] Cai et al. (2007) document an average of 47 basis points of underpricing for high-yield bond initial price offerings (IPOs), as measured

[7]SIFMA 2018: Common Stock issuance (including IPOs and follow-ons issued in the US) was $199.3 bn in 2017; Corporate Debt issuance (including public and private, IG and high yield bonds issued in the US) was $1.637 trillion

[8]See Myers and Majluf (1984): bond issuance is higher in the "pecking order" than equity issuance due to less information sensitivity

[9]See Diamond (1991): in the presence of moral hazard, borrowers start out by being monitored by banks, and graduate from bank loans to bond issuance once they have acquired better reputations

[10]Goldstein and Hotchkiss (2020) find evidence that while initial underpricing is small, prices continue to rise in the two weeks following issuance.

by the initial excess return of a given bond relative to a benchmark. Consistent with the paper's finding that underpricing is higher for riskier bonds, in my sample of safer, investment grade firms, underpricing per bond is on average 29 basis points by their metric.[11] Rationales behind underpricing typically focus on information asymmetries between firm and investor (Myers and Majluf (1984)), between investor and underwriter (Benveniste and Spindt (1989)), or between informed and uninformed investors (Rock (1986)).

In a typical corporate bond deal, a firm hires a median of four banks to underwrite the planned bond before the intended issuance date. The bond underwriting market is relatively concentrated.[12] There are 87 active bank underwriters in my sample (i.e., banks that underwrote at least three deals before and after June 2016). The top five most active banks participate (Bank of America, Citi, JP Morgan, Morgan Stanley, and Goldman Sachs) in 89% of the issuer-days in my sample. As a result, the bank-level variation in my sample mostly comes from smaller banks that likely have more limited and distinct sets of investor relationships. For banks that underwrite bonds, bond underwriting is a material portion of their business. According to a trade report by SIFMA, between 19-29% of investment bank revenues arise from debt underwriting and related activities.[13]

The primary market for corporate bonds has a unique feature that provides exclusivity to underwriters for selling new bonds. That is, the only way in which institutional investors can purchase newly issued bonds when firms raise bond capital is through the underwriters chosen by the firm. In the investment grade market, the primary services that the bank provides are: (1) searching for investors, collecting orders, setting pricing, and allocating the security and (2) ensuring post-issuance price stability.[14] Banks incur costs in the initial assessment of a firm's management, operations and creditworthiness. If a bank has already worked with a firm, the marginal cost of

[11] In Cai et al. (2007), underpricing is measured as the return within a 7-day window following issuance, or $(P_{t+n} - P_t)/P_t$, relative to a comparable index of bonds in the same ratings and maturity. In translating the average 3.4 basis point annual new issue concession (see Table 3.2) to the Cai et al. (2007) metric, I assume a 10-year bond issued with a coupon of 3.485% issued at par, which trades to a yield of 3.451% in the first day following issuance. I also assume zero return on the market index.

[12] See Manconi et al. (2018) for a discussion on underwriter competition and how it impacts bond pricing

[13] Source: SIFMA 2020, page 88: https://www.sifma.org/wp-content/uploads/2020/09/US-Fact-Book-2021-SIFMA.pdf

[14] Yasuda (2005) discusses another service that underwriting banks provide: insurance for unsold securities. However, this is more likely to be the case for non-investment grade issues.

marketing and selling the firm's securities is lower. James (1992) calls the setup of a bank-firm relationship as investing in "durable transactor-specific assets", rationalizing persistent bank-firm linkages.[15] In the next section, I directly test the supposition of bank-firm relationships.

3.1.2 Bank relationships

The methodological approach of the paper relies on (1) persistent bank relationships with both investors and issuers, and (2) the constancy of these relationships throughout the European Central Bank's monetary policy program. These institutional factors allow me to identify heterogeneous outcomes from the bond buying program for U.S. firms based on their bank underwriting networks. The empirical literature on corporate-bond bank-firm relationships shows evidence of persistent firm-bank underwriting relationships (Chakraborty and MacKinlay (2020), Yasuda (2005), Daetz et al. (2018)). The literature on investor-bank relationships in the bond primary markets is less developed.[16] While in equity underwriting, investor-bank relationships may be persistent due to information asymmetries (see Benveniste and Spindt (1989) and Cornelli and Goldreich (2001)), in investment grade markets, information asymmetries are likely less critical. Instead, bank-investor relationships may persist due to search frictions (see Duffie et al. (2007) and Henderson and Tookes (2012)) or profit-sharing with investors active in secondary market trading (see Nikolova et al. (2020) and Loughran and Ritter (2002)). Consistent with this literature, I first present evidence of persistence in bank-firm and bank-investor links. I then show that there is exclusivity among both sets of relationships.

First, I compare bank relationships prior to the start of the CSPP to those after the start of the CSPP. See Table 3.1 for the results. I find that firms typically choose bank underwriters with whom they have worked in the past. On average, 87% of banks that firms choose are from pre-existing

[15] It is also well established in the literature that firm-bank relationships in the bank loan market are sticky; see Darmouni (2019) or Schwert (2018) for recent discussions. Theories behind firm-bank lender persistence include market participants trying to avoid adverse selection (Sharpe (1990)), costly information acquisition (Sufi (2007)), moral hazard (Holmstrom and Tirole (1997)), and costly monitoring (Williamson (1987)).

[16] See Hendershott et al. (2020) for evidence of persistent investor-bank relationships in secondary corporate bond markets. The literature on investor-bank relationships is extensive in the equity IPO literature; see Binay et al. (2007) for a survey

relationships. Importantly, this is true in both the pre- and post-CSPP periods. Moreover, in only 1% of cases do firms choose entirely new banks to underwrite a bond. This suggests that bank-firm relationships are relatively persistent.

Bank-investor relationships are not fully disclosed. However, I can identify trades of insurance investors from the National Association of Insurance Commissioners (NAIC) regulatory filings, which constitute on average 11% of the buyers in the primary market for investment grade bonds in my sample period. I follow Nikolova et al. (2020) and identify primary market investors as those that buy a bond on the issuance date at the initial offer price and from one of the bond's initial underwriters. I find that, similar to bank-firm relationships, bank-investor relationships also tend to be sticky. On average, 90% of identified sales volume is attributed to investors with whom banks have existing relationships, and this is the same both pre- and post-CSPP. In a low proportion of days (3.5%), banks sell to a new set investors, and this share does not change after the CSPP program begins.

The results suggest that in the two-year period before and after the implementation of the CSPP, bank-firm and bank-investor relationships are persistent. Firms tend to work with banks with whom they have existing relationships. Similarly, banks tend to work with investors with whom they have existing relationships. I make the assumption that bank-investor relationships among insurance investors do not differ significantly from bank-investor relationships among other classes of investors. This evidence shows that the underlying bank-firm-investor underwriting network is reasonably persistent.

Next, I show evidence that these relationships are, for the most part, exclusive. Absent some degree of exclusivity, banks could link with all firms and all investors, thus invalidating my identification strategy. I plot histograms of the number of banks with whom an agent has a relationship from 2000-2018. If there were no relationship exclusivity in firm-bank links, then I would expect to see the full mass of firms at the maximum number of banks. Similarly, if there were no exclusivity in investor-bank links, then I should see all investors linked with all banks. Instead, what I find in Figure 3.2 is that most firms hire fewer than 10 bank underwriters, and most investors buy from fewer than 10 banks. This suggests that there is some degree of exclusivity to bank relationships.

Given these two pieces of evidence on bank relationships, I posit that there is a persistent firm-bank-investor relationship network where firms have heterogeneous exposure to banks, and banks have heterogeneous exposure to investors. These two layers of heterogeneity are reasonably persistent. This allows me to trace demand shocks from the ECB's monetary policy through the network.

3.1.3 ECB Quantitative Easing Program

I focus on the European Central Bank's (ECB) implementation of the Corporate Sector Purchase Program (CSPP) between June 8, 2016 and December 19, 2018 as an extension of its expansionary monetary policy efforts. The CSPP was part of a broader ECB asset purchase program (APP) that was designed to stimulate the economy in an environment where key interest rates were hitting their lower bound.[17] The average monthly net purchase under CSPP was 5.7 billion euros, with an monthly average of 17% of purchases done in primary markets.[18] Eligible bonds included investment grade Euro-denominated bonds issued by Euro-area non-bank corporations with remaining maturity of six months to 30 years. Within these criteria,the ECB targeted a wide range of ratings, sectors, countries, and issuers in order to remain market-neutral.

Following the start of the CSPP, yields for both eligible and non-eligible bonds in the Euro-area dropped. Issuance by Euro-are firms also increased.[19] For the set of investment grade bond issuers in my sample, I plot the average weekly yield on new bonds in Figure 3.3. I find, consistent with the literature, that there is a significant drop in new issue yields for Euro-denominated corporate bonds, and a similarly timed but smaller drop in yields for USD-denominated corporate bonds.

[17]The APP included 4 programs introduced between 2014-2016: the Third Covered Bond Purchase Programme (CBPP3), the Asset-backed Securities Purchase Programme (ABSPP), the Public Sector Purchase Programme (PSPP), and the CSPP. The decision to add corporate bonds to the assets purchased was released on March 10, 2016, with the stated goal to "further strengthen the pass-through of the Eurosystem's asset purchases to the financing conditions of the real economy." Source: ECB Economic Bulletin Issue No. 5/2016 (August 2016)

[18]Source: ECB website: Asset Purchase Programmes, retrieved July 2021.

[19]See Grosse-Rueschkamp et al. (2019), Todorov (2020), De Santis and Zaghini (2019), Arce et al. (2018) for a discussion of effects on Euro zone markets.

In response, institutional investors in the Euro-area invested more in USD denominated corporate bonds.[20] In 2016, Euro-area investors holdings of USD non-financial corporate debt securities issued by U.S. firms increased by 17 percent, with the bulk of the increase occurring in the second quarter following the start of bond purchases. Meanwhile, total U.S. corporate bonds outstanding increased by only 5%. Euro-area holdings of U.S. debt securities continued to rise in 2017 at 15%, compared to an increase in U.S. corporate bonds outstanding of 4%.[21] Indeed, this is consistent with Becker and Ivashina (2015), who find that conditional on credit ratings, investors are biased toward higher yielding bonds. In this setting, the ECB's policy drove down the yields of Euro corporate bonds, thus making U.S. investment grade corporate bonds relatively more attractive.

The pattern of growth in aggregate Euro-area holdings of USD non-financial corporate bond securities, plotted in Figure 3.4, is consistent with this story. There is a spike in the growth of Euro-area holdings of U.S. non-financial corporate bonds that corresponds with the start of the ECB's purchases in June 2016, as Euro-area investors began acquiring U.S. corporate bonds in larger quantities.[22] The only way European investors can access U.S. corporate bonds in primary markets is through their existing bank underwriting relationships. Thus, banks that already had existing relationships with Euro-zone investors would have access to this surge in demand for investment grade securities. U.S. firms that had relationships with these banks would benefit from greater demand for their new bonds.

[20] In September 2016, the bond fund PIMCO published a report advising European investors to cross the Atlantic, stating "the U.S. corporate bond market still remains the most attractive credit market, even after adjusting for currency hedging costs". Source: Kiesel and Dragesic, 2016. "U.S. Corporates: Crossing the Atlantic to Find Value." PIMCO. **?**

[21] Overall foreign holdings of U.S. corporate bonds (including ABS and MBS) increased by 11% in 2016. Sources: ECB Securities Holdings Statistics Warehouse, SIFMA 2020 Capital Markets Factbook.

[22] Note that it is not necessary for European issuers to be directly comparable to U.S. bond issuers. Rather, the key is there is some level of substitutability for European investors between U.S. investment grade bonds and European investment grade bonds. Indeed, Carey and Nini (2007) find that lenders cross borders more readily than borrowers in the syndicated loan market. Moreover, Berg et al. (2017) find that systematic pricing differences between U.S. and European syndicated loans can be partially explained by participation of institutional investors.

3.2 Data

A key innovation in this paper is the use of a new industry dataset, collected by Informa Global Markets, that has bond-level issuance data from September 2010 - June 2018.[23] The data aggregator surveys bank underwriters on a daily basis and collects new variables including the oversubscription and new issue discounts of each bond issuance. The dataset also provides the underwriters and other bond characteristics (including ratings, tenor, size, coupon, initial yield, and price). I restrict the sample to US dollar denominated corporate bonds issued in the investment grade market.

To obtain borrower firm characteristics, I merge the bond-level data with Compustat. Because there is no common firm identifier between my dataset and Compustat, I do a combination of fuzzy string merging and manual matches. In my core analysis, I include only the bond issuances for which I can match with Compustat company characteristics.[24] For primary market buyer information, I use the National Association of Insurance Commissioners (NAIC) Schedule D regulatory filings. Following Nikolova et al. (2020), I identify all primary market bond buying as purchases on the bond's issuance date, at the issuance price, and from one of the underwriters.

My identification strategy relies on the bank-level exposure to the European institutional investor market. To get to this information, I look at the 2010 10-K SEC filing (or international equivalent) for all 87 bank underwriters that underwrote at least three deals before and after June 2016 (the start of the corporate bond buying program). To measure the exposure of a bank's capital markets business to the Euro-zone, I compute the ratio of "institutional securities revenues" that are earned in the Euro-zone, and call that "euro-exposure".

The new data provides several variables of interest. One outcome variable of interest is the oversubscription of a bond issue, measured as the ratio of that order book to the amount issued. I use this metric to test if firms exposed to the Eurozone received more orders for their bonds. A second outcome variable is the new issue concession, or the difference between the yield to maturity in the primary market and contemporaneous secondary market trading for a comparable

[23]This dataset is also used in contemporaneous work, Siani (2021)

[24]Issuers that cannot be matched to Compustat are either private, foreign, or sovereign or supra-sovereign entities.

security. This is analogous to the security's underpricing at issuance.[25] The secondary market for corporate bonds is typically not very liquid, making underpricing inherently difficult to measure. The data aggregator overcomes this hurdle by identifying similar securities to the newly issued bond and collecting both trader quotes and trades prior to the announcement of a new bond. A third new variable is the number of hours it takes to underwrite a bond. To uncover this metric for each bond, I write a code that scrapes the news headlines in Informa's website for both the announcement and pricing of every bond issuance, and compute the difference in hours.

In my sample, I include non-financial, non-sovereign issuers that I can match to Compustat. To focus purely on the effect of the demand shock through bank underwriting networks, I further exclude firms domiciled in the Euro-zone. I include only the bonds for which the primary variables of interest, oversubscription and new issue concessions, are reported by the data aggregator, which reduces my sample by 24%. The final sample for my baseline analysis consists of 4,629 bonds issued in 2,613 unique transactions by 833 non-European issuers. The median bond in my 2010-2018 sample is a 10-year bond, \$500 million in size, rated BBB+/A-, with a coupon of 3.5%. It is underwritten in one day by 4 banks, is over 3x oversubscribed, and takes over 6 hours to price after announcement. The average bond has 3.4 basis points of underpricing, which for the median \$500 million 10-year bond, represents an additional \$1.7 million in interest cost on an undiscounted basis. See Table 3.2 for summary statistics.

3.3 Empirical Strategy

The purpose of the primary empirical analysis is to understand the causal effect of the ECB's bond buying program on U.S. firms. Thus, while there may be aggregate effects of ECB's QE program on the U.S. capital markets through secondary market trading and fund flows, I focus exclusively on the primary market for corporate bonds, where European investors can only partic-

[25] See Goldstein et al. (2019), Nagler and Ottonello (2019) for a discussion of underpricing in new bonds; Benveniste and Spindt (1989), Booth and Chua (1996), Ellul and Pagano (2006) on securities in general. See Ljungqvist (2007) for a survey on IPO underpricing. Note that in some markets, corporate bonds can be overpriced; see Ding et al. (2020) for a discussion.

ipate via the bank underwriters hired by U.S. corporate issuers. This way, I can identify causality by exploiting the cross-sectional heterogeneity of (1) firms' underwriting relationships in bond issuance markets and of (2) underwriters' investor relationships. I argue that a firm's exposure to the Eurozone through this network of relationships is orthogonal to its demand for capital. Note that I difference out any aggregate effects, so my results likely underestimate the total effect of the ECB's policies on U.S. firms.

I construct the treatment variable as follows. To identify the bank network channel, I need to quantify how exposed each firm is to the Eurozone via its bank underwriting relationships. First, I estimate how exposed each *bank underwriter* is to the Eurozone via its institutional investor relationships. In the ideal data scenario, I would observe all bank-investor relationships, and directly compute each underwriter's exposure to the Euro-zone by the proportion of existing investor relationships. I would compute firm exposure as the weighted average of this measure across all banks hired by the firm.

Unfortunately, I do not observe the identities of European investors in the primary market. To overcome this empirical challenge, I construct a proxy for a bank's exposure to the Eurozone institutional investor base. From interviews with industry participants, I find that selling primary market securities to investors is heavily relationships based.[26] Thus, in order to sell to Eurozone investors in the primary market, underwriters must have an office in the Eurozone that conducts securities underwriting business. Following this notion, I construct a metric for how much of a physical presence each underwriter has in Institutional Securities (IS) business in the Eurozone. Bank-level exposure is measured as follows:

$$Eurexp_u = \frac{euro\_ISrev_{2010}}{total\_ISrev_{2010}} \tag{3.1}$$

I collect the data for both numerator and denominator from 2010 bank company filings. The denominator is the bank's revenues from Institutional Securities: that is, any business associated

[26] See also Nikolova et al. (2020)

with the trading or underwriting of securities.[27] The numerator is the bank's revenues from Institutional Securities made in the Eurozone. I exclude M&A advisory, commercial lending, mortgages, and other lines of business not directly related to building relationships with local institutional investors. I collect this metric for all banks that underwrite bonds at least three times pre- and post-QE from 10-Ks, 20-Fs, annual reports, or investor presentations. The average bank-level metric of exposure to the Eurozone is 18%, with a standard deviation of 27%. Bank-level exposure ranges from 0% to 97%, with a median of 4%.

To get to firm-level *Eurexp*, I compute a weighted average of the firm's bank relationships based on all firm-bank underwriting interactions between 2009-2011.[28] I include only underwriters listed as active lead banks, to ensure that lower-tiered underwriters that do not participate in the bond allocation process, such as passive underwriters and co-managers, are not taken into account. I first compute the average exposure across all underwriters for a given bond to compute a bond-specific Euro-exposure. Then, I compute the average bond exposure across all bonds for a given firm to compute a firm-specific Euro-exposure. It is reasonable to average across all of the underwriters for a given bond because the bond allocation is split evenly across all underwriters. Across non-financial corporate issuers that are not located in the Eurozone, the average euro-exposure at the firm level is 22%, with a standard deviation of 11%. Firm-level exposure ranges from 0% to 79%. The inter-quartile range is 14%.

$$Eurexp_i = \frac{1}{N_{d,i}} \sum_{\forall d \in D_i} \frac{\sum_{\forall u \in U_{d,i}} Eurexp_u}{N_{u,d,i}} \tag{3.2}$$

Note that for the baseline analyses, the treatment variable is time-invariant across firms. Thus, the interpretation of $Eurexp_i$ is the firm-level exposure to the Eurozone via bank underwriting networks, holding the network fixed. This allows me to run analyses unconditional on issuance. In

[27]Only 87% of banks in my sample report revenues segmented into geographies and business lines. In the absence of revenue numbers, I use assets for both the numerator and denominator, excluding assets associated with retail or mortgage lending (9%). In the absence of revenue *and* asset numbers, I use employee headcount (4%).

[28]Results reported are based on a firm's bank network as of 2009-2011 in order to capture the period prior to the start of the Euro-zone crisis. However, benchmark results for bond-level oversubscription and new issue concessions are robust to using underwriting relationships for 2010-2012, 2011-2013, and 2012-2014.

the robustness checks, I rerun the first set of conditional regressions using a time-varying exposure metric that exploits the exact makeup of underwriting syndicates for each bond, which yields similar results to my baseline strategy.

I use the firms' exposure to the Eurozone through their bank underwriting networks as the continuous treatment variable for a series of difference-in-differences regressions. I then run two sets of diff-in-diff analyses: first, I condition on bond issuance and compare issuance outcomes; second, I run unconditional regressions that compare the extensive margin of borrowing across the full universe of firms that issue bonds in my sample. In the first set of analyses, the "control" group consists of firms that issue bonds in the sample period that have low exposure to the Eurozone via their bank underwriting networks, while the "treatment" group consists of bond issuers that have high exposure to the Eurozone via their bank underwriting networks.[29] By conditioning on actual issuance, these regressions focus only on the subset of firms that have demonstrated demand for capital (similar to the logic in Becker and Ivashina (2014)), allowing me to identify effects of the shock to supply of capital. Outcome variables include oversubscription and new issue concessions.

In the second set of analyses, my aim is to identify how firms respond to changes in observed issuance outcomes. To do so, I aggregate the data to the firm-quarter level, and include observations unconditional on issuance. For these analyses, the "control" group consists of firms that are bond issuers at any point in the sample period that have low exposure to the Eurozone via their bank underwriting networks, while the "treatment" group consists of firms that are bond issuers in the sample period that have high exposure to the Eurozone via their bank underwriting networks.

Finally, I identify long-term effects of increased issuance resulting from the bond buying program. To do this, I first identify the set of U.S. firms who issue more as a result of greater exposure to the ECB's CSPP by running a simple predictive model of bond issuance and computing realized residuals. I classify "treated" firm-quarters as firms that issue more than predicted by the firms' past issuance and characteristics, conditional on being more exposed to the CSPP. I run an event study analysis on various balance sheet characteristics and plot the differing patterns in post-issuance

[29] To check that the results are not being driven by firms switching underwriters, I run my baseline analyses excluding any firms that may have switched bank underwriters during the period, and I find similar results. See Appendix C.1.

investment activity for firms issuing as a response to central bank bond-buying demand vs. firms issuing on their own accord.

A key identifying assumption in a difference-in-differences model is parallel pre-trends. To test this assumption, I compare the pre-trends of several key firm characteristics for firms in the highest tercile of exposure to the Eurozone vs. all other bond issuing firms from 2010-2015, and report the findings in Table 3.3. I find no discernible difference in growth rates between the two groups for any of the characteristics. I cannot reject the null hypothesis that the mean growth rates in total debt, revenue, size, and cash holdings of the two groups of firms are the same prior to the ECB's CSPP, suggesting the existence of parallel pre-trends. I also compare the levels of leverage, log revenues, log assets, and log cash. There is no meaningful difference between the two groups in leverage, suggesting the riskiness of firms in the treatment and control groups is comparable. Moreover, while the high exposure group is on average slightly larger and higher rated, it is the difference in growth rates between the two groups that matters for the parallel trends assumption. In my regressions, I control for the levels of these balance sheet characteristics and ratings. I discuss further robustness checks in Section 3.4.

3.4 Results

In this section, I present my results for the effect of the ECB's bond purchasing program on bond issuance outcomes for U.S. firms and discuss robustness checks. Overall, I find that the aggregate demand shock introduced by the ECB's QE program impacts US firms' capital raising decisions and outcomes heterogeneously based on their bank relationships. Conditional on issuing bonds, 'treated' firms receive more orders and have less underpricing per bond. In addition, 'treated' firms issue more bonds.

3.4.1 More treated issuers receive more orders

First, I find that treated firms had larger order books for their bonds following the start of the ECB program. Specifically, I run the following regression:

$$Y_{it} = \beta_{DID} Eurexp_i Post_t + \beta_1 Post_t + X'_{it}\gamma_i + \alpha_i + \alpha_{ind,post} + \alpha_q + \epsilon_{it} \tag{3.3}$$

Note that $Post_t$ is based on day-level variation. I include firm fixed effects (α_i), which absorbs the non-interacted firm-specific $Eurexp_i$, industry by post fixed effects ($\alpha_{ind,post}$), and quarter fixed effects (α_q) to absorb macro credit variation. Table 3.4 show the first results from my main specification. The dependent variable is *Oversubscription*, a metric of the ratio of the order book size and the amount ultimately issued. The median oversubscription ratio is 3.2, while the mean is 3.7 (see Table 3.2). The statistically significant and positive coefficient on β_{DID} indicates that "treated" firms achieve bigger order books after the ECB's CSPP begins. In terms of economic magnitude, an increase from the 25th to 75th percentile of *Eurexp* increases the median orderbook of the median \$500 million bond by \$200 million (increase the mean orderbook of the average \$727 million bond by \$250 million). Another way to interpret this coefficient is the following: the average firm with 22% exposure to the Eurozone would see an increase in its orderbook on the average bond by \$465 million.

I include firm fixed effects, thus controlling for all time-invariant firm characteristics that could impact credit demand.[30] I also include quarter fixed effects to account for business cycle variations in credit supply. To absorb any significant sector-wide changes from the pre-2016 to post-2016 periods, I include industry x post fixed effects in all of my main specifications. To account for variations in investor behavior due to day-to-day changes in how busy the primary bond markets are, I control for the total dollar amount issued in the corporate bond market on day t. To account for unobservable potential complexity of a bond issuance, I control for the number of banks underwriting the deal.

[30] Within my sample period, non-financial, non-Euro-zone corporate issuers issue on average 6 bonds.

In Column (2), I add firm and deal controls. This absorbs key firm characteristics that can vary over time, such as size, revenue, and rating. It also ensures that any firm decisions to change tenor or size of the bond issuance do not bias my results. The addition of these controls increases my point estimate to $\hat{\beta}_{DID} = 2.697$. One potential source of bias in Column (1) is that an increase in the size of the bond mechanically decreases oversubscription. As I will discuss below, I find that treated firms issue more after the ECB shock, so this could have biased my coefficient downward. In specification (3), I add Leverage x Post and Size x Post controls, which absorbs any significant level changes in firm size or leverage.

3.4.2 More treated issuers have less underpricing

In Table 3.5, I estimate the impact of the ECB QE program on the pricing of new securities. By focusing on the new issue concessions, a measure of the difference between primary and secondary market yields, I effectively control for underlying changes in firm-specific expected cash flow realizations or default probabilities. Moreover, because secondary market prices may also improve in response to bond buying, these estimates represent a lower bound for improvements in a firm's cost of capital resulting from the ECB policy.

The primary specification is the same as Table 3.4, as detailed in the previous section. For regressions (2)-(3), the $\hat{\beta}_{DID}$ is negative and statistically significant to the 1% level, indicating that the ECB QE program had a positive impact on "treated" firms. The magnitude of this effect is also economically significant: the estimate of $\hat{\beta}_{DID}$ for regression (3) can be interpreted as follows: for the average exposed firm, concessions drop by 4.6 basis points following the start of CSPP. For the median 10-year bond of \$500 million, that is over \$2 million in additional present value coupon cost.[31]

[31] Note that firms in the treated and controls groups are subject to the same underwriting fees.

3.4.3 More treated firms issue more

Next, I focus on changes in the firm issuance decision as a result of treatment. Consistent with the literature on market timing (see, for example, Bolton et al. (2013), Baker and Wurgler (2002), Jenter et al. (2011)), firms more impacted by the ECB bond buying program should respond to the lower cost of bond capital by issuing more bonds. To test if this is the case, I aggregate the data up to the firm-quarter level so that I can incorporate both the intensive and extensive margin of borrowing from the bond market, and my regressions are no longer conditional on issuance. In this analysis, the “control" group consists of bond issuers with low exposure to the Eurozone via their bank underwriting networks, while the “treatment" group consists of bond issuers with high exposure to the Eurozone.

$$Y_{iq} = \beta_{DID} Eurexp_i Post_q + X'_{iq}\gamma + \alpha_i + \alpha_{ind,q} + \epsilon_{iq} \tag{3.4}$$

The outcome variable for regressions (1)-(2) is the amount issued in billions of USD at the firm-quarter level plus one, logged. In this difference-in-difference specification, “Post" refers to after Q1 2016. For all of the specifications, I find an economically significant uptick in issuance by treated firms after the ECB shock. Column (3) of Table 3.6 includes firm fixed effects to isolate within-firm variation in issuance volume, industry-quarter fixed effects to absorb any industry specific shocks, and controls for firm revenue, size, leverage, and credit rating. I also account for any changes in firm size pre- and post-QE with total assets x post controls. I interpret the estimate $\hat{\beta}_{DID}$ as follows: if a firm moves from the 25th percentile to the 75th percentile of firm exposure, it increases its issuance volume by 4%. Conditional on issuance, the mean quarterly issuance volume per quarter for firms in the sample is \$1.4 billion, so the estimate corresponds to an increase of \$56 million in issuance within quarter.[32] Another way to interpret this estimate is that the average issuer by exposure will increase its issuance volume by 6.5% within quarter in response to the CSPP,

[32]The unconditional mean issuance per firm-quarter for active issuers in the sample period is \$436 million (the median is \$0), so this is an overall unconditional increase per firm-quarter of roughly \$17.5 million

unconditionally.

Regression (3) is a linear probability model that includes all of the fixed effects of regression. The coefficient is positive and statistically significant at the 5% level, suggesting that treated firms have a higher probability of issuing. In regression (4), the dependent variable is the number of bonds issued. I find an economically meaningful and statistically significant positive coefficient on the number of bonds, suggesting that treated firms not only issue more in volume, but they also choose to issue more bonds.

A potential concern with the analysis is that the time period for the diff-in-diff analysis is quite long. In Table C.1, I test if the same effect results when I narrow the sample period. In the first two regressions, I narrow the window to 18 months and one year before and after the start of CSPP, respectively, and find a very similar coefficient estimate as the baseline model (0.286 and 0.231). While the 18 month time window is statistically significant to the 1% level, the 12 month window loses some statistical significance due to a much smaller sample. However, the baseline results are robust to studying a narrower time period.

3.4.4 What are the longer term effects of the program?

The ECB bond buying program lasted through December 2018. How did firms respond to this temporary decrease in their cost of accessing bond capital? Theory predicts that firms would respond to favorable external capital conditions by issuing more securities (Bolton et al. (2013)) and paying out to shareholders. In this section, I follow Darmouni and Siani (2020) and relate firm balance sheet characteristics up to two years following issuance during the bond buying program to explore how firms that issued more in response to the ECB policy used the proceeds relative to a control group of firms that either issued bonds pre-ECB policy or were not affected by the ECB. I find suggestive evidence that firms used the proceeds to pay down equity holders rather than increasing real investments.

Concretely, I first identify all firms that issued more than they normally would as a result of the ECB policy, and call these firms “treated". I then compare the balance sheet adjustments prior to and following bond issuance for treated and controls firms. To be defined as firms that issued more than they normally would have, I look at firms whose issuance from June 2016 - December 2018 is statistically greater than issuance June 2013 - December 2015, controlling for industry trends and firm characteristics. I run a predictive model where issuance during CSPP is a function of firm issuance in 2013-2015 and a vector of 2015 characteristics including firm credit rating, size, return on assets, and leverage: $Y_{i,16Q2-18Q4} = f(Y_{i,2013-2015}, X_{i,2015})$. I collect the residuals from the following regression.

$$Y_{i,16Q2-18Q4} = \sum_{m=2013}^{2015} \beta_m Y_{im} + X'_{i,2015}\gamma + \epsilon_i \tag{3.5}$$

Treated firm-quarters are the intersection of firms that (1) have realized residuals $\hat{\epsilon}_i$ above the median in the cross section, (2) are issuing during the bond buying program, and (3) have exposure to the Eurozone through their bank underwriting network in the top tercile of firms. The control group includes any firm-quarters that are either in the bottom tercile of the Euro exposure metric, have $\hat{\epsilon}_i$ realizations below the median, or issued prior to the ECB's bond buying program. Note that this definition divides firm-quarters into control and treatment groups, allowing the same firm to be included in both groups. I then run the following event study regression separately for treatment and control groups:

$$Y_{iq} = \sum_{m\in[-4,8]} \beta_m B_{i,q+m} + X'_{iq}\gamma + \alpha_i + \alpha_{ind,q} + \epsilon_{iq} \tag{3.6}$$

The outcome variable, Y_{iq}, is the relevant quarterly balance sheet variable for firm i. $\alpha_{ind,q}$ are industry-quarter fixed effects to absorb time-varying industry shocks, α_i is a firm fixed effect to absorb between-firm time-invariant variation, $B_{i,q}$ is amount issued in quarter q by firm i (2015Q4 is the omitted time period), and I include controls for issuer credit rating and return on assets to account for time-varying within-firm heterogeneity. Standard errors are clustered at the firm level to account for potential serial correlation across time.

Figure 3.7 plots the estimate β_t for each quarter, with the 95% confidence interval bars marked around each point estimate. First, I find that firms that issued more as a result of the bond buying program continue to have higher leverage up to two years following issuance, similar to bond issuance in the control group. Secondly, whereas control firms pay down debt coming due in the coming year with new bond proceeds, treated issuers did not have a significant decrease in current debt, suggesting that the ECB-encouraged bond issuance was not used to pay down debt coming due. Moreover, using non-cash assets as a proxy for operating assets, I find that treated firms invest less in real operations than control group issuance. Finally, treated firms had a greater increase in net equity payouts than the control group in the quarters following bond issuance. This result suggests that demand spillovers via bond underwriting networks are unlikely to have real effects.[33]

3.4.5 Pre-trends analysis

It is possible that results are driven by pre-existing trends. For example, perhaps treated firms had already begun to issue more prior to the ECB's program, and the effect is unrelated to spillovers. To ensure that the findings are not driven by pre-existing trends, I run the Granger (1969) causality test:

$$Y_{iy} = \alpha_{ind,y} + \alpha_i + \sum_{\tau=0}^{6} \beta_{-\tau} Eurexp_i \times D_{y-\tau} + \sum_{\tau=1}^{3} \beta_{+\tau} Eurexp_i \times D_{y+\tau} + X'_{iy}\gamma + \epsilon_{iy} \quad (3.7)$$

The outcome variable, Y_{iq}, is the amount issued by firm i in year y. $\alpha_{ind,y}$ are industry-quarter fixed effects to absorb time-varying industry shocks, α_i is a firm fixed effect to absorb between-firm time-invariant variation, $Treat_i$ is an indicator variable equal to one if the firm is in the top tercile of exposure to the Euro-zone and zero if the firm is in the bottom tercile, D_t is an indicator for each quarter (2015Q4 is the omitted time period), $Treat_i \times D_t$ is the interaction term between quarter dummies and the firm's exposure status, and X_{it} are firm-level control variables including return on assets (net income divided by total assets) and size (log of total assets) to account for within-firm time-varying heterogeneity. Standard errors are clustered at the firm level to account

[33]This is consistent with findings of Sharpe and Suarez (2020), who survey CFOs and find that investment is relatively insensitive to changes in interest rates.

for potential serial correlation across time.

Figure 3.5 plots the estimates of coefficients on the difference-in-differences term, β_t for each quarter, with the 95% confidence intervals bars. This parameter captures the difference in the respective outcome variable between firms that are most exposed to the ECB's policy and firms that have little exposure. Estimating coefficients on amount issued is challenging given the lumpiness of issuance data, but it is a reasonable first pass to understand potential pre-trends. Prior to the start of CSPP (the first dashed line), coefficients are not significantly different from zero, helping to rule out pre-trends. After the start of the ECB's program, treated firms have a higher yearly issuance volume than control firms, with a steadying increasing effect that continues into 2019, after the end of the bond buying program.

3.4.6 Robustness check: Ruling out changes in firm demand for capital

Did treated firms have an increase in demand for capital that is unobserved to the econometrician? To see if this is driving the result, I compare the same firm's bond issuance from one set of banks relative to another set of banks in the same broader time period. By using a within-firm-time comparison, I aim to absorb firm-specific changes in demand for bond credit over time.[34] Thus, the difference in bond issuance outcomes can be directly attributed to shocks from the bank underwriting network.

Concretely, I compute firm-level $Eurexp_{it}$ for each firm again. In this iteration, I allow the exposure metric to vary across bonds within firm. The logic is the following: while firms typically have a set group of banks from which they choose each bond issuance's underwriters, each individual bond issuance may have a slightly different set of banks. Thus, a firm's exposure to the Eurozone will change from one bond to the next based on the set of underwriters they choose. I use this time-varying exposure metric as the continuous treatment variable for my Diff-in-diff. I then absorb firm-year fixed effects. The identifying assumption is that a firm's demand for capital does not change significantly within one year. Thus, any changes in outcomes of bond issuance

[34] This is akin to the approach in Chakraborty et al. (2020). Thanks to

will stem entirely from the ECB's QE program heterogeneously impacting firms via different underwriters.

I estimate the following model for firm i issuing a bond on day t:

$$Y_{it} = \beta_{DID} Eurexp_{it} Post_t + \beta_1 Post_t + \beta_2 Eurexp_i + X'_{it}\gamma + \alpha_{i,year} + \alpha_{ind} + \epsilon_{it} \tag{3.8}$$

Results are in Table 3.7. I find very similar results to my benchmark specification. That is, there is a statistically significant (at the 5% level) reduction in underpricing of bonds for firms when they are more exposed to the Eurozone via their underwriter, confirming the supposition that the results are firms responding to a shift in supply of capital, rather than an increase in demand for capital.

3.4.7 Robustness check: Effects of concurrent government QE programs

The CSPP coincided with many other programs in the Eurozone. Notably, in March 2015, the ECB began net purchases of large amounts of bonds issued by governments, agencies, and multilateral organizations under the Public Sector Purchase Programme (PSPP). The first phase of the program began March 9, 2015 and ended December 19, 2018. Because the PSPP overlapped with the CSPP, it is possible that some of the impact on U.S. firms results from the government bond purchase program and not exclusively from the corporate bond purchase program. That is, as the ECB purchased government bonds, Euro-zone investors could also rebalance portfolios towards purchasing U.S. corporate bonds.

I can test this directly in the data by splitting my data and analyzing exclusively the period prior to the start of CSPP. Specifically, I run my baseline regression on a restricted sample period of Q1 2014 - Q1 2016, and change the "Post" dummy to March 9, 2015. I thus focus on the heterogeneous impact of the government bond purchases on U.S. firms in the two-year window surrounding the start of PSPP. The results for changes in underpricing and oversubscription are in Table 3.8, and the results for amount issued by quarter are in Table 3.9. I include the same controls and fixed effects as the main regressions to absorb potential confounders. I find that there is no significant difference in outcomes between firms with greater exposure to the Eurozone after the start of ECB government QE and firms with less exposure to the Eurozone. While coefficients for amount issued in Table 3.9 are positive, they are much smaller in magnitude and not statistically significant from zero. Thus, my results support the notion that the ECB's government bond purchases had a negligible effect on U.S. firms via the bank underwriting channel. Instead, heterogeneous impacts across U.S. firms from the ECB's policies can be attributed primarily to spillover effects of the CSPP.

Another potential confounder arises from U.S. monetary policy. The Federal Reserve purchased large amounts of government bonds and mortgage-backed securities from September 2012 to October 2014 in the third wave of its quantitative easing program (QE3). These purchases likely had an impact on corporate bond markets in the U.S., and my baseline results may be picking up part of this effect. To test if this is the case, I restrict my sample to begin first quarter of 2015, after the end of the Federal Reserve's QE3 program. I find very similar results (see last column of Table C.1), suggesting that my results are driven by the CSPP , and not the Fed's bond buying program.

3.4.8 Robustness check: excluded industries

As a further test of ECB spillovers, I check if U.S. industries excluded from the CSPP were impacted. Since the CSPP included only non-financial corporate issuers, I check if my baseline result holds for U.S. financial issuers. Investors substituting away from securities issued by Euro-area firms to those issued by U.S. firms are purchasers of non-financial corporate bonds, thus I should find that my baseline results do not hold for U.S. financial firms. To test this, I estimate my benchmark difference-in-differences model on the subset of non-Eurozone financial firms issuing in U.S. dollars.[35] My results are in Table 3.10. I find there is no significant increase in oversubscription or prices for financial issuers that are more exposed to the Eurozone area via their bank underwriting relationships. I interpret these results as further evidence that the ECB's bond buying program spilled over to the U.S. non-financial sector.

[35]For this exercise, I define a financial firm as one with a NAICS2 category of 52

3.4.9 Robustness check: endogenous bank-firm relationships

A potential threat to identification is that the bank-firm relationship is endogenous. Firms do not select banks randomly. In the syndicated loan market, Chen and Song (2013) have found that firms and banks match by size, and Schwert (2018) find that bank-dependent firms match with well-capitalized lead arrangers.[36] Banks that are more exposed to the Euro-area market may match with firms that are also more exposed to the Euro-area. This would invalidate my identification strategy, because the ECB's QE program could then impact firms with Euro-area operations through a demand-side channel. For example, a U.S. firm with retail branches in the Euro-area may experience an increase in demand for its products sold in Europe following the QE program, and thus raise more debt.

To shut down this channel of firm-bank endogenous choice, I run two tests. First, I check how much the stock market returns of each firm i in my sample are correlated with the Euro-area stock market returns. The logic is the following: if firms are more exposed to the Euro-zone outside of their bank networks, then their stock returns should be more strongly correlated with Euro-market stock returns. Because the Euro-area stock markets is strongly correlated with the U.S. stock market index, I first run a regression of Euro-area stock market returns on the S&P index returns: $r_t^e = \beta r_t^\$ + \epsilon_t$, and recover the residuals $\hat{\epsilon}_t$. I then find the correlation between the stock return of each of the firms in my sample with the stock market residuals over the period 2010-2016 (i.e., before the start of the CSPP): $corr_{i,t} = corr(\hat{\epsilon}_t, r_{i,t})$, and plot these against *Eurexp* in Figure 3.8. Firms with higher *Eurexp* do not appear to have stock returns more correlated with Euro-zone stock market returns. Thus, it is unlikely that firms with higher *Eurexp* are systematically operating more in the Euro-zone in a way that would invalidate my identification strategy.

The second check of firm-bank endogenous choice uses financial reports to explore whether banks with more exposure to European investors also work with firms that are more exposed to the Euro-area economies. To quantify how exposed each firm is to the Euro-zone, I scrape the text of the 2010 10-K (or 20-F) for each firm and count (1) the number of times the word "Euro"

[36]See Schwert (2018) for a recent survey of ways firms and banks match in the bank lending market

or “Europe" occurs; and (2) the number of times each country in the Euro-zone is mentioned, weighted by the GDP of the respective country to account for the relative importance of each country. I weight both metrics by the number of total words in each filing to avoid arbitrarily over-weighting longer documents. I plot these metrics along an x-axis of 50 bins of *Eurexp* in Figure 3.9. I find no systematic correlation between a firm having operations in Europe according to its company filings and the *Eurexp* I measure via its bank, suggesting a firm's operational exposure to Europe is not correlated with the firm's underwriting network exposure to Europe.

Next, I use the metrics constructed above to ensure that the firm's operational exposure to the Euro-zone does not drive my results. Firms that are exposed to Europe through their bank relationships may simply be exposed to Europe via their operations. To address this issue, I employ the core diff-in-diff specification using the two alternative, operations-based measures of firm-level exposure to the Euro-zone described above. The estimated coefficients, reported in Table 3.11, are not statistically different from 0. This suggests that the spillovers from the CSPP were channeled through the bank underwriting network, and not through firm operations.

3.5 Discussion

3.5.1 Economic Magnitudes

The paper's empirical strategy identifies heterogeneous spillover effects of the ECB's CSPP across U.S. firms through the bond underwriting channel. What is the magnitude of this global demand spillover? Here, I compute back of the envelope magnitudes for the ECB's bond purchases. The baseline results indicate an increase in the USD issuance per quarter of 6.5% for the average exposed firm. Applying this to the average quarterly issuance volume by firms in my sample of \$90 billion, this suggests an increase of \$5 billion in quarterly issuance volume. This is a significant response to ECB bond purchases, which averaged a net \$17.2 billion per quarter.

How are different kinds of firms impacted? In principle, frequent issuers or firms that otherwise have stronger brand name recognition may benefit less from their bank's relationships, because they may have their own relationships with investors. To check if this is the case, I run the quarterly issuance regression in equation 3.4 on the following subsets of firms: frequent and infrequent issuers, and highly rated (A and above) and lower rated (BBB and below) firms. I define frequent issuers as the top 25% of issuers by number of bonds in the sample period (specifically, firms that issued more than 13 bonds). See Table 3.12 for the results. I find that the positive shock to supply of capital stemming though bank underwriting networks impacts infrequent issuers and riskier firms more than frequent issuers and safer firms. In magnitudes, riskier firms with an average level of exposure increased issuance by 10.7% per quarter following the start of CSPP (statistically significant to 1% level). In comparison, higher rated firms increased issuance by 5.4% (statistically significant to the 10% level). This suggests that firms that are more financially constrained (i.e., lower rated) may be more susceptible to demand shocks from investors, and thus benefit more from the spillover effects. Data limitations prevent further exploration into riskier, high yield firms, but additional research on spillover effects for financially constrained firms would be fruitful.

The magnitudes discussed should be considered a lower bound for the aggregate spillover effects of central bank corporate bond purchases. There are many other avenues through which the U.S. real economy may be impacted by the ECB QE program in aggregate. I discuss potential alternative stories in the next subsection.

3.5.2 Alternative stories

First, non-European investors may be exposed to the ECB bond purchases through their holdings of Euro corporate bonds, leading them to substitute towards comparable U.S. bonds (see Koijen et al. (2020)). This channel would impact both secondary and primary market bonds. A firm's exposure to the ECB through its bank underwriting network is unlikely to be correlated with the makeup of its U.S. investors' portfolios. The difference-in-difference specification nets out any common shock to U.S. investor portfolios that is not correlated with underwriting networks. Thus, the heterogeneous effect measured in the cross-section of U.S. firms in this paper can be considered a lower bound that would be additive to other potential impacts of the ECB's bond purchase program on U.S. firms.

Second, certain global firms that operate in both the U.S. and Europe may experience real benefits from the ECB's stimulative response to the Eurozone crisis, for example from improved access to trade credit (see Adelino et al. (2020)). Again, my results can be considered as a lower bound for the overall spillover effect. My finding that firms exposed to the ECB's bond purchase program through bond underwriting networks did not have long-term increases in real investment further supports the idea that the underwriting network channel is orthogonal to any cross sectional heterogeneity in real effects.

Finally, U.S. firms in my sample could also be directly impacted by CSPP by issuing bonds more cheaply directly in the Eurozone. While U.S. issuers would be ineligible to benefit directly from ECB purchases due to the European local eligibility requirement, many papers document the spillover effects within the Eurozone of the CSPP to ineligible borrowers (Zaghini (2019), Abidi and Miquel-Flores (2018), Arce et al. (2018)). For U.S. firms that issue both USD and Euro-denominated bonds, they may increase leverage through issuing directly into the Euro market, taking advantage of lower yields as Euro-zone investors rebalance their portfolios towards ineligible Euro-denominated bonds. If firms did indeed substitute away from USD borrowing into Euro borrowing,[37] I would expect to see an increase in the Euro-denominated bond issuance volume by U.S. firms. To check if this is the case, I consider the 119 U.S. firms in my sample that issue both Euro-denominated and USD-denominated bonds (including companies like 3M, Coca Cola, McDonald's, WalMart). I find that the proportion of bond issuance that these firms issued in Euros vs. USD is 18% in 2014, stays at 20% in 2015 and 2016, and drops to 17% in 2017. Thus, the direct effects of ECB corporate bond purchasing on the Euro-denominated issuance of U.S. firms does not appear to be economically significant.

[37] See Maggiori et al. (2020) for a discussion of large firms borrowing from foreigners

3.5.3 Mechanism

In this subsection, I explore potential mechanisms that drive the results. What is preventing every bank underwriter from selling to institutional investors in Europe in order to take advantage of these positive demand shocks? One potential mechanism is that primary markets are partially geographically segmented. That is, consistent with the well-established home bias of investors, banks with more European investor clients also have more European issuer clients. To test this hypothesis empirically, I plot a binscatter of bank-level exposure $Eurexp_u$ (on the x-axis) vs. the number of bonds underwritten for Eurozone corporate clients (on the y-axis). I absorb year fixed effects to control for macro trends and I control for the number of bonds underwritten by that bank-year to deal with potential bias from underwriter size. In Figure 3.10, I find that there is a close link between $Eurexp_u$ and the presence of underwriter u in the Eurozone corporate bond market. This suggests that underwriters that have strong institutional investor relationships in the Eurozone also have a larger proportion of their corporate issuer relationships in the Eurozone.

Another related mechanism is the following: banks may have a set of long-term investor relationships, and could face search costs to find incremental investors, a common cost associated with dealers in the secondary market (see, for example, Duffie et al. (2005)). If this is the case, I would expect (1) when a bank's existing institutional investor base puts in more orders for bonds, search costs are lower; and (2) when banks have more bonds to issue than usual, they incur greater costs to sell those bonds than on days with fewer bonds to underwrite.

To test this empirically, I use novel data on the time it takes to sell a bond, from announcement to pricing, as a proxy for search costs. To test hypothesis (1), I check if the cost of banks placing bonds for a given firm goes down with the ECB shock by running the following regression:

$$time_{uit} = \beta_{DID} Eurexp_u \times Post_t + \beta_1 \times Post_t + X'_{it}\gamma_1 + \alpha_{u,q} + \alpha_i + \epsilon_{uit} \tag{3.9}$$

See Table 3.13 for the results. I include bank-quarter fixed effects which control for time-varying bank characteristics and firm fixed effects to absorb cross-sectional variation in investor preferences across firms. This is economically significant, since the median time to issue a bond is 6.7 hours. Column (3) further controls for the total number of bonds that were issued on day t. The estimated coefficient in Column (3) indicates that moving from the 25th to the 75th percentile of bank exposure decreases the time it takes to price the bond by over 1 hour.

Next, I test hypothesis (2): when banks have more bonds to underwrite than usual, they incur greater costs to sell those bonds, controlling for bond characteristics.

$$time_{uit} = \beta_1 \text{Amt underwritten by bank}_{ut} + X'_{it}\gamma_1 + \alpha_{u,q} + \alpha_i + \epsilon_{uit} \tag{3.10}$$

Indeed, I find evidence (in Table C.2) consistent with this hypothesis. Because I include bank-quarter fixed effects, I am holding fixed the size of the bank's investor base. If there are more sellers than buyers on a given day, banks will take *more* time to place the bond. The magnitude is not large: it takes an extra 8 minutes for every 10% increase in the bank's underwritten issuance on a given day; however, the coefficient is statistically significant, suggesting that there is an increase in cost to the bank's placement of bonds in the primary market when there are more sellers than usual. I interpret this finding to mean that the relative mass of buyers and sellers for any given bank is reasonably persistent.

I interpret these results to support the hypothesis that banks incur search costs to find incremental investors beyond their typical investor base. This is consistent with a story in which banks prefer to maintain the same investor base. For the bond underwriting market as a whole, this suggests that local demand shocks can propagate through the bank-investor network to impact the issuing decisions of firms in other geographies.

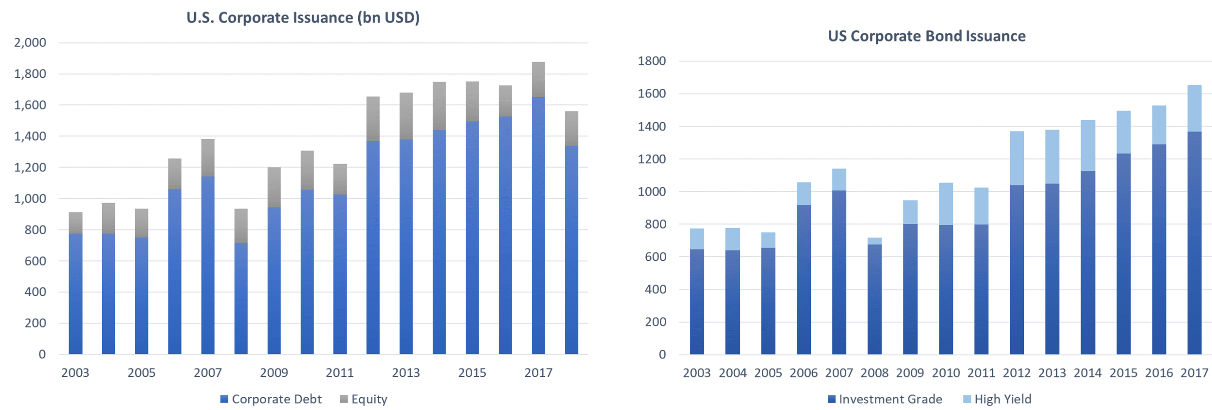
3.6 Concluding Remarks

In this paper, I have identified how monetary policy-driven demand shocks propagated from the Eurozone to the U.S. corporate issuer market through the pre-existing network of firms, underwriters and investors. Using data that is novel to the literature on bond underwriting, I find that firms are differentially impacted by European demand shocks due to their bank relationships. Firms that are more “treated" have larger order books and achieve lower underpricing. Moreover, the average treated firm increased average quarterly issuance volume by 6.5% relative to unexposed firms. Riskier firms and firms that issue less frequently end up increasing quarterly issuance by more than safer and more frequent issuers. There is evidence suggesting that treated firms pay out equity holders more than control firms in the quarters following the bond-buying program initiation, while there is a smaller increase in real asset acquisition relative to normal bond issuance. I implement a number of robustness checks to ensure that the results do not arise from a demand-side channel or endogenous firm-bank selection.

The results raise important implications for unconventional monetary policy. Large, prolonged central bank purchases of corporate bonds can have spillover effects to other economies. As the U.S. and the Eurozone add corporate bond purchases to their unconventional monetary policy toolkit, unintended effects on other economies should be taken into consideration. In particular, the channel of portfolio rebalancing occurring through bank underwriting networks is important for primary markets, where firms raise bond capital. The ECB’s bond purchase program caused a capital raising effect but no increase in real investment in U.S. firms. The magnitude of my results should be considered a lower bound for the overall spillover effects of these bond purchasing policies.

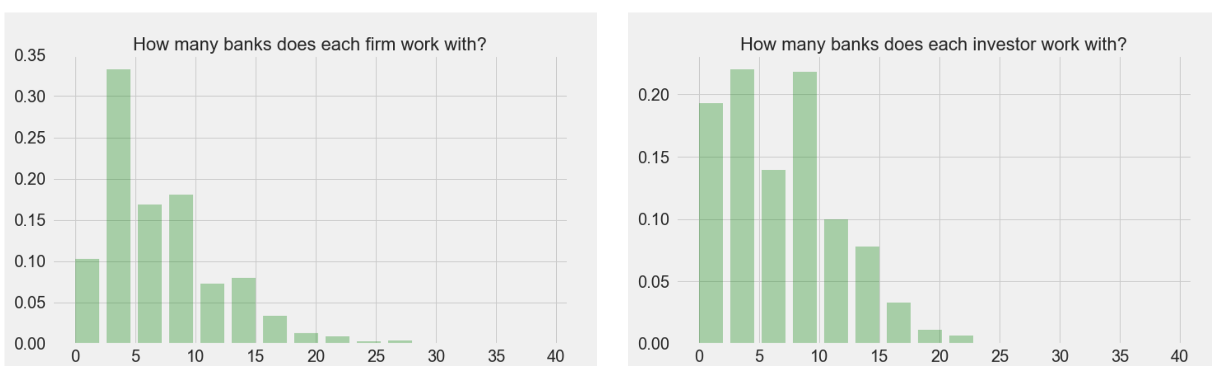
3.7 Figures and Tables

Figure 3.1: Total Corporate Issuance



Source: SIFMA 2018

Figure 3.2: Exclusivity of underwriting relationships



(a) Firm-bank underwriting relationships

(b) Investor-bank underwriting relationships

Source: National Association of Insurance Commissioners

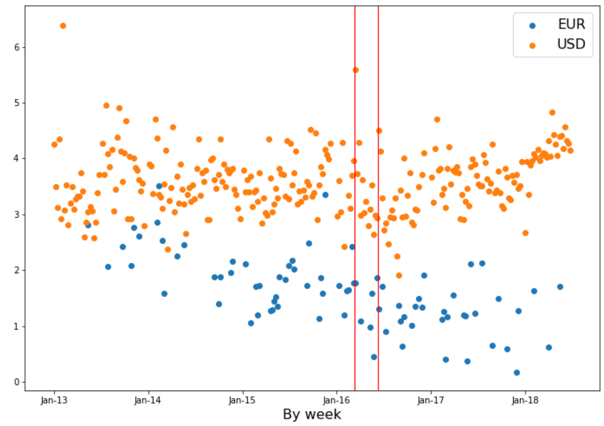


Figure 3.3: Offering yield on newly issued bonds

Notes: I compute the weekly averages of yields on newly issued bonds rated at least BB+ in Euros vs. in US Dollars. Vertical lines indicate the announcement (March 2016) and start (June 2016) of the ECB CSPP.
Source: Mergent FISD, IGM

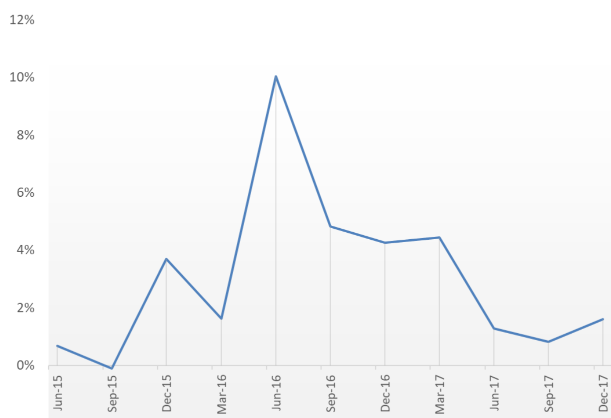


Figure 3.4: Growth in U.S. non-financial corporate debt securities held by Euro-area residents

Source: ECB Securities Holdings Statistics (SHS)

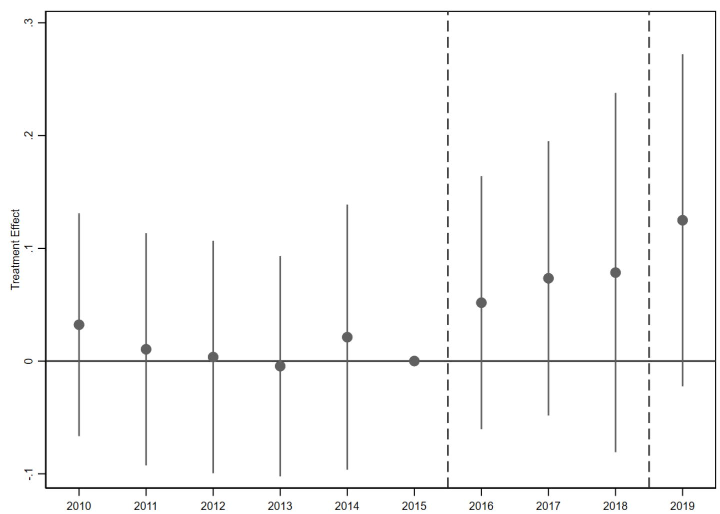
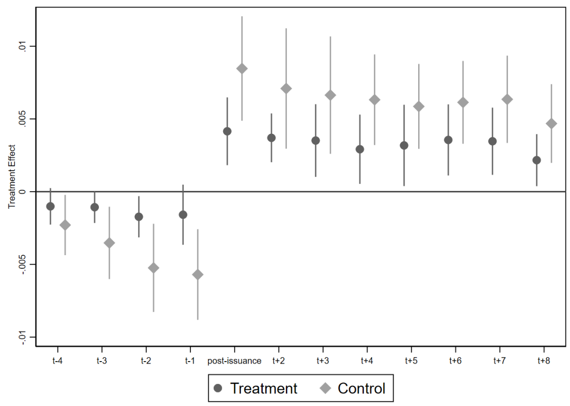
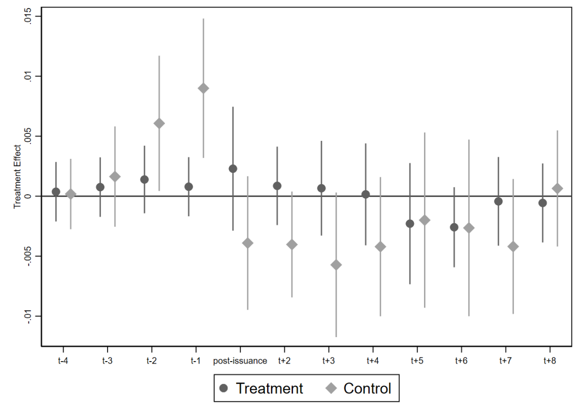


Figure 3.5: Yearly coefficient plot for amount issued

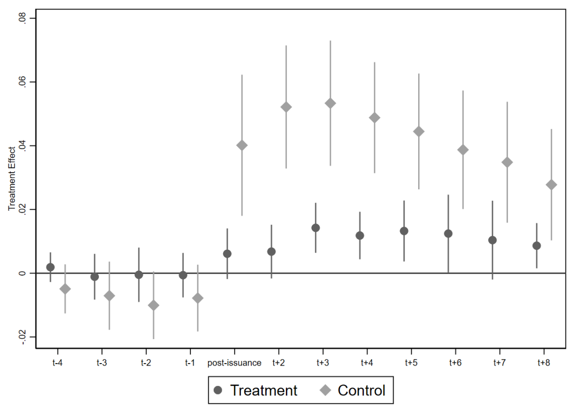
Notes: Excludes financial and Eurozone issuers, includes only firms reporting in US dollars. Vertical bands represent ± 1.96 times the standard error of each point estimate, as per Autor (2003). Here, 2015 is omitted due to collinearity. Firm controls include issuer credit rating, log(total assets) and return on assets (net income divided by total assets). Includes firm and industry year fixed effects. Standard errors clustered by firm. Vertical dashed lines signify the rough start and end dates of the ECB's bond buying program.



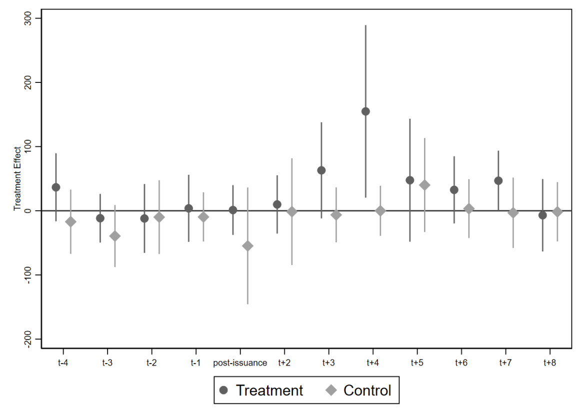
(a) Leverage ratio



(b) Current debt ratio



(c) Operating assets



(d) Net equity payout

Figure 3.7: Coefficient plots on exposed vs. unexposed firms

Notes. Plots point estimates of coefficients corresponding to amount issued in each quarter. Observations include firm-quarters in which bond issuance occurred in the next 4 quarters or the prior 8 quarters. Vertical bands represent ± 1.96 times the standard error of each point estimate. “Treatment" includes firms that that (1) have realized residuals $\hat{\epsilon}_i$ above the median in the cross section, (2) are issuing during the bond buying program, and (3) have exposure to the Eurozone through their bank underwriting network in the top tercile of firms for the Euro exposure metric. “Control" are firm-quarters that are either in the bottom tercile of the Euro exposure metric, have $\hat{\epsilon}_i$ realizations below the median, or issued prior to the ECB’s bond buying program. Outcome variables are (1) leverage ratio, as measured by total long term debt divided by total assets, (2) current debt ratio, as measured by debt due in one year divided by total long term debt outstanding, (3) log of non-cash assets (*at-che*), and (4) net equity payout (equity purchases minus equity issuance plus dividends). I include firm fixed effects, industry-quarter fixed effects, and control for firm quarterly profitability (ni/at) and credit rating.

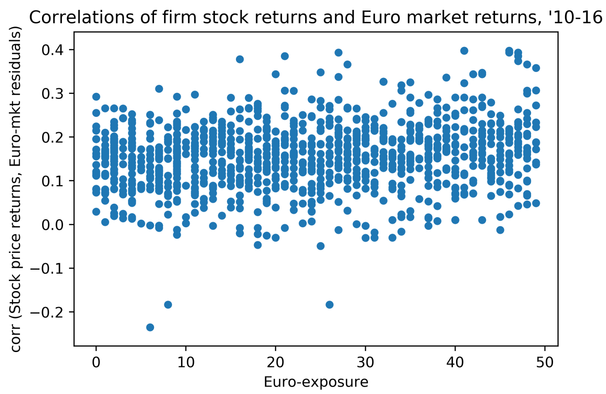


Figure 3.8: Correlations of firm stock returns and Euro market returns, 2010-2016

Notes. Y-axis is $corr_{i,t} = corr(\hat{\epsilon}_t, r_{i,t})$, where $\hat{\epsilon}_t$ is the residual from a regression of Euro stock market returns on US stock market returns: $r_t^e = \beta r_t^{\$} + \epsilon_t$. X-axis is the $Eurexp_u$ as defined in the text.

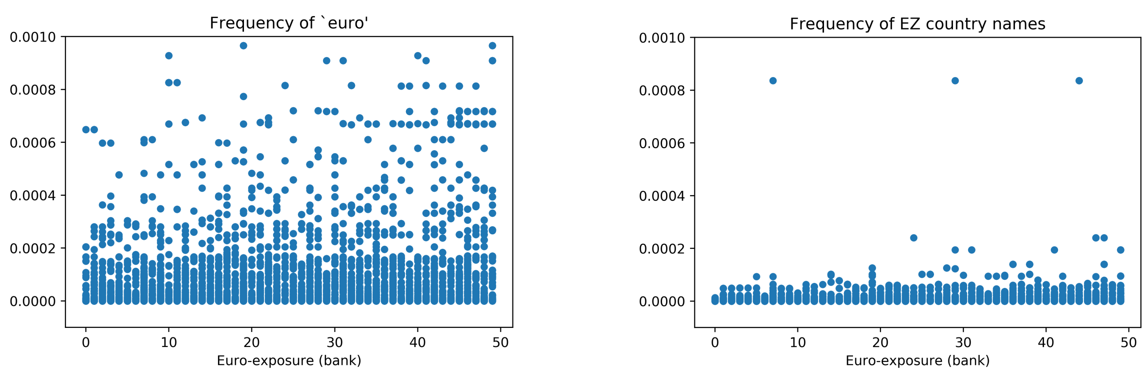


Figure 3.9: Frequency of Euro-zone words in SEC filing texts, 2010

Notes. Y-axis is (1) the number of times the word “Euro", “euro", or “Europe" occurs in each text, weighted by length of text; and (2) the number of times each country in the Euro-zone is mentioned in each text, weighted by the GDP of the respective country to account for the relative importance of each country to the firm’s overall exposure to the Euro-zone, weighted by length of text. X-axis is the $Eurexp_u$ as defined in the text.

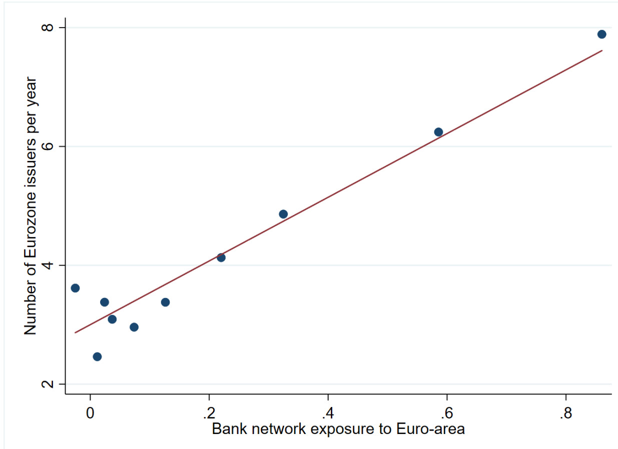


Figure 3.10: Correlations of $Eurexp_u$ and frequency of underwriting for Eurozone firms

Notes. Bin scatter for banks' $Eurexp_u$ metric vs. the frequency of underwriting for Eurozone corporate bonds issuances in the sample period September 2010-June 2018. I absorb year fixed effects and control for the number of total deals the bank underwrites in a given year.

Table 3.1: Bank relationships, pre- and post-CSPP

	Pre-CSPP	**Post-CSPP**	**p-value**
Firm-bank selection			
Average % of banks with existing firm relationships	86.9%	86.7%	0.781
% of deals with all new relationships	1.3%	1.4%	0.797
Bank-investor selection			
Average % of sale volume to existing relationships	90.3%	90.7%	0.687
Average % of investors with existing bank relationships	84.3%	85.4%	0.326
% of deals with all new relationships	3.6%	3.5%	0.899

Notes. I compare the two years prior to the start of ECB's CSPP to the two years after the program: "Pre-CSPP" is January 1, 2014 - December 31, 2015, while "Post-CSPP" is June 8, 2016 - June 8, 2018. To compute the *Average % of banks with existing firm relationships*, I count for each bond issuance the number of banks that each issuer chooses for which there is a pre-existing relationship, conditional on the firm having issued at least 3 times since 2000. The *% of deals with all new relationships* is the percent of bond issuances in the sample period that have zero pre-existing bank-firm relationships. *Average % of sale volume to existing relationships* is the proportion of identified primary market sales sold to existing relationships, averaged across each bond. To compute *Average % of investors with existing bank relationship*, I count for each day the number of investors that each bank chooses for which there is a pre-existing relationship, conditional on the bank having underwritten at least 3 times since 2000. The *% of deals with all new relationships* is the percent of bond issuances in the sample period that have zero pre-existing bank-investor relationships. P-values are computed using a two-sided t-test on the null hypothesis that the means for pre- and post-CSPP are the same. Because p-values are well greater than 10%, I cannot reject the null hypothesis that the means of bank-firm and bank-investor relationship persistence are the same before and during CSPP.

Table 3.2: Sample Summary Statistics

	Mean	Std Dev	10%	50%	90%
Bond characteristics					
Amount per bond (MM)	726.9	628.9	300.0	500.0	1,250.0
Credit spread (bps)	132.9	74.4	57.0	117.5	227.5
Tenor (years)	12.3	10.2	3.0	10.0	30.0
Coupon	3.485%	1.169%	1.900%	3.500%	4.900%
New Issue Concession	3.4	13.2	-9.0	2.5	16.0
Oversubscription	3.7	2.0	1.8	3.2	6.2
Credit Rating	15.7	2.1	13.0	15.5	18.5
Time (hours)	7.1	3.5	5.2	6.7	8.6
Issuer characteristics					
Amount raised per year (MM)	3,265.9	5,008.1	400.0	1,500.0	7,650.0
Number of issues per firm	6.4	4.3	2.0	6.0	13.0
Number of bonds per firm	14.4	12.8	3.0	11.0	33.0
Number of bonds per issuance	2.6	1.8	1.0	2.0	5.0
Number underwriters per bond	4.2	2.3	2.0	4.0	7.0
Firm Leverage (LT debt / Assets)	31%	14%	15%	29%	49%
Cash to Assets	10%	13%	0%	5%	23%

Source: Informa Global Markets, Compustat. See Table C.3 for ratings information

Table 3.3: Parallel pre-trends: Treated vs. Control firms

	z				
	Exp_high=:Mean	Exp_high=:SD	Exp_high=:Mean	Exp_high=:SD	.:StandardDiff
Growth(Debt)	.022783	.17795	.0201434	.3037339	.010604
Growth(Revenue)	.005914	.2376398	-.0002481	.1946043	.0283722
Growth(Assets)	.0156701	.1003874	.0118045	.070981	.0444638
Growth(Cash)	-.0041961	.7293638	.0015124	.7130185	-.0079148
Leverage	.2534093	.1606761	.264257	.1422444	-.0714885
Revenues	7.728998	1.877097	8.252946	2.060455	-.2658406
Size	10.28285	2.108609	10.89028	2.29947	-.2753395
Cash	7.07548	2.870106	7.508742	3.225616	-.1419117
Ratings	15.7411	2.04385	16.0108	2.064953	-.131275

Notes: I compare growth in various firm characteristics of the bottom and top quartile of firms sorted by *Eurexp*. Growth in characteristic X_t is measured as $log(X_t) - log(X_{t-1})$. The mean and standard deviations are computed on firm-quarter data from 2010. Firms that issue bonds at any point in the sample are included, and firm-quarters are included unconditional on issuance in that quarter. The standardized difference is computed: $diff = \frac{\mu_1 - \mu_2}{\sqrt{\frac{\sigma_1^2 + \sigma_2^2}{2}}}$, and has the interpretation of the difference in means of the two groups in units of standard deviation, as per Austin (2009). A standardized difference of less than 10% is considered indicative that there is lack of meaningful correlation between the group definition and covariate, though there is not a consensus on the appropriate threshold (see Austin et al. (2007) for a discussion) By definition, this test statistic is not impacted by sample size. *Source*: Compustat

Table 3.4: Increase in interest for treated firms' bonds

	(1) Oversubscription	(2) Oversubscription	(3) Oversubscription
Eurexp_i x Post_t	2.456**	2.697**	2.908**
	(1.194)	(1.221)	(1.239)
Size of bond (USD mm)		-0.193***	-0.196***
		(0.0561)	(0.0570)
Tenor of bond (years)		0.0346	0.0317
		(0.0308)	(0.0309)
Rating of bond		-0.537***	-0.493**
		(0.193)	(0.201)
Revenue that quarter		0.533	1.001
		(0.415)	(0.678)
Number of lead underwriters		-0.0875	-0.0806
		(0.0828)	(0.0817)
Other bonds issued same day		-0.0189	-0.0205
		(0.0482)	(0.0478)
Post_t×Size			-1.131
			(1.041)
Post_t×Lev			-0.121
			(0.198)
Constant	3.554***	3.770***	3.661***
	(0.0777)	(0.271)	(0.289)
Firm FE	✓	✓	✓
Ind x Post FE	✓	✓	✓
Quarter FE	✓	✓	✓
Observations	3037	3037	3037
R-squared	0.404	0.412	0.415

Notes: Includes non-Eurozone USD non-financial corporate issuance, September 2010-June 2018. Post is after June 8, 2016. Estimation is via OLS. Controls are normalized to variance 1 and include issuer credit rating, tenor, amount issued, firm revenue, the dollar amount issued on day t other than firm i, and the number of underwriting banks. Size refers to total assets, leverage refers to the ratio of total long-term debt to total assets. Standard errors, in parentheses, are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 3.5: Decrease in underpricing for treated firms' bonds

	(1) Underpricing (bps)	(2) Underpricing (bps)	(3) Underpricing (bps)
Eurexp_i x Post_t	-20.62**	-21.88***	-20.95***
	(8.267)	(7.635)	(7.364)
Size of bond (USD mm)		2.349***	2.270***
		(0.271)	(0.254)
Tenor of bond (years)		0.745***	0.760***
		(0.163)	(0.164)
Rating of bond		1.068	1.632
		(1.259)	(1.322)
Revenue that quarter		3.471**	1.976***
		(1.362)	(0.697)
Number of lead underwriters		-0.0151	-0.0489
		(0.440)	(0.438)
Other bonds issued same day		0.0867	0.115
		(0.288)	(0.290)
Post_t×Size			3.256***
			(0.915)
Post_t×Lev			1.681
			(1.237)
Firm FE	✓	✓	✓
Ind x Post FE	✓	✓	✓
Quarter FE	✓	✓	✓
Observations	3037	3037	3037
R-squared	0.501	0.522	0.526

Notes: Includes non-Eurozone USD non-financial corporate issuance, September 2010-June 2018. Post is after June 8, 2016. Estimation is via OLS. Controls are normalized to variance 1 and include issuer credit rating, tenor, amount issued, firm revenue, the dollar amount issued on day t other than firm i, and the number of underwriting banks. Size refers to total assets, leverage refers to the ratio of total long-term debt to total assets. Standard errors, in parentheses, are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 3.6: Increase in issuance at firm level

	(1) Amt issued (log)	(2) Amt issued (log)	(3) Pr(Issue)	(4) # Bonds
Eurexp_i x Post_t	0.287^{***}	0.288^{***}	0.284^{**}	0.722^{***}
	(0.0863)	(0.0846)	(0.120)	(0.256)
Post_t×Log(Total Assets)		0.133^{***}	0.0534^{*}	0.398^{***}
		(0.0323)	(0.0302)	(0.0929)
Rating of bond		-0.418^{***}	-0.581^{***}	-1.155^{***}
		(0.0319)	(0.0325)	(0.0764)
Revenue		0.00577	-0.0381	-0.00576
		(0.0171)	(0.0455)	(0.0419)
Size		0.00763	0.122^{***}	0.0628
		(0.0235)	(0.0447)	(0.0675)
Leverage		0.831^{***}	0.725^{***}	2.191^{***}
		(0.120)	(0.124)	(0.348)
Constant	0.146^{***}	5.195^{***}	8.457^{***}	14.05^{***}
	(0.00395)	(0.612)	(0.508)	(1.546)
Firm FE	✓	✓	✓	✓
Ind x Qtr FE	✓	✓	✓	✓
Observations	8639	8639	8639	8639
R-squared	0.244	0.379	0.365	0.361

Notes: Includes non-Eurozone USD corporate issuance, by firm-quarter. Amt issued (log) is the logged amount of firm-quarter bond issuance plus one. Post is after Q1 2016. Controls for firm revenue, total assets, credit rating. Controls are normalized to variance 1. Size refers to total assets, leverage refers to the ratio of total long-term debt to total assets. Standard errors, in parentheses, are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 3.7: Ruling out firm demand explanations

	(1) Underpricing (bps)	(2) Underpricing (bps)	(3) Underpricing (bps)
Post_t×Eurexp_b	-14.72**	-13.86**	-14.31**
	(6.470)	(6.826)	(6.906)
Post_t	-0.471	-1.021	-0.729
	(2.012)	(1.947)	(2.048)
Eurexp_b	5.425	5.453	5.535
	(5.071)	(5.074)	(5.127)
Other bonds issued same day		0.334	0.342
		(0.468)	(0.467)
Size of bond (USD mm)		0.626	0.631
		(0.420)	(0.422)
Tenor of bond (years)		0.892***	0.893***
		(0.146)	(0.146)
Rating of bond		0.746	0.682
		(3.116)	(3.113)
Number of lead underwriters		0.0980	0.101
		(0.697)	(0.692)
Revenue that quarter		1.708**	2.018**
		(0.775)	(0.970)
Post_t×Size			0.283
			(0.319)
Post_t×Lev			-0.753
			(1.575)
Firm x Year FE	✓	✓	✓
Industry FE	✓	✓	✓
Observations	3104	3104	3104
R-squared	0.830	0.835	0.835

Notes: Includes non-Eurozone USD non-financial corporate issuance, September 2010-June 2018. Post is after June 8, 2016. Estimation is via OLS. Controls are normalized to variance 1 and include rating, tenor, amount, amount issued by other firms on the same day, revenue, and number of underwriting banks. Standard errors, in parentheses, are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 3.8: Impact of Government QE: Underpricing and Oversubscription

	(1) Underpricing (bps)	(2) Oversubscription
Eurexp_i x Post_QE2015	-4.273	-2.060
	(14.70)	(2.280)
Size of bond (USD mm)	0.171	-0.238***
	(0.439)	(0.0870)
Tenor of bond (years)	1.344***	-0.0358
	(0.248)	(0.0674)
Rating of bond	-2.313	-0.939
	(6.681)	(0.623)
Revenue that quarter	-301.1***	7.489
	(81.16)	(11.36)
Number of lead underwriters	-0.791	-0.0215
	(0.865)	(0.253)
Other bonds issued same day	-0.0248	0.0674
	(0.612)	(0.0975)
post_2015×Size	262.6***	-7.249
	(74.74)	(10.40)
post_2015×Lev	3.843	0.476
	(2.409)	(0.414)
Firm FE	✓	✓
Ind x Post_QE2015 FE	✓	✓
Quarter FE	✓	✓
Observations	942	942
R-squared	0.678	0.502

Notes: Includes non-Eurozone USD corporate issuance, by firm-quarter. Sample includes all bonds issued between January 2014 and February 2016. Post is after March 9, 2015. Controls for firm revenue, total assets, credit rating. Controls are normalized to variance 1. Size refers to total assets, leverage refers to the ratio of total long-term debt to total assets. Standard errors, in parentheses, are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 3.9: Impact of Government QE: Volume Issued

	(1) Amount (USD Bn)	(2) Amount (USD Bn)	(3) Pr(Issue)	(4) # Bonds
Eurexp_i x Post_QE2015	0.417	0.418	0.0667	0.503
	(0.395)	(0.339)	(0.140)	(0.348)
post_2015×Log(Total Assets)		0.405	0.100	0.518
		(0.471)	(0.0763)	(0.320)
Rating of bond		-1.652***	-0.759***	-1.875***
		(0.286)	(0.0582)	(0.160)
Revenue		0.147	0.0163	0.125
		(0.102)	(0.0908)	(0.126)
Size		-0.149	0.115	-0.0113
		(0.331)	(0.140)	(0.294)
Leverage		3.434***	1.149***	3.840***
		(1.038)	(0.230)	(0.762)
Firm FE	✓	✓	✓	✓
Ind x Qtr FE	✓	✓	✓	✓
Observations	2909	2909	2909	2909
R-squared	0.232	0.381	0.384	0.427

Notes: Includes non-Eurozone USD corporate issuance, by firm-quarter. Sample includes all bonds issued between January 2014 and February 2016. Post is after Q1 2015. Controls for firm revenue, total assets, credit rating. Controls are normalized to variance 1. Size refers to total assets, leverage refers to the ratio of total long-term debt to total assets. Standard errors, in parentheses, are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 3.10: Financial issuers do not benefit from ECB program

	(1) Oversubscription	(2) Oversubscription	(3) Underpricing (bps)	(4) Underpricing (bps)
Eurexp_i x Post_t	-0.408	-1.280	-5.579	2.243
	(1.816)	(2.282)	(10.37)	(9.390)
Size of bond (USD mm)		-0.0791		0.565^{**}
		(0.0969)		(0.268)
Tenor of bond (years)		-0.0235		1.614^{***}
		(0.131)		(0.460)
Rating of bond		-0.573^{**}		0.756
		(0.281)		(1.920)
Revenue that quarter		-3.117^{***}		-18.27^{***}
		(0.444)		(3.173)
Number of lead underwriters		0.0935		1.662^{**}
		(0.0844)		(0.658)
Other bonds issued same day		-0.105^{**}		-0.681^{**}
		(0.0521)		(0.302)
Post_t×Size		0.161^{*}		-0.470
		(0.0932)		(1.383)
Post_t×Lev		0.467^{*}		-1.671
		(0.279)		(1.188)
Firm FE	✓	✓	✓	✓
Ind x Post FE	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓
Observations	1118	1118	1118	1118
R-squared	0.375	0.391	0.415	0.453

Notes: Includes non-Eurozone USD financial firm issuance, September 2010-June 2018. Financial firms are defined as those with NAIC2 = 52. Post is after June 8, 2016. Estimation is via OLS. Controls are normalized to variance 1 and include rating, tenor, amount, amount issued by other firms on the same day, revenue, and number of underwriting banks. Standard errors, in parentheses, are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 3.11: Increase in issuance at firm level on operational exposure to Euro-zone

	(1) Amount (USD Bn)	(2) Pr(Issue)	(3) # Bonds	(4) Amount (USD Bn)	(5) Pr(Issue)	(6) # Bonds
Num Words Euro x Post_t	-107.9	-34.91	-258.5			
	(306.0)	(99.35)	(240.4)			
Wtd Country x Post_t				-1377.2	-556.1	-2070.1
				(2301.0)	(905.2)	(2087.9)
Post_t×Log(Total Assets)	-0.164	0.0297	0.240*	-0.164	0.0299	0.238*
	(0.219)	(0.0499)	(0.127)	(0.217)	(0.0500)	(0.127)
Controls	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Ind x Qtr FE	✓	✓	✓	✓	✓	✓
Observations	7457	7457	7457	7457	7457	7457
R-squared	0.309	0.366	0.364	0.309	0.366	0.364

Notes: Includes non-Eurozone USD corporate issuance, by firm-quarter. Post is after Q1 2016. Controls, normalized to variance 1, include credit rating, firm revenue, total assets, and leverage. Standard errors, in parentheses, are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 3.12: Heterogeneous increase in issuance at firm level

	(1) Frequent Issuers	(2) Infrequent Issuers	(3) A-rated and above	(4) BBB rated
Eurexp_i x Post_t	0.357	0.305***	0.241*	0.461***
	(0.291)	(0.0830)	(0.131)	(0.176)
Post_t×Log(Total Assets)	0.169**	0.132***	0.172**	0.154***
	(0.0831)	(0.0314)	(0.0840)	(0.0458)
Constant	8.296***	3.634***	9.695***	3.640***
	(1.372)	(0.582)	(1.809)	(0.757)
Controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Ind x Qtr FE	✓	✓	✓	✓
Observations	2068	6424	3475	2926
R-squared	0.415	0.344	0.402	0.462

Notes: Includes non-Eurozone USD corporate issuance, by firm-quarter. Frequent issuers are those that issued more than 13 bonds in the sample period; infrequent issuers issued 13 or fewer. Post is after Q1 2016. Controls for firm revenue, total assets, credit rating. Controls are normalized to variance 1. Standard errors, in parentheses, are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 3.13: More buyers, less time spent on placement

	(1) Time (hours: ann. to price)	(2) Time (hours: ann. to price)	(3) Time (hours: ann. to price)
Eurexp_b x Post_t	-3.743**	-3.721**	-3.603**
	(1.592)	(1.602)	(1.562)
Post	0.0934	-0.412	-0.141
	(0.327)	(0.329)	(0.335)
Number of bonds			0.0531***
			(0.00599)
Controls		✓	✓
Bank x Qtr FE	✓	✓	✓
Firm FE	✓	✓	✓
Observations	10496	10496	10496
R-squared	0.813	0.820	0.823

Notes: Dataset includes one observation per deal for each bank. I exclude financial issuance. Controls include amount issued, tenor, firm revenue, firm size, and leverage. Standard errors are clustered at the bank level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

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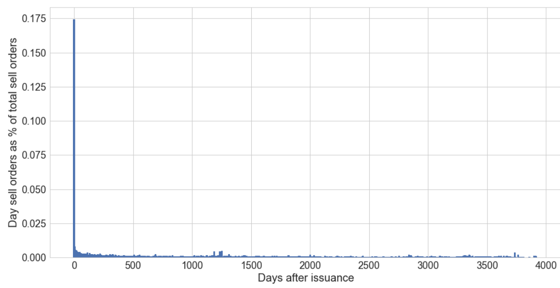
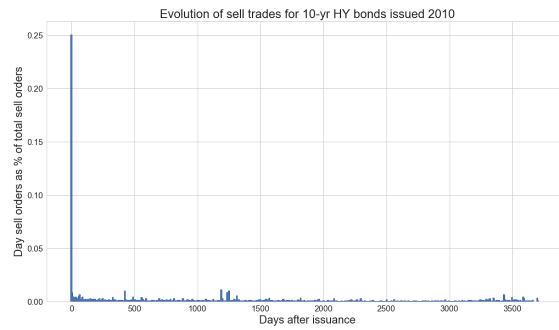
Appendix A: Chapter 1

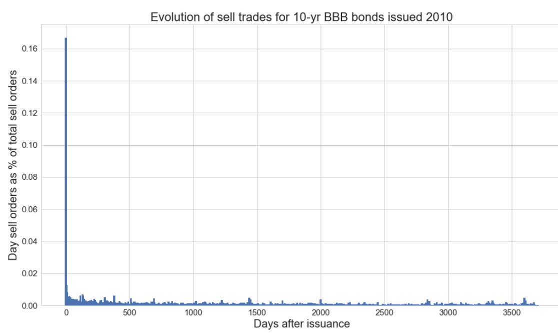
Figure A.1: Evidence from TRACE: heterogeneous bond buyers



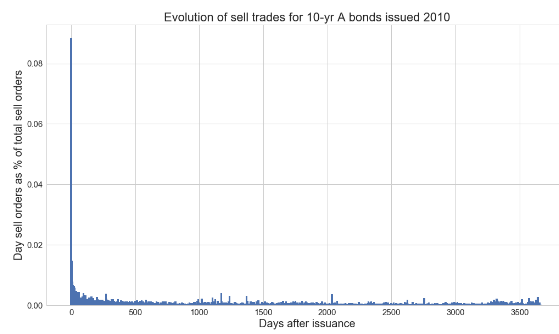
(a) All 10-year bonds issued 2010



(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.

Table A.1: 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

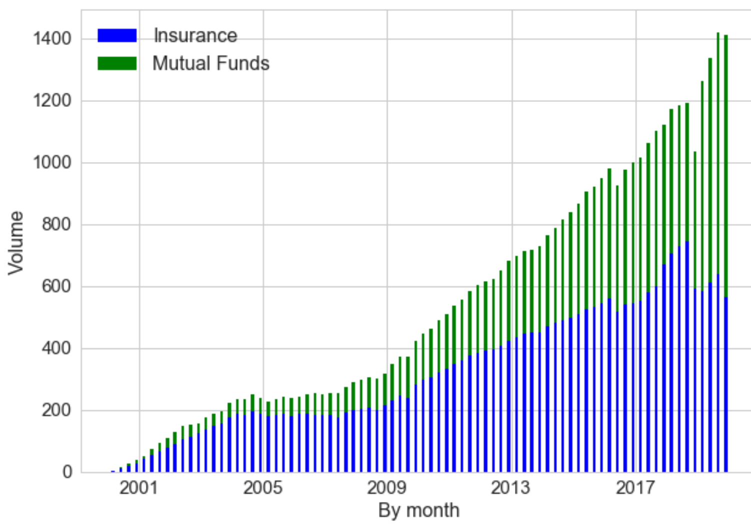


Figure A.2: Share of insurance versus mutual fund holders of corporate bonds

Source: Thomson Reuters eMAXX
Note: The figure shows the quarterly volume of mutual funds and insurance companies reported to hold corporate bonds in the sample.

A.1 Proofs

Proof of equation (1.24)**: 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:

$$Q^{D,PM}(r_b^*) = Q^S. \tag{A.11}$$

The expression for $q^D(r^*) = \ln\big(Q^D * (r^*)\big)$ is derived as below. Note that I model an expectation of rationing ω, 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:

$$Q_{bt}^D = W_t\theta_t \frac{\exp\left(\delta_{ST,b}\right)}{\exp\left(\frac{\sigma_t^2}{2k_{ST}}\right) + \sum_m \exp(\delta_{ST,m})} \frac{1}{1-\omega_{ST}} + W_t(1-\theta_t) \frac{\exp\left(\delta_{LT,b}\right)}{\exp\left(\frac{\sigma^2}{2k_{LT}}\right) + \sum_m \exp(\delta_{LT,m})} \frac{1}{1-\omega_{LT}}. \tag{A.12}$$

For ease of exposition, I make the following substitutions:

$$d_1 = \exp\left(\frac{\sigma^2}{2k_{ST}}\right) + \sum_m \exp(\delta_{ST,m}), \tag{A.13}$$

$$d_2 = \exp\left(\frac{\sigma^2}{2k_{LT}}\right) + \sum_m \exp(\delta_{LT,m}). \tag{A.14}$$

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

$$
\begin{aligned}
q_{bt}^D &= \ln\bigl(Q_{bt}^D\bigr) \\
&= \ln(W_t) - \ln(1-\omega) + \ln\Bigl[\frac{\theta\exp(\delta_{1b})}{d_1} + \frac{(1-\theta)\exp(\delta_{2b})}{d_2}\Bigr] \\
&= \ln(W_t) + \omega + \ln\Bigl[\exp(\delta_{2b})\frac{\theta\exp(\delta_{1b}-\delta_{2b})}{d_1} + \frac{(1-\theta)}{d_2}\Bigr] \\
&= \ln(W_t) + \omega + \delta_{2b} + \ln\Bigl[\frac{\theta\exp(\delta_{1b}-\delta_{2b})}{d_1} + \frac{(1-\theta)}{d_2}\Bigr] \\
&= \ln(W_t) + \omega + \theta\delta_{1b} + (1-\theta)\delta_{2b} - \theta\ln(d_1) - (1-\theta)\ln(d_2).
\end{aligned} \tag{A.15}
$$

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

$$
\begin{aligned}
f(\theta) &= \ln\Bigl[\frac{\theta\exp(\delta_{1b}-\delta_{2b})}{d_1} + \frac{(1-\theta)}{d_2}\Bigr] \\
&\approx f(0) + f'(\theta)\Big|_{\theta=0} \times \theta \\
&= -\ln\bigl(d_2\bigr) + d_2\Bigl(\frac{\exp(\delta_{1b}-\delta_{2b})}{d_1} - \frac{1}{d_2}\Bigr)\theta \\
&\approx -\ln\bigl(d_2\bigr) + \Bigl(\frac{d_2}{d_1}\exp(\delta_{1b}-\delta_{2b}) - 1\Bigr)\theta \\
&= -\ln\bigl(d_2\bigr) + \Bigl(\exp\Bigl(\delta_{1b}-\delta_{2b}+\ln\Bigl(\frac{d_2}{d_1}\Bigr)\Bigr) - 1\Bigr)\theta \\
&\approx -\ln\bigl(d_2\bigr) + \Bigl(\delta_{1b}-\delta_{2b}+\ln\Bigl(\frac{d_2}{d_1}\Bigr)\Bigr)\theta.
\end{aligned} \tag{A.16}
$$

I then have

$$
\begin{aligned}
q_{bt}^D = {} & w_t + (r_b - r^{SM})\bigl(\alpha_1\theta_t + \alpha_2(1-\theta_t)\bigr) + r^{SM}\bigl(\alpha_{1,SM}\theta_t + \alpha_{2,SM}(1-\theta_t)\bigr) \\
& + X_b\bigl(\beta_1\theta_t + \beta_2(1-\theta_t)\bigr) + \xi_b + \omega \\
& + (\theta-1)\ln\Bigl(\exp\bigl(-k_2/\sigma^2\bigr) + \sum_m \exp(\alpha_2 r_m + \beta_2 X_m + \xi_m)\Bigr) \\
& - \theta\ln\Bigl(\exp\bigl(-k_1/\sigma^2\bigr) + \sum_m \exp(\alpha_1 r_m + \beta_1 X_m + \xi_m)\Bigr).
\end{aligned} \tag{A.17}
$$

I substitute this last expression into (A.11) to get

$$
\begin{aligned}
r_b^* = \frac{1}{\alpha_1\theta_t + \alpha_2(1-\theta_t)} \Big(& q^S - w_t - \omega \\
& + r^{SM}\big((\alpha_1 - \alpha_{1,SM})\theta_t + (\alpha_2 - \alpha_{2,SM})(1-\theta_t)\big) \\
& - X_b\big(\beta_1\theta_t + \beta_2(1-\theta_t)\big) - \xi_b \\
& + (1-\theta)\ln\Big(\exp\big(-k_2/\sigma^2\big) + \sum_m \exp(\alpha_2 r_m + \beta_2 X_m + \xi_m)\Big) \\
& + \theta\ln\Big(\exp\big(-k_1/\sigma^2\big) + \sum_m \exp(\alpha_1 r_m + \beta_1 X_m + \xi_m)\Big)\Big).
\end{aligned}
\tag{A.18}
$$

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

$$
\begin{aligned}
\xi_b = q^D & - w_t - \omega \\
& - (r_b^o - r^{SM})(\alpha_1\theta + \alpha_2(1-\theta)) - r^{SM}(\alpha_{1,SM}\theta + \alpha_{2,SM}(1-\theta)) \\
& - X_b\big(\beta_1\theta_t + \beta_2(1-\theta_t)\big) \\
& + (1-\theta)\ln\Big(\exp\big(-k_2/\sigma^2\big) + \sum_m \exp(\alpha_2 r_m + \beta_2 X_m + \xi_m)\Big) \\
& + \theta\ln\Big(\exp\big(-k_1/\sigma^2\big) + \sum_m \exp(\alpha_1 r_m + \beta_1 X_m + \xi_m)\Big).
\end{aligned}
\tag{A.19}
$$

I can then rewrite r^* as

$$
\begin{aligned}
r_b^* &= \frac{1}{\alpha_1\theta_t + \alpha_2(1-\theta_t)}\Big(q^S - q^D + r_b^o(\alpha_1\theta + \alpha_2(1-\theta))\Big) \\
&= \frac{1}{\alpha_1\theta_t + \alpha_2(1-\theta_t)}\Big(q^S - q^D\Big) + r_b^o.
\end{aligned}
\tag{A.20}
$$

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:

$$r_b^o - r_b^* = \frac{q^D - q^S}{\alpha_1 \theta_t + \alpha_2 (1 - \theta_t)}. \tag{A.21}$$

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 (1.20).

Using properties of the lognormal distribution, I rewrite the investor's objective function as

$$\max_b - \exp\Big(-\frac{1}{k_i}\mu_{ihb} + \frac{\sigma^2}{2k_h^2}\Big) \tag{A.22}$$

where

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

or

$$\max_b - \exp\Big(-\frac{1}{k_i} U_i(b)\Big) \tag{A.23}$$

where

$$U_i(b) = \delta_{hb} + \epsilon_{ib} - \frac{\sigma^2}{2k_h}. \tag{A.24}$$

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

$$U_i(b) > U_i(m) \qquad \forall m \neq b, \tag{A.25}$$

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:

$$\begin{aligned}
P(i \text{ choose } b) &= P(U_{ib} > U_{im}\ \forall m \neq b) \\
&= P(\delta_{hb} + \epsilon_{ib} - \frac{\sigma^2}{2k_h} > \delta_{hm} + \epsilon_{im} - \frac{\sigma^2}{2k_h}\ \ \forall m \neq b) \\
&= P(\epsilon_{im} < \delta_{hb} - \delta_{hm} + \frac{\sigma^2}{2k_h} - \frac{\sigma^2}{2k_h} + \epsilon_{ib}\ \ \forall m \neq b).
\end{aligned} \tag{A.26}$$

Suppose first that ϵ_{ib} is known. Since the ϵ terms are independent, the probability of investor i choosing b is just the cumulative distribution function (CDF) for each potential value of ϵ_{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:

$$P(i \text{ choose } b|\epsilon_{ib}) = \prod_{m \neq b} \exp\big(-\exp\Big(-(\delta_{hb} - \delta_{hm} + \frac{\sigma^2}{2k_h} - \frac{\sigma^2}{2k_h} + \epsilon_{ib})\Big)\big). \tag{A.27}$$

Since I do not observe any of the ϵ_{ib} values in reality, I evaluate the unconditional probability that investor i chooses bond b by integrating over all potential values of ϵ_{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:

$$\begin{aligned}
P_{ib} = P(i \text{ choose } b) &= \int \prod_{m \neq b} \exp\big(-\exp\Big(-(\delta_{hb} - \delta_{hm} + \frac{\sigma^2}{2k_h} - \frac{\sigma^2}{2k_h} + \epsilon_{ib})\Big)\big) f(\epsilon_{ib}) d\epsilon_{ib} \\
&= \frac{\exp\big(\delta_{hb} - \frac{\sigma^2}{2k_h}\big)}{1 + \sum_m \exp\Big(\delta_{hm} - \frac{\sigma^2}{2k_h}\Big)} \\
&= \frac{\exp\big(\delta_{hb}\big)}{\exp\Big(\frac{\sigma^2}{2k_h}\Big) + \sum_m \exp(\delta_{hm})}.
\end{aligned} \tag{A.28}$$

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:

$$Q_{bt}^D = \sum_h P_{hbt} M_{ht}. \tag{A.29}$$

Assume there are only two types of investors: a proportion θ_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

$$Q_{bt}^D = W_t\theta_t \frac{\exp\left(\delta_{ST,b}\right)}{\exp\left(\frac{\sigma^2}{2k_{ST}}\right) + \sum_m \exp(\delta_{ST,m})} + W_t(1-\theta_t)\frac{\exp\left(\delta_{LT,b}\right)}{\exp\left(\frac{\sigma^2}{2k_{LT}}\right) + \sum_m \exp(\delta_{LT,m})}. \tag{A.30}$$

■

Derivation of firm's supply of bond in equation (1.6).

Note that given the normal error, I can write the unconditional expectation of issuance q for a given firm as

$$\begin{aligned} E[q|Z] &= Pr(q > 0|Z) \times E[q|Z, q > 0] \\ &= \Phi((\gamma_r r + Z\gamma - c)/\sigma_e) \times E[q|Z, q > 0], \end{aligned} \tag{A.31}$$

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

$$E[q|Z, q > 0] = \gamma_r r + Z\gamma + E[u|u > c - \gamma_r r - Z\gamma] = \gamma_r r + Z\gamma + \sigma_e \left[\frac{\phi((\gamma_r r + Z\gamma - c)/\sigma_e)}{\Phi((\gamma_r r + Z\gamma - c)/\sigma_e)}\right]. \tag{A.32}$$

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

$$\frac{\partial E[q|Z, r]}{\partial r} = \gamma_r \Phi\big((\gamma_r r + Z\gamma - c)/\sigma_e\big), \tag{A.33}$$

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.

■

Appendix B: Chapter 2

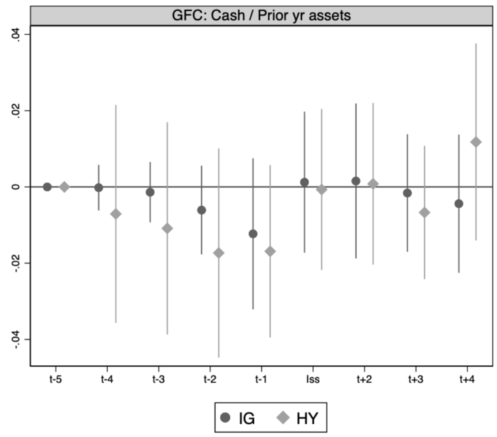


Figure B.1: Liquid Assets: Coefficient plots – Global Financial Crisis

Notes: Each point is an estimate of β_{t+m} from the regression $Y_{fq} = \sum_{m=-5}^{4} \beta_m Issue_{f,t+m} + \alpha_f + \alpha_{ind \times year} + \epsilon_{fq}$, with 95% confidence intervals. Cash is cash and short term investments. The circles are investment grade firms (rated BBB- and above), while the diamonds are high yield firms (rated below BBB-). Observations are firm-quarters up to five quarters prior to a bond issuance and four quarters following a bond issuance. "Iss" denotes the quarter ending immediately after issuance We include firm and industry-year fixed effects. Standard errors are clustered by 2-digit industry level. All ratios are winsorized at the 1% level. GFC times includes bonds issued October 1, 2007 - June 30, 2009.

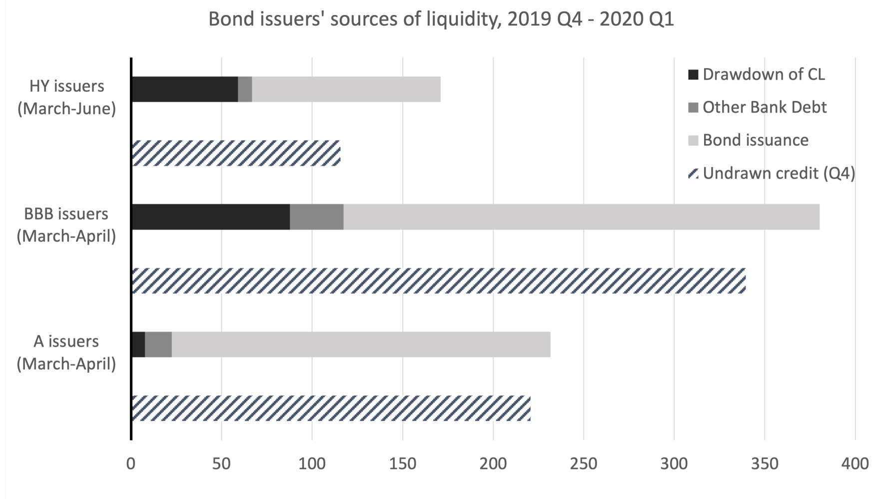


Figure B.2: Visualizing dry powder: Debt Composition Aggregate Flow

Notes: This figure classifies aggregate debt flows based on FISD bond issuance data as well as changes in outstanding debt for other credit instruments during 2020Q1 based on Capital IQ Capital Structure Summary table. Undrawn credit EOY 2019 is the outstanding available Undrawn Revolving Credit at the end of 2019. See Table 2.1 for underlying numbers. Issuers include all U.S. firms that issued a bond between issued March 23 - June 30, 2020 that we could merge with Capital IQ information.

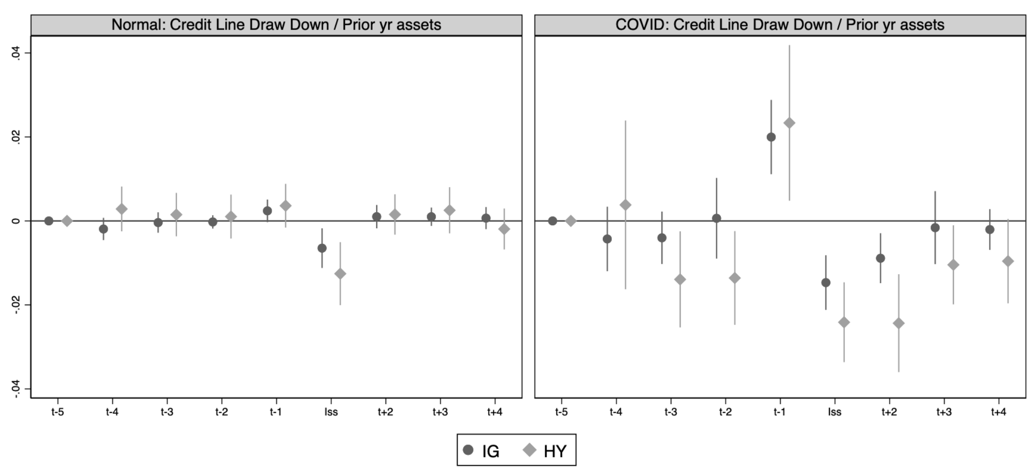


Figure B.3: Drawn amount on credit lines: Coefficient plots

Notes: Each point is an estimate of β_{t+m} from the regression
$Y_{fq} = \sum_{m=-5}^{4} \beta_m Issue_{f,t+m} + \alpha_f + \alpha_{ind \times year} + \epsilon_{fq}$, with 95% confidence intervals. Credit Line Drawn Down is the amount drawn down on bank credit line at quarter end (negative values are repayments). Observations are firm-quarters up to five quarters prior to a bond issuance and four quarters following a bond issuance. "Iss" denotes the quarter ending immediately after issuance. We include firm and industry-year fixed effects. Standard errors are clustered by 2-digit industry level. "Normal" times includes bonds issued between 2010-2019, "Covid" times includes bonds issued March 23 - June 30, 2020.

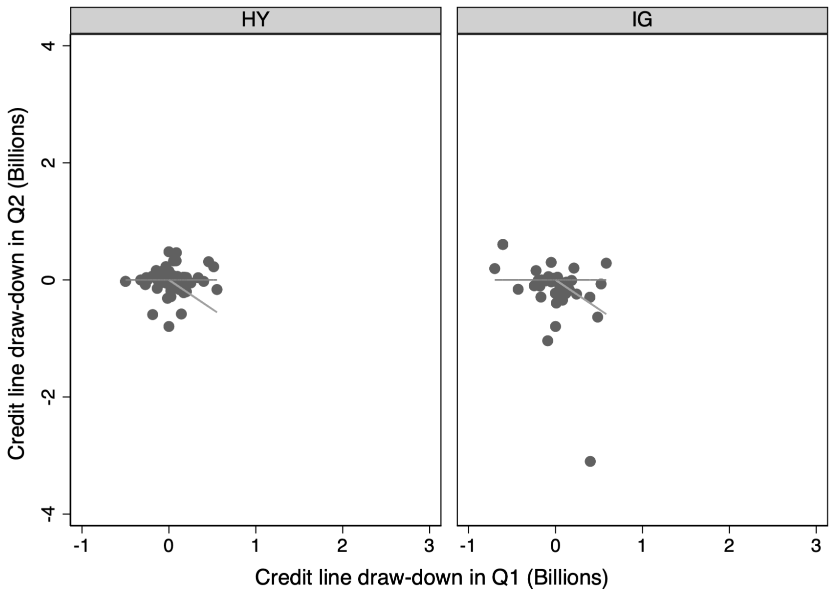


Figure B.4: Visualizing crowding out: Credit line draw-downs in 2019Q2 vs. 2019Q1

Note: This figures plots credit line repayment in 2019Q2 against 2019Q1 credit line draw-downs, based on Capital IQ Capital Structure Summary table, separately by high-yield and investment grade issuers. For ease of interpretation, the figure also displays the negative 45 degree line (exact repayment in Q2) and horizontal line (no change in credit line in Q2). Excludes firms that did not draw down in 2019Q1, and excludes the outlier HCA Inc.

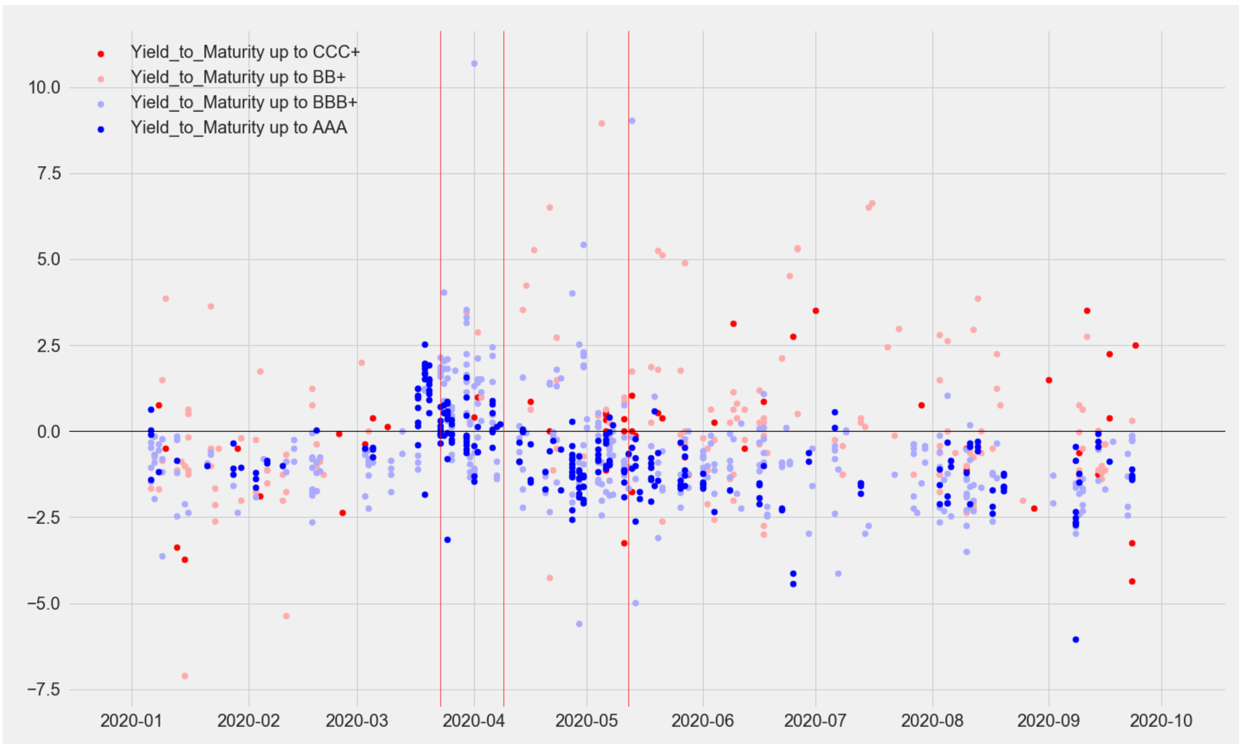


Figure B.5: Yield to maturity vs. most recent issuance by same issuer

Source: Mergent FISD, retrieved via WRDS October 21, 2020.
Note: Each point is the yield to maturity on a new issuance, net of the yield to maturity on the most recent issuance by the same issuer of the same tenor (within 1 year). A value greater than zero means the new bond has a higher cost of capital (credit spread) than the most recent bond issued by the same firm. Note red lines correspond to March 23, 2020 (first Fed announcement to buy corporate bonds); April 9, 2020 (first Fed announcement to buy high yield corporate bonds); and May 12, 2020 (start of Fed bond buying program).

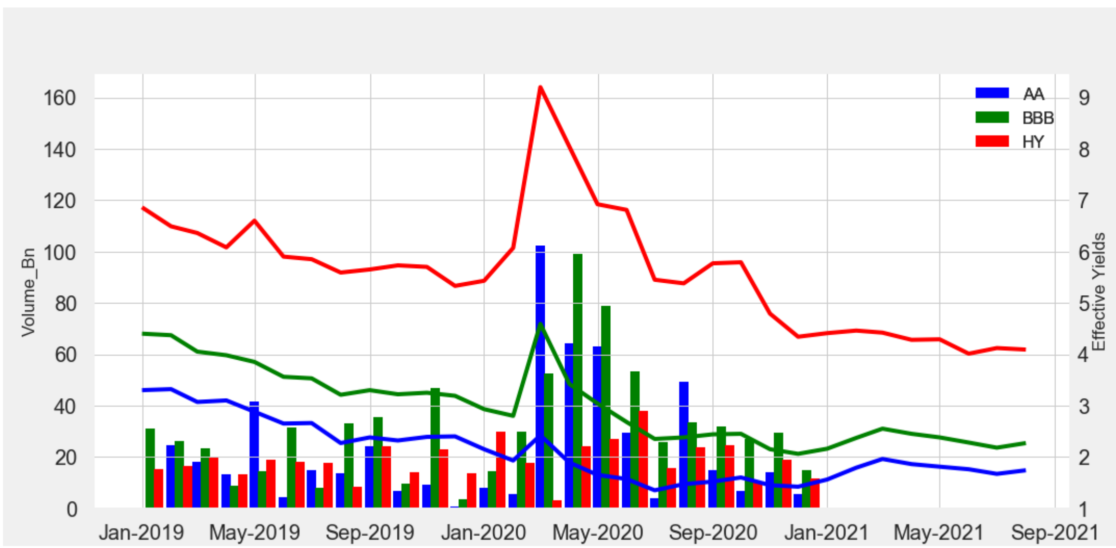


Figure B.6: Bond Issuance volume and yields through 2020

Notes: Bars represent monthly issuance volumes, in billions of dollars, for rating categories AA and above, BBB- to BBB+, and high yield (BB+ and below). Lines represent yields for the ICE Bank of America U.S. Indices for U.S. dollar denominated corporate debt publicly issued in the U.S. domestic market in the same three ratings categories, as pulled from the Federal Reserve Economic Data.

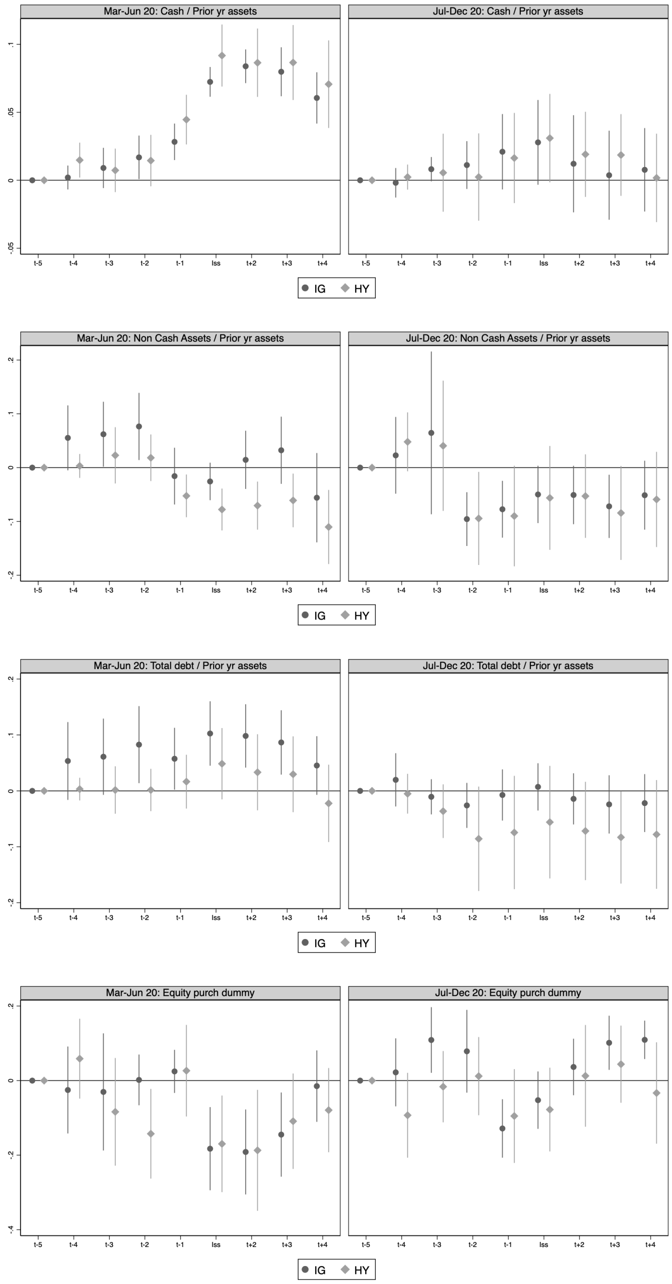


Figure B.7: Coefficient plots – Early vs. late issuers

Notes: Each point is an estimate of β_{t+m} from the regression $Y_{fq} = \sum_{m=-5}^{4} \beta_m Issue_{f,t+m} + \alpha_f + \alpha_{ind \times year} + \epsilon_{fq}$, with 95% confidence intervals. “Cash” is cash and short term investments. “Non-cash assets” is total assets minus cash and short term investments. “Total debt” is total long term debt plus debt in current liabilities. “Equity purchase dummy” is an indicator for positive purchases of common or preferred shares in that quarter. The circles are investment grade firms (rated BBB- and above), while the diamonds are high yield firms (rated below BBB-). Observations are firm-quarters up to five quarters prior to a bond issuance and four quarters following a bond issuance. "Iss" denotes the quarter ending immediately after issuance. Left panels include U.S. firms that issued bonds March 23 - June 30, 2020. Right panels include U.S. firms that issued bonds July 1 - December 31, 2020. We include firm and industry-year fixed effects. Standard errors are clustered by 2-digit industry level. All ratios are winsorized at the 1% level in the entire sample. To further limit the impact of outliers, cash ratios of the March-June sample is further winsorized at the 1% level.

Table B.1: Summary statistics: bond issuance, 2019-2020

	Num Offerings	Amount (Bn)	Tenor	Rating	Credit Spread	Yield
IG Issuance: 2019						
10%	2	1.4	9.5	13.7	92	2.89%
50%	5	6.0	13.3	14.8	137	3.78%
90%	10	21.2	19.1	16.7	193	4.46%
IG Issuance: Weeks since March 2020						
2020-03-02	11	7.8	12.7	14.5	141	2.46%
2020-03-09	3	3.9	12.2	14.2	211	2.91%
2020-03-16	11	45.2	15.6	17.2	270	3.93%
2020-03-23	28	64.2	13.2	16.0	273	3.68%
2020-03-30	19	60.1	14.0	15.2	346	4.24%
2020-04-06	12	22.7	10.8	15.5	314	3.82%
2020-04-13	11	28.4	12.1	15.3	237	3.22%
2020-04-20	15	19.5	10.6	14.6	260	3.37%
2020-04-27	23	68.0	13.9	15.6	214	3.11%
2020-05-04	28	56.7	12.9	15.2	255	3.31%
2020-05-11	20	37.5	15.2	14.8	251	3.54%
2020-05-18	10	35.0	17.0	16.3	170	2.73%
2020-05-25	9	11.2	14.5	15.6	169	2.51%
2020-06-01	12	24.4	12.0	14.9	156	2.35%
2020-06-08	8	9.1	10.4	13.8	180	2.62%
2020-06-15	15	30.6	11.4	14.4	196	2.60%
2020-06-22	6	10.1	11.7	15.8	156	2.25%
2020-06-29	3	8.8	18.7	14.0	170	2.62%
HY Issuance: 2019						
10%	2	1.5	6.8	8.0	314	5.16%
50%	5	4.2	7.9	8.9	410	6.25%
90%	10	8.5	9.3	10.3	534	7.47%
HY Issuance: Weeks since March 2020						
2020-03-02	3	2.5	8.7	10.0	447	5.46%
2020-03-30	4	2.3	5.0	9.5	662	6.56%
2020-04-06	3	1.6	5.0	7.0	814	8.62%
2020-04-13	11	14.2	5.5	10.4	709	7.73%
2020-04-20	17	12.6	5.2	9.5	689	7.24%
2020-04-27	6	3.0	5.0	8.7	551	6.91%
2020-05-04	10	7.8	6.1	10.6	562	6.83%
2020-05-11	11	8.1	6.2	8.2	662	7.23%
2020-05-18	11	5.9	6.3	9.3	607	7.72%
2020-05-25	8	9.6	6.2	8.8	631	7.59%
2020-06-01	14	10.7	6.7	9.7	569	6.43%
2020-06-08	13	9.4	7.4	9.2	454	5.49%
2020-06-15	19	13.2	7.4	9.1	542	6.34%
2020-06-22	9	8.2	7.6	9.2	586	7.45%
2020-06-29	5	3.0	7.2	7.2	658	7.08%

Source: Mergent FISD, retrieved via WRDS October 21, 2020.
Note: Summary table includes all U.S. dollars (USD) corporate bond issuance of over $100 million in size issued by U.S. domiciled companies or companies that report in USD. Excludes sovereign, supra-sovereign, financial, and utility offerings, convertible notes, impact bonds, bonds issued directly in exchange of existing bonds, PIK notes, and reopening issuance of existing bonds. Variables are averaged across week, except number of offerings and amount issued, which are summed across weeks.

Table B.2: Summary statistics: bond issuers, 2017-2020

	Normal times			Covid times		
	10%	50%	90%	10%	50%	90%
Balance sheet metrics						
Cash/Assets (prior Q4)	0.5%	5.1%	20.6%	0.8%	4.7%	19.9%
Cash/Assets (Q1)	0.5%	4.9%	20.2%	1.3%	7.5%	22.3%
Debt/Assets (prior Q4)	16.8%	38.1%	64.1%	22.2%	39.8%	68.1%
Debt/Assets (Q1)	18.5%	39.5%	63.3%	24.9%	43.1%	72.7%
Current debt/Debt (prior Q4)	0.0%	2.9%	15.4%	1.0%	5.5%	15.9%
Log assets (prior Q4)	7.2	9.1	10.9	8.1	9.7	11.3
Cash flow metrics						
Sales growth	-18%	-1%	17%	-26%	-5%	10%
Profit growth	-187%	-29%	116%	-325%	-30%	105%
Cash flow growh	-137%	-43%	69%	-149%	-58%	44%
Cash growth	-47%	-1%	94%	-24%	17%	362%
Bond metrics						
Amount per bond (MM)	300.0	500.0	1160.0	400.0	600.0	1395.0
Credit spread (bps)	92.0	245.0	518.1	148.0	320.0	718.4
Yield	3.271%	5.125%	7.824%	2.192%	4.074%	8.513%
Tenor (years)	5.0	8.0	13.2	5.0	8.0	11.0
Coupon	2.875%	5.000%	7.675%	2.172%	4.000%	8.613%
Rating	7.0	12.0	16.0	8.0	13.0	17.0
Days since last issuance	178.8	561.0	2224.8	128.0	431.5	1860.5
Days to next maturity	34.0	647.0	3959.0	133.9	491.5	1693.2

Source: Mergent FISD, retrieved via WRDS October 21, 2020 and Compustat.

Note: Summary table includes all USD corporate bond issuance of over $100 million in size issued by U.S. domiciled companies or companies that report in USD. “COVID" refers to bond issuers from March 1 - June 30, 2020. “Normal" refers to bond issuers from March 1 - June 30, 2017-2019. Growth variables are measured from Q4 of prior year to Q1 in year of issuance. Excludes sovereign, supra-sovereign, financial, and utility offerings, convertible notes, impact bonds, bonds issued directly in exchange of existing bonds, PIK notes, and reopening issuance of existing bonds. See Table B.13 for mapping of credit ratings to the numerical aggregation shown here.

Table B.3: Cash, Real Assets, and Total Debt: Cross-sectional regressions

	(1) Delta Cash / Assets 2019 Q4	(2) Delta Non-Cash assets / Assets 2019 Q4	(3) Delta Total Debt / Assets 2019 Q4
Exposure to COVID shock	0.00898*	0.0201***	-0.00208
	(0.00456)	(0.00569)	(0.00433)
HY	0.0120	0.0209	-0.00347
	(0.0136)	(0.0154)	(0.0134)
IG, BBB	-0.00584	-0.00195	0.0264**
	(0.0106)	(0.0134)	(0.0119)
Cash/Assets (2019Q4)	0.176**	0.193***	0.158***
	(0.0741)	(0.0589)	(0.0475)
Current Debt/Assets (2019Q4)	0.0487	-0.0601	-0.0799
	(0.0973)	(0.145)	(0.0924)
Undrawn credit EOY 2019 / Assets (2019Q4)	0.0658	-0.0813	0.194*
	(0.0700)	(0.0871)	(0.116)
Observations	271	260	271
R-squared	0.0893	0.119	0.0886

Notes: This table reports cross-sectional regressions of our sample of bond issuers on different balance sheet variables. Delta Cash / Assets is the firm-level change in cash and short term investments between 2019Q4-2020Q2 divided by the total assets in 2019Q4. Delta Non-Cash assets / Assets (2019Q4) and Delta Total Debt / Assets (2019Q4) are computed similarly, using total assets minus cash and short term investments, and total long term debt plus current liabilities, respectively, in the numerator, and total assets in 2019Q4 in the denominator. Exposure to COVID is constructed as per Chodorow-Reich et al. (2020) using abnormal employment decline in 2020Q1 at the industry level according to BLS data. The omitted category for ratings dummies is IG, A-rated or above. Issuers include all U.S. non-financial firms that issued a bond March 23 - June 30, 2020 that we could merge with Compustat data.

Table B.4: Aggregate Flows for COVID issuers

	Aggregate flow
Amt Issued (March 23-June 30th 2020)	576.23
Cash Increase (2019Q4 to 2020Q2)	473.82
Non-Cash Increase (2019Q4 to 2020Q2)	-254.75
Bank Debt Increase (2019Q4 to 2020Q2)	74.05
Total Debt Increase (2019Q4 to 2020Q2)	506.54
Total Sr Bonds and Notes Increase (2019Q4 to 2020Q2)	336.56
Share Repurchase (2020Q2-2020Q4)	162.26

Notes: This table reports aggregate numbers for firms that issued a bond during the COVID period (March 23rd-June 30th), in billions of USD. The first row, amount issued denotes FISD bond issuance volumes. Rows 2 through 5 rows report the change between 2019Q4 quarter end and 2020Q2 quarter end. “Cash” (cheq) is cash and short term investments. “Non cash assets” is total assets minus cash and short term investments. “Total debt” (dltt + dlc) is total long term debt plus debt in current liabilities. Cash, non-cash and total debt are all reported from Compustat. “Bank Debt” and “Total Sr Bonds and Notes” are based on Capital IQ Capital Structure Summary tables. Finally the last row reports share repurchases (prstkcy), from Compustat, as the aggregate repurchases from 2020 Q2 through 2020 Q4.

Table B.5: Spring 2020 bond issuers with a bond due later in the year

	All	IG	HY
Number of issuers (Spring 2020)	314	195	125
Issued amount (Spring 2020)	582	477	105
Number issuers with upcoming maturity	91	77	16
Amount issued by firms with upcoming maturity	261	243	18
Total amount maturing in 2020 for Spring 2020 issuers	182	137	36

Notes: Includes all USD corporate bond issuance March 23 - June 30, 2020 of over $100 million in size issued by U.S. domiciled companies or companies that report in U.S. dollars and have a credit rating.

Table B.6: Sample Summary Statistics: All bond issuers versus. Capital IQ

	Bond issuers: 2000-2020	CIQ Sample: 2000-2020	Bond issuers: COVID	CIQ Sample: COVID
Total Assets (log)	9.25	9.26	9.90	9.91
Leverage	0.46	0.46	0.46	0.46
Cash / Assets	0.06	0.06	0.06	0.06
Total bonds issued	7.54	7.88	2.00	2.03
Average bond size ($MM)	515.27	533.18	780.11	784.85
Credit Rating	11.23	11.19	12.56	12.57
Average tenor (years)	9.31	9.26	10.44	10.45
Bonds issued 2019 (#)	0.49	0.54	1.06	1.07
Bonds issued 2019 ($MM)	407.43	455.68	924.17	941.99
Bonds issued COVID (#)	0.37	0.41	1.49	1.51
Bonds issued COVID: ($MM)	360.35	407.39	1454.86	1484.73
Number of firms	1623.00	1425.00	402.00	391.00

Source: Mergent FISD, retrieved via WRDS October 21, 2020, Compustat, and Capital IQ retrieved via S&P Global March 1, 2021.
Note: Capital IQ sample includes all bond issuers matched to the Capital IQ database where there is a reported value for Drawn Credit Line or Undrawn Credit Line. All bond issuers include USD corporate bond issuance of over $100 million in size issued by U.S. domiciled companies or companies that report in USD. “COVID" refers to bond issuers from March 1 - June 30, 2020. Excludes sovereign, supra-sovereign, financial, and utility offerings, convertible notes, impact bonds, bonds issued directly in exchange of existing bonds, PIK notes, and reopening issuance of existing bonds. See Table B.13 for mapping of credit ratings to the numerical aggregation shown here.

Table B.7: Credit line draw-downs in 2020Q1: Cross-sectional regressions

	(1) Maxed out CL	(2) Did not draw CL	(3) Av. drawdown rate
Exposure to COVID shock	0.121***	-0.122***	0.168***
	(0.0315)	(0.0251)	(0.0478)
HY	0.134**	-0.321***	0.280***
	(0.0664)	(0.0870)	(0.0786)
IG, BBB	0.0196	-0.186**	0.133**
	(0.0541)	(0.0808)	(0.0576)
Cash/Assets (2019Q4)	0.124	0.672*	-0.159
	(0.250)	(0.377)	(0.298)
Current Debt/Assets (2019Q4)	0.452	-0.545	0.829*
	(0.523)	(0.587)	(0.477)
Undrawn credit EOY 2019 / Assets (2019Q4)	-0.779***	-1.215**	-0.639
	(0.281)	(0.534)	(0.478)
Observations	263	263	237
R-squared	0.136	0.175	0.188

Notes: This table reports cross-sectional regressions of our sample of U.S. firms that issued a bond March 23 - June 30, 2020 that we could merge with Capital IQ information. Outcome variables include various credit line drawdown activities in 2020Q1, based on the Capital IQ Capital Structure Summary tables. “Maxed out CL” is a dummy variable that equals 1 if the bond issuers drew down at least 90% of its Undrawn Revolving Credit at the end of 2019, and equals 0 otherwise. “Did not draw CL” is a dummy variable that equals 1 if the bond issuer drew down 0% or less of Undrawn Revolving Credit at the end of 2019, and equals 0 otherwise. “Av. drawdown rate ” is the amount drawn as a ratio of Undrawn Revolving Credit at the end of 2019. Exposure to COVID is constructed as per Chodorow-Reich et al. (2020), using abnormal employment decline in 2020Q1 at the industry level according to BLS data. The omitted category for ratings dummies is IG, A-rated or above. Cash, Current debt, and Assets are from Compustat.

Table B.8: Bond-loan substitution: Distribution of firms

Panel A: Share of bond issuers repaying credit lines in Q2

	Mean
HY	
Share Repaid some credit line in Q2, conditional on Q1 draw-down	0.72
Share Repaid all credit line in Q2, conditional on Q1 draw-down	0.40
IG, BBB	
Share Repaid some credit line in Q2, conditional on Q1 draw-down	0.91
Share Repaid all credit line in Q2, conditional on Q1 draw-down	0.65
IG, A or above	
Share Repaid some credit line in Q2, conditional on Q1 draw-down	0.77
Share Repaid all credit line in Q2, conditional on Q1 draw-down	0.77

Panel B: Fraction of credit line repayment conditional on repaying

	Mean	25%	50%	75%
HY				
Q2 CL repayment/Q1 CL drawdown (%)	201.0	37.2	100	108.1
Q2 CL repayment/Bond issuance (%)	64.8	8.90	54.1	97.5
IG, BBB				
Q2 CL repayment/Q1 CL drawdown (%)	154.7	98.4	100	102.7
Q2 CL repayment/Bond issuance (%)	79.8	30.0	65.0	100
IG, A or above				
Q2 CL repayment/Q1 CL drawdown (%)	577.5	100	100	153.7
Q2 CL repayment/Bond issuance (%)	67.2	5.73	33.4	100

Notes: Panel A displays the share of HY, BBB-rated, and A-rated firms that issued bonds March 23 - June 30, 2020 and drew down on their credit lines in 2020Q1 that repaid some or all of their credit line balance 2020Q2, based on Capital IQ. Panel B displays the distribution of credit line repayment in 2020Q2 as a share of 2020Q1 credit line draw-downs (Row 1) or as a share of bond issuance in 2020 between March and June (Row 2), conditional on repaying some positive amount in 2020Q2.

Table B.9: Bond-loan substitution: aggregate flows over 2020Q1 vs. 2020Q2

	HY Billions of USD	IG, BBB Billions of USD	IG, A or above Billions of USD
Bond issuance March 23-June 30th	104.2	262.9	209.1
Credit line Q1	59.1	87.7	7.68
Credit line Q2	-16.2	-52.4	-6.88
Total bank debt Q1	66.8	117.4	22.5
Total bank debt Q2	-20.4	-75.4	-16.1

Notes: This table classifies aggregate debt flows based on FISD bond issuance data (Row 1) as well as changes in outstanding debt for credit lines and total bank debt based on Capital IQ Capital Structure Summary tables. Rows 2 and 4 displays the change between 2019Q4 quarter end and 2020Q1 quarter end. Rows 2 and 4 displays the change between 2020Q1 quarter end and 2020Q2 quarter end. Issuers include all U.S. firms that issued a bond March 23 - June 30, 2020 that we could merge with Capital IQ.

Table B.10: Bank borrowing in 2019Q1 for bond issuers

	HY Share	IG, BBB Share	IG, A or above Share
Maxed out CL	0.017	0	0
Drew some CL	0.40	0.24	0.12
Did not draw CL	0.58	0.76	0.88
No net bank funds	0.57	0.59	0.81

Notes: This table classifies bond issuers based on changes in outstanding debt for different credit instruments during 2019Q1, based on the Capital IQ Capital Structure Summary tables. Row 1 includes issuers that maxed out their credit lines, i.e. the increase in Revolving Credit is at least 90% of Undrawn Revolving Credit at the end of 2018. Row 2 includes issuers that drew some of their credit lines, i.e. the increase in Revolving Credit as a ratio of Undrawn Revolving Credit at the end of 2018 is between 0% and 90%. Row 3 includes issuers that did not draw, i.e. the increase in Revolving Credit is 0 or less. Row 4 includes issuers with no net bank funding, defined as the sum of Revolving Credit, Term Loans and Federal Home Loan Bank borrowings. Bond issuers are all U.S. firms that issued a bond in 2019Q1 that we could merge with Capital IQ information.

Table B.11: Non-Price Terms and Covenants

	Bonds:				Loans:	
	IG-normal	HY-normal	IG-covid	HY-covid	IG	HY
Maintenance covenants:						
Leverage test	0.0%	0.0%	0.0%	0.0%	64.3%	46.2%
Net earnings test	0.0%	0.0%	0.0%	0.0%	43.2%	39.0%
Maintenance net worth	2.4%	7.2%	0.0%	0.0%	7.1%	4.2%
Incurrence covenants:						
Dividend related payments	0.1%	35.7%	1.0%	28.6%	13.2%	30.7%
Sale of assets	79.7%	81.4%	89.0%	96.4%	1.8%	21.2%
Senior debt issuance	0.0%	0.0%	0.0%	0.0%	1.4%	17.0%
Stock issuance issuer	0.0%	10.1%	0.0%	0.0%	0.4%	4.2%
Secured	0.5%	9.4%	1.9%	23.2%	9.3%	66.7%

Notes: This table computes (1) the percentage of bonds that report covenants that have each covenant and (2) the percentage of loans with each covenant. Bond statistics include all bonds issued 2010-2019 and March 23 - June 30, 2020 that also have loans available or outstanding as of end of 2019. Loan statistics computed over all bond issuers 2010-2019 and March-June 2020 that have bank loans available or outstanding as of end of 2019. The following loan types are included: Revolver/Line, Standby Letter of Credit, Revolver/Term Loan, 364-Day Facility. "Normal" times includes bonds issued 2010-2019, while "Covid" times includes bonds issued between March 23 - June 30, 2020. Source: Mergent FISD, retrieved via WRDS October 21, 2020 and Dealscan, retrieved October 18, 2020

Table B.12: Share repurchases in 2019-2020: Cross-sectional regressions

	(1) 2019 Q4 Repurchase	(2) 2020 Q2 Repurchase	(3) 2020 Q3 Repurchase	(4) 2020 Q4 Repurchase
Exposure to COVID shock	0.0673**	0.0368	0.0273	-0.0455
	(0.0307)	(0.0341)	(0.0345)	(0.0339)
HY	-0.167*	-0.124	-0.113	-0.0169
	(0.0854)	(0.0947)	(0.0908)	(0.0907)
IG, BBB	-0.0416	-0.0465	-0.0443	0.0878
	(0.0770)	(0.0899)	(0.0886)	(0.0880)
Cash/Assets (2019Q4)	0.826***	1.085***	1.012***	0.801**
	(0.307)	(0.326)	(0.329)	(0.318)
Current Debt/Assets (2019Q4)	-0.410	0.682	-0.723	-0.457
	(0.623)	(0.668)	(0.688)	(0.653)
Undrawn credit EOY 2019 / Assets (2019Q4)	-0.922***	-0.837**	-0.268	-0.283
	(0.338)	(0.402)	(0.444)	(0.441)
Observations	277	277	277	277
R-squared	0.0820	0.0722	0.0482	0.0389

Notes: This table reports cross-sectional regressions on the probability to repurchase shares of our sample of U.S. firms that issued a bond March 23 - June 30, 2020 that we could merge with Capital IQ. Dependent variables in Columns 1-4 are dummy variables that equal 1 if the firm repurchased shares in 2019Q4, 2020Q2, 2020Q3, and 2020Q4, respectively, and equal 0 otherwise. Exposure to COVID is constructed as per Chodorow-Reich et al. (2020), using abnormal employment decline in 2020Q1 at the industry level according to BLS data. The omitted category for ratings dummies is IG, A rated or above. Equity repurchases, Cash, Current debt, and Assets are from Compustat.

Table B.13: 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

Appendix C: Chapter 3

C.1 Further Robustness Checks

One potential source of endogeneity is the following: some firms anticipate the increase in demand for more European-exposed banks. These firms switch to work with more European banks. Firms that switch banks have some characteristic, unobserved by the econometrician, that is correlated with demand shocks following the ECB QE program. To check if switching is driving my results, I conduct the following test. I exclude any firm that has switched banks following the start of CSPP. That is, any firms that issue bonds with a bank that it has not previously worked with in my sample (2000-2016) are excluded from the analysis. I run my primary Diff-in-diff specification on the subset of firms that work exclusively with banks with which they had prior relationships after June 2016. That is, firms that select *any* new banks after June 8, 2016 are excluded from the analysis. The results are in Appendix Table (C.4). The coefficients do not change in economic or statistical significance. Even narrowing down to bond issuances where the firm exhibits zero switching behavior, the effect still holds. Thus, firms switching banks cannot be driving my result.

C.2 Additional Tables

Table C.1: Increase in issuance at firm level, different time windows

	(1) Window +/- 18 months	(2) Window +/- 12 months	(3) Post-QE3
Eurexp_i x Post_t	0.286***	0.231*	0.321***
	(0.102)	(0.133)	(0.107)
Post_t×Log(Total Assets)	0.320***	0.421***	0.320***
	(0.0973)	(0.147)	(0.0782)
Rating of bond	-0.582***	-0.574***	-0.549***
	(0.0462)	(0.0503)	(0.0442)
Revenue	-0.0350	-0.00465	-0.0365
	(0.0439)	(0.0533)	(0.0427)
Size	-0.0459	-0.208*	-0.0549
	(0.0989)	(0.117)	(0.0926)
Leverage	1.270***	1.585***	1.412***
	(0.271)	(0.351)	(0.277)
Constant	5.663***	4.420**	5.114***
	(1.278)	(1.721)	(1.126)
Firm FE	✓	✓	✓
Ind x Qtr FE	✓	✓	✓
Observations	3144	2148	3283
R-squared	0.465	0.494	0.479

Notes: Includes non-Eurozone USD corporate issuance, by firm-quarter. Sample for first model includes all issuance from January 2015 - December 2017; second model includes all issuance from July 2015 - June 2017; third model includes all issuance from January 2015 - June 2018. Post is after Q1 2016. Controls for firm revenue, total assets, credit rating. Controls are normalized to variance 1. Size refers to total assets, leverage refers to the ratio of total long-term debt to total assets. Standard errors, in parentheses, are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table C.2: More sellers, more time spent on placement

	(1) Time (hours: ann. to price)	(2) Time (hours: ann. to price)
Log(Amount underwritten by the bank)	0.236***	0.130***
	(0.0267)	(0.0239)
Log(Amount issued in the market on that day)	0.176***	0.147***
	(0.0476)	(0.0451)
Controls		✓
Bank x Qtr FE	✓	✓
Firm FE	✓	✓
Observations	10479	10479
R-squared	0.816	0.821

Notes: Dataset includes one observation per deal for each bank. I exclude financial issuance. Standard errors are clustered at the bank level. Controls include amount issued, tenor, firm revenue, firm size, leverage, the log of the total amount of bonds issued on that day, and the log of the total amount underwritten by that bank on that day. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table C.3: 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

Table C.4: Main specification, excluding switching firms

	(1) Oversubscription	(2) Oversubscription	(3) Underpricing (bps)	(4) Underpricing (bps)
Eurexp_i x Post_t	3.250**	4.477***	-20.62**	-19.48**
	(1.481)	(1.492)	(8.267)	(9.682)
Post_t×Size		-1.210		2.873***
		(0.752)		(0.958)
Post_t×Lev		-0.249		1.670
		(0.215)		(1.626)
Controls		✓		✓
Firm FE	✓	✓	✓	✓
Ind x Post FE	✓		✓	
Quarter FE	✓	✓	✓	✓
Observations	2826	2620	3037	2620
R-squared	0.418	0.450	0.501	0.544

Notes: Includes non-Eurozone USD non-financial corporate issuance, September 2010-June 2018. Post is after June 8, 2016. Estimation is via OLS. Excludes firms that select any new bank underwriter after June 8, 2016. Controls are normalized to variance 1 and include issuer credit rating, tenor, amount issued, firm revenue, the dollar amount issued on day t other than firm i, and the number of underwriting banks. Size refers to total assets, leverage refers to the ratio of total long-term debt to total assets. Standard errors, in parentheses, are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

C.3 Other references

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