Exorbitant Privilege? Quantitative Easing and the Bond Market Subsidy of Prospective Fallen Angels*

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Abstract

We document capital misallocation in the U.S. investment-grade (IG) corporate bond market, driven by quantitative easing (QE). Prospective fallen angels—risky firms just above the IG cutoff—enjoyed subsidized bond financing in 2009-19. This effect is driven by prolonged cumulative Fed purchases of securities inducing long-duration IG-focused investors to rebalance their portfolios towards higher-yielding IG bonds. The benefiting firms (i) exploited the sluggish downward adjustment of credit ratings after M&A to finance risky acquisitions with bond issuances, (ii) increased market share affecting competitors' employment and investment, but (iii) suffered severe downgrades at the onset of the pandemic.

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1 Introduction

The unprecedented scale of monetary policy interventions since the Global Financial Crisis (GFC) has left many commentators wondering whether central banks have left too large a footprint in financial markets, potentially distorting asset prices and capital allocation.[1] Our paper provides novel evidence in this direction by showing that the Federal Reserve's Quantitative Easing (QE) program—especially when the prolonged cumulative purchases peaked—appears to have distorted prices in an important segment of the U.S. corporate bond market, viz., the riskiest BBB-rated bonds, leading to a misallocation of capital in the economy.

By way of motivation, we start with some striking observations (documented in Appendix A) about the corporate bond market. Its size doubled since the GFC, largely driven by the BBB-rated segment. Its growth has resulted in non-financial sector debt being the fastest-growing component of private-sector debt (including household and financial sector debt). Between 2008 and 2020, the amounts outstanding of BBB-rated bonds more than tripled to $3.5 trillion, representing 55% of all investment-grade (IG) debt, up from 33% in 2008. During the same period, BBB spreads dropped from around 400 to around 150 basis points even though the profitability of BBB-rated firms did not keep up with their increased indebtedness and their book and market leverage rose. These dynamics are unique to the BBB segment. Other IG bond spreads did not fall as much and other IG-rated issuers in fact improved their debt-to-profitability and leverage ratios during the same period. Furthermore, risky firms just above the IG cutoff (risky BBB-rated firms)—which face the prospect of becoming "fallen angels" upon a downgrade and experiencing a steep increase in their cost of borrowing—are largely responsible for the growth of the BBB market since 2009.

[1] These concerns were echoed in the remarks made on March 20, 2020 by the Secretary of the Treasury Yellen, who stated that *"Non-financial corporations entered this crisis with enormous debt loads, and that is a vulnerability. They had borrowed excessively in my view through issuing corporate bonds and leveraged loans. Arguably, this was a borrowing binge that was incented by the long period we had of low interest rates. Investors were also engaged in a search for yield, so this debt was attractive to pension funds, insurance companies, and investors [...]"*. Remarks made at the "COVID-19 and the economy" webinar at Brookings (link). See Gilchrist et al. (2020) for details on the effect of the Federal Reserve's intervention on fallen angels.

In many respects, the growth in issuance of risky IG bonds could be considered a desired outcome of monetary policy easing after the GFC. In particular, QE is aimed at pushing investors into riskier assets by lowering the yields on government and mortgage-backed bonds (Gagnon et al., 2011), and lowering in turn the yields on other long-term riskier assets (Krishnamurthy and Vissing-Jorgensen, 2011). However, the growing concentration of issuance in the riskiest IG bucket also comes with a buildup of vulnerabilities in the corporate sector, which materialized at the onset of the COVID-19 pandemic. The volume of debt downgraded from BBB in a few weeks at the beginning of 2020—in many cases by multiple notches—was more than two times larger than the volume of similar downgrades during the *entire* GFC. The materialization of this vulnerability, among other market-wide stresses, led to the Federal Reserve stepping in to stabilize the corporate bond market in April 2020.

In this paper, we investigate these trends, provide detailed evidence that they are—at least in part—a consequence of the QE programs on financial and real sectors, and document their consequences. Specifically, we document the existence of a bond market subsidy for "prospective fallen angels", i.e., downgrade-vulnerable BBB-rated firms which are on the cusp of the IG cutoff. The subsidy originates from a demand for riskier BBB-rated bonds by yield-hungry IG-focused long-term investors highly exposed to QE.[2] In response, prospective fallen angels issue more bonds, largely to finance M&A activity. This way, they (i) meet the heightened investor demand for BBB-rated bonds, and (ii) take advantage of the reluctance of credit rating agencies to downgrade issuers after M&A, effectively guaranteeing that their rating remains BBB for a few more years. This creates, in equilibrium, a privilege in the cost of bond financing of prospective fallen angels. The benefiting firms increase their market share via M&A, exerting negative externalities on other firms that are similar to the congestion effects created by zombie firms on healthier firms (Caballero et al., 2008).[3]

[2]For example, investors such as insurance companies seek out a greater quantity of riskier IG assets to meet their promised liabilities given that IG assets are close substitutes for securities such as Treasuries purchased (and whose yields as a result get compressed) by the Federal Reserve in QE programs, and given that IG assets can be held at relatively low capital requirements.

[3]Anecdotal evidence supports our narrative. For example, consider the consumer product giant Newell Brands, which we classify as a "prospective fallen angel" since 2014. Newell Brands enjoyed bond spreads

We tease out this mechanism by combining various data sources at the issuer-, bond-, and investor-level. We use issuer-level data from Compustat and WRDS Capital IQ, and ratings data from Standard and Poor's, Moody's, and Fitch. Our bond-level data consists of primary market prices from Mergent and secondary market prices from TRACE. Finally, for a crucial part of our analysis that highlights the demand for bonds from investors exposed to QE, we use investor security-level holdings data from eMAXX Bond Holders from Refinitiv matched with holdings in the Federal Reserve System Open Market Account (SOMA) portfolio.

We begin our empirical analysis by introducing a measure of downgrade-vulnerability based on the Altman Z"-score (Altman, 2020), a variable built with balance sheet and income statement information. Specifically, we classify a firm as "downgrade-vulnerable" if its Z"-score is lower than the historical median Z"-score of the next lowest rating category. We confirm the validity of our measure by documenting that downgrade-vulnerable firms (i) look worse along various observable firm characteristics, such as leverage, profitability, net worth, and interest coverage ratio; (ii) exhibit lower employment growth, investment, sales, and asset growth once they become downgrade-vulnerable; and (iii) are more likely to be downgraded or put on negative watchlist/outlook than non-downgrade-vulnerable firms.

Using this measure, we define a "prospective fallen angel" as a BBB-rated firm that is vulnerable to being downgraded. We show that prospective fallen angels benefit from a reduction in bond spreads relative to the rest of the BBB segment, especially from September 2012 (QE3) to the withdrawal of monetary stimulus between November 2015 (lift-off of the Federal Funds rate from the effective lower bound) and September 2017 (Quantitative Tightening, or QT). Crucially, this pattern—lower spreads for downgrade-vulnerable firms in a rating category—is not present for other rating classes. This pattern is also not

30–50 basis points below the median bond spreads of BBB-rated firms and used this cheap financing, at least partly, to finance acquisitions from 2014 to 2017. For example, Newell Brands acquired Jarden in 2016, leading to an increase in leverage (gross debt/EBITDA) from 3 to 4.5. While the acquisition was accompanied by a promise to delever to 3–3.5 in 2–3 years, Newell Brands became more fragile post-M&A, an evolution not reflected by its credit ratings. In 2015, S&P rated the firm BBB- while our balance sheet implied rating was just B. S&P maintained a BBB- rating until 2018 even though our balance sheet implied rating dropped to CCC+ by that time. Newell Brands became eventually a fallen angel, dropping below the IG cutoff in 2019.

observed in corporate bond markets pre-2009. Moreover, when replacing bond spreads with equity-market-based measures of expected default, or spreads in syndicated loan markets, or bond spreads before the GFC, we find that across all rating categories (including BBB), downgrade-vulnerable firms have higher—not lower—funding costs. In other words, we identify for the BBB-rated firms a corporate bond market *subsidy*, which we refer to as the "exorbitant privilege" of prospective fallen angels. We estimate that, depending on reasonable assumptions, the bond market subsidy accruing to prospective fallen angels amounted to between \$47 billion and \$129 billion between 2009 and 2019.

We provide a conceptual framework that helps understand why investors price the riskiest IG bonds with a subsidy. As the duration of QE becomes prolonged and the stock of securities purchased by the Fed expands (e.g., by QE3 when the stock surpassed \$3 trillion), financial institutions such as insurance companies hold more and more of securities such as corporate bonds which incur higher capital requirements relative to the securities (such as Treasuries and Agency MBS) purchased by the Fed. This rebalancing induces in these investors a preference for IG bonds, which incur a relatively lower capital charge, and especially for those IG bonds which have higher yields but are the least likely to be downgraded, as this lowers the expected capital charge over the holding period. In equilibrium, this search for "capital efficiency" by institutional investors is met by subsidized bond issuances of prospective fallen angels to finance M&A with (eventually broken) promises of debt reduction, as prospective fallen angels benefit the most from the sluggishness of credit rating agencies to a downward rating adjustment.

Our empirical tests seek to identify these driving mechanisms behind the subsidy and are structured in three parts. First, we show that investors exposed to QE drive the demand for corporate bonds issued by prospective fallen angels as they rebalance their portfolio away from Treasuries, especially during QE3. We define investor-level time-varying QE exposure as the share of investors' total Treasury holdings that are purchased by the Federal Reserve. Exploiting the granularity of our bond holdings data, we compare in each quarter holdings of bonds issued by the *same* firm that are held by investors with a different exposure to QE.[4] We find that the correlation between investor exposure to QE and investor bond holdings is more pronounced for (i) bonds issued by prospective fallen angels, and (ii) long-duration investors that invest mostly in IG bonds, in particular, insurance companies with minimum guarantee variable annuities and open-ended debt mutual funds focused on IG bond investments.

Second, we show that prospective fallen angels meet the QE-induced demand of IG investors by supplying bonds largely for the purpose of financing risky acquisitions. These M&A deals allow prospective fallen angels to delay downgrades. In particular, the short-term probability of being downgraded to speculative grade is close to zero for prospective fallen angels that conduct an M&A transaction. Announcements effects of these acquisitions in the stock market suggest that they are value-destroying. However, announcements are usually accompanied by a promise by firms to the public to reduce the debt taken on to finance the acquisitions, which induces rating agencies to be more sluggish in downgrading these firms: data indicate that these mostly end up being broken promises. The resulting buildup of vulnerability of these firms over the extended period of QE led to an unprecedented wave of fallen angels that were downgraded often by multiple notches at the onset of the COVID-19 pandemic.

Third, we find that across rating classes, BBB-rated firms have the highest market share by sales that has been increasing over the last decade, and this increase is entirely driven by the prospective fallen angels that engaged in M&A activity. We then show that this dynamic adversely affects competing firms and has real spillovers. Non-downgrade-vulnerable IG firms operating in an industry with a larger share of prospective fallen angels have lower employment growth rates, lower investment levels, lower sales growth rates, and lower markups compared with non-downgrade-vulnerable firms operating in an industry with a lower share of prospective fallen angels. Crucially, we do not find negative spillover effects

[4] In addition to helping understand the mechanism behind the subsidy for prospective fallen angels, the *within-firm* test based on QE-exposure of different investors clarifies that it is unlikely that the bond-market subsidy we uncover is driven by a BBB-firm-level "error" in Altman Z"-score rendering it mistakenly as a downgrade-vulnerable firm.

when focusing on the overall share of downgrade-vulnerable firms (not just BBB-rated), highlighting that the spillover effects arise only from prospective fallen angels which enjoy the exorbitant privilege in bond markets from long-duration IG-focused QE-exposed investors.

The remainder of the paper is structured as follows. Section 2 discusses the related literature. Section 3 presents the data, our measure of downgrade vulnerability, and the definition of prospective fallen angels. Section 4 documents that prospective fallen angels have benefited from a bond financing subsidy—especially with QE3 until the withdrawal of monetary stimulus with the lift-off of the Federal Funds rate and QT. Section 5 shows that this subsidy originates from the demand for high-yield, yet IG, corporate bonds as investors rebalanced their portfolios away from Treasuries. Section 6 documents the sizable increase in M&A activity of prospective fallen angels and explains how this dynamic is consistent with an equilibrium response to the QE-induced demand for riskier IG bonds. Section 7 quantifies the overall bond market subsidy enjoyed by prospective fallen angels and discusses its industry spillovers. Section 8 concludes.

2 Related literature

Our findings contribute to four inter-related strands of literature.

First, we contribute to the literature on the transmission of QE. This large literature has documented the effect of QE on asset prices (e.g., Krishnamurthy and Vissing-Jorgensen (2011)), lending outcomes (e.g., Acharya et al. (2019); Luck and Zimmermann (2020); Rodnyansky and Darmouni (2017)), and firm financing constraints (e.g., Di Maggio et al. (2020); Foley-Fisher et al. (2016)). In terms of macroeconomic outcomes, Fabo et al. (2021) documents that only half of the academic papers find a statistically significant effect of QE on output. Our paper documents QE-induced capital misallocation, especially once the QE cumulative purchases peaked with QE3, that might contribute to financial vulnerability such as the materialization of corporate bond market stress at the onset of the pandemic. In this vein, our paper is related to speeches by Rajan (2013) and Stein (2013) who warned about the risks of QE in terms of excessive financial risk-taking; while they focused on likely distortions in the speculative-grade bond market, leveraged loan market, and real-estate investment trust

(REIT) borrowings, our paper shows that distortions have materialized even in the space of investment-grade bonds.

Second, we contribute to the literature on fragility in corporate borrowing markets. The documented vulnerability of the IG bond market since 2009 is consistent with warning signs from academics and practitioners about the BBB market (Altman, 2020; S&P Global, 2020a; Çelik et al., 2020; Blackrock, 2020; Morgan Stanley, 2018a,b) and partly explains the large price drop of IG corporate bonds at the onset of the COVID-19 pandemic (Haddad et al., 2021; Boyarchenko et al., 2022; Altman, 2020).[5] The special role of the BBB market is consistent with the role of fire-sale "cliff" risk documented in the literature (Falato et al., 2021a,b; Gilchrist et al., 2020; Acharya and Steffen, 2020). More generally, our findings are also related to the literature on the misallocation of bank credit (Caballero et al., 2008; Acharya et al., forthcoming) and of other forms of financing (Midrigan and Xu, 2014; Whited and Zhao, 2021), as well as on the role of low interest rates on misallocation (Banerjee and Hofmann, 2018, 2020). Our findings also fit the broader historical evidence documenting that low credit spreads and credit growth increase the probability of financial crises (Krishnamurthy and Muir, 2020; Gilchrist and Zakrajsek, 2012; Greenwood et al., 2022) and the literature on the distribution of financially unsound firms (Atkeson et al., 2017).

Third, we contribute to the literature on the real effects of frictions in investor portfolio choice. Consistent with the framework in Vayanos and Vila (2021), a few recent papers document the role of bond investors in the transmission of monetary policy (e.g., Ahmed et al. (2022); Darmouni et al. (2021)).[6] Our paper documents that the reliance of some bond investors on the IG cutoff has interacted with QE policies—especially via their impact on yields of long-duration assets—to create capital misallocation and buildup of vulnerabilities

[5]Haddad et al. (2021) shows that the extreme price movements at the onset of the COVID-19 pandemic were mostly in the safer end of the investment-grade market, consistent with investors trying to liquidate a large set of positions in bonds. See also Ivashina and Vallée (2022) for an analysis of fragility and reaching-for-yield behavior in the leveraged loan market.

[6]See also Kubitza (2021) and Greenwood and Vissing-Jorgensen (2018) that analyze how the portfolio choice of insurance companies affects firms and the yield curve, respectively. Li and Yu (2022) shows that investor concentration plays an important role in corporate bond pricing and liquidity.

in the massive BBB corporate bond market.

Fourth, we contribute to the literature on credit ratings. A large body of literature has shown that credit ratings affect investors' portfolio choice (Guerrieri and Kondor, 2012; Cornaggia and Cornaggia, 2013; Iannotta et al., 2019; Baghai et al., 2022). Becker and Ivashina (2015) shows that, within rating categories, investors reaching-for-yield might tilt their portfolio towards riskier assets. Goldstein and Huang (2020) shows that this behavior might, in equilibrium, induce credit rating agencies to inflate their ratings. Credit ratings inflation is discussed in, among others, Herpfer and Maturana (2021) that shows that credit rating agencies are less likely and slower to downgrade firms with "performance-sensitive debt". Finally, our paper is also related to Aktas et al. (2021) that shows that investment-grade firms are concerned about acquisition-related downgrades in their M&A activity. However, we find that such concern appears to be muted in the case of prospective fallen angels due to QE-induced demand for their bonds and the sluggishness of credit rating agencies in downgrading after M&A.

Overall, our results point out that the recent vulnerability in corporate bond markets may be due to a rather complex interaction of the distorted incentives of financial institutions and investors in response to easy monetary policy, and the sluggishness of rating agencies in responding to foreseeable risks. In this sense, our results are reminiscent of the rich interplay of forces at work in leading to the mortgage excess around AAA-rated mortgage-backed securities in the buildup to the GFC (Gennaioli and Shleifer, 2018).

3 Identifying prospective fallen angels

In this section, we (i) describe our data sources and construction (Section 3.1); (ii) introduce our definition of downgrade-vulnerable firms, showing the sluggishness of credit rating agencies in downgrading BBB-rated firms to speculative grade (Section 3.2); and, (iii) document the realized fragility of BBB-rated downgrade-vulnerable firms during COVID-19 (Section 3.3).

3.1 Data

Our main data set consists of firm-level, bond-level, and investor-level data from 2009 to 2019, described in detail in Appendix C. The firm-level data includes debt capital structure data, balance sheet information, and rating information. The debt capital structure data is from WRDS Capital IQ, which provides information for over 60,000 public and private companies globally. The balance sheet data is from Compustat North America, which provides annual report information of listed American and Canadian firms. Rating information is from Refinitiv Eikon, which provides worldwide coverage on ratings from S&P, Moody's, and Fitch. We follow Becker and Milbourn (2011) in mapping credit ratings into numerical values (see Appendix C). Lastly, we use ThomsonOne for mergers and acquisitions data. Combining these various data sources, we analyze 6,145 firms.

The bond-level data set consists of pricing information for the U.S. corporate bond market. For the primary market, we use Mergent Fixed Income Securities Database (FISD), which includes issue details of publicly-offered U.S. bonds. We examine 7,891 bond issues by 1,329 issuers. For the secondary market, we obtain data from TRACE database of real-time secondary market information on transactions in the corporate bond market. We examine 7,065 outstanding bonds issued by 916 firms. To compute primary and secondary market corporate bond spreads, we follow Gilchrist and Zakrajsek (2012) and compute the spread relative to the yield on a synthetic U.S. Treasury with the same cash flows as the corporate bond. In addition, we follow Faust et al. (2013) and further adjust the spreads of callable bonds to account for the influence of risk-free rates on the option value of these bonds. In our analysis of the COVID-19 crisis, we extend our data set to 2020.

The investor-level data is from eMAXX Bond Holders data from Refinitiv security-level holdings by individual investors at a quarterly frequency.[7] We match this data with the Federal Reserve's security-level holdings in the SOMA portfolio (this data is publicly available on the website of the New York Fed). We further match this data with issuer- and security-

[7] This data set has been used in several papers in the literature, including Becker and Ivashina (2015), Bretscher et al. (2022), and Cai et al. (2019).

level data from the rest of our analysis and collapse holdings within an investor at the issuer-level. The investor-level data has information on 7,253 investors, mostly property and casualty insurers (1,996), open-ended mutual funds (1,948), (other) life and health insurers (1,174), and insurers with annuities with minimum guarantees (674). The investor-level data covers around 20%-25% (depending on the date and rating category) of the stock of corporate bonds outstanding.

3.2 Downgrade-vulnerable firms

We define "downgrade-vulnerable" firms based on the Altman Z"-score, a measure of credit risk calculated from income statement and balance sheet information (Altman, 2020). The Altman Z"-score is defined as:

$$Z" = 3.25 + 6.56 \times \frac{Curr.\,Assets - Curr.\,Liabilities}{Total\,Assets} + 3.26\frac{Retained\,Earnings}{Total\,Assets} + 6.72\frac{EBIT}{Total\,Assets} + 1.05\frac{Book\,Value\,of\,Equity}{Total\,Liabilities}$$

Specifically, we classify a firm as downgrade-vulnerable if its Z"-score is lower than the historical median Z"-score of the next lowest rating category.[8] For example, a BBB-rated firm is classified as downgrade-vulnerable if its Z"-score is below the median Z"-score of BB-rated firms. A "prospective fallen angel" is a BBB-rated firm classified as downgrade-vulnerable.

We validate our measure of downgrade-vulnerability in Appendix D.1, where we show that (i) downgrade-vulnerable firms look worse along observables compared with non-downgrade-vulnerable firms (e.g., lower net worth, sales growth, investments, employment growth, interest coverage ratio, profitability, and higher leverage); (ii) firms' performance deteriorates after becoming downgrade-vulnerable (decline in sales growth, investments, firm size, and employment); and (iii) downgrade-vulnerable firms are more likely to be downgraded and to be assigned a negative credit watch or outlook relative to non-downgrade-vulnerable firms.[9]

[8] We thank Ed Altman for providing us with these median "benchmark" Z"-scores for each rating category. The bond rating equivalents are determined by calibrating the Z"-scores to median values of each of the S&P rating categories for various years over the last 50 or more years (Altman, 2020). For a discussion on Z"-models, we refer to Altman (2018) and Altman et al. (2019).

[9] We also document that the post-GFC to pre-COVID growth of the BBB market is driven by prospective

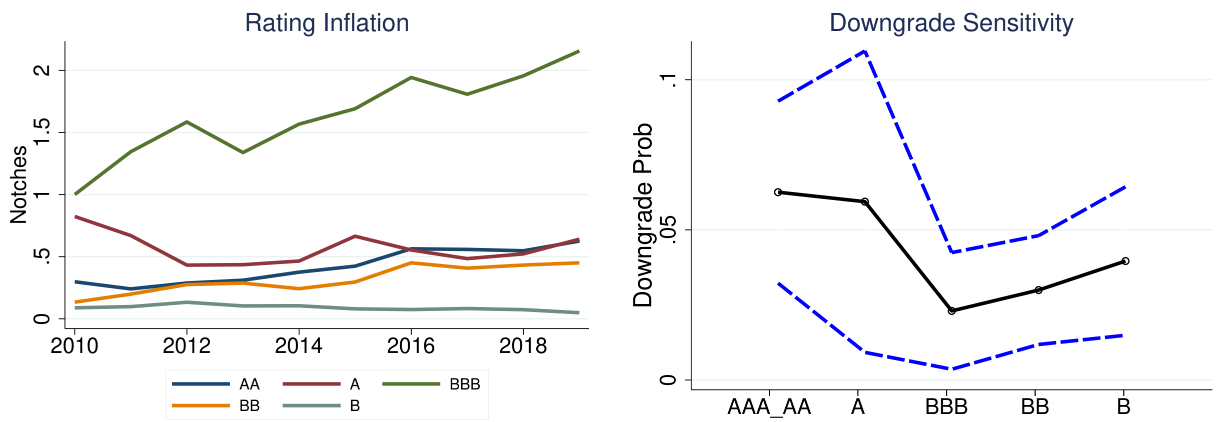

Figure 1: High and rising credit ratings inflation for BBB-rated issuers. This figure shows credit ratings inflation across rating categories. The left panel shows asset-weighted credit ratings inflation. Credit ratings inflation is equal to zero if an issuer has a Z"-score above the median Z"-score of firms in the next lower rating category, otherwise credit ratings inflation is calculated as the number of notches between the issuer's credit rating notch (e.g., AA+, AA, AA-, A) and the credit rating notch implied by its Z"-score. The right panel shows the sensitivity of downgrades of downgrade-vulnerable issuers relative to non-downgrade-vulnerable issuers by rating category. Specifically, the figure shows the estimated coefficient, β_1, from the following regression specification estimated in each rating category separately: $Y_{it+1} = \beta_1 Vulnerable_{it} + \beta_2 X_{it} + \mu_{ht} + \epsilon_{it+1}$, where i is a firm, h an industry, t a year, Y_{it+1} is a dummy equal to one in the case of a downgrade event in $t+1$, $Vulnerable_{it}$ is a dummy equal to one if a firm is downgrade-vulnerable in period t, μ_{ht} are industry-year fixed effects, and X_{it} is a vector of controls (log of total assets, leverage, and interest coverage ratio). Dashed lines show 95 percent confidence intervals, with standard errors clustered at the firm-level.

The validation exercise also uncovers that BBB-rated downgrade-vulnerable firms appear to be treated differently by rating agencies compared to other downgrade-vulnerable firms. Specifically, we document a substantial and increasing ratings inflation for BBB-rated issuers which markedly increased after 2009 (Figure 1, left panel), where ratings inflation is defined as the difference between the issuer credit rating notch (e.g., AA+, AA, AA-) and the credit rating notch implied by its Z"-score for issuers that have a Z"-score below the median of firms in the next lower rating category or zero otherwise.[10] In addition, the right panel of

fallen angels (Figure A.2). Since 2009, the stock of BBB bonds outstanding tripled in size to \$1.5 trillion in 2018. During the same period, the non-downgrade-vulnerable BBB-rated segment increased only from \$0.2 to \$0.5 trillion. While the risk in the BBB segment increased substantially, bond spreads of BBB-rated firms decreased over our sample period (see Figure A.5).

[10]For example, Bruno et al. (2016) shows that Moody's avoids downgrading issuers of corporate bonds that are close to losing their investment-grade status. Investment bank analysts paint a similar picture of ratings inflation. For example, in 2018, a research note by Morgan Stanley noted that, *"... where 55% of BBB debt would have a speculative-grade rating if rated based on leverage alone. Meanwhile, interest coverage*

Figure 1 shows that although downgrade-vulnerable firms are more likely to be downgraded in each rating bucket compared to their non-downgrade-vulnerable peers, this correlation is the weakest for BBB-rated issuers. Both these findings are consistent with other studies and anecdotal evidence on the sluggishness of rating agencies in downgrading BBB-rated firms to speculative grade.

3.3 Prospective fallen angels during COVID-19

The downgrade vulnerability of BBB-rated firms, and especially prospective fallen angels, manifested itself during COVID-19. The volume of debt downgraded from BBB to speculative-grade in just a few weeks at the beginning of 2020 was more than two times larger than the volume of similar downgrades during the entire Global Financial Crisis. Figure 2 shows that, in 2020, the total debt of fallen angels amounted to an unprecedented $320 billion of which the vast majority was debt of firms classified as prospective fallen angels before the COVID shock. This wave of fallen angels only stopped when the Federal Reserve expanded its corporate buying program on April 9, 2020 to include those issuers downgraded from BBB to fallen angels between March 22, 2020 and April 9, 2020.[11]

Furthermore, a formal test shows that BBB firms with more inflated credit ratings experienced sharper increases in spreads in 2020. Specifically, using the following specification, we relate the degree of ratings inflation at the start of 2020 with the change in a firm's bond spreads:

$$\Delta Spread_{bi} = \beta_1 \text{Ratings Inflation}_i + \beta_2 X_i + \phi_h + \epsilon_{bi}, \tag{1}$$

where $\Delta\, Spread_{bi}$ is the change in secondary market spread between January 2020 and March 2020 of bond b of firm i, Ratings Inflation_i is the difference between the issuer rating at the start of 2020 and the implied rating based on Altman Z"-score, X_i are firm (log) assets, and

has declined steadily since 2014, particularly for BBB issuers..." (Morgan Stanley, 2018a).

[11] Some examples of firms eligible for the program are Ford Motor, Macy's, and Occidental Petroleum (S&P Global, 2020b), all of which are classified as prospective fallen angels in our data.

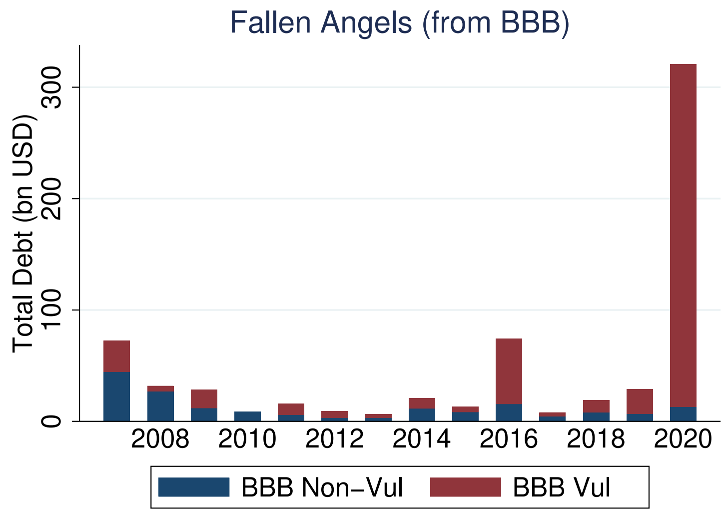

Figure 2: Risk materialization during COVID-19. This figure shows that the vulnerability of the BBB market materialized at the onset of the COVID-19 pandemic. The figure shows total debt downgraded from BBB to speculative-grade for (non-)downgrade-vulnerable firms from 2007 to 2020.

ϕ_h are industry fixed effects. Table 1 presents our results. In Column (1), we show that for downgrade-vulnerable BBB firms, issuers with higher ratings inflation experienced a greater widening of their spreads in the first months of the pandemic. In particular, a one-notch inflated issuer rating is on average associated with a 16 basis points increase in bond spreads for prospective fallen angels. In contrast, the second column shows that no such relationship exists for the other downgrade-vulnerable investment-grade rated firms.

We interpret this episode as ex-post evidence of the increased vulnerability of BBB-rated firms, and of prospective fallen angels in particular, in conjunction with lack of such observed vulnerability for other IG ratings.

	ΔSpread	ΔSpread
Rating Inflation	16.245***	1.099
	(6.103)	(5.124)
Sample	Vuln. BBB	Vuln. A-AAA
Industry FE	✓	✓
Firm Controls	✓	✓
Observations	699	380
R-squared	0.501	0.478

Table 1: Change in spreads at the onset of COVID-19. This table presents estimation results from the bond-level regression (1) in the subsample of downgrade-vulnerable firms. The dependent variable is ΔSpread, defined as the change in secondary market spread between January 2020 and March 2020 of a single bond. The independent variable is Ratings Inflation, defined as the issuer rating at the start of 2020 minus the implied rating based on Altman Z"-score. We add firm log assets as firm control and a set of industry fixed effects. In the first column, the subsample consists of BBB rated firms. In the second column, the subsample consists of non-BBB investment-grade rated firms. Standard errors are clustered at the firm j level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4 The exorbitant privilege

In this section, we document the extraordinarily low bond financing costs of prospective fallen angels—BBB-rated downgrade-vulnerable firms—since 2009, which we call the "exorbitant privilege". We find that this subsidy emerges with QE3 in September 2012 and diminishes with the withdrawal of monetary stimulus with the lift-off of the Federal Funds rate and QT.

Non-parametric evidence. To describe the time-series of the exorbitant privilege, Figure 3 plots the difference in secondary market spreads between downgrade-vulnerable and non-downgrade-vulnerable BBB issuers as well as those rated AAA-A and BB. The difference in the spread between downgrade-vulnerable and non-downgrade-vulnerable BBB-rated firms is (i) generally positive until the GFC; (ii) *negative* from QE3 until the withdrawal of monetary stimulus; and, (iii) almost always smaller than the same difference for the AAA-A and BB segments over the same period, which by and large tend to be positive.[12]

[12] Appendix D.2 provides additional descriptive statistics on bond-level characteristics, showing that, within each rating category, secondary market spreads of bonds issued by downgrade-vulnerable firms are higher than those of their non-downgrade-vulnerable peers across the distribution. The one exception is the BBB segment where downgrade-vulnerable firms had *lower* spreads across the distribution between 2009 and 2019.

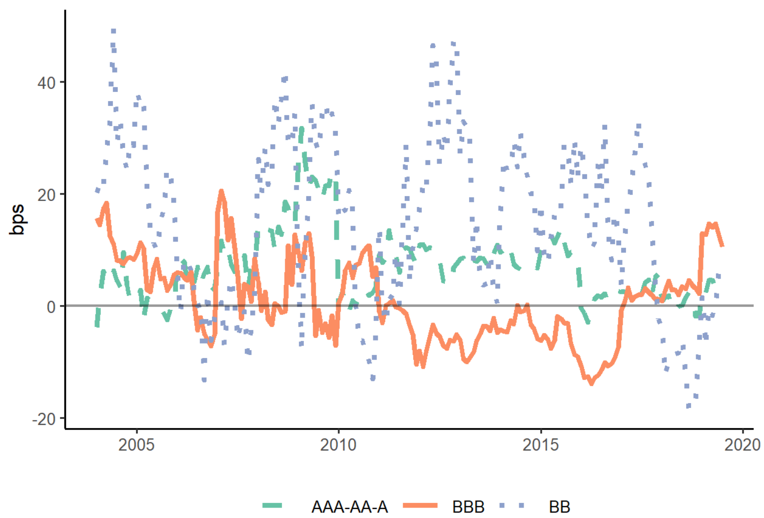

Figure 3: Bond spreads: downgrade-vulnerable minus non-downgrade-vulnerable issuers. This figure shows the difference in secondary market spreads between downgrade-vulnerable and non-downgrade-vulnerable issuers for issuers rated AAA, AA and A (dashed line), BBB (solid line), and B (dotted line), controlling for year×month fixed effects and bond-level controls for remaining maturity, offering amount, coupon and dummy variables for callable, convertible and senior bonds.

Parametric test. We confirm the emergence of this privilege for prospective fallen angels in bond markets using a formal test that compares the bond spreads of downgrade-vulnerable and non-downgrade-vulnerable firms *within* a rating category:

$$\begin{aligned}\text{Spread}_{bit} =& \boldsymbol{\beta_1}\textbf{Rating}_{it} + \boldsymbol{\beta_2}\text{Vulnerable}_{it} \times \textbf{Rating}_{it} \\ &+ \boldsymbol{\delta}\mathbf{X}_{bt} + \boldsymbol{\gamma}\textbf{Liquidity}_{bt} \times \textbf{Rating}_{it} + \boldsymbol{\mu}_{ht} + \epsilon_{bit} \end{aligned} \tag{2}$$

where Spread_{bit} is the spread (in basis points) of bond b issued by firm i in period t. We reiterate that we follow (i) Gilchrist and Zakrajsek (2012) and compute spreads relative to the yield on a synthetic US Treasury with the same cash flows as the corporate bond and (ii) Faust et al. (2013) to further adjust the spreads of callable bonds to account for the influence of risk-free rates on the option value of these bonds. As Becker et al. (2021) shows, changes in credit quality can also influence the spread on bonds with a call option. We therefore include control variables to absorb the influence of changes in credit quality on callable bond spreads by adding an indicator variable for callable bonds, another for bonds which are trading above par but below a price of 105 as well as the interaction of the two.[13] $\mathbf{Rating}_{it}$ is a vector of dummy variables corresponding to firm's i rating in period t and Vulnerable$_{it}$ is an indicator variable equal to one if issuer i is classified as downgrade-vulnerable in year $t-1$ and year t and retains the same rating across both years.[14] We include a vector $\mathbf{X}_{bt}$ of bond-level characteristics (remaining maturity, log of the offering amount and dummy variables taking the value of one for bonds with covenants, convertible bonds and senior bonds, respectively). We also include control variables to capture the influence of bond liquidity on spreads by adding bid-ask spreads which we allow to vary by rating bucket, $\mathbf{Liquidity}_{bt} \times \mathbf{Rating}_{it}$. We further include industry-year-month fixed effects $\boldsymbol{\mu}_{ht}$ to absorb unobserved time variation in spreads within an industry. Due to the relatively low number of bonds with a AAA rating, we combine AAA-rated and AA-rated firms into one category.

Table 2 presents the estimation results. Panel A shows the estimation result for secondary market spreads. The first column shows results estimated over the full sample period. The interaction terms between ratings and the vulnerable firm dummy variable show that in all rating categories, *except* BBB, downgrade-vulnerable firms have either higher financing costs (AAA-AA, BB, B ratings) or statistically indistinguishable financing costs (A rating) compared with non-downgrade-vulnerable firms.[15]

The remaining columns show estimates in subsamples covering the different phases of the Federal Reserve's monetary policy stance from QE1 until QT. The second column shows estimates during QE1 (November 2008 until June 2010). During this period, the Vulnerable $\times$ BBB coefficient is negative but statistically insignificant. The third column shows estimates in the subsample starting with QE2 until the start of QE3 (November 2010

[13]As shown in Table D.3, around 90% of bonds in our sample are callable. Since 2010, the share has remained relatively constant. Our estimated regression coefficient suggests that when callable bonds trade close to the call barrier they trade at a 40 basis point discount to non-callable bonds, not far from Becker et al. (2021) estimates based on matched bonds from the same issuer.

[14]Results are qualitatively and quantitatively similar if we employ a less stringent definition and define downgrade-vulnerable firms simply based on whether they are classified as downgrade-vulnerable in year t.

[15]See Table D.4 for estimates of the uninteracted rating variables. In Table D.7 we show that these results are robust to using bond instead of issuer rates and in Table D.8 we show the results are robust to the further controls for bond liquidity captured by the number of times a bond is traded within a month or whether the bond is a newly issued on-the-run bond, or a seasoned off-the-run issue.

Panel A	Secondary market spread					
	Full sample	QE1	QE2 until QE3	QE3 until FFR	QE3 until QT	QT
Vulnerable × AAA-AA	10.671**	-7.713	17.286*	14.645***	11.602***	4.959
	(4.397)	(25.104)	(9.521)	(4.930)	(3.913)	(4.582)
Vulnerable × A	5.260	11.019	12.949**	8.190*	5.289	-1.255
	(3.490)	(7.574)	(5.954)	(4.191)	(4.221)	(4.797)
Vulnerable × BBB	-5.533**	-5.717	-1.790	-7.047**	-10.034***	2.048
	(2.659)	(6.996)	(4.867)	(3.245)	(3.145)	(3.330)
Vulnerable × BB	19.190***	9.719	7.723	21.910***	30.272***	10.088
	(5.451)	(9.034)	(8.597)	(7.510)	(8.192)	(9.165)
Vulnerable × B	26.171***	53.274**	36.133**	31.824**	23.233**	-44.679*
	(9.060)	(23.818)	(13.336)	(13.136)	(11.065)	(23.786)
Industry-Year-Month FE	✓	✓	✓	✓	✓	✓
Bond-level controls	✓	✓	✓	✓	✓	✓
Observations	247,165	23,996	33,312	73,858	122,657	53,824
R-squared	0.724	0.733	0.739	0.744	0.757	0.760

Panel B	Primary market spread					
	Full sample	QE1	QE2 until QE3	QE3 until FFR	QE3 until QT	QT
Vulnerable × AAA-AA	13.584		113.929	16.438	10.943	
	(14.844)		(113.187)	(21.570)	(17.758)	
Vulnerable × A	11.866	16.285	12.421	22.354*	22.515**	-2.163
	(8.637)	(21.759)	(21.123)	(11.216)	(11.007)	(23.233)
Vulnerable × BBB	-27.502***	-37.305	-12.712	-28.881*	-32.975***	-23.633**
	(7.633)	(28.359)	(10.304)	(14.855)	(11.672)	(9.442)
Vulnerable × BB	37.677**	78.725	69.409**	21.839	23.956	1.426
	(15.733)	(51.909)	(27.611)	(18.112)	(22.044)	(29.709)
Vulnerable × B	64.410***	62.978	54.904	52.436	73.449**	
	(22.709)	(47.857)	(39.126)	(43.976)	(33.317)	
Industry-Year-Month FE	✓	✓	✓	✓	✓	✓
Bond-level controls	✓	✓	✓	✓	✓	✓
Observations	2,761	287	405	985	1,534	477
R-squared	0.876	0.896	0.896	0.904	0.889	0.851

Panel C	Δ Secondary market spread					
	Full sample	QE1	QE2 until QE3	QE3 until FFR	QE3 until QT	QT
Vulnerable × AAA-AA × D(event day)	0.1468	0.4247	-1.015	-0.2442	0.1354	-0.5118
	(0.2401)	(0.9713)	(0.7947)	(0.4102)	(0.2672)	(0.6654)
Vulnerable × A × D(event day)	0.3618	2.144**	-0.6229	0.1039	-0.1403	0.5761
	(0.2707)	(1.005)	(0.6013)	(0.2984)	(0.2511)	(0.6718)
Vulnerable × BBB × D(event day)	-0.0051	0.8682	0.3090	-0.6846**	-0.2539	-0.0834
	(0.2430)	(1.667)	(0.3946)	(0.3235)	(0.2676)	(0.2692)
Vulnerable × BB × D(event day)	0.1125	0.7609	1.226	-0.5375	0.2087	-0.9219
	(0.6089)	(1.526)	(1.553)	(0.9724)	(0.8280)	(1.871)
Vulnerable × B × D(event day)	1.072	-1.787	-1.015	2.205	2.048	0.8380
	(1.240)	(4.426)	(2.029)	(2.092)	(1.943)	(1.934)
Industry-Year-Month-Day FE	✓	✓	✓	✓	✓	✓
Bond-level controls	✓	✓	✓	✓	✓	✓
Observations	2,432,415	184,764	220,548	501,154	950,273	555,720
R-squared	0.17388	0.19163	0.18192	0.12759	0.12888	0.11865

Table 2: The exorbitant privilege of prospective fallen angels. Panels A and B show the estimation results of specification (2), Panel C shows the estimation results of the event study with specification (3). Panel A dependent variable: secondary market bond spread, Panel B: primary market spread, Panel C: one day change in the secondary market spread. Bond spreads are measured in basis points. Vulnerable is a dummy variable equal to 1 if issuer i is downgrade-vulnerable in date $t-1$ and t. D(event day)_t is a dummy variable indicating monetary policy announcements days in which the 10-year Treasury futures contract declined in a short event window. Additional bond-level controls include residual maturity, amount outstanding and bid-ask spreads. Coefficients on the latter are allowed to vary by rating. The specification also includes dummy variables for senior bonds, callable bonds, bonds with a price above par but below a price of 105 and the interaction between the latter two variables to account for changes in credit quality affecting spreads on callable bonds. These control variables are included in the estimation but not reported for brevity. Also omitted for brevity are the coefficients on the uninteracted ratings. Standard errors in panels A and B are clustered at the firm and year-month level. In Panel C they are clustered at firm and year-month-day level. *** p<0.01, ** p<0.05, * p<0.1.

to September 2012). Again, the Vulnerable × BBB coefficient is statistically insignificant. The fourth and fifth columns show estimates for the subsamples starting with QE3 and ending with either the lift-off of the Federal Funds rate (September 2012 to November 2015) or the start of QT (September 2012 to September 2017), respectively. Estimates for these two periods show that the Vulnerable × BBB coefficient is negative and statistically significant. The exorbitant privilege appears to emerge with QE3. Finally, the sixth column shows that the privilege disappears from secondary markets in the QT period (October 2017 to September 2019).

Panel B shows similar estimation results using primary market offering spreads as the dependent variable. Notwithstanding the smaller sample of observations relative to Panel A, the estimates again indicate that the downgrade-vulnerable BBB funding subsidy consistently emerged with QE3. The point estimates of the subsidy in primary markets during the QE3 to QT period are somewhat higher compared with the results based on secondary market spreads. The sixth column shows that the subsidy diminishes in magnitude, but remains statistically significant during the QT period in contrast to the results from secondary market bond spreads.[16]

Event study. We further examine the privilege for prospective fallen angels with an event study analysis by estimating the following specification:

$$\begin{aligned}\Delta\text{Spread}_{bit} =& \boldsymbol{\beta_1}\textbf{Rating}_{it} + \boldsymbol{\beta_2}\text{Vulnerable}_{it} \times \textbf{Rating}_{it} \\ &+ \boldsymbol{\beta_3}\textbf{Rating}_{it} \times \text{D(event day)}_t + \boldsymbol{\beta_4}\text{Vulnerable}_{it} \times \textbf{Rating}_{it} \times \text{D(event day)}_t \\ &+ \boldsymbol{\delta}\mathbf{X}_{bt} + \boldsymbol{\gamma}\textbf{Liquidity}_{bt} \times \textbf{Rating}_{it} + \boldsymbol{\mu}_{ht} + \epsilon_{bit} \qquad (3)\end{aligned}$$

where $\Delta\text{Spread}_{bit}$ is the one day change in the corporate bond spread (in basis points) and D(event day)_t is a dummy variable equal to one for expansionary monetary policy announcement days, i.e., days when the yield on 10-year Treasury futures contract declined

[16]See Table D.5 for estimates for the uninteracted rating variables.

within a −15 to +15 minute window around the monetary policy announcement. For press conferences and release of minutes the window is slightly longer, from −15 to +90 minutes, given that these communications are more extensive and contain broader information which may take longer for investors to process. The monetary policy announcement dates are from Cieslak and Schrimpf (2019), updated to end 2019.

Panel C of Table 2 shows event study estimates with the same sample splits as Panel A and Panel B. The event study analysis shows that the bond spreads of downgrade-vulnerable BBB firms declined relative to the non-downgrade-vulnerable BBB peers on monetary policy event days during the period including QE3 until the Fed Funds rate lift-off in November 2015 (fourth column).[17] In all other periods, monetary policy announcements did not have significantly different effects on the spread between downgrade-vulnerable and non-downgrade-vulnerable firms with the exception of QE1 when spreads on A-rated vulnerable issuers increased. Taken together, the results in Table 2 suggest that the exorbitant privilege of prospective fallen angels emerged with QE3 and diminished with the Federal Reserve's withdrawal of monetary stimulus.

Exorbitant privilege uniquely a QE3 bond market phenomenon. Table 3 shows that this privilege is unique to the corporate bond market in the last decade. The first two columns use the (log) expected default frequency derived from equity markets at the 2-year horizon as the dependent variable for the full sample and the QE3 until the Fed Funds rate lift-off period, respectively. While we confirm that the estimated coefficients on the uninteracted terms increase monotonically as ratings deteriorate, downgrade-vulnerable BBB firms have significantly higher EDFs compared to their non-downgrade-vulnerable peers suggesting that the exorbitant privilege is not evident in equity markets. Rather, equity markets view downgrade-vulnerable BBB firms as more risky than their non-downgrade vulnerable peers.

The third and fourth columns show that prospective fallen angels did not enjoy a similar

[17] See Table D.6 for estimates of the rating variable interacted with the event day dummy variable.

Sample	(1) EDF 2Y Full sample	(2) EDF 2Y QE3 to FFR	(3) Loan spread Full sample	(4) Loan spread QE3 to FFR	(5) Spread 2002–07	(6) CDS Full sample	(7) CDS QE3 to FFR
BBB	0.623***	0.553***	7.350	21.238	22.146***	50.00***	53.61***
	(0.082)	(0.093)	(16.390)	(22.225)	(4.722)	(5.245)	(6.046)
BB	1.528***	1.334***	51.534**	62.816**	88.018***	184.8***	175.8***
	(0.104)	(0.113)	(19.590)	(29.134)	(8.113)	(14.75)	(18.91)
B	2.851***	2.563***	114.606***	118.614***	155.357***	452.8***	338.1***
	(0.126)	(0.170)	(20.325)	(26.049)	(11.485)	(35.43)	(32.86)
CCC	4.211***	3.894***	216.636***	240.055***	306.994***	1,370.6***	813.8***
	(0.219)	(0.309)	(70.905)	(83.979)	(62.100)	(357.0)	(175.2)
Vulnerable × AAA-A	0.303**	0.346***	-4.242	2.066	8.898**	-3.345	0.3827
	(0.125)	(0.126)	(24.623)	(34.461)	(3.683)	(5.814)	(6.749)
Vulnerable × BBB	0.220**	0.286**	15.367	23.190*	9.221*	-0.6811	-13.43*
	(0.100)	(0.112)	(10.106)	(13.678)	(5.422)	(5.300)	(6.846)
Vulnerable × BB	0.472***	0.545***	34.985**	52.667***	13.405*	100.2***	145.0***
	(0.113)	(0.158)	(14.396)	(17.484)	(7.282)	(23.83)	(46.65)
Vulnerable × B	0.661***	0.686***	46.086**	53.789**	29.766	114.8	72.54
	(0.128)	(0.162)	(18.966)	(21.737)	(23.898)	(98.74)	(54.87)
Industry-Year-Month FE	✓	✓	✓	✓	✓	✓	✓
Observations	56,675	18,079	3,009	1,529	23,144	147,960	41,406
R-squared	0.755	0.747	0.713	0.694	0.780	0.68531	0.76936

Table 3: The exorbitant privilege is unique to the bond market post-2009. This table shows the estimation results of specification (2). This table provides robustness checks on the vulnerable BBB subsidy in different markets and time periods. Vulnerable is a dummy variable equal to 1 if issuer i is downgrade-vulnerable in date $t-1$ and t. The dependent variable in columns (1)-(2) is the log 2-year expected default frequency between 2009 to 2019 and between QE3 to the Fed Funds rate lift-off in November 2015, respectively. The dependent variable in columns (3)-(4) is the the all-in-drawn spread for syndicated loans taken from DealScan. The dependent variable in column (5) is the secondary market bond spread in the pre-GFC period (2002–2007). The dependent variable in columns (6)-(7) is the spread on the CDS contract maturity matched to the corporate bond sample in Panel A of Table 2. The CDS contracts are interpolated to have the same remaining maturity as the corresponding bond. The specifications include industry-year-month fixed effects (2-digit SIC). Columns (1) and (2) are at the firm-level, so we do not include bond level controls but control for firm size. Loan-level controls included in columns (3) and (4) are maturity, loan size, and dummy variable for dividend restrictions and for agent consent in trading the loan. Controls included in column (5) are residual maturity, amount outstanding, coupon, firm size, bid-ask spreads; coefficients on the latter variable are allowed to vary by rating. Columns (6) and (7) include maturity controls. The specification also includes dummy variables for senior bonds as well as callable bonds, bonds with a price above par but below a price of 105 and the interaction between the two variables to account for changes in credit quality affecting spreads on callable bonds. These control variables are included in the estimation but not reported for brevity. Standard errors are clustered at the firm and year-month level. *** p<0.01, ** p<0.05, * p<0.1.

funding advantage in the syndicated loan market during this period.[18] The Vulnerable × BBB coefficient is higher in the QE3 to Fed Funds rate lift-off period compared to the full sample, suggesting that, in contrast to bond markets, loan markets perceived the relative risk of these firms to have increased in this period. The fifth column shows that between 2002 and 2007 (the last business cycle before the GFC), prospective fallen angels did not benefit from a similar privilege in the corporate bond market. In fact, prospective fallen angels paid higher spreads in this period, in line with other rating categories. However, the sixth and seventh columns suggest that credit default swap markets priced a similar privilege for prospective fallen angels. In particular, the point estimate of the Vulnerable × BBB interaction term is negative and similar in magnitude to our baseline results in the first column of Table 2 for corporate bonds spreads—and statistically significant during the period from QE3 to Fed Funds rate lift-off. These results are consistent with the growing evidence that the CDS market essentially appears to be a substitute for corporate bond markets (Oehmke and Zawadowski, 2015; Jager and Zadow, 2022).[19]

Taken together, these results suggest that the exorbitant privilege of prospective fallen angels is unique to corporate bonds (and replication markets such as CDS) and particularly pronounced in the period starting with QE3 and ending with the withdrawal of monetary stimulus by the Federal Reserve.

[18]Given a limited number of observations in the highest rating buckets AAA and AA, especially in the syndicated loan market data, we further combine AAA-A ratings into a single rating category.

[19]Our interpretation is that the drivers of the prospective fallen angel privilege also influence the pricing of CDS contracts. In particular, an investor can gain credit exposure to a firm by either buying the bond or through a replication strategy of selling a CDS contract on the same firm and buying a US Treasury. Two pieces of evidence suggests that the same influence in corporate bond markets also affects CDS markets. First, for insurance companies, whose participation in investment-grade CDS markets is particularly relevant given the significantly higher capital requirements for sub-investment-grade risks, the capital treatment of selling CDS in a replication strategy is the same as holding a corporate bond of the same rating according to the risk-based capital regulation issued by the National Association of Insurance Commissioners (NAIC). Second, replication strategies overwhelmingly account for insurance company exposure in CDS markets (around 75%), see for example NAIC (2015). Finally, BIS Derivative Statistics also show that insurance companies have been consistent net sellers of CDS protection on non-financial corporates to dealers between 2009 and 2019 (see Table D10.1 of the BIS Derivative Statistics), the same directional position as being long corporate bonds.

5 The origins of the exorbitant privilege

We now discuss the origins of this exorbitant privilege and the role of QE. Section 5.1 presents a conceptual framework that explains how the exorbitant privilege can arise in equilibrium due to the sluggishness of credit ratings and the presence of an investment-grade threshold—and especially during the QE-induced rebalancing of investors' portfolios. Consistent with the prediction of this framework, Section 5.2 documents the role of QE in driving investors' demand for IG downgrade-vulnerable corporate bonds, especially those issued by BBB-rated firms, i.e., the prospective fallen angels.

5.1 Theoretical framework

Our explanation for the origin of the exorbitant privilege relies on the interplay between two well-documented factors. First, a large demand for BBB-rated bonds—the highest yielding, yet IG-rated, corporate bonds. Second, the sluggishness of credit rating agencies in downgrading, especially from IG to speculative-grade, after M&A. See Appendix B for the formal model.

Consider the portfolio choice of an investor that allocates capital across assets. There are two possible states of the world, a good state and a bad state. See Figure 4 for a schematic. The representative investor problem is:

$$max_{\beta_i} \left(\mathbb{E}(C_i) - p_i\right)\beta_i - f\left(\sum_i \beta_i \mathbb{E}(K)_i\right) \tag{4}$$

where $\mathbb{E}(C_i)$ is the discounted expected future cash flow of asset i over the two states, p_i is the price of asset i, and β_i is the allocation chosen in asset i. The function $f(\cdot)$ captures the expected balance sheet cost of all assets held, where $\mathbb{E}(K)_i$ is the balance sheet cost of asset i.

Note that the balance sheet cost of asset i depends on (i) the probability q_i of downgrade, (ii) the regulatory capital requirement κ_i, (iii) the sluggishness θ_i of credit ratings, and (iv) the additional cliff (downgrade) risk cost α_i. Credit ratings are sluggish. In the good state, there are no downgrades (nor upgrades, for simplicity) and the balance sheet cost of asset i is simply driven by its regulatory capital requirement κ_i. In the bad state, asset i is downgraded

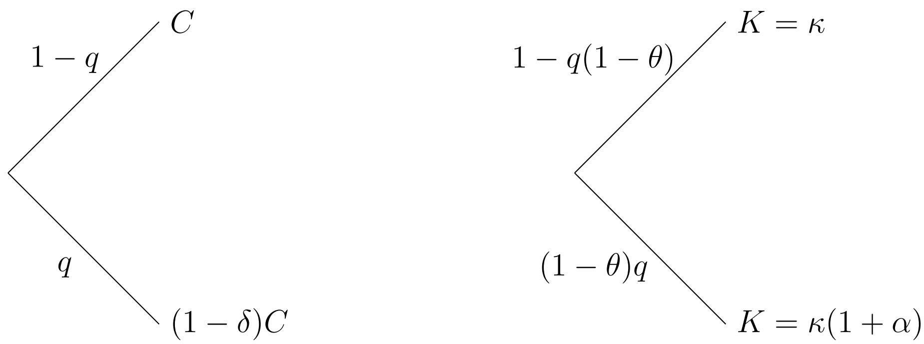

Figure 4: Cash flows and balance sheet costs in good and bad state. This figure shows the discounted cash flows (left) and the balance sheet costs (right) in the good and bad state of the world.

with probability $1-\theta_i$, i.e., the rating is sluggish with a probability $\theta_i \in (0,1)$. In the case of a downgrade, the balance sheet cost of asset i is $\kappa_i(1+\alpha_i)$, where α_i captures the incremental cost associated with investors forced selling of downgraded bonds, particularly pronounced at the investment-grade threshold for insurance companies and IG-focused mutual funds (see, e.g., Ellul et al. (2011)).

In this framework, taking the first-order condition of the investor's problem and setting the bond demand equal to the aggregate supply S_i (market-clearing) leads to:

$$p_i = \mathbb{E}(C_i) - \underbrace{\mathbb{E}(K)_i f'\left(\sum_i \mathbb{E}(K)_i S_i\right)}_{\substack{\text{Marginal contribution to the} \\ \text{aggregate balance sheet cost}}} \tag{5}$$

The price of bond i is given by its expected discounted cash flow minus its marginal expected contribution to the balance sheet cost. This second term is, in turn, a function of (i) the outstanding bond supply S_i (larger contribution if the outstanding supply is larger), (ii) the credit rating sluggishness to downgrades (smaller contribution if credit ratings are more sluggish), (iii) the capital requirements (larger contribution if requirements are higher), (iv) the cliff risk (larger contribution if the cliff risk is larger), and (v) the probability of the bad state (larger contribution if the bond is riskier).

Figure 5 shows the dynamics of bond prices for a plausible calibration of the framework described above. See Appendix B for a detailed description of this calibration. Firms are ordered by decreasing quality on the x-axis and grouped in credit ratings. The three panels

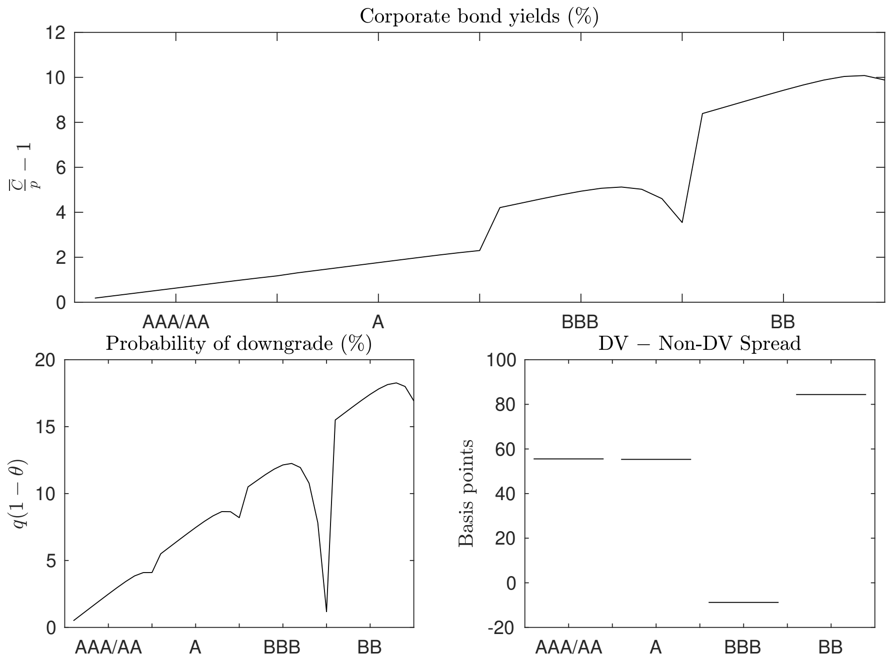

Figure 5: Model calibration results. This figure shows the model calibration results where the parameters match those in Figure B.5. On the x-axis, issuers are ordered by decreasing quality and grouped in four credit ratings: AAA/AA, A, BBB, and BB. The top panel shows corporate bond yields. The bottom left panel shows the probability of downgrade. The bottom right panel shows the spread, within each rating category, between downgrade-vulnerable and non-downgrade-vulnerable issuers.

show the cross-section of bond yields (top panel), the probability of downgrade (bottom left), and the spread between downgrade-vulnerable and non-downgrade-vulnerable issuers (bottom right) for each rating category. As the quality of issuers deteriorates, the probability of downgrades increases, with the notable exception of bonds that are close to being downgraded, especially at the investment-grade cutoff. These bonds benefit from the sluggishness of credit ratings that supports bond prices by delaying a downgrade. To see why, note that the sluggishness, by delaying downgrades, decreases the balance sheet costs of the bond portfolio (i) by reducing the required regulatory capital, and (ii) by avoiding the forced selling of bonds that do not comply with the rating mix desired/allowed by the investor, i.e., by avoiding the materialization of cliff risks. Both these forces are particularly pronounced for BBB-rated issuers. During periods of protracted QE, as shown in the calibration in Figure B.5, these effects are quantitatively larger because investors hold a larger stock of BBB-rated and speculative-grade securities, namely assets with a relatively high balance sheet cost for investors relative to Treasuries purchased by the Fed during QE.[20]

5.2 QE-driven demand by investment-grade investors

A testable prediction of the conceptual framework above is that investors exposed to the Federal Reserve QE programs drive the demand for IG corporate bonds, especially those issued by prospective fallen angels. This dynamic is particularly pronounced during QE3 and entirely driven by investors that predominantly hold IG bonds and whose portfolio consists of mostly long-term bonds—which are the most affected by QE purchases.

The left panel of Figure 6 shows that investors substituted holdings of Treasuries with holdings of corporate bonds during QE3 until the withdrawal of monetary accommodation with the lift-off of the Federal Funds rate and QT.[21] The solid line shows the size of the Fed balance sheet and the dashed line shows investors' holdings of corporate bonds as a share of the entire bond portfolio (Treasuries and corporate bonds). The share of corporate bonds held by investors increases markedly right after QE3 in 2012, stays somewhat constant around the liftoff in the Federal Funds rate in 2015, before decreasing at the time of QT in 2017.

To formally analyze the preference for bonds issued by high-yield, yet IG, corporate bonds, we measure investor-level exposure to QE. To this end, we merge our granular holdings-

[20] There is an interesting parallel between such QE-induced capital misallocation and the zombie-lending related credit misallocation. In the latter, banks extend subsidized credit to distressed firms to gamble for resurrection and/or to not recognize them as non-performing assets (which would induce higher provisioning and capital requirements). In the former, each investor such as an insurance firm can be considered relatively atomistic; nevertheless, the sluggishness of credit rating downgrades can act as a coordinating mechanism whereby each such investor can search for yield to gamble over the cliff risk of IG to sub-IG downgrade. Materialization of the cliff risk may be associated with liquidation costs, in case of investors restricted to investing in IG, and/or higher capital requirements, in case of investors such as insurance companies.

[21] By lowering yields on government bonds and mortgage-backed securities, QE induces investors to adjust their portfolio choice (Gagnon et al., 2011; Krishnamurthy and Vissing-Jorgensen, 2011). In practice, investors such as life insurers and mutual funds seek out a greater quantity of (BBB-rated) IG assets to meet their promised liabilities (e.g., variable annuities with minimum guarantees) since yields, as well as quantities of their traditional investments, are compressed by the Federal Reserve in QE programs. This mechanism is consistent with anecdotal evidence. For example, the Financial Times reports that *"insurance companies such as AIG and MetLife hold huge investment books, mainly consisting of bonds, to back the promises they make to their customers. Over the past decade, they have increasingly moved into riskier assets, according to Fitch, as yields in safer categories have fallen under aggressive easing policies from the world's central banks."* Source: "Search for yield draws U.S. life insurers to risky places," Financial Times, February 21, 2019.

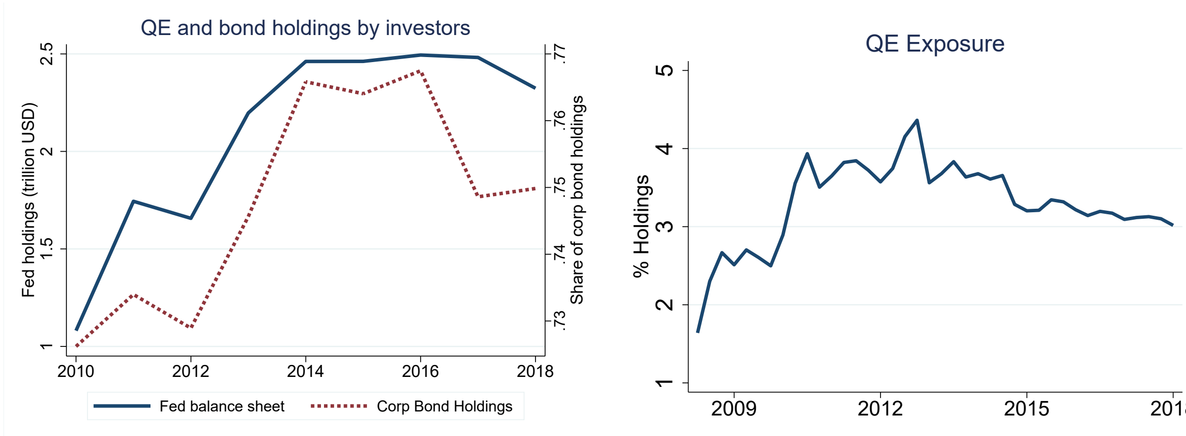

Figure 6: Investors' holdings and QE. This figure analyzes the interaction between investors' bond holdings and QE. The left panel shows the size of the Fed balance sheet (solid line) and investors' holdings of corporate bonds as a share of corporate bonds and Treasuries (dashed line). The right panel shows the evolution of the cross-sectional mean of the QE Exposure$_{kt}$ variable. This variable is defined as the share of investor total holdings that are held by the Federal Reserve in the SOMA Treasury portfolio, where holdings are weighted by the share of amounts outstanding held by the Federal Reserve. These figures are based on a balanced sample of investors.

level data with the Federal Reserve SOMA holdings data. Investor *time-varying* (quarterly frequency) exposure to QE is defined as the share of investor total holdings that are held by the Federal Reserve in the SOMA Treasury portfolio, where holdings are weighted by the share of amounts outstanding held by the Federal Reserve. The idea is that investors with a substantial share of their security holdings held by the Federal Reserve at time t are the ones more affected by QE. Formally, we define the variable QE Exposure$_{kt}$ as follows:

$$\text{QE Exposure}_{kt} = \frac{\sum_b (Holdings_{bkt} \times SOMA_{bt})}{\sum_b Holdings_{bkt}} \tag{6}$$

where b is a security, k is an investor, and t is a date. $SOMA_{bt}$ is the share of Treasury security b held by the Federal Reserve at date t. $Holdings_{bkt}$ are the holdings of security b held by investor k at time t. This variable is calculated at a quarterly frequency. The right panel of Figure 6 shows the time-series evolution of average QE Exposure$_{kt}$. Interestingly, the increase from 2012:Q3 to 2015:Q3 in the share of corporate bond holdings documented in the left panel is driven by high-exposure investors, i.e., in the cross-section of investors, a regression of the difference in the share of corporate bonds from 2012:Q3 to 2015:Q3 on investor-level QE exposure as of 2012:Q3 is positive (5.7% p-value).

Next, we analyze investors' demand for bonds issued by prospective fallen angels by estimating the following specification:

$$Holdings_{ikt} = \beta_1 \text{QE Exposure}_{kt-1} \times Vulnerable_{it} + \eta_{kt} + \mu_{it} + \epsilon_{ikt} \tag{7}$$

where k is an investor, i is an issuer, and t is a quarter. The dependent variable is the log of holdings by investor k in year t of bonds issued by issuer i. The independent variable of interest is the interaction between the lagged QE Exposure$_{kt-1}$ and $Vulnerable_{it}$, a dummy equal to one if issuer i is downgrade-vulnerable in year t.

The coefficient of interest β_1 captures whether investors more exposed to QE hold more or less bonds issued by downgrade-vulnerable issuers compared with less exposed investors. In the most stringent specification with investor-time and issuer-time fixed effects, we are effectively comparing bonds, at time t, issued by the *same issuer* that are held by investors with a different QE exposure. Investor-time fixed effects, η_{kt}, control for the potential differential portfolio choice by high- vs. low-exposure investors, with respect to downgrade-vulnerable and non-downgrade-vulnerable bonds, for reasons unrelated to QE. Issuer-time fixed effects, μ_{it}, control for the potentially different characteristics of downgrade-vulnerable and non-downgrade-vulnerable bonds (e.g., issuance volume) that might interact with the portfolio choice of high- vs. low-exposure investors for reasons, again, unrelated to QE.

Table 4 shows the estimation results. In Panel A, the estimated coefficient β_1 is positive and significant, suggesting that more exposed investors have a higher demand for bonds issued by downgrade-vulnerable issuers compared with less exposed investors. The last two columns also include, as independent variables, the downgrade-vulnerable dummy interacted with investors' bond portfolio maturity and maturity squared, respectively. Our coefficient of interest is stable and significant. This suggests that differential corporate bond holdings by downgrade-vulnerability are not driven by variation in portfolio maturity over time for a given investor, but instead by the time-series variation in the exposure of investors' portfolio to QE. We will, however, see below that, for a given exposure to QE, it matters whether the investor on average has longer or shorter portfolio maturity.

In Panel B, we show sample splits based on issuer ratings. In the four columns, the estimation is run in the subsample of AAA/AA, A, BBB, and speculative-grade (or high-yield)

Panel A	*Holdings$_{ikt}$*					
QE Exposure$_{kt-1}$ × $Vulnerable_{it}$	1.227***	1.356***	1.239***	1.362***	1.352***	1.356***
	(0.249)	(0.256)	(0.263)	(0.272)	(0.272)	(0.273)
Maturity$_{kt-1}$ × $Vulnerable_{it}$					−0.019**	−0.007
					(0.008)	(0.015)
(Maturity)$^2_{kt-1}$ × $Vulnerable_{it}$						−0.000
						(0.000)
Fixed Effects						
Issuer i	✓	✓				
Investor k	✓		✓			
Time t	✓					
Investor k - Time t		✓		✓	✓	✓
Issuer i - Time t			✓	✓	✓	✓
Sample investors	Full	Full	Full	Full	Full	Full
Sample issuers	Full	Full	Full	Full	Full	Full
Observations	6,595,196	6,581,548	6,594,446	6,580,797	6,579,884	6,579,884
R-squared	0.542	0.600	0.558	0.615	0.614	0.614

Panel B	*Holdings$_{ikt}$*			
QE Exposure$_{kt-1}$ × $Vulnerable_{it}$	0.348	1.259***	1.794***	−0.245
	(0.497)	(0.477)	(0.389)	(0.451)
Fixed Effects				
Investor k - Time t	✓	✓	✓	✓
Issuer i - Time t	✓	✓	✓	✓
Sample investors	Full	Full	Full	Full
Sample issuers	AAA/AA	A	BBB	HY
Observations	399,373	1,392,209	2,321,124	1,348,483
R-squared	0.744	0.690	0.656	0.585

Table 4: Demand for bonds issued by prospective fallen angels. This table presents estimation results from specification (7). The unit of observation is investor k, issuer i, date t. The dependent variable is $log(1 + Holdings_{ikt})$, where $Holdings$ are holdings by investor k in year t of corporate bonds issued by issuer i (thousands dollars). QE exposure$_{kt-1}$ is defined in (6). $Vulnerable_{it}$ is a dummy equal to 1 if issuer i is downgrade-vulnerable in date t. $Maturity_{kt-1}$ is the maturity (in years) of the bond portfolio of investor k at time t (maturity is divided by 100 in this table for readability). The uninteracted $Vulnerable_{it}$ and QE exposure$_{kt}$ terms are included in the estimation but not reported for brevity. In Panel A, the specification is estimated in the full sample of investors. In Panel B, the specification is estimated in the full sample of investors and in the subsample of issuers based on their rating category. Standard errors double clustered at the investor k level and issuer j level reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

issuers, respectively. The results show that the overall effect is more pronounced in BBB-rated bonds. In unreported results, we find that the coefficients are somewhat stable throughout our sample period. Hence, the investor QE-exposure peaking in the middle of our sample period (see Figure 6, right panel) implies a rise in demand for bonds issued by prospective fallen angels roughly coinciding with the greater privilege in borrowing costs for these firms starting with QE3 (see Figure 3). In unreported results, we also confirm that these results are robust to using a balanced sample of investors during our sample period.

	Holdings$_{ikt}$				
QE Exposure$_{kt-1}$ $\times$ $Vulnerable_{it}$	0.441	1.098***	2.311***	1.710***	2.268***
	(0.425)	(0.366)	(0.510)	(0.597)	(0.549)
Fixed Effects					
Investor k - Time t	✓	✓	✓	✓	✓
Issuer i - Time t	✓	✓	✓	✓	✓
Observations	419,017	455,083	1,446,578	784,276	662,133
R-squared	0.637	0.659	0.664	0.653	0.675
Sample issuers	BBB	BBB	BBB	BBB	BBB
Sample investors (portfolio duration)	< 5Y	(5Y,7Y)	> 7Y	> 7Y	> 7Y
Sample investors (portfolio IG rating share)	Full	Full	Full	< 0.75	> 0.75
Share of investors (by type) with a given portfolio duration and IG rating share in 2016					
Share of Annuities	17%	17%	66%	26%	40%
Share of Life & Health Insurance	35%	17%	48%	22%	25%
Share of Property & Casualty Insurance	57%	21%	21%	16%	15%
Share of Open Ended Mutual Fund	28%	17%	55%	22%	33%

Table 5: Demand for bonds issued by prospective fallen angels, sample splits. This table presents estimation results from specification (7). The unit of observation is investor k-issuer i-date t. The dependent variable is $log(1 + Holdings_{ikt})$, where $Holdings$ are holdings by investor k in year t of corporate bonds issued by issuer i (thousands dollars). QE exposure$_{kt-1}$ is defined in (6). $Vulnerable_{it}$ is a dummy equal to 1 if issuer i is downgrade-vulnerable to a downgrade in date t. The uninteracted $Vulnerable_{it}$ and QE exposure$_{kt}$ terms are included in the estimation but not reported for brevity. All the regressions are estimated in the subsample of BBB-rated issuers. In columns (1)-(3), the results are estimated in the subsample of investors with a portfolio maturity of below five years, between five and seven years, and above seven years, respectively. In column (4), the results are estimated in the subsample of investors with a portfolio maturity above seven years and with a share of investment-grade bonds smaller than 75%. In column (5), the results are estimated in the subsample of investors with a portfolio maturity above seven years and with a share of investment-grade bonds greater than 75%. Standard errors double clustered at the investor k level and issuer j level reported in parentheses. The bottom panel shows, for each investor type, the share of number of investors that, as of 2016:Q4, have a given bond portfolio duration and a given share of IG bonds. *** p<0.01, ** p<0.05, * p<0.1.

Table 5 shows the estimation results for holdings of BBB-rated bonds in various subsamples of investors. The first three columns include investors with a portfolio maturity of less than five years, between five and seven years, and more than seven years, at each date t, respectively. The last two columns only include investors with a portfolio maturity of more than seven years. The fourth column only includes investors with a share of IG securities of less than 75% at each date t. The last column only includes investors with a share of IG securities of at least 75% at each date t. These estimation results show that the results in Table 4 are driven by investors holding a long-maturity portfolio and predominantly investment-grade securities. These findings are consistent with QE reducing long-term yields and the BBB-threshold affecting primarily those investors that mostly hold IG bonds.

The investors most represented in our sample are property and casualty insurers (27%), open-ended mutual funds (27%), (other) life and health insurers (16%), and insurers with annuities with minimum guarantees (9%). As shown at the bottom of Table 5, variable annuities with minimum guarantees hold the longest maturity portfolio—in addition to being extremely exposed to QE. Other life and health insurers also hold a long maturity portfolio but are less exposed to QE as their liabilities do not induce as much preference for risk as variable annuities do. Property and casualty insurers are highly exposed to QE but hold a somewhat short-term portfolio, mostly made of IG securities.[22] These observations are related to (i) Koijen and Yogo (2021, 2022) that document the fragility of such products in a low interest rate environment and how the minimum return guarantees have changed the primary function of life insurers from traditional insurance to financial engineering, and (ii) Fringuellotti and Santos (2022) that shows that insurance companies have almost nonupled their investments in CLOs post-GFC, largely driven by IG-rated mezzanine debt tranches of CLOs. Finally, open-ended mutual funds have a moderate exposure to QE, while also holding a long-term portfolio not too concentrated in the IG market. It is interesting to note that during the COVID-19 outbreak, debt mutual funds experienced significant redemptions and contributed to corporate bond fire sales (see, among others, Haddad et al. (2021) and Falato et al. (2021a)).

6 M&A as an equilibrium response to investor demand

In this section, we discuss how the sizable increase in M&A activity of downgrade-vulnerable firms (and prospective fallen angels in particular) appears to be an equilibrium response to the QE-induced demand for bonds by IG-focused and long-duration investors. The core of our argument is that M&A, mostly debt-funded, allows issuers to meet the high demand for IG bonds, while delaying an eventual downgrade given that credit ratings are extremely sluggish in the few years after M&A deals, a dynamic unique to the BBB rating category.

[22]See Table E.1 for summary statistics by investor type for the main types of investors in our data.

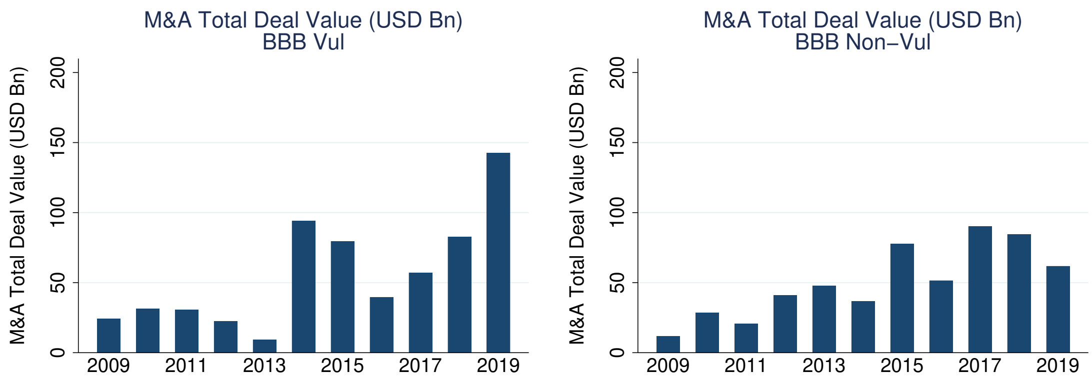

Figure 7: M&A activity, BBB-rated issuers. This figure shows the M&A activity by BBB-rated issuers. The left panel shows deal volume for downgrade-vulnerable issuers. The right panel shows deal volume for non-downgrade-vulnerable issuers.

Section 6.1 shows the increase in M&A activity by prospective fallen angels. Section 6.2 documents the sluggishness of credit rating agencies in downgrading post-M&A. Section 6.3 shows ex-ante evidence linking M&A and the increased vulnerability of prospective fallen angels. Section 6.4 shows that the unprecedented wave of fallen angels in March 2020 was almost entirely driven by prospective fallen angels that engaged in M&A, confirming its role in enhancing leverage and, therefore, credit risk.

6.1 The increase in M&A

Prospective fallen angels drive the increase in M&A activity since 2014 in the BBB market. The left panel of Figure 7 shows that for prospective fallen angels M&A deal volume increases substantially in 2014, while the right panel shows that such increase is less pronounced for the non-downgrade-vulnerable BBB-rated firms. In fact, downgrade-vulnerable BBB-rated firms saw an increase in the average total deal volume from \$24 billion in the years 2009–2013 to \$83 billion in the years thereafter.[23]

[23] In the online appendix, we additionally show that the substantial increase in investment-grade bond issuance since 2013–15 was in large part to fund M&A activity (Figure F.1).

	Ratings inflation	Ratings inflation
BBB_{it}	0.474**	0.110
	(0.200)	(0.278)
$\text{M\&A}_{it}$		-0.332*
		(0.197)
$\text{M\&A}_{it} \times \text{BBB}_{it}$		0.635**
		(0.300)
Industry-Year FE	✓	✓
Controls	✓	✓
Sample	Vulnerable	Vulnerable
Observations Observations	2,424	2,424
R-squared	0.404	0.408

Table 6: The role of M&A in prolonging ratings inflation. This table presents estimation results from specification (8) in the sample of downgrade-vulnerable firms. The dependent variable is ratings inflation—calculated as the number of notches between the issuer's credit rating notch (e.g., AA+, AA, AA-, A) and the credit rating notch implied by its Z"-score. M&A is a dummy variable equal to one for the year and the years after a firm has conducted M&A. The specifications include industry-year fixed effects and firm-level controls (including log(total assets), leverage, net worth and tangibility (ppent / assets)). Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

6.2 The sluggishness of credit ratings post-M&A

A crucial part of the exorbitant privilege mechanism is the sluggishness of downgrades after M&A. One way of demonstrating the post-M&A sluggishness is to examine whether our measure of ratings inflation is higher for BBB-rated downgrade-vulnerable firms, especially following M&A. To this end, we estimate the following specification in the subsample of downgrade-vulnerable firms:

$$Y_{it} = \beta_1 \text{BBB}_{it} + \beta_2 \text{M\&A}_{it} + \beta_3 \text{M\&A}_{it} \times \text{BBB}_{it} + \delta X_{it} + \eta_{ht} + \epsilon_{it} \tag{8}$$

where i is a firm, h an industry, and t a year. The dependent variable Y_{it} is ratings inflation, defined as the number of notches between the issuer's credit rating notch and the credit rating notch implied by its Z"-score. The key independent variable is the interaction between BBB_{it} and $\text{M\&A}_{it}$, where $\text{M\&A}_{it}$ is a dummy equal to one in the year firm i has conducted an M&A deal and for the years thereafter. BBB_{it} is a dummy equal to one if firm i has a BBB rating in t. X_{it} represents a set of firm controls (log assets, leverage, and net worth) and η_{ht} are industry-year fixed effects.

Table 6 shows the estimation results. The first column suggests that prospective fallen

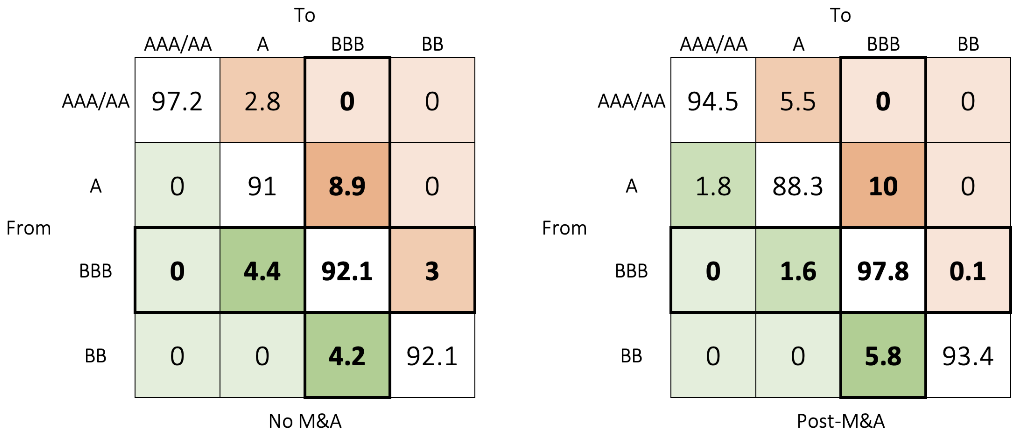

Figure 8: The sluggishness of credit ratings post-M&A. This figure shows the debt-weighted share (in %) of firms transitioning across issuer rating groups (AAA/AA, A, BBB, and BB and below) in one calendar year. The left matrix includes only firms without an M&A transaction within the past two years. The right matrix includes only firms within a two-year period after an M&A transaction. The one-year transition probabilities are measured for the years 2011 to 2018, to account for the $t-2$ M&A lag and to exclude the COVID-19 period.

angels enjoy an additional 0.5 notches in ratings inflation compared with downgrade-vulnerable issuers in other rating groups. The second column shows that, within downgrade-vulnerable firms, ratings inflation is largely driven by firms that have undertaken an M&A and is in fact higher at 0.6 notches. This M&A ratings inflation is, however, only enjoyed by prospective fallen angels.

An alternative way to examine post-M&A ratings sluggishness is to examine ratings transition matrices. These confirm that M&A deals are associated with sluggishness of credit ratings. Figure 8 shows two transition matrices, reporting the debt-weighted share of issuers transitioning across rating groups. The left matrix only covers firms without an M&A transaction in the past two years, while the right matrix only includes firms that have conducted an M&A transaction in the past two years. The left matrix shows that in the non-M&A sample, 8.9 percent of A-rated firms are typically downgraded to BBB and that 3.0 percent of BBB-rated firms are typically downgraded to BB and below. By contrast, the right matrix shows that after M&A, the downgrade probability of BBB rated firms falls to almost zero, but rises for all other IG-rating groups.

This fact is consistent with anecdotal evidence as well as a large body of practitioners' research pieces which note that the announcement of an M&A deal is almost always accompanied by rosy forecasts of synergies that will reduce costs and increase revenues and, even more importantly, a leverage-reduction plan.[24] These plans promise to reduce the debt taken on to finance the acquisition in an attempt to convince credit rating agencies about the issuer's future prospects.

6.3 M&A and the vulnerability of prospective fallen angels

We now provide ex-ante evidence linking M&A activity with increased vulnerability. In particular, we show that prospective fallen angels (i) engage in relatively larger M&A transactions compared to other rated firms, (ii) substantially increase their total debt without a comparable increase in profitability post-M&A, and (iii) experience negative cumulative abnormal returns around the M&A announcement date (unlike non-downgrade-vulnerable BBB-rated issuers).

Specifically, we estimate the following specification in the sample of firms which announced an M&A in year t:

$$\begin{aligned} Y_{it} &= \beta_1 \, BBB_{it} + \beta_2 \, Vulnerable_{it} + \beta_3 \, Vulnerable_{it} \times BBB_{it} \\ &+ \gamma \times X_{it} + \eta_{ht} + \epsilon_{it}, \end{aligned} \tag{9}$$

where i is a firm, h an industry, and t is the year (or month) of the M&A. Y_{it} measures either the relative deal size, net debt/EBITDA, or the cumulative abnormal return (CAR). The coefficient of interest, β_3, captures the relative effect of M&A by prospective fallen angels relative to other downgrade-vulnerable firms and non-downgrade-vulnerable BBB firms. We include industry-year fixed effects to absorb time-varying industry level heterogeneity and time-varying firm level controls.

The first column of Table 7 shows that the M&A deal size of prospective fallen angels

[24] Figure F.2 shows that this promise is often broken, consistent with market participants' observations. For example, Morgan Stanley (2018a) states that *"...M&A has driven big increases in leverage and BBB debt outstanding. And while these companies may pledge to delever over time, those promises often don't materialize..."* And, again, Morgan Stanley (2018b) writes that *"...forward-looking assumptions often assume all goes well and earnings growth is strong. In reality, issuers have been slow to actually delever..."*

	$Relative\,Deal\,Size_{it}$	$Net\,Debt/EBITDA_{it}$	$CARs_{ijt}$
BBB	−0.043***	−0.124	0.001
	(0.013)	(0.116)	(0.003)
Vulnerable	−0.038**	−0.097	0.005
	(0.017)	(0.170)	(0.004)
Vulnerable × BBB	0.056**	0.365*	−0.012**
	(0.027)	(0.210)	(0.006)
Controls	✓	✓	✓
Industry-Year FE	✓	✓	✓
Sample	M&A Rated	M&A Rated	M&A Rated
Level	Firm	Firm	Deal
Observations	1,829	2,950	2,412
R-squared	0.268	0.535	0.198

Table 7: M&A and risk-taking by prospective fallen angels. This table presents estimation results from specification (9) in the sample of rated firms that announced an M&A in year t. The dependent variable in column (1) is the relative deal size, which is measured by the total M&A transaction value of a firm in a given year over its lagged assets. The dependent variable in column (2) is the net debt/EBITDA levels for the M&A rated firms. For Columns (1) and (2) the firm controls consist of the log of assets, profitability, leverage, and tangibility. Column (3) presents the 5-day cumulative abnormal returns for the M&A deals performed by the rated firms in our sample, for which we run the specification on a deal (j) level. The total return value-weighted index is used as benchmark over a -210 to -11 day period. Control variables include the logarithm of total assets, leverage, profitability, an indicator variable for whether the deal is at least partially financed with stock, an indicator variable for whether the target has the same 2-digit SIC code as the acquirer, an indicator variable for whether the deal is cross-border, an indicator variable for a publicly listed target, and the pre-deal buy-and-hold returns of the acquirer from -210 to -11 days. A t-test shows that on average the CARs of BBB vulnerable firms are -1 percent. In all columns, $Vulnerable$ is a dummy variable equal to one if a firm is downgrade-vulnerable in period t. BBB is a dummy variable equal to one if a firm has a BBB rating in period t. All specifications are in the sample of firm-years with positive total transaction value and include industry-year fixed effects. Standard errors are clustered at the firm level.

is larger. The second column shows that as a result, net debt to EBITDA rises after prospective fallen angels announce an M&A. The same dynamic is not evident in M&A's of other downgrade-vulnerable firms. Finally, the third column shows that only M&A deals by prospective fallen angels are associated with negative CARs, suggesting that their M&A activity is value-destroying. Taken together, these findings suggest that M&A activity contributed to a buildup of vulnerabilities among prospective fallen angels.

6.4 Fallen angels at the onset of COVID-19: The role of M&A

This vulnerability of prospective fallen angels materialised in just a few weeks at the onset of the COVID-19 pandemic, where the volume of BBB debt downgraded was more than two times larger than during the entire GFC. As Figure 2 showed, prospective fallen angels accounted for the vast majority of fallen angel debt. Moreover, the debt downgraded from

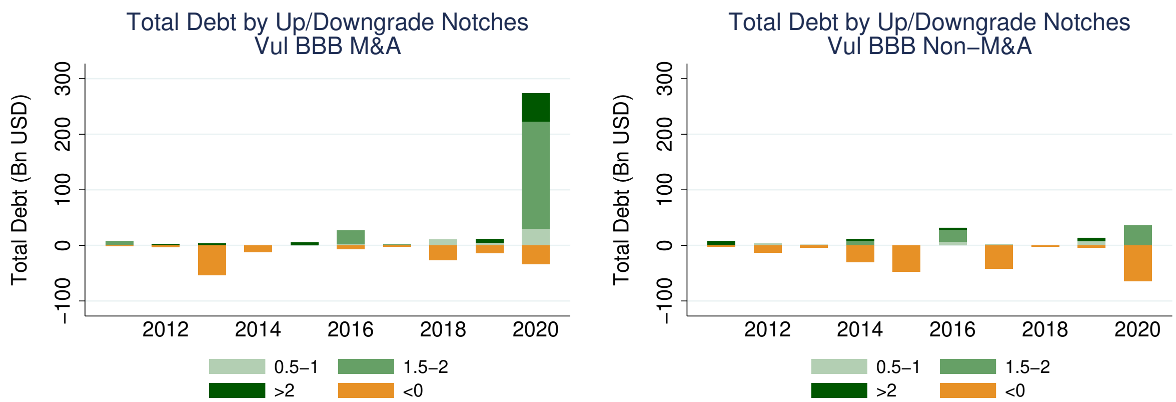

Figure 9: Downgrade materialization of (prospective) fallen angels. This figure shows the total debt of vulnerable BBB-rated firms that has been upgraded and downgraded in the years 2011 to 2020. The downgraded debt is grouped according to their downgrade severity. The downgrade severity is measured by the number of notches a firm is being downgraded, and is subdivided into three broad categories: 0.5-1, 1.5-2, >2 notches, as reflected by the green shades. The upgraded debt is shown by the orange bars, and is represented by the notches below zero. The left panel plots the total amount of up/downgraded debt for vulnerable BBB firms that have conducted an M&A since the year that they have become vulnerable. The right panel shows the total amount of up/downgraded debt for firms that have not conducted an M&A since the year that they have become vulnerable.

BBB to speculative-grade in 2020 was almost entirely driven by prospective fallen angels that engaged in M&A. The green bar in the left panel of Figure 9 shows that around $275 billion of prospective fallen angel debt was downgraded in 2020 by issuers which had undertaken M&As, while the right panel shows that those that had not done so amounted to less that $50 billion. The different shades indicate the severity of the downgrade (number of notches) showing that prospective fallen angels that had undertaken M&A were also downgraded by more notches.[25]

7 The cost of the subsidy

Having established the magnitude of the subsidy in bond-market financing costs of prospective fallen angels and the economic mechanisms driving it, we quantify the overall bond market subsidy (Section 7.1) and examine an indirect economic cost that arises from spillovers to

[25]A similar pattern is evident when looking at the number of issuers downgraded, not weighted by debt volume (Figure F.3).

competing firms (Section 7.2).

7.1 Quantifying the subsidy for prospective fallen angels

In this section, we show that estimates of the subsidy enjoyed by prospective fallen angels range from around $47 to $129 billion during 2009 to 2019, depending on assumptions about their underlying risk.

The subsidy enjoyed by prospective fallen angels consists of two components. First, a within-rating component originating from the fact that prospective fallen angels pay lower bond financing costs compared to non-downgrade-vulnerable BBB-rated firms, as shown by our estimates in Table 2. The subsidy also consists of a second "downgrade-avoidance" component originating from the fact that, by benefiting from delay to downgrades, prospective fallen angels avoid paying the much higher financing costs of speculative-grade issuers.[26] This second component is measured by the difference in spreads between a non-downgrade-vulnerable BBB firm and a non-downgrade-vulnerable BB firm. In the left panel of Figure 10, the black arrows indicate the two subsidy components for the downgrade-vulnerable BBB firms, using the offering spreads in the first column of Table 2 Panel B and Table D.5.[27] The sum of the two components results in a subsidy of 151 basis points.

The total subsidy in dollar terms that accrues to prospective fallen angels over the lifetime of their issued bonds can be computed by multiplying the spread difference of 151 basis points between the downgrade-vulnerable BBB firms and non-downgrade-vulnerable BB firms by the average bond duration and the total bond offering amount of prospective fallen angels

[26] Differences in the investor clientele and capital requirements between IG and speculative-grade segments drive a big wedge in funding costs. For example, insurance companies face risk-based capital requirements for their holdings of corporate bonds. These requirements are progressively steeper with credit ratings, especially if the IG threshold is crossed (https://content.naic.org/sites/default/files/legacy/documents/committees_e_capad_investment_rbc_wg_related_irbc_factors.pdf). (The mapping from NAIC ratings designations and those of ratings agencies can be found here https://content.naic.org/sites/default/files/inline-files/Master%20NAIC%20Designation%20and%20Category%20grid%20-%202020.pdf).

[27] We are grateful to our NBER Corporate Finance discussant, Annette Vissing-Jorgensen, for this representation of the subsidy.

over the years 2009–19. This calculation results in a subsidy estimate of $129 billion.

The above calculation implicitly assumes that the actual credit risk of prospective fallen angels is identical to that of the average non-downgrade-vulnerable BB firm. However, it is possible that this may overstate the subsidy because of remaining unobserved differences. We therefore complement our baseline subsidy estimate with two alternatives. In the right panel of Figure 10, we provide an overview of our ballpark figures, which ultimately range from $47 billion to $129 billion. The first assumes that the "true" counterfactual spread on downgrade-vulnerable BBB-rated bonds can be inferred by interpolating between the spreads of downgrade-vulnerable A-rated and downgrade-vulnerable BB-rated firms (see Figure G.1). Taking the yield differential between the prospective fallen angel spread and the linearly interpolated counterfactual spread implies a subsidy of 82 basis points, resulting in a total dollar subsidy of around $70 billion. The second approach assumes that actual firm risk is evident in equity prices and thus captured by the EDF. Using the log 2-year EDF of prospective fallen angels and then backing out the counterfactual spread based on the relationship between the EDFs and the offering spreads of all other ratings categories with a quadratic function, we find that downgrade-vulnerable BBB firms receive a 55 basis points subsidy and a total dollar subsidy of $47 billion (see Figure G.1).

7.2 Spillovers to competing firms

Finally, we examine spillovers in the real economy from prospective fallen angels to competing firms. We show (i) that the market share of prospective fallen angels increases substantially in our sample period, and especially since 2013–14, largely driven by M&A; and, (ii) that non-downgrade-vulnerable firms are negatively affected by the presence of prospective fallen angels in their market.

Figure 11 shows the increase in market shares by prospective fallen angels over our sample period. The figure breaks down each rating category into the downgrade-vulnerable and non-downgrade-vulnerable groups. The entire increase in BBB-rated issuers' market share is

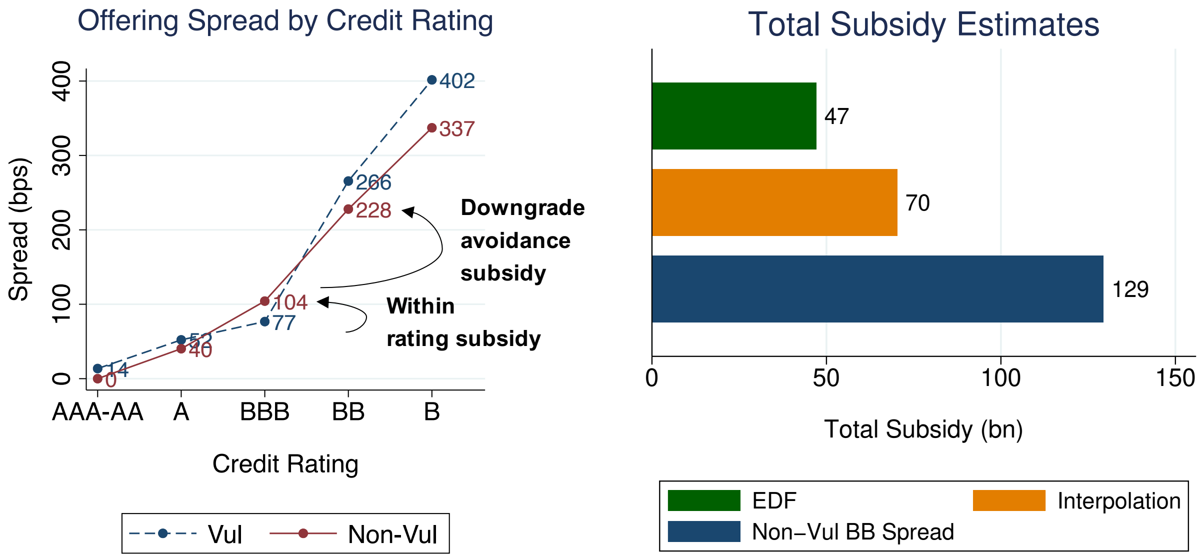

Figure 10: Prospective fallen angel subsidy. The left panel plots the offering spreads by credit rating from the first column of Table 2 Panel B and Table D.5 for downgrade-vulnerable and non-downgrade-vulnerable issuers, and shows the downgrade avoidance and within-rating subsidy components for prospective fallen angels. The right panel presents a range of estimates for the total subsidy of prospective fallen angels in dollar terms based on alternative counterfactual spreads of prospective fallen angels. EDF: counterfactual spread based on firm risk measured by the log of 2-year EDFs. Interpolation: counterfactual spread based on linear interpolation between spreads of downgrade-vulnerable A and downgrade-vulnerable BB-rated firms that are reported in the first column of Table 2 Panel B and Table D.5. Non-downgrade-vulnerable BB spread: counterfactual spread based on the offering spreads of non-downgrade-vulnerable BB firms estimated in Table 2 Panel B and Table D.5. The total dollar subsidy is computed as the difference of the counterfactual spread relative to the prospective fallen angel spread multiplied by the average duration and the total offering amount of bonds issued by prospective fallen angels between 2009–19.

driven by prospective fallen angels.[28]

We next investigate possible spillovers from prospective fallen angels to competing firms in a manner akin to the congestion externality documented in the context of zombie lending. Hence, we follow that literature (most notably Caballero et al. (2008)) and estimate the following regression at the firm-year level:

$$\begin{aligned} Y_{it} &= \beta_1 \text{Non-Vulnerable}_{it} \\ &+ \beta_2 \text{Non-Vulnerable}_{it} \times \text{Share Vulnerable BBB}_{ht-1} + \eta_{ht} + \epsilon_{it}, \end{aligned} \tag{10}$$

[28]Moreover, the increase in market share of BBB-rated firms from 2014 to 2019 has been driven largely by prospective fallen angels engaging in M&A (Figure F.4).

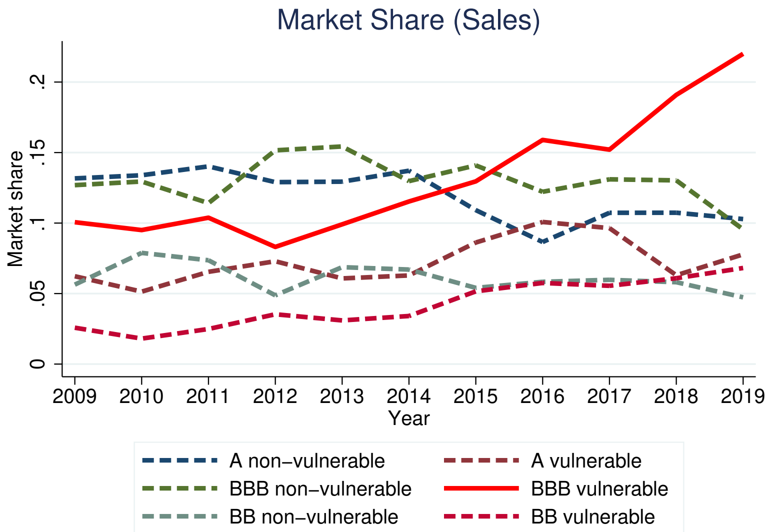

Figure 11: The increase in market share of prospective fallen angels. This figure shows the evolution of firm market share (share of sales in an industry, weighted by the relative size of the respective industry). Firms are grouped by credit rating from A to BB and further distinguished between downgrade-vulnerable and non-downgrade-vulnerable within each rating.

where i is a firm, h an industry, and t is a year. The dependent variables are employment growth, investment, sales growth, and markups. We also include industry-year fixed effects. Our coefficient of interest, β_2, captures whether non-downgrade-vulnerable firms that operate in industries with a high share of prospective fallen angels perform differently than non-downgrade-vulnerable firms in industries with a lower share of prospective fallen angels.

Table 8 reports the estimation results. Panel A shows that, in the sample of rated firms, non-downgrade-vulnerable IG firms are negatively affected by the presence of prospective fallen angels. More precisely, the first two columns show that, while non-downgrade-vulnerable firms have on average higher employment growth rates and invest more, both employment and investment are impaired by the presence of prospective fallen angels. Moreover, these firms face lower sales growth and lower markups compared with firms that do not compete with a large share of prospective fallen angels. To assess the economic magnitude of these spillover effects, consider a one standard deviation increase in the share of prospective fallen angels (0.136). This increase implies that non-downgrade-vulnerable investment-grade firms face a 1.1pp lower employment growth, 1.4pp lower investment, and a 1.2pp lower sales growth.

Panel B shows that these spillover effects are not present when we replace the share

	Emp Growth	CAPX	Sales Growth	Markup
Panel A: Rated Firms - Vulnerable IG				
Non-vulnerable IG_{it}	0.018*	0.031***	0.005	0.589**
	(0.009)	(0.012)	(0.009)	(0.277)
Non-vulnerable IG_{it} × Share Vulnerable BBB_{ht-1}	-0.082**	-0.104**	-0.086**	-1.555**
	(0.037)	(0.046)	(0.036)	(0.766)
Observations	7,078	7,276	7,284	7,283
R-squared	0.097	0.314	0.258	0.257
Panel B: Rated Firms - Placebo				
Non-vulnerable IG_{it}	0.034*	0.026*	0.025*	0.344
	(0.017)	(0.013)	(0.015)	(0.269)
Non-vulnerable IG_{it} × Share $Vulnerable_{ht-1}$	-0.028	-0.023	-0.037	0.281
	(0.031)	(0.021)	(0.025)	(0.320)
Observations	7,078	7,276	7,284	7,283
R-squared	0.106	0.313	0.264	0.270
Panel C: All Firms				
$Non\text{-}vulnerable_{it}$	0.043***	0.043***	0.044***	0.379**
	(0.011)	(0.010)	(0.012)	(0.172)
$Non\text{-}vulnerable_{it}$ × Share Vulnerable BBB_{ht-1}	-0.074**	-0.098**	-0.079***	-0.923**
	(0.035)	(0.043)	(0.027)	(0.434)
Observations	26,163	27,635	27,142	27,035
R-squared	0.042	0.191	0.045	0.136
Industry-Year FE	✓	✓	✓	✓
Firm-level Controls	✓	✓	✓	✓

Table 8: Negative spillovers on other firms. This table presents estimation results from specification (10). The dependent variables are employment growth, CAPX/PPE, sales growth, and markups (defined as sales/cost of goods sold). Vulnerable (and non-vulnerable) is defined in Section 3.2. Panel A focuses on the congestion effects of prospective fallen angels on non-downgrade-vulnerable investment-grade firms. The sample is limited to firms with a rating from at least one rating agency. Panel B focuses on the same sample as Panel A but examines the congestion effects of all downgrade-vulnerable firms. Panel C focuses on the congestion effects of prospective fallen angels on all non-downgrade-vulnerable firms using the entire sample of firms. Share Vulnerable BBB measures the asset-weighted share of prospective fallen angels in a two-digit SIC industry. Firm-level control variables include log of total assets, leverage, net worth, and an indicator variable for the rating bucket (AAA, AA, A, etc.). Standard errors clustered at the industry-level reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

of prospective fallen angels with the overall share of downgrade-vulnerable firms. This result confirms the uniqueness of prospective fallen angels, also when it comes to driving negative spillover effects, and is consistent with only the prospective fallen angels enjoying the bond-market subsidy. Panel C confirms our main results for the full sample of firms rather than just IG-rated firms.

8 Conclusion

In summary, we document an exorbitant privilege in the form of a bond market borrowing cost subsidy for prospective fallen angels, namely firms on the cusp of the investment-grade cutoff. This subsidy was especially prevalent during QE3 until the withdrawal of monetary stimulus with the lift-off of the Federal Funds rate and QT. We find the subsidy to be driven by QE-induced demand for investment-grade bonds in IG-focused and long-duration investors such as annuities. This demand, in turn, induces prospective fallen angels to engage in risky M&A, exploiting the leniency of credit rating agencies, in order to increase their market share with adverse spillovers on competing firms.

Our results suggest that although the growth of investment-grade bond segment may have been a desired consequence of QE, the growing concentration of issuance in the *riskiest* investment-grade (BBB) bucket also comes at a cost that may run counter to central bank objectives. First, the subsidised firms grow disproportionately large and become more fragile, as evidenced by the unprecedented wave of fallen angels that were downgraded by multiple notches at the onset of the COVID-19 crisis. Second, the resulting spillover effects force their competitors to reduce employment, investment, markups, and sales growth.

This capital misallocation cost of QE has not been documented hitherto, to the best of our knowledge, and may need to be factored in while considering the desirability, scale, scope, and duration of QE interventions in the future. Equally, the financial vulnerability of (hitherto privileged) prospective fallen angels may have to be considered in the present discussions to normalize central bank balance sheet size following the extraordinary size of post-COVID QE programs. Indeed, the ongoing crash of IG-rating indices (during 2022), which seems to have outpaced that of high-yield indices, suggests that the impact of central bank interventions on the pricing and issuance of investment-grade corporate bonds during the post-COVID period is worthy of careful scrutiny in future research.

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Online Appendix

Exorbitant Privilege? Quantitative Easing and the Bond Market Subsidy of Prospective Fallen Angels

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May 2023

Structure

This online appendix is structured as follows. Appendix A shows aggregate trends on the build up of non-financial sector debt, especially in downgrade-vulnerable BBB firms. Appendix B presents our theoretical framework. Appendix C explains the data construction. Appendix D provides validation tests of our downgrade-vulnerability measure and additional robustness tests on the existence of the prospective fallen angel bond financing privilege. Appendix E presents summary statistics about investor types. Appendix F presents additional results about M&A activity. Appendix G shows how we calculate counterfactual spreads for our prospective fallen angel subsidy estimates.

Appendix A Aggregate facts

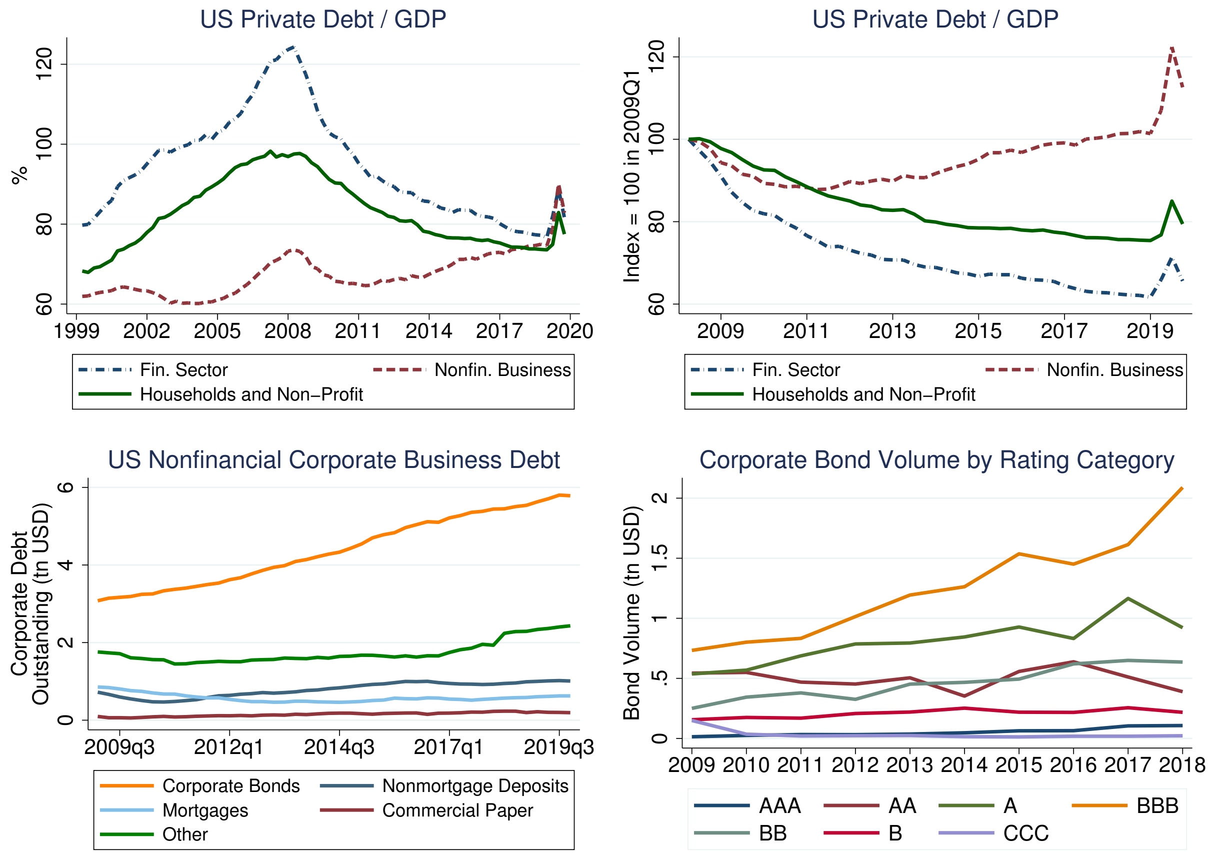

Figure A.1: The growth of the U.S. non-financial corporate debt. This figure shows the growth of the U.S. non-financial corporate debt and, in particular, of the U.S. corporate bond market. The top left panel shows the evolution of the financial sector debt, non-financial sector debt, and household debt, normalized by GDP. The sources are series dodfs, tbsdodns and cmdebt from FRED. The top right panel is an index where these series are normalized to 100 in 2009Q1. The bottom left panel shows the evolution of corporate bonds, mortgages, non-mortgage deposits (includes loans from banks, credit unions, and savings and loans associations), commercial paper and other (loans from non-bank institutions, excluding mortgages, and industrial revenue bonds). The sources are series cblbsnncb, mlbsnncb, ncbilia027n, cplbsnncb and olalbsnncb from FRED. The bottom right panel shows the evolution of the stock outstanding of corporate bonds, grouped by rating category. Sources: Capital IQ and Thomson Reuters.

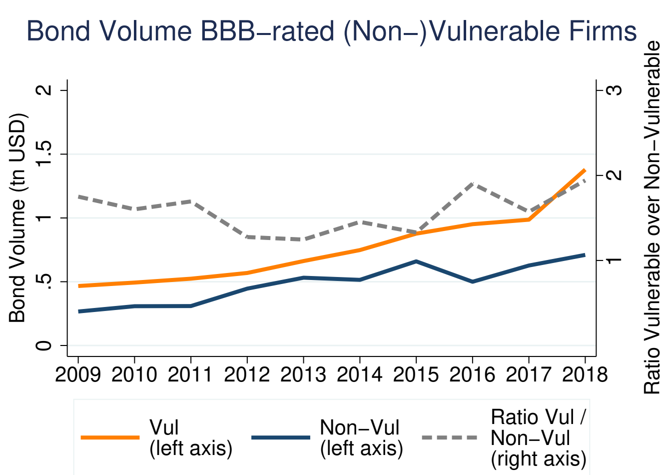

Figure A.2: Increased downgrade-vulnerability of BBB-rated firms. This figure shows the increased downgrade-vulnerability of BBB-rated firms. The figure shows, within the BBB rating category, the share of bonds outstanding issued by vulnerable and non-vulnerable BBB-rated firms. The dashed line is the ratio between these two series.

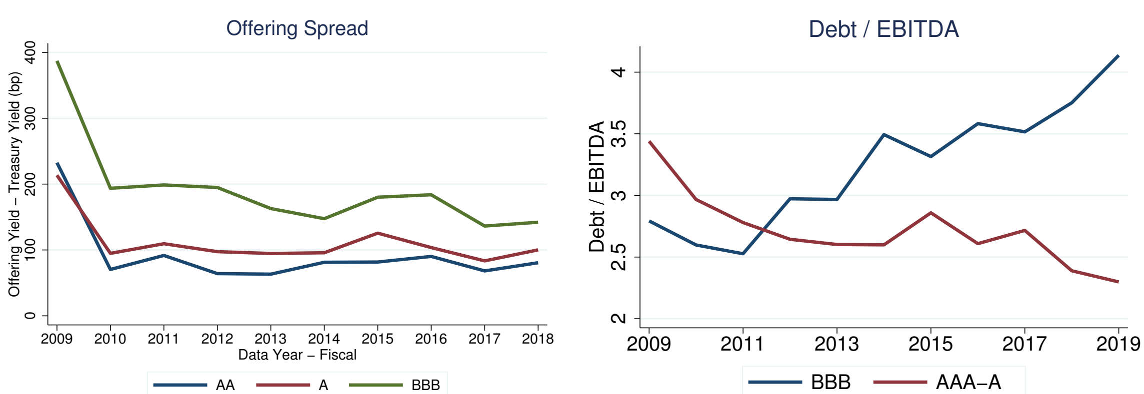

Figure A.3: Increased fragility and lower bond financing costs for BBB-rated firms. This figure shows the increasing fragility and the declining bond financing costs for BBB-rated firms. The left panel shows the offering spread (primary market bond yields minus the Treasury yield with a similar maturity) for newly issued bonds. The right panel shows the asset-weighted debt over EBITDA for BBB and other IG-rated firms. Figure A.5 provides further non-parametric evidence that the bond financing cost of BBB firms dropped significantly, more than the financing costs of other IG issuers.

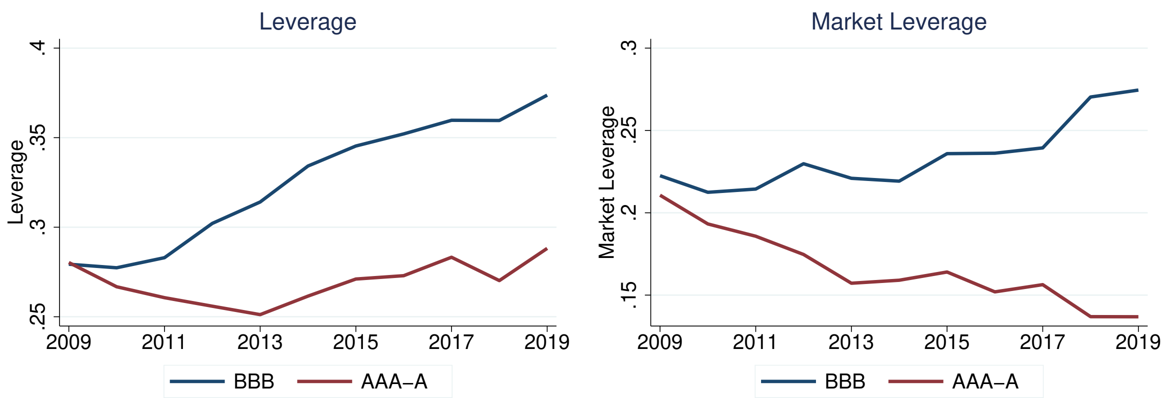

Figure A.4: Leverage over time. This figure shows the leverage evolution for BBB and IG-rated firms over the years 2009 to 2019. The left panel shows the asset-weighted book leverage, which is defined by a firm's total debt over assets. the right panel shows the asset-weighted market leverage, which is defined by a firm's total debt over the market value of its assets.

Compression of BBB spreads

We provide further evidence that the bond financing cost of BBB firms dropped significantly, and more than the financing costs of other investment-grade issuers, since 2009. In Figure A.5, we show the compression of bond spreads by tracking the distribution of primary market spreads (top panel) and secondary market spreads (bottom panel) from 2010–12 (dashed lines) to 2013–16 (solid lines). The left panels compare the distribution of BBB bond spreads with the distribution of A bond spreads. The right panels compare the distribution of BBB bond spreads with the distribution of AA bond spreads. The four panels document a pronounced leftward shift of BBB spreads in the primary and the secondary market. If anything, we observe a slight *rightward* shift for A and AA spreads. In Figure A.6, we show that the 2013–16 is characterized by a substantial monetary easing by the Federal Reserve.

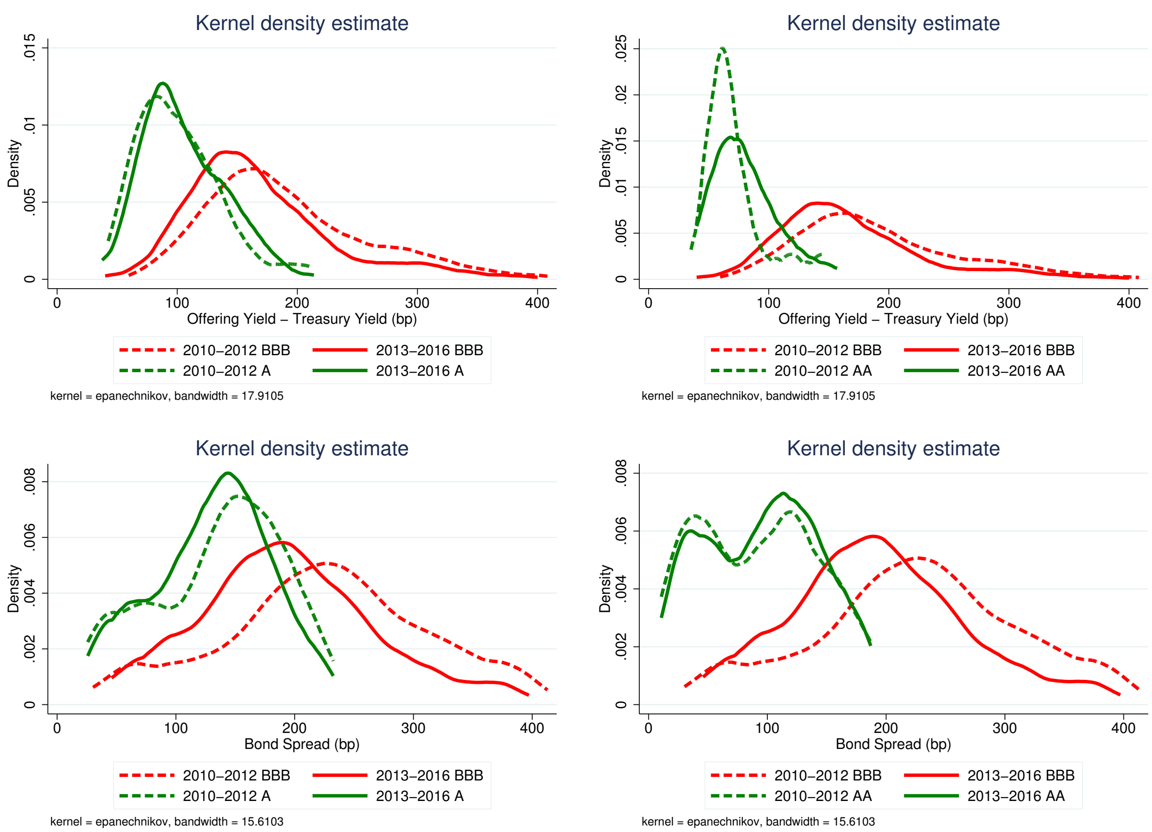

Figure A.5: Shift in bond spread distributions from 2010–12 to 2013–16. This figure shows how bond spreads distributions changed from 2010–12 (dashed lines) to 2013–16 (solid lines). The top panels show the distribution of offering spreads for newly issued bonds. The bottom two panels show the distribution of secondary market spreads for traded bonds. The left and right panels compare the distributions of BBB bond spreads (red lines) with the distributions of A bond spreads and AA bond spreads (green lines), respectively.

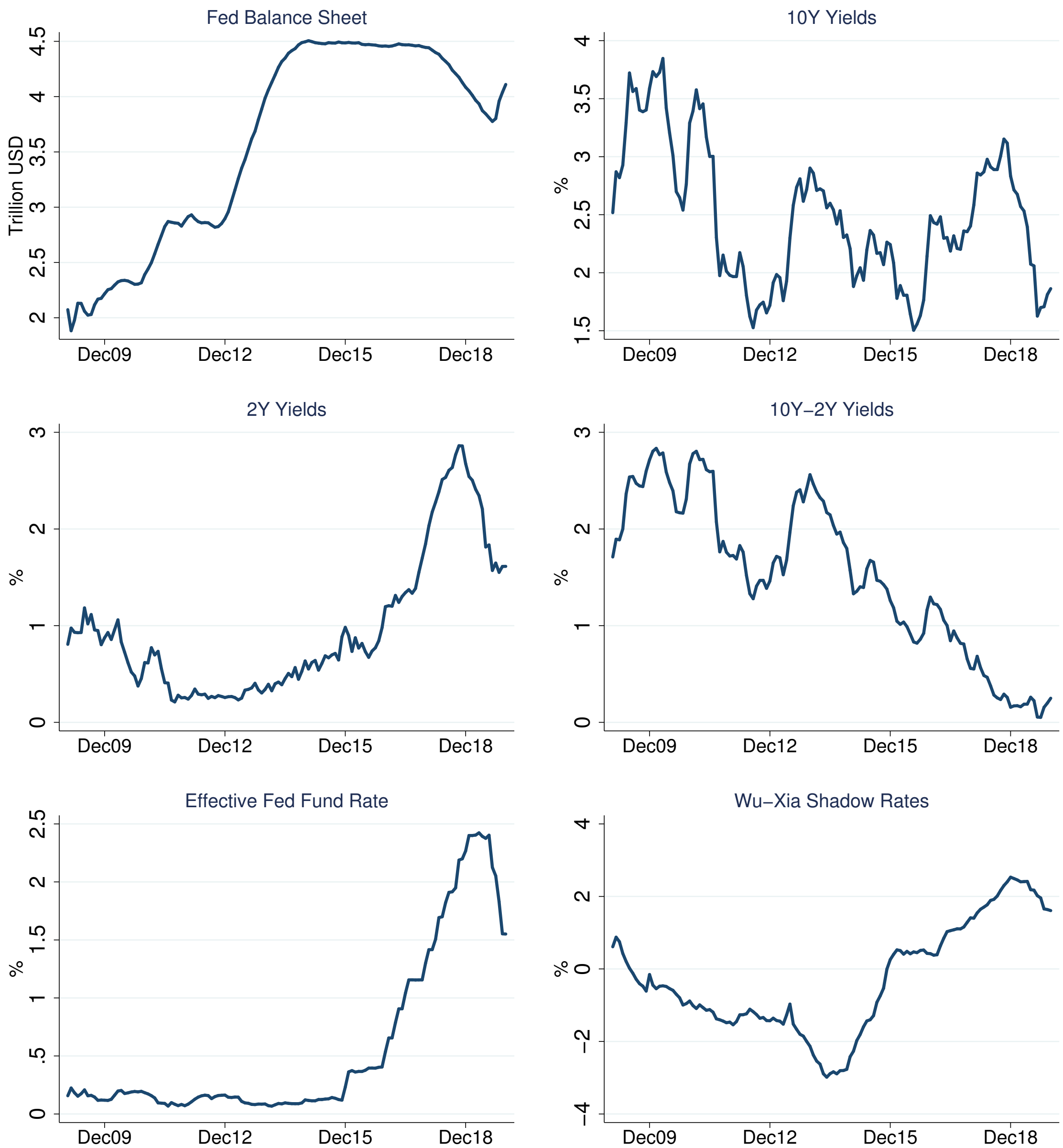

Figure A.6: Monetary policy stance. This figure shows the monetary policy stance in the U.S. during our sample period. The six panels show the size of the Fed balance sheet (trillion dollars), the 10-year Treasury yields (%), the 2-year Treasury yields (%), the difference between the 10-year and the 2-year Treasury yields, the effective fed fund rate, and the shadow rate developed in Wu and Xia (2016). The series are plotted with observations at a monthly frequency. The 10-year yields, the 2-year yields, and the effective fed fund rate are monthly averages of daily data. The Fed balance sheet size is the monthly average of weekly data.

Appendix B Theoretical framework

In this section, we present a model that shows how the sluggishness of credit ratings, especially at the investment-grade cutoff, might induce prospective fallen angels to pay lower bond financing costs than non-downgrade-vulnerable BBB-rated firms.

Setup There are two states of the world. The bad state of the world materializes with probability $q \in (0, 1)$. The good state materializes with probability $1 - q$. Consider the portfolio choice of an investor that allocates capital across assets $i \in \mathcal{I}$.[29] In the good state, the cash flow (i.e., the present value of future cash flows) of asset i is $\overline{C}_i$. In the bad state, the cash flow of asset i is $(1 - \delta)\overline{C}_i$, where $\delta \in (0, 1)$. The investor problem is:

$$max_{\beta_i} \left(\mathbb{E}(C_i) - p_i\right)\beta_i - f\left(\sum_i \mathbb{E}(K)_i \beta_i\right) \tag{B1}$$

$$\begin{aligned} \text{where} \quad \mathbb{E}(C_i) &= (1 - q_i)\overline{C}_i + q_i(1 - \delta)\overline{C}_i \\ &= (1 - \delta q_i)\overline{C}_i \\ \mathbb{E}(K)_i &= \Delta\kappa_i \Big(1 - q_i(1 - \theta_i) + (1 + \alpha_i)q_i(1 - \theta_i)\Big) \\ &= \Delta\kappa_i \left(1 + \alpha_i q_i(1 - \theta_i)\right) \end{aligned}$$

where i is an asset, p_i is the price of asset i, and β_i is the allocation chosen by the investor in asset i. The function $f(\cdot)$ captures the balance sheet costs of all the assets $i \in \mathcal{I}$ held by the investor. Note that the balance sheet cost term in each β_i optimization problem is based on the *entire* portfolio choice, i.e., the common portfolio effect on each first-order condition.[30]

$\mathbb{E}(K)_i$ is the balance sheet cost of asset i. It depends on (i) the probability q_i of being downgraded, (ii) the sluggishness θ_i of credit ratings, (iii) the capital requirement κ_i, and (iv) the additional balance sheet cost α_i. The parameter Δ is just a scaling parameter. Credit ratings are sluggish. In the good state, there are no downgrades (nor upgrades, for simplicity). In the bad state, asset i is downgraded with probability $1 - \theta_i$, i.e., the rating is sluggish with a probability $\theta_i \in (0, 1)$. In the case of a downgrade, the balance sheet cost of asset i is $\kappa_i(1 + \alpha_i)$, where α_i captures the incremental cost associated with being downgraded. One example of this cost is the drop in bond prices caused by investors forced selling of downgraded bonds, particularly pronounced at the investment-grade threshold for insurance companies and high-yield mutual funds (see, e.g., Ellul et al. (2011)).

Figure B.1 shows the cash flows (left panel) and the balance sheet costs (right panel) in the good and bad states of the world.

[29] We assume that investors are symmetric and atomistic.

[30] This setup is similar to the standard mean-variance portfolio problem in which the variance term is affected by the entire portfolio choice, but there is a first-order condition with respect to each asset holding. Here, the variance aversion is replaced by a convex capital cost.

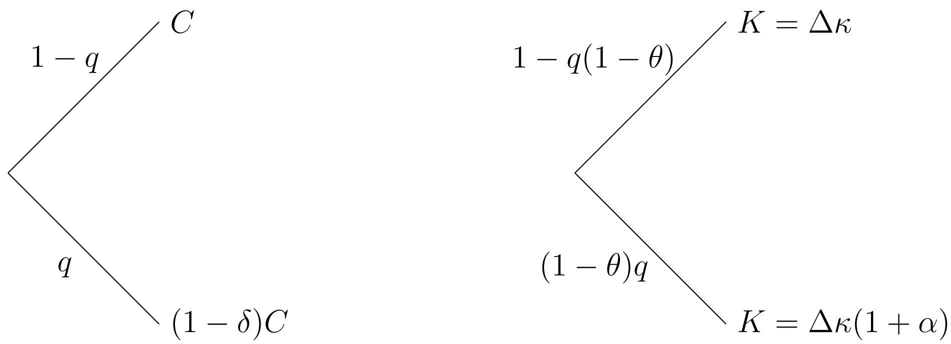

Figure B.1: Cash flows and balance sheet costs in good and bad state. This figure shows the discounted cash flows (left) and the balance sheet costs (right) in the good and bad state of the world.

The first-order condition can be written as:

$$\mathbb{E}(C_i) - p_i - f'\left(\sum_i \mathbb{E}(K)_i \beta_i\right) \frac{\partial\left(\sum_i \mathbb{E}(K)_i \beta_i\right)}{\partial \beta_i} = 0$$

$$\Leftrightarrow \; p_i = \mathbb{E}(C_i) - f'\left(\sum_i \mathbb{E}(K)_i \beta_i\right) \frac{\partial\left(\sum_i \mathbb{E}(K)_i \beta_i\right)}{\partial \beta_i} \tag{B2}$$

The exogenous supply of asset i is S_i. Market clearing $\beta_i = S_i$ implies:

$$p_i = \underbrace{\overline{C}_i(1 - q_i\delta)}_{\mathbb{E}(C_i)} - \mathbb{E}(K)_i f'\left(\sum_i \mathbb{E}(K)_i S_i\right) \tag{B3}$$

To characterize the effect of asset risk on price, we calculate $\frac{dp_i}{dq_i}$ as follows:

$$\frac{dp_i}{dq_i} = -\overline{C}_i\delta - f'\left(\sum_i \mathbb{E}(K)_i S_i\right)\kappa_i \Delta\alpha q_i(1-\theta_i) \tag{B4}$$

where the object inside the f' function is taken as given.

Mapping the model to data We assume a quadratic functional form for the balance sheet costs, i.e., $f(x) = \frac{1}{2}x^2$. Hence, we can write the first-order condition as:

$$p_i = \overline{C}_i(1 - q_i\delta) - \mathbb{E}(K)_i\left(\sum_i \mathbb{E}(K)_i S_i\right) \tag{B5}$$

Our goal is to characterize the evolution of bond prices as a function of credit risk. Table B.1 shows the mapping of model parameters to data. The credit risk of issuer i is captured by the probability of the low state q_i. Both $\overline{C}_i = \overline{C}$ and $\delta_i = \delta$ are identical across issuers. Hence, there is a natural mapping between q_i and credit rating buckets, with a lower q_i corresponding to a higher credit rating. For simplicity, we consider four rating issuer categories: AAA/AA, A, BBB, and B. We set $\overline{C}$ equal to 100 and $\delta = 0.2$.

Parameter	Values	Description
δ	0.2	Haircut in low state
$\overline{C}$	100	Bond cash flow in high state
$\mathbb{E}(K)_{AAA/AA}$	0.025	Balance sheet cost of AAA/AA-rated bonds
$\mathbb{E}(K)_{A}$	0.035	Balance sheet cost of A-rated bonds
$\mathbb{E}(K)_{BBB}$	0.524	Balance sheet cost of BBB-rated bonds
$\mathbb{E}(K)_{BB}$	0.625	Balance sheet cost of B-rated bonds
θ_i	See figures B.3-B.5	Sluggishness of credit ratings
$S_{AAA/AA}$	0.20	Supply of bonds (share of total)
S_{A}	0.29	Supply of bonds (share of total)
S_{BBB}	0.39	Supply of bonds (share of total)
S_{BB}	0.12	Supply of bonds (share of total)

Table B.1: Model calibration. This table shows the parameters chosen to map the model to data, their values, and their description. Note that, for simplicity, we consider four issuer rating categories: AAA/AA, A, BBB, and B.

Capital requirements κ_i depend on credit ratings. We follow the capital requirements for insurance companies set by the National Association of Insurance Commissioners (NAIC). Hence, we set κ_i equal to 0.4%, 1.3%, and 4.6% for AAA/AA/A, BBB, BB, B-rated issuers, respectively. We set the parameter Δ, which captures the strength of the balance sheet regulatory costs, equal to 5. The variable θ_i is the probability of no downgrade in the low state, thus capturing the sluggishness of credit ratings. This variable varies across ratings (BBB ratings are more sluggish than A ratings) and within ratings (downgrade-vulnerable bonds are more sluggish than non-downgrade-vulnerable bonds because because of M&A). We set θ_i to match the probability of downgrades observed in the data for each rating bucket.

The parameter α_i captures the additional cost of downgrade. We set this cost 7 times larger for BBB-rated issuers compared with AAA/AA-rated, A-rated, and BB-rated issuers to capture the cliff risk associated with a different investor base in the high-yield market. Finally, the supply of bonds in each rating category matches the share of the stock of AAA/AA, A, BBB, BB rated bonds outstanding in 2012. We set the aggregate stock of bonds outstanding equal to 10.

Calibration results In Figures B.2-B.5, we show the calibration results. Figure B.2 shows the benchmark case with no credit rating sluggishness and no cost of downgrade. Figure B.3 shows the case with cost of downgrade but no credit rating sluggishess. Figure B.4 shows the case with cost of downgrade and credit rating sluggishness. Figure B.5 shows the case with cost of downgrade, credit rating sluggishness, and a lower supply of AAA/AA/A-rated bonds and a higher supply of BBB/BB-rated bonds—mimicking the increased stock of lower-rated bonds outstanding from QE3 to QT. In each figure, we show eight panels. The two top panels are the corporate bond yields (defined as $\overline{C}/p_i - 1$) and the probability of downgrade ($q_i(1-\theta_i)$). The third and fourth panels show the sluggishness of credit ratings (θ_i) and the expected cash flow ($\overline{C}(1-q_i\delta)$). The fifth and sixth panels show the aggregate balance sheet cost ($\mathbb{E}(K)_i \sum_i \mathbb{E}(K)_i S_i$) and the difference, within each rating, between the average bond yields paid by downgrade-vulnerable issuers and the average bond yields paid by non-downgrade-vulnerable issuers. Finally, the last two panels show the balance sheet

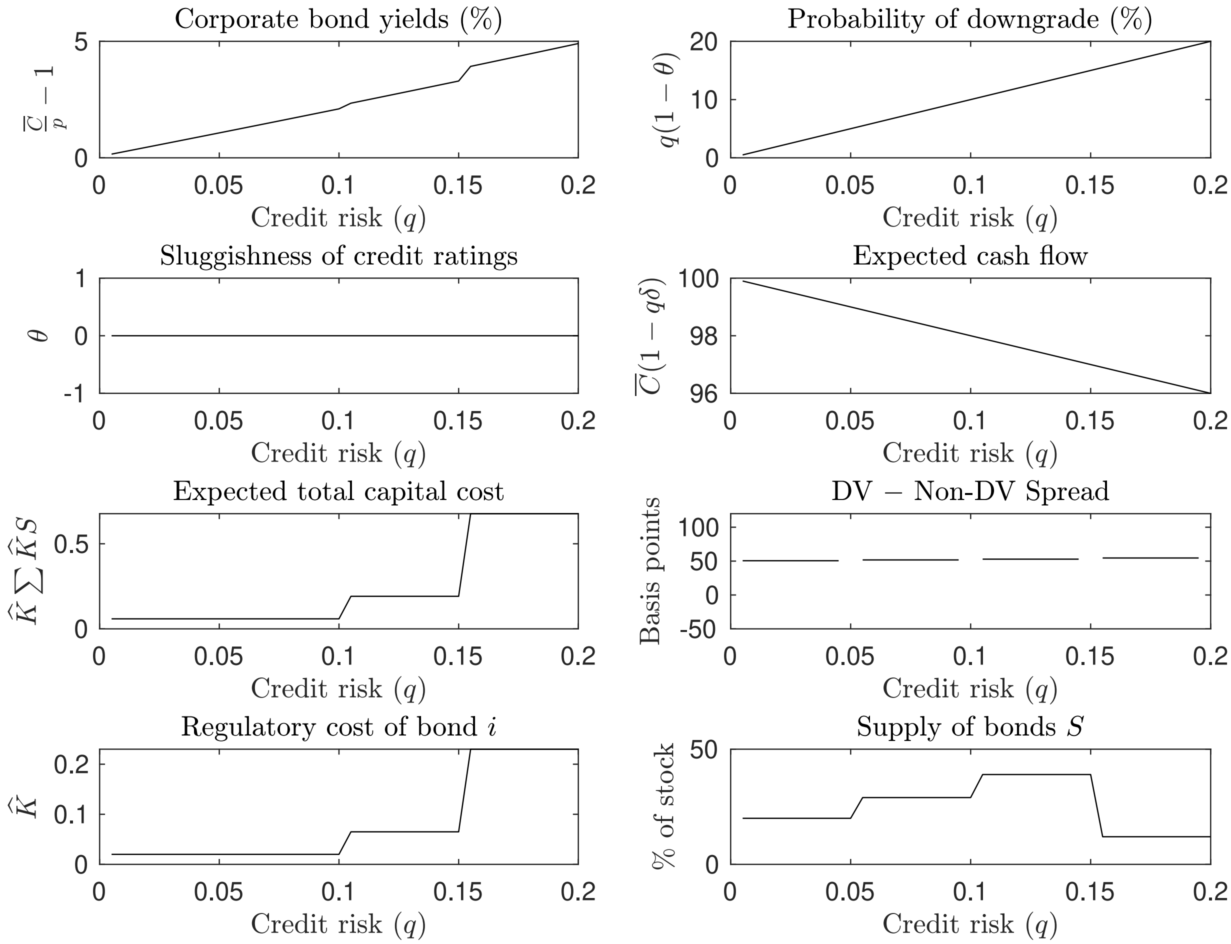

Figure B.2: Model calibration results, no cost of downgrade and no credit rating sluggishness. This figure shows the model calibration results where the parameters are shown in Table B.1 with the exception of $\alpha_i = \alpha = 0$ and $\theta_i = \theta = 0$.

cost of an individual bond and the exogenous supply of bonds.

(i) No cost of downgrade, no credit rating sluggishness. Figure B.2 shows the calibration results in the case where there is no credit rating sluggishness ($\theta_i = \theta = 0$) and there is no cost of downgrade ($\alpha_i = \alpha = 0$). As credit risk increases, the probability of downgrade increases linearly. The aggregate balance sheet cost shows two jumps at the A/BBB threshold and at the BBB/BB threshold, respectively. These jumps only reflect the higher capital requirements required for lower rated bonds. The corporate bond yields are increasing in credit risk. The jump in bond yields around the two credit rating thresholds above are quantitatively small.

(ii) No cost of downgrade. Figure B.3 shows the calibration results in the case where there is no cost of downgrade ($\alpha_i = \alpha = 0$). As credit risk increases, the probability of downgrade generally increases, with the notable exception of bonds that are close to being downgraded, especially at the investment-grade cutoff. In these cases, the sluggishness reduces the probability of a downgrade. The effect on corporate bond yields is, again, small because of the assumption of no cost of downgrade.

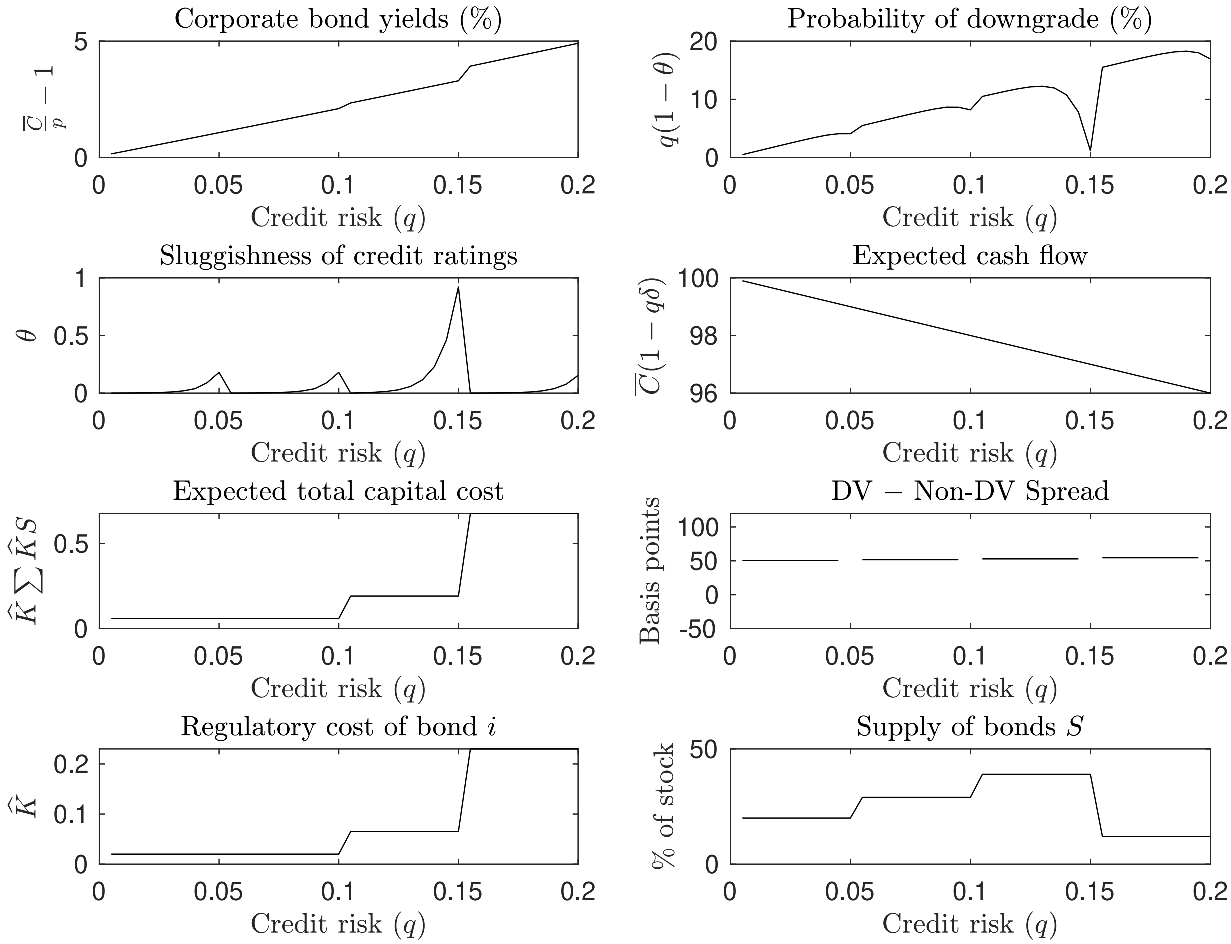

Figure B.3: Model calibration results, no cost of downgrade. This figure shows the model calibration results where the parameters are shown in Table B.1 with the exception of $\alpha_i = \alpha = 0$.

(iii) Baseline. Figure B.4 shows the baseline calibration results. As credit risk increases, the probability of downgrade generally increases, with the notable exception of bonds that are close to being downgraded, especially at the investment-grade cutoff. As in the previous case, these bonds benefit from the sluggishness of credit ratings. The sluggishness—now interacting with the cost of downgrade—has a sizable effect on the balance sheet cost and, in turn, on corporate bond yields. In the sixth panel, we observe that, in the BBB rating category, downgrade-vulnerable issuers pay, on average, *lower* bond financing costs than non-downgrade-vulnerable issuers.

(iv) Baseline with QE. Figure B.5 shows the baseline calibration results. As credit risk increases, the probability of downgrade generally increases, with the notable exception of bonds that are close to being downgraded, especially at the investment-grade cutoff. The sluggishness, again, interacts with the cost of downgrade, thus having a sizable effect on the balance sheet cost and, in turn, on corporate bond yields. In the sixth panel, we observe that, in the BBB rating category, downgrade-vulnerable issuers pay, on average, *lower* bond financing costs than non-downgrade-vulnerable issuers. The results are quantitatively larger than in the baseline case because QE causes the investor

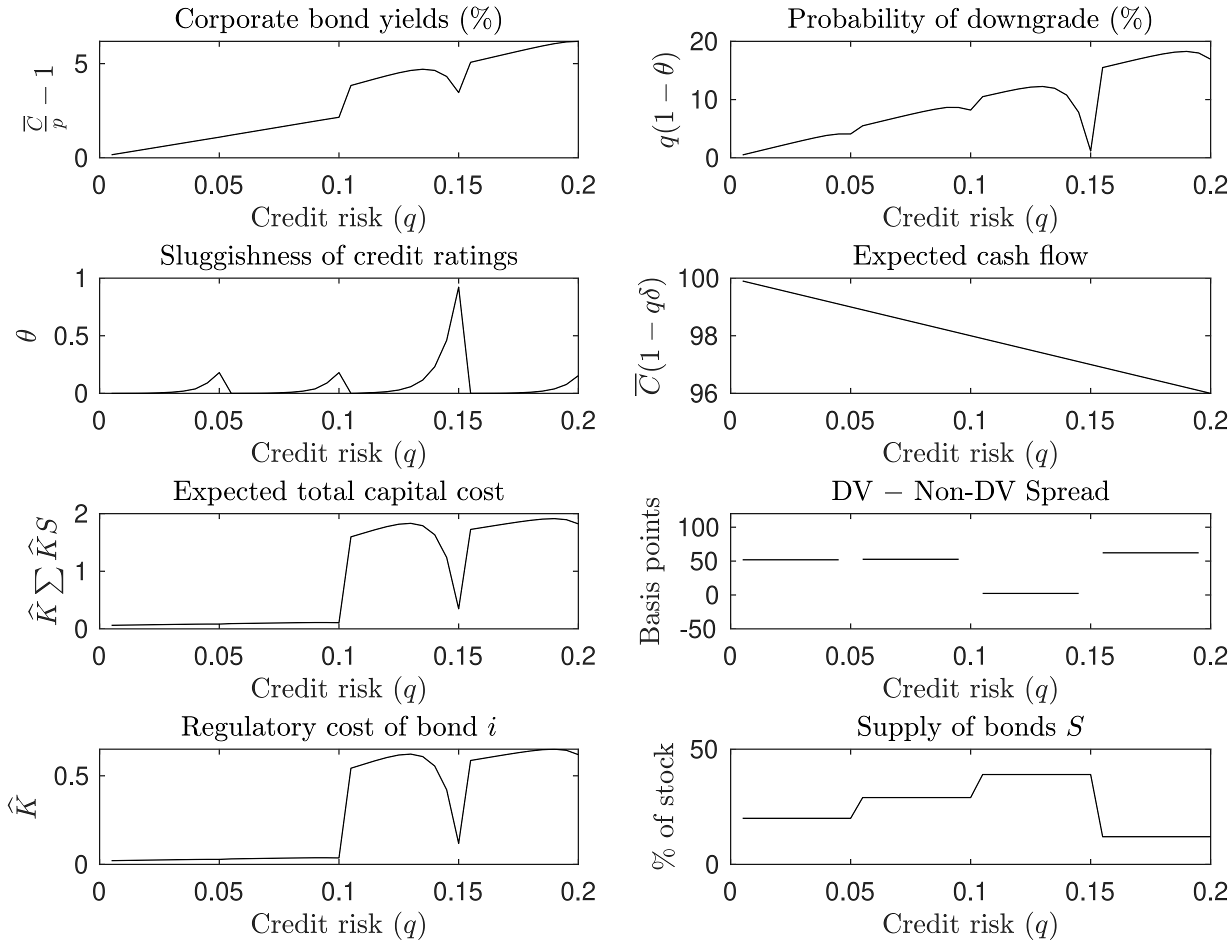

Figure B.4: Model calibration results. This figure shows the model calibration results where the parameters are shown in Table B.1.

to hold more high balance sheet cost assets (BBB/BB-rated bonds) and fewer low balance sheet cost assets (AAA/AA/A-rated bonds).

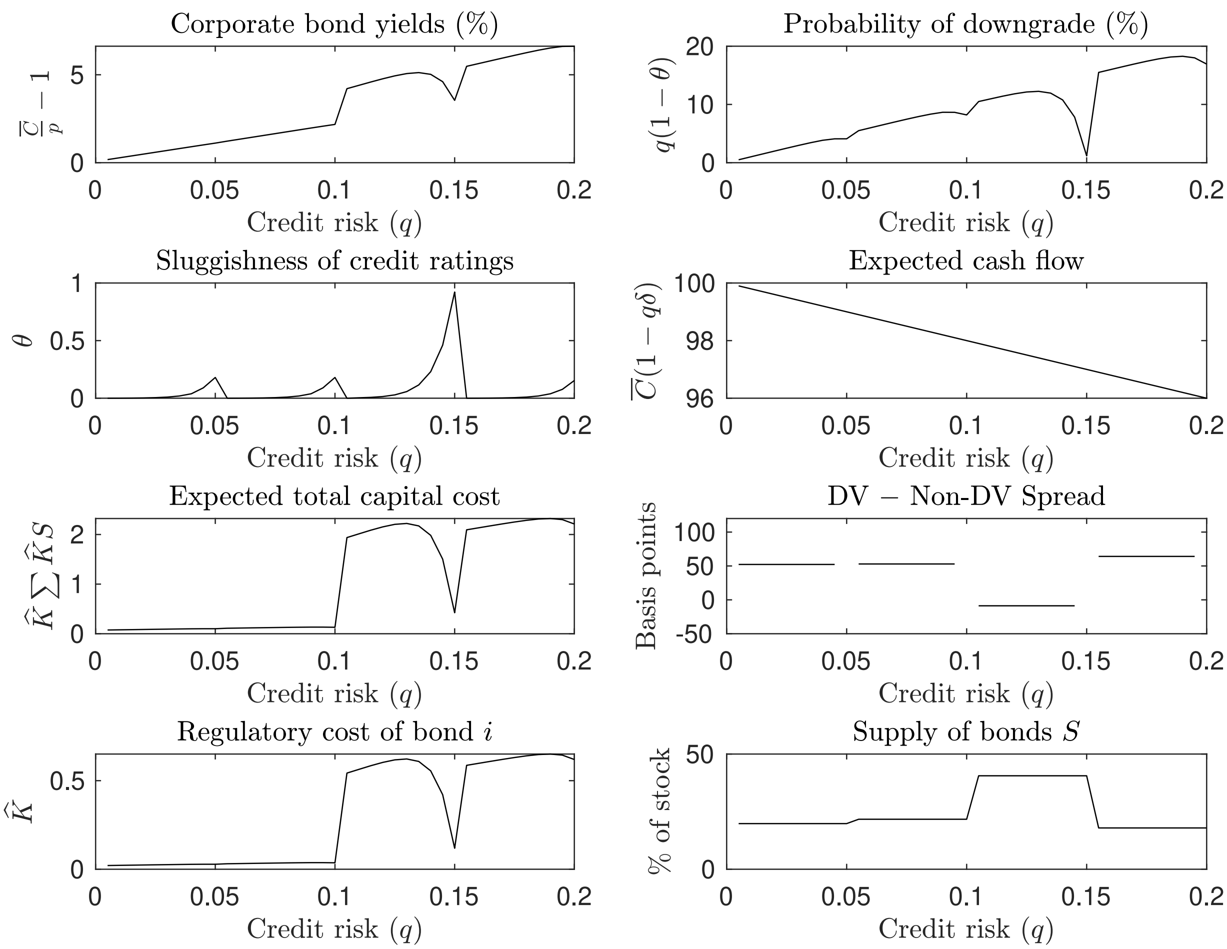

Figure B.5: Model calibration results. This figure shows the model calibration results where the parameters are shown in Table B.1 with the exception of $S_{AAA/AA} = S_A = 15000$ and $S_{BBB} = S_{BB} = 45000$.

Appendix C Data construction

Issuer-level analysis We start with the capital information provided by WRDS Capital IQ, which covers over 60,000 public and private companies globally. The data set describes the firms' debt capital structure over the years 2009 to 2019. We drop the observations for which the debt categories[31] do not add up to 100 per cent and deviate by more than 5 per cent. Moreover, we exclude the observations for which the principal debt amount percentage is missing.[32]

We then combine the CapitalIQ data with the company specific information from Compustat North America, which provides the financial statements of listed American and Canadian firms. We further reduce the sample by dropping firms that are not incorporated in the U.S. or have a SIC-code between 6000-6999. In addition, we exclude the observations that contain missing values for the CapitalIQ debt categories or the Compustat debt items. To merge the debt items of the two providers, we match the total amount of debt outstanding of CapitalIQ to the sum of the current liabilities (DLC) and long-term debt (DLTT) items of Compustat. We drop the observations for which the two values vary by more than 10 per cent to assure a clean matching procedure. Moreover, we drop firms that have a leverage ratio exceeding one.

The issuer CUSIPs allow us to merge the Capital IQ Compustat data set to the rating data from Thomson Reuters, which provides worldwide coverage on ratings from S&P, Moody's and Fitch. We follow Becker and Milbourn (2011) in transferring the ratings into numerical values to estimate the firms' median ratings. For the rating classification, we refer to Table C.1 in the Appendix. Furthermore, we use the issuer CUSIPs to obtain M&A deal information from ThomsonOne. Combining all the data sources, we investigate a total of 6,145 firms.

Moody's	**S&P/Fitch**	**Numerical value assigned**
AAA	AAA	28
Aa	AA	24, 25, 26
A	A	21, 22, 23
Baa	BBB	18, 19, 20
Ba	BB	15, 16, 17
B	B	12, 13, 14
Caa	CCC	9, 10, 11
Ca	CC	7
C	C	4
D	D	-

Table C.1: Rating classification. This table presents the rating mapping used in this paper, taken from Becker and Milbourn (2011).

[31]The debt categories consist of commercial paper, revolving credit, subordinated bonds and notes, senior bonds and notes, general/other borrowings, capital leases, and term loans. We also take into account the total trust preferred, unamortized premium, unamortized discount and adjustment items.

[32]The principal debt amount outstanding percentage can deviate from 100 per cent due to potential debt adjustments. The percentage is used to scale the principal debt outstanding to the total amount of debt outstanding.

Ratings	Z"-score 2006	Z"-score 2013
AAA	7.78	8.40
AA	7.60	8.22
A	6.47	5.80
BBB	6.25	5.60
BB	5.05	4.81
B	2.98	2.84
CCC	0.84	0.05

Table C.2: Z"-score cutoff points This table presents the Z"-score values below which a firm in a given rating bucket will be classified as vulnerable for each rating category from Altman (2020).

Bond-level analysis The second type of data sets we create are on a bond-level and are used to investigate primary and secondary market pricing. For the primary market analysis, we use Mergent Fixed Income Securities Database (FISD), a fixed income database that includes issue details of publicly-offered U.S. bonds. This sample consists of 6,460 bond issues and 909 issuers. For the second market pricing, we use TRACE, which is a database that constitutes of real-time secondary market information on transactions in the corporate bond market. This analysis is based on 7,741 outstanding bonds by 1,146 issuers, with bond b, firm j, year t as unit of observation. For the COVID analysis, we extend our data set to 2020.

Investor-level analysis Our investor-level analysis is based on a data set constructed using the eMAXX Bond Holders data from Refinitiv, matched with the Fed SOMA portfolio data and our issuer-level and bond-level information. The data set is constructed as follows.

The data set from eMAXX has security level holdings at a quarterly frequency from 2009Q1. Securities are identified with cusips and the holdings amount are in par amount and denominated in USD. There are two investors' identifiers: firmid (uniquely identifies a managing firm) and fundid (uniquely identifies a sub-account). Note that one firmid might have several different fundid (there might be multiple funds per firm) and one fundid might have several different firmid (funds might be co-managed by different firms). We use fundid to identify investors in our analysis.

We measure investor-level exposure to QE in quarter t calculating the share of investor total holdings that are held by the Fed (holdings are weighted by the share of amounts outstanding held by the Fed). Having calculated this exposure (and total holdings and total corporate bond holdings for each fund), we only keep observations corresponding to securities issued by the 6,179 issuers at the intersection of Compustat and CapIQ that have bonds outstanding in the period from June 30, 2009 to December 31, 2019. We identify issuers using the first six digits of securities' cusips and gvkeys. We match the data set with investor level characteristics from eMAXX Bond Holders and security-level characteristics (amount issued, issued date, maturity, M&A purpose dummy).

We then collapse our data set at the issuer-investor-quarter level. Our data runs quarterly from 2009Q1 to 2018Q4 and features 7,253 investors and 1,632 corporate bond issuers. Out of the 7,253 funds, 674 are annuities, 1,174 are life and health insurance, 1,996 are property and casualty insurance, and 1,948 are mutual funds, at some point during the sample period. Out of the 1,632 corporate bond issuers, 3 are rated AAA, 24 are rated AA, 138 are rated A, 361 are rated BBB, 390 are rated BB, and 355 are rated B, at some point during the sample period.

Transferring ratings into numerical values Following Becker and Milbourn (2011), we transfer the ratings of S&P, Moody and Fitch into numerical values using Table C.1. This way we can estimate the median rating for each rated firm in our data set.

Z"-score cutoff points We take median Z"-score values for each rating category from Altman (2020). These medians are measured in 2013 for the main analysis and in 2006 for the pre-GFC sample.

Appendix D The exorbitant privilege

D.1 Validating the downgrade-vulnerability measure

In this section, we first show how the balance sheet characteristics of downgrade-vulnerable firms differ from those of non-downgrade-vulnerable firms. Thereafter, we show how a firm's downgrade probability, balance sheet characteristics and firm performance change after a firm is classified as downgrade-vulnerable.

In Table D.1, we present the descriptive statistics for the rated firms in our sample, separated for firms that are downgrade-vulnerable and firms that are not downgrade-vulnerable. The sample means highlight that downgrade-vulnerable firms are larger and riskier along all dimensions. In particular, downgrade-vulnerable firms have higher leverage, lower profitability, lower net worth, and a lower interest coverage ratio. Their sales growth, employment growth, and investment ratio are also significantly lower than those of non-downgrade-vulnerable firms. The last column shows a test for the difference in means.

Next, we show that downgrade-vulnerable firms are more likely to be downgraded and to be assigned a negative credit watch or outlook status relative to non-downgrade-vulnerable firms. To this end, we estimate the following specification:

$$Y_{it+1} \quad = \quad \beta_1 Vulnerable_{it} + \beta_2 X_{it} + \mu_{ht} + \epsilon_{it+1},$$

where i is a firm, h an industry, and t a year. Our dependent variable Y is a dummy equal to one in the case of a negative watch event in t or $t+1$, or a downgrade event in $t+1$. To qualify as downgrade event, a firm must be downgraded by at least one rating category in year $t+1$, i.e. a firm that has a rating of A+, A, or A- is downgraded to at least BBB+. $Vulnerable$ is a dummy equal to one if a firm is downgrade-vulnerable in period t and μ_{ht} are industry-year fixed effects. X_{it} is a vector of controls, namely the logarithm of total assets, leverage, and the interest coverage ratio.

Table D.2 presents the estimation results. The first two columns show that a downgrade-vulnerable company in year t is more likely to have a negative watch event in year t or

	Downgrade-vulnerable	Non-downgrade-vulnerable	Difference
Total Assets	24,082	11,756	12,326***
Leverage	0.418	0.349	0.069***
EBITDA/Assets	0.102	0.131	−0.029***
Interest Coverage	7.001	13.152	−6.151***
Sales Growth	0.035	0.056	−0.021***
CAPX	0.183	0.223	−0.040***
Employment Growth	0.005	0.036	−0.031***
Net Worth	0.160	0.254	−0.094***

Table D.1: Descriptive statistics: downgrade-vulnerable and non-downgrade-vulnerable firms. This table presents descriptive statistics for rated firms in our sample, separated into downgrade-vulnerable and non-downgrade-vulnerable firms. *Total Assets* is in millions, *Leverage* is total debt over total assets, *Interest Coverage* is EBITDA over interest expenses, *Sales Growth* is the growth rate in sales, $CAPX$ is capex over PPE, *Employment Growth* is the growth rate in employment, *Net Worth* is the difference between common equity and cash divided by total assets.

	Negative Watch	Negative Watch	Downgrade	Downgrade
Vulnerable	0.078***	0.040**	0.024***	0.019***
	(0.018)	(0.019)	(0.006)	(0.006)
Size		0.012*		0.003*
		(0.007)		(0.002)
Leverage		0.108*		0.013
		(0.058)		(0.015)
IC Ratio		−0.010***		−0.001**
		(0.001)		(0.000)
Industry-Year FE	✓	✓	✓	✓
Observations	7,192	7,127	9,431	9,341
R-squared	0.228	0.240	0.094	0.097

Table D.2: Credit rating actions after being classified as vulnerable. This table presents the estimation results from Specification (D1) for our sample of rated firms. The dependent variable *Negative Watch* is a dummy variable equal to one if a firm is placed on negative credit watch or outlook in year t or $t+1$. The dependent variable *Downgrade* is a dummy variable equal to one if a firm is downgraded by at least one rating category in year $t+1$, i.e., a firm that has a rating of A+, A, or A- is downgraded to at least BBB+. *Vulnerable* is a dummy equal to one if a firm is vulnerable in period t. Firm level control variables are size (log of total assets), leverage and IC ratio. Standard errors clustered at the firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

$t+1$. Similarly, the last two columns show that a downgrade-vulnerable firm has a higher probability to be downgraded by at least one rating category in the next year.

Finally, we examine how the balance sheet characteristics of downgrade-vulnerable firms change after the obtaining the vulnerability status. Following Banerjee and Hofmann (2020), we create a local linear projection specification, based on a sequence of regression models where the dependent variable is shifted several steps forward and backward in time, relative to a reference point. Our reference point is the date at which a firm is classified as downgrade-vulnerable for the first time. Specifically, we estimate the following specification:

$$Y_{it+q} \quad = \quad \beta_q EnterVulnerable_{it} + \gamma_q Vulnerable_{it} + \eta_q X_{it+q} + \mu_{ht+q} + \epsilon_{it+q}, \qquad \text{(D1)}$$

where i is a firm, h an industry, t a year, and $q \in \mathcal{Q}$, where $\mathcal{Q} = \{-3, -2, -1, 0, 1, 2, 3\}$. The dependent variable Y is asset growth, employment growth, sales growth, and capital expenditures in period $t+q$. *EnterVulnerable* is a dummy equal to one if a firm becomes vulnerable for the first time in period t. *Vulnerable* is a dummy equal to one if a firm is downgrade-vulnerable in period t, but did not become downgrade-vulnerable in period t for the first time, i.e., it has been classified as downgrade-vulnerable before. This specification ensures we compare firms becoming downgrade-vulnerable for the first time only to non-vulnerable firms. X_{it+q} is the logarithm of total assets and μ_{ht+q} are industry-year fixed effects.

The coefficient of interest β_q measures a downgrade-vulnerable firm's development, in the three years before and after the firm is classified as downgrade-vulnerable, of sales growth, investments, asset growth, and employment growth. A positive (negative) coefficient implies that a downgrade-vulnerable firm has a higher (lower) value of the respective dependent variable compared to a non-downgrade-vulnerable firm. Figure D.1 shows the estimated β_q

coefficients, documenting that firm performance deteriorates once it becomes downgrade-vulnerable. Its sales growth and investment decline significantly, a dynamic also reflected in the drop in firm size and employment growth.

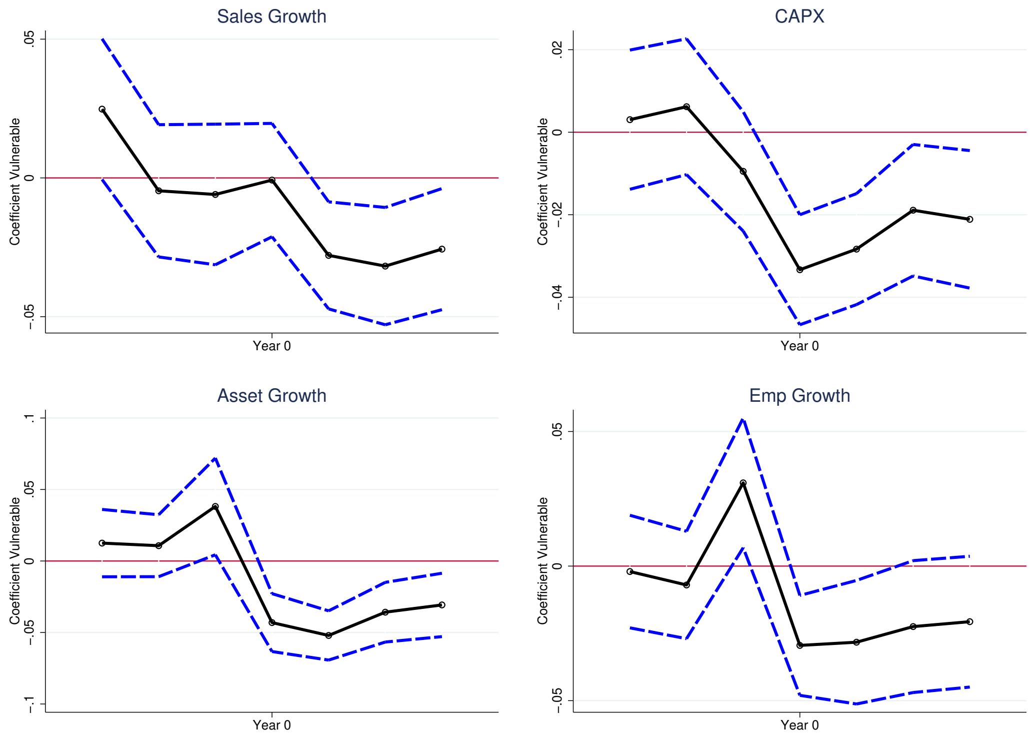

Figure D.1: Firm performance after being classified as downgrade-vulnerable. This figure shows the evolution of the estimated coefficient β_q from Specification (D1) three years before and after a firm becomes downgrade-vulnerable. Year zero corresponds to the first year a firm is classified as downgrade-vulnerable. The 95% confidence interval is reported, with standard errors clustered at the firm level.

D.2 Descriptive statistics of bonds by vulnerability

Panel A of Table D.3 shows that the characteristics of bonds issued by downgrade-vulnerable firms are similar to those issued by non-downgrade-vulnerable firms. The remaining maturities are similar, with a median remaining maturity of 6.4 and 6.3 years respectively. The offering amounts are also similar as is the likelihood of bonds being classified as senior and also whether the bond is callable. On average, secondary market spreads on bonds issued by downgrade-vulnerable firms are *lower* than spreads of non-downgrade-vulnerable firms. Panel B, however, shows that this is driven by a composition effect across the sample. Within each rating category secondary market spreads of bonds issued by downgrade-vulnerable firms are *higher* than those of their non-downgrade-vulnerable peers across the distribution. The one exception is the BBB segment where bond spreads are lower than their non-downgrade-vulnerable peers.

Panel A: Bond-level descriptive statistics

Variable	Vulnerable	Mean	StDev	p25	p50	p75
Remaining maturity	No	9.5	8.6	3.8	6.3	9.6
Remaining maturity	Yes	9.9	9.0	3.7	6.4	10.3
log(offering amount)	No	13.1	0.6	12.6	13.1	13.5
log(offering amount)	Yes	13.3	0.7	12.8	13.2	13.8
Senior bond	No	1.0	0.2	1.0	1.0	1.0
Senior bond	Yes	1.0	0.2	1.0	1.0	1.0
Callable bond	No	0.9	0.3	1.0	1.0	1.0
Callable bond	Yes	0.9	0.2	1.0	1.0	1.0
Spread	No	134.0	148.3	56.7	93.4	157.6
Spread	Yes	121.8	130.4	55.3	88.5	141.5

Panel B: Bond spreads by rating

Rating	Vulnerable	Mean	p25	p50	p75	Std Dev
AAA-AA	No	35.9	19.4	31.5	46.9	23.0
AAA-AA	Yes	37.8	19.8	32.6	50.1	23.6
Difference		*1.9*	*0.5*	*1.1*	*3.2*	
A	No	51.2	32.2	46.7	62.8	25.7
A	Yes	60.0	37.9	54.6	75.8	29.3
Difference		*8.7*	*5.7*	*8.0*	*13.0*	
BBB	No	103.8	68.6	93.5	125.2	48.5
BBB	Yes	96.7	62.2	84.5	116.8	47.7
Difference		*-7.1*	*-6.4*	*-9.0*	*-8.4*	
BB	No	222.9	158.6	208.9	272.4	94.0
BB	Yes	234.2	166.0	220.0	285.2	98.4
Difference		*11.3*	*7.4*	*11.1*	*12.8*	
B	No	374.6	231.3	319.0	435.9	221.8
B	Yes	457.3	284.0	394.1	547.2	251.6
Difference		*82.7*	*52.7*	*75.1*	*111.3*	
CCC	No	975.8	493.8	691.6	1269.1	718.8
CCC	Yes	1330.7	648.4	866.4	1809.2	904.1
Difference		*354.8*	*154.6*	*174.8*	*540.1*	

Table D.3: Bond-level summary statistics. This table reports bond-level summary statistics. Panel A shows descriptive statistics for all bonds in our sample. Panel B shows secondary market spreads by issuers' downgrade-vulnerability. Sample period 2009 to 2019.

D.3 Baseline results of the exorbitant privilege

Dependent Variable:	Secondary mkt Spread					
	Full sample	QE1	QE2 until QE3	QE3 until FFR	QE3 until QT	QT
A	24.395***	50.803**	39.327***	22.051***	21.499***	20.507***
	(3.999)	(18.695)	(9.213)	(4.068)	(3.396)	(4.301)
BBB	67.711***	117.275***	92.656***	64.772***	64.581***	53.768***
	(4.239)	(20.047)	(10.114)	(4.469)	(3.818)	(4.594)
BB	145.853***	203.173***	172.843***	131.968***	137.753***	133.105***
	(5.840)	(19.728)	(13.278)	(7.955)	(6.827)	(6.380)
B	233.812***	279.412***	254.801***	216.457***	225.146***	219.029***
	(7.187)	(23.695)	(15.409)	(9.858)	(8.245)	(10.491)
CCC	414.535***	364.689***	303.775***	455.710***	446.219***	358.142***
	(21.211)	(38.249)	(20.171)	(41.490)	(29.409)	(20.313)
Vulnerable × AAA-AA	10.671**	-7.713	17.286*	14.645***	11.602***	4.959
	(4.397)	(25.104)	(9.521)	(4.930)	(3.913)	(4.582)
Vulnerable × A	5.260	11.019	12.949**	8.190*	5.289	-1.255
	(3.490)	(7.574)	(5.954)	(4.191)	(4.221)	(4.797)
Vulnerable × BBB	-5.533**	-5.717	-1.790	-7.047**	-10.034***	2.048
	(2.659)	(6.996)	(4.867)	(3.245)	(3.145)	(3.330)
Vulnerable × BB	19.190***	9.719	7.723	21.910***	30.272***	10.088
	(5.451)	(9.034)	(8.597)	(7.510)	(8.192)	(9.165)
Vulnerable × B	26.171***	53.274**	36.133**	31.824**	23.233**	-44.679*
	(9.060)	(23.818)	(13.336)	(13.136)	(11.065)	(23.786)
Industry-Year-Month FE	✓	✓	✓	✓	✓	✓
Bond-level controls	✓	✓	✓	✓	✓	✓
Observations	247,165	23,996	33,312	73,858	122,657	53,824
R-squared	0.724	0.733	0.739	0.744	0.757	0.760

Table D.4: The exorbitant privilege of prospective fallen angels. This table shows the estimation results of specification (2). The dependent variable is the secondary market bond spread. Bond spreads are measured in basis points. Vulnerable is a dummy variable equal to 1 if issuer i is downgrade-vulnerable in date $t-1$ and t. Additional bond-level controls include residual maturity, amount outstanding and bid-ask spreads. Coefficients on the latter are allowed to vary by rating. The specification also includes dummy variables for senior bonds, bonds with covenants, callable bonds, bonds with a price above par but below a price of 105 and the interaction between the latter two variables to account for changes in credit quality affecting spreads on callable bonds. These control variables are included in the estimation but not reported for brevity. These specifications include industry-year-month fixed effects (2-digit SIC). Standard errors are clustered at the firm and year-month level. *** p<0.01, ** p<0.05, * p<0.1.

Dependent Variable:	Primary mkt Spread					
	Full sample	QE1	QE2 until QE3	QE3 until FFR	QE3 until QT	QT
A	40.255***	40.489	110.062	36.092*	35.969**	-0.804
	(11.501)	(24.742)	(104.710)	(18.401)	(14.017)	(9.707)
BBB	104.219***	129.572***	164.636	92.944***	100.464***	52.148***
	(12.125)	(32.179)	(106.037)	(19.778)	(14.931)	(7.981)
BB	227.909***	212.148***	254.214**	232.650***	238.795***	187.304***
	(14.922)	(53.549)	(96.562)	(20.305)	(15.856)	(25.108)
B	337.159***	321.523***	392.330***	357.844***	350.162***	256.404***
	(17.235)	(36.992)	(100.093)	(28.411)	(23.751)	(32.033)
CCC	269.510***	350.508***		420.846***	431.204***	
	(78.306)	(61.658)		(44.595)	(37.796)	
Vulnerable × AAA-AA	13.584		113.929	16.438	10.943	
	(14.844)		(113.187)	(21.570)	(17.758)	
Vulnerable × A	11.866	16.285	12.421	22.354*	22.515**	-2.163
	(8.637)	(21.759)	(21.123)	(11.216)	(11.007)	(23.233)
Vulnerable × BBB	-27.502***	-37.305	-12.712	-28.881*	-32.975***	-23.633**
	(7.633)	(28.359)	(10.304)	(14.855)	(11.672)	(9.442)
Vulnerable × BB	37.677**	78.725	69.409**	21.839	23.956	1.426
	(15.733)	(51.909)	(27.611)	(18.112)	(22.044)	(29.709)
Vulnerable × B	64.410***	62.978	54.904	52.436	73.449**	
	(22.709)	(47.857)	(39.126)	(43.976)	(33.317)	
Industry-Year-Month FE	✓	✓	✓	✓	✓	✓
Bond-level controls	✓	✓	✓	✓	✓	✓
Observations	2,761	287	405	985	1,534	477
R-squared	0.876	0.896	0.896	0.904	0.889	0.851

Table D.5: The exorbitant privilege of prospective fallen angels. This table shows the estimation results of specification (2). The dependent variable is the primary market spread. Bond spreads are measured in basis points. Vulnerable is a dummy variable equal to 1 if issuer i is downgrade-vulnerable in date $t-1$ and t. Additional bond-level controls include residual maturity and amount outstanding. Coefficients on the latter are allowed to vary by rating. The specification also includes dummy variables for senior bonds, bonds with covenants, callable bonds, bonds with a price above par but below a price of 105 and the interaction between the latter two variables to account for changes in credit quality affecting spreads on callable bonds. These control variables are included in the estimation but not reported for brevity. These specifications include industry-year-month fixed effects (2-digit SIC). Standard errors are clustered at the firm and year-month level. *** p<0.01, ** p<0.05, * p<0.1.

Dependent Variable:	Δ Spread					
	Full sample	QE1	QE2 until QE3	QE3 until FFR	QE3 until QT	QT
AAA-AA × D(event day)	-10.31	-31.23***	-7.748**	-1.338	0.0483	10.47
	(6.356)	(6.295)	(3.498)	(3.353)	(2.842)	(23.73)
A × D(event day)	-10.62*	-31.36***	-8.281**	-1.306	-0.0053	10.07
	(6.380)	(6.879)	(3.858)	(3.458)	(2.875)	(23.90)
BBB × D(event day)	-10.06	-28.90***	-8.110***	-0.9405	0.2571	10.76
	(6.382)	(7.561)	(2.864)	(3.334)	(2.816)	(23.81)
BB × D(event day)	-9.772	-26.76***	-8.426***	-0.2838	-0.1729	14.68
	(6.509)	(8.396)	(1.549)	(2.898)	(2.716)	(23.79)
B × D(event day)	-9.631	-28.02**	-5.709***	-0.1494	-0.1322	17.89
	(6.789)	(11.71)	(1.011)	(3.097)	(2.866)	(22.23)
Vulnerable × AAA-AA × D(event day)	0.1468	0.4247	-1.015	-0.2442	0.1354	-0.5118
	(0.2401)	(0.9713)	(0.7947)	(0.4102)	(0.2672)	(0.6654)
Vulnerable × A × D(event day)	0.3618	2.144**	-0.6229	0.1039	-0.1403	0.5761
	(0.2707)	(1.005)	(0.6013)	(0.2984)	(0.2511)	(0.6718)
Vulnerable × BBB × D(event day)	-0.0051	0.8682	0.3090	-0.6846**	-0.2539	-0.0834
	(0.2430)	(1.667)	(0.3946)	(0.3235)	(0.2676)	(0.2692)
Vulnerable × BB × D(event day)	0.1125	0.7609	1.226	-0.5375	0.2087	-0.9219
	(0.6089)	(1.526)	(1.553)	(0.9724)	(0.8280)	(1.871)
Vulnerable × B × D(event day)	1.072	-1.787	-1.015	2.205	2.048	0.8380
	(1.240)	(4.426)	(2.029)	(2.092)	(1.943)	(1.934)
Industry-Year-Month-Day FE	✓	✓	✓	✓	✓	✓
Bond-level controls	✓	✓	✓	✓	✓	✓
Observations	2,432,415	184,764	220,548	501,154	950,273	555,720
R-squared	0.17388	0.19163	0.18192	0.12759	0.12888	0.11865

Table D.6: The exorbitant privilege of prospective fallen angels. This table shows shows the estimation results of the event study with specification (3). The dependent variable is the one day change in the secondary market spread. Bond spreads are measured in basis points. Vulnerable is a dummy variable equal to 1 if issuer i is downgrade-vulnerable in date $t-1$ and t. D(event day)$_t$ is the a dummy variable taking on the value of one on days with monetary policy announcements in which the 10-year Treasury futures contract declined within a -15 to $+15$ minute window around the monetary policy announcement or -15 to $+90$ minutes for press conferences and release of minutes. Monetary policy announcement dates from Cieslak and Schrimpf (2019) updated to end 2019. Additional bond-level controls include residual maturity, amount outstanding, bid-ask spreads. Coefficients on the latter variable are allowed to vary by rating. The specification also includes dummy variables for senior bonds, bonds with covenants, callable bonds, bonds with a price above par but below a price of 105 and the interaction between the latter two variables to account for changes in credit quality affecting spreads on callable bonds. These control variables are included in the estimation but not reported for brevity. Also omitted for brevity are the coefficients the uninteracted rating and on the interaction between the rating and the downgrade-vulnerable dummy variables. These specifications include industry-year-month-day fixed effects (2-digit SIC). Standard errors are clustered at the firm and year-month-day level. *** p<0.01, ** p<0.05, * p<0.1.

D.4 Additional robustness tests of the exorbitant privilege

In this section, we provide additional tests examining the exorbitant privilege of downgrade-vulnerable BBB firms. We first examine the sensitivity of our baseline results in Table 2 to the use of bond instead of firm-level ratings and additional controls for bond liquidity.

Table D.7 shows that the downgrade-vulnerable BBB exorbitant privilege remains if we use bond-level ratings to define vulnerability. The point estimates are almost unchanged compared with our baseline results. The results with bond-level ratings also confirm the finding of higher spreads in the period from QE3 until the withdrawal of monetary stimulus in secondary.

The second set of tests examine whether systematic differences in the liquidity of downgrade-vulnerable and non-downgrade-vulnerable bonds may drive our results. In addition to controlling for bid-ask spreads at the rating level, the two column of Table D.8 additionally control for the number of times a bond is traded in a month. Similar to bid-ask spreads we allow the coefficients of the number of trades to vary by ratings category. The first column shows that bonds which tend to trade more frequently have higher spreads. Nevertheless, the point estimates of the prospective fallen angel subsidy remains almost unchanged. In columns (2) to (3) we examine if the age of the bond affects our results. Column (1) confirms the fallen angel privilege in on-the-run bonds that were issued over the past twelve months, while column (2) shows that this is also present and with an almost identical magnitude in older bonds off-the-run bonds.

Dependent Variable:	Secondary mkt Spread					
	Full sample	QE1	QE2 until QE3	QE3 until FFR	QE3 until QT	QT
A	25.231***	67.444***	40.278***	20.664***	20.410***	17.575***
	(5.427)	(17.843)	(9.462)	(4.320)	(4.219)	(5.868)
BBB	67.919***	128.641***	88.941***	63.572***	62.711***	51.563***
	(5.754)	(19.650)	(10.373)	(5.078)	(4.945)	(6.283)
BB	143.842***	211.205***	168.944***	122.854***	129.061***	131.397***
	(6.995)	(19.415)	(12.931)	(7.776)	(7.233)	(8.065)
B	208.597***	256.898***	229.146***	189.558***	201.220***	186.746***
	(8.191)	(20.509)	(15.771)	(10.091)	(9.359)	(10.842)
CCC	274.154***	278.393***	266.264***	279.449***	288.558***	314.252***
	(11.511)	(23.585)	(20.483)	(20.925)	(15.457)	(21.101)
Vulnerable × AAA-AA	4.680	-13.088	13.854	5.139	3.480	-0.299
	(5.959)	(26.743)	(9.304)	(4.264)	(4.502)	(5.353)
Vulnerable × A	3.498	11.456	8.437	7.520*	2.520	-1.263
	(2.969)	(6.948)	(4.982)	(4.091)	(3.460)	(3.999)
Vulnerable × BBB	-5.913**	-3.972	-4.192	-8.076***	-9.957***	2.948
	(2.334)	(6.075)	(4.128)	(2.926)	(2.809)	(3.250)
Vulnerable × BB	18.212***	6.124	5.432	32.309***	31.606***	6.455
	(4.867)	(9.077)	(8.373)	(7.752)	(6.888)	(9.219)
Vulnerable × B	26.932***	11.576	37.251***	44.605***	29.862***	9.616
	(8.516)	(16.551)	(9.516)	(12.141)	(10.338)	(25.367)
Vulnerable × CCC	49.180*	132.258***	113.465**	24.604	14.946	-104.665***
	(24.912)	(37.876)	(49.300)	(22.913)	(18.631)	(29.140)
Industry-Year-Month FE	✓	✓	✓	✓	✓	✓
Bond-level controls	✓	✓	✓	✓	✓	✓
Observations	239,229	25,344	33,593	72,547	120,536	49,965
R-squared	0.725	0.715	0.766	0.736	0.756	0.753

Table D.7: Baseline results with bond-level ratings. This table shows the estimation results of specification (2), where bond-level ratings are used instead of issuer-level ratings. The dependent variable in each column is the secondary market bond spread. Bond spreads are measured in basis points. Vulnerable is a dummy variable equal to 1 if issuer i is downgrade-vulnerable in date $t-1$ and t, based on bond ratings.Additional bond-level controls include residual maturity, amount outstanding and bid-ask spreads. Coefficients the latter variable are allowed to vary by rating. The specification also includes dummy variables for senior bonds, bonds with covenants, callable bonds, bonds with a price above par but below a price of 105 and the interaction between the latter two variables to account for changes in credit quality affecting spreads on callable bonds. These control variables are included in the estimation but not reported for brevity. These specifications include industry-year-month fixed effects (2-digit SIC). Standard errors are clustered at the firm and year-month level. *** p<0.01, ** p<0.05, * p<0.1.

	Spread_{it}	Spread_{it}	Spread_{it}
A	24.830***	15.586***	26.511***
	(4.469)	(3.344)	(5.010)
BBB	66.740***	56.376***	71.737***
	(4.421)	(3.382)	(5.249)
BB	142.313***	151.949***	147.346***
	(5.631)	(5.758)	(6.702)
B	230.269***	236.125***	238.262***
	(6.929)	(7.141)	(8.230)
CCC	427.224***	381.327***	414.435***
	(22.594)	(43.052)	(16.560)
Vulnerable × AAA_AA	8.658*	10.331***	8.672
	(4.418)	(3.284)	(5.454)
Vulnerable × A	5.819*	5.255	7.170*
	(3.348)	(4.148)	(3.695)
Vulnerable × BBB	-6.003**	-6.543**	-6.130**
	(2.589)	(3.187)	(2.690)
Vulnerable × BB	18.074***	17.117**	18.818***
	(5.649)	(7.967)	(5.581)
Vulnerable × B	25.365***	20.002*	28.573***
	(9.417)	(10.488)	(10.291)
Trades × AAA	0.005		
	(0.010)		
Trades × AA	0.023***		
	(0.005)		
Trades × A	0.016***		
	(0.004)		
Trades × BBB	0.026***		
	(0.005)		
Trades × BB	0.041***		
	(0.007)		
Trades × B	0.056***		
	(0.009)		
Trades × CCC	-0.049**		
	(0.021)		
Industry-Year-Month FE	✓	✓	✓
Bond-level controls	✓	✓	✓
Sample	2010–19	2010–19	2010–19
Bond age	All	< 12 months	>12 months
Observations	238,044	46,679	190,325
R-squared	0.740	0.814	0.730

Table D.8: Additional bond liquidity controls. This table shows the estimation results of specification (2), with tests for bond liquidity. The dependent variable in all columns is the secondary market bond spread. The first column include additional control variables for the number of times a bond is traded in a month. We allow coefficients to vary by ratings category. In the second column, the sample is restricted to bonds that have been issued within the past 12 months, while the third column only includes bonds issued at least 12 months earlier. In all regressions, the dependent variable in each column is the secondary market bond spread. Bond spreads are measured in basis points. Additional bond-level controls include residual maturity, amount outstanding and bid-ask spreads. Coefficients on the latter are allowed to vary by rating. The specification also includes dummy variables for senior bonds, bonds with covenants, callable bonds, bonds with a price price above par but below a price of 105 and the interaction between the two variable to account for changes in credit quality affecting spreads on callable bonds. These control variables are included in the estimation but not reported for brevity. These specifications include industry-year-month fixed effects (2-digit SIC). Standard errors are clustered at the firm and year-month level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix E Investor types

	N_k^{09q1}	N_k^{13q1}	N_k^{17q1}	$Hold_k^{09q1}$	$Hold_k^{13q1}$	$Hold_k^{17q1}$
Annuities	540	473	467	\$60.50 b	\$162.52 b	\$147.77 b
Life & Health Insurance	1072	1184	976	\$438.98 b	\$804.57 b	\$874.27 b
Property & Casualty Insurance	2035	2106	1822	\$105.17 b	\$166.91 b	\$152.61 b
Open Ended Mutual Funds	1207	1535	1692	\$336.53 b	\$1015.93 b	\$1315.54 b

QE Exposure$_{kt}$	mean	stdev	p25	p50	p75
Annuities	0.029	0.005	0.027	0.030	0.032
Life & Health Insurance	0.014	0.002	0.013	0.013	0.015
Property & Casualty Insurance	0.027	0.003	0.024	0.027	0.029
Open Ended Mutual Funds	0.025	0.004	0.022	0.024	0.026

Corporate and Treasury Bond Portfolio Maturity$_{kt}$	mean	stdev	p25	p50	p75
Annuities	12.968	7.217	8.422	9.212	16.010
Life & Health Insurance	11.730	2.135	10.950	11.342	11.631
Property & Casualty Insurance	7.134	3.186	5.937	6.148	6.738
Open Ended Mutual Funds	12.871	6.991	8.425	8.781	19.913

Treasury Bond Portfolio Maturity$_{kt}$	mean	stdev	p25	p50	p75
	11.881	5.294	8.499	9.193	13.900
Life & Health Insurance	11.176	1.996	10.426	10.706	11.290
Property & Casualty Insurance	6.941	1.950	6.216	6.359	6.719
Open Ended Mutual Funds	12.365	4.962	8.914	9.664	16.718

Share of IG Corporate and Treasury Bonds$_{kt}$	mean	stdev	p25	p50	p75
Annuities	0.559	0.055	0.510	0.556	0.609
Life & Health Insurance	0.724	0.024	0.703	0.734	0.744
Property & Casualty Insurance	0.790	0.012	0.782	0.790	0.800
Open Ended Mutual Funds	0.565	0.021	0.551	0.564	0.581

Table E.1: Summary statistics by investor type. This table shows summary statistics for the main types of investors, namely annuities, life and health insurers, property and casualty insurers, and open ended mutual funds. The top table shows the number of funds in each fund class and the total holdings of corporate and government bonds as of 2009:Q1, 2013:Q1, and 2017:Q1. The last four tables show summary statistics about the QE Exposure variable, the maturity of the corporate and Treasury bond portfolio, the maturity of the Treasury bond portfolio, and the share of IG corporate and Treasury bonds.

Appendix F M&A

F.1 Additional figures

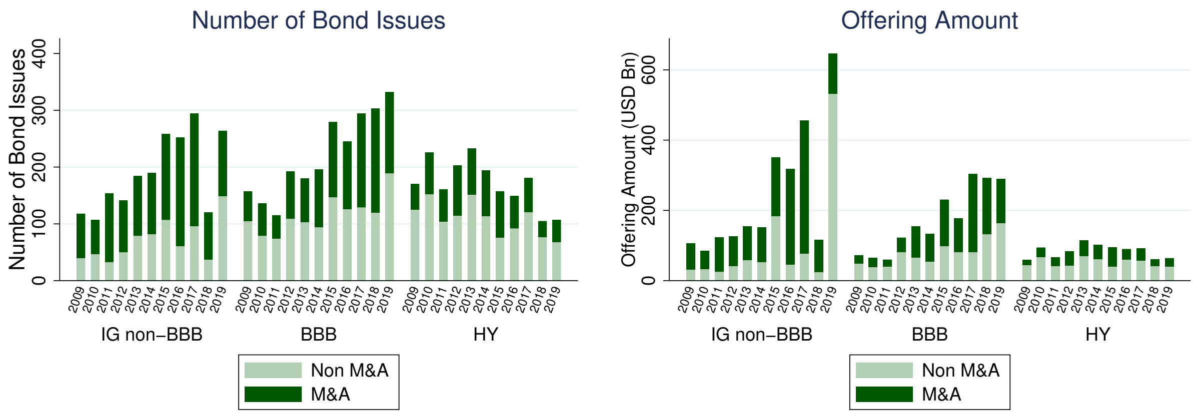

Figure F.1: Bond issuance and volume. This figure shows the number of bond issues and the bond issuance volume for high-yield, BBB-rated, and A/AA/AAA-rated firms from 2009 to 2019. The left panel shows the total number of bond issues, separated by M&A and non-M&A bond issues. The right panel shows the total offering amount, separated by M&A and non-M&A bond issues. A bond issue is considered to be M&A-related if a firm issues a bond in the year it does at least one M&A deal.

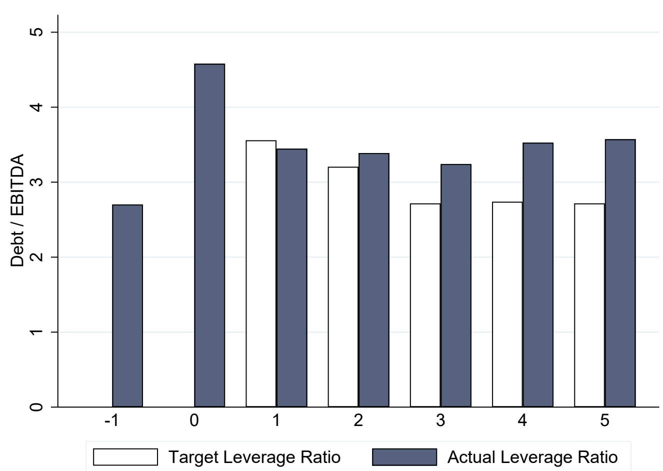

Figure F.2: Broken promises about debt reduction after M&A. This figure compares the year-by-year promised path of debt reduction with observed debt after firm M& A. The x-axis shows the years since transaction. The y-axis is debt divided by EBITDA. We assume that debt reduction plans (e.g., leverage from 10 to 5 in 5 years) have a linear schedule (i.e., leverage of 6 next year). In the case a target year is not specified, we assume a two-year deadline (the modal deadline). Source: data collected by the author from firms' official presentations, press releases, investor calls, and Fitch ratings.

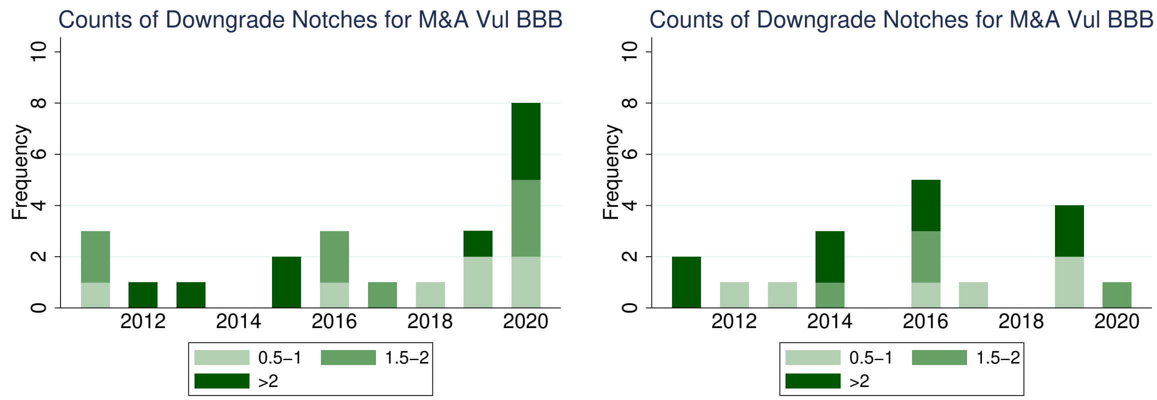

Figure F.3: Downgrade materialization of (prospective) fallen angels. This figure shows the number of downgrades that downgrade-vulnerable BBB-rated firms have experienced in the years 2011 to 2020, and groups them according to their downgrade severity. The downgrade severity is measured by the number of notches a firm is being downgraded, and is subdivided into three broad categories: 0.5-1, 1.5-2, >2 notches. The left panel plots the downgrade (notch) frequency for downgrade-vulnerable BBB firms that have conducted an M&A since the year that they have become vulnerable. The right panel shows the downgrade (notch) frequency for firms that have not conducted an M&A since the year that they have become downgrade-vulnerable.

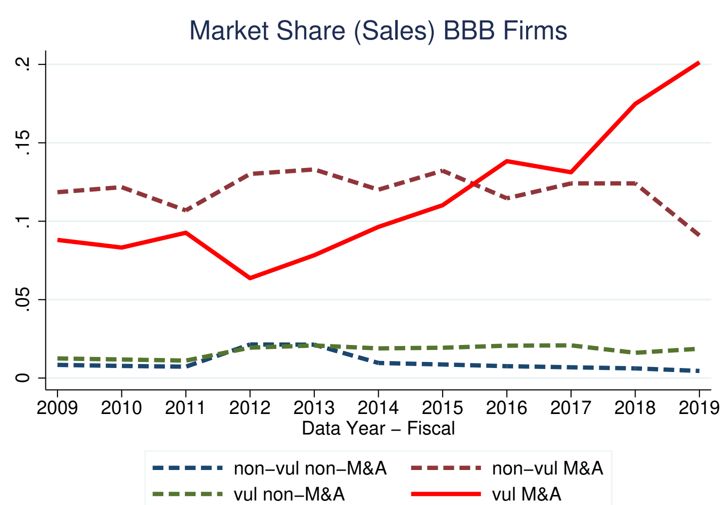

Figure F.4: M&A and the increase in market share of prospective fallen angels. This figure shows the evolution of firm market share (share of sales, weighted by the relative size of the respective industry)) for BBB-rated issuers, broken down by downgrade-vulnerability and whether a firm engages in an M&A transaction during our sample period.

Appendix G Quantifying the subsidy

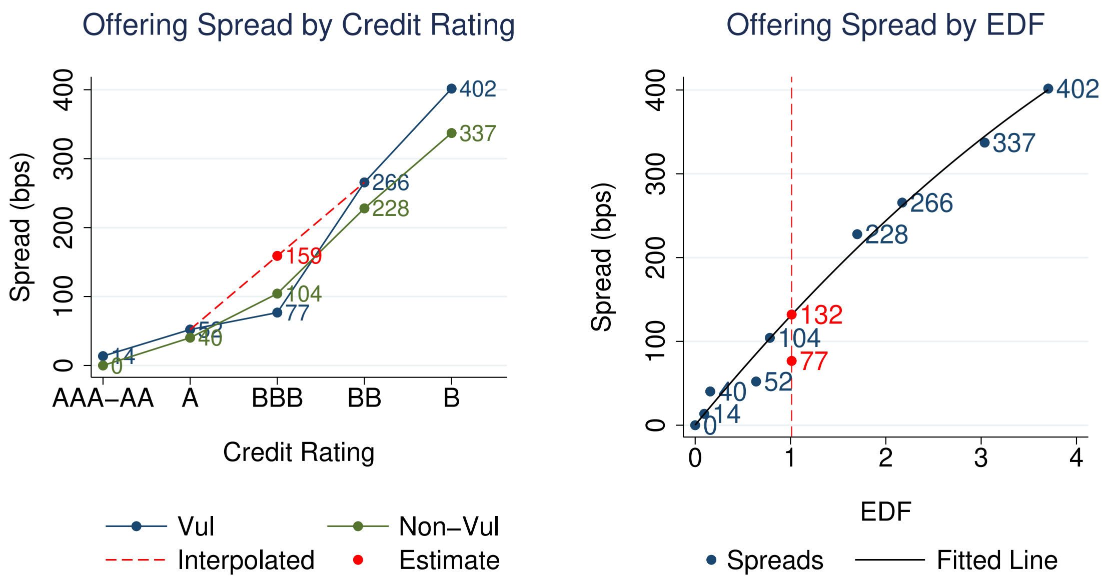

Figure G.1: Subsidy alternative calculations. The left panel shows in red the counterfactual vulnerable BBB rated spread, based on the spread interpolation between the downgrade-vulnerable rating categories. The right panel plots the relationship between the 2-year expected default frequencies and offering spreads. The red dotted line is used to estimate the yield differential between the counterfactual and the measured downgrade-vulnerable BBB spread.