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 rating cutoff—enjoyed subsidized bond financing between 2009 and 2019, especially when the scale of QE purchases peaked and from long-duration IG-focused investors that held more securities purchased in QE programs. The benefiting firms financed risky acquisitions with bond issuances, exploiting the sluggish adjustment of credit ratings in downgrading issuers after M&A. This activity increased the firms' market share, adversely affecting competitors' employment and investment. Eventually, these firms 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.[1,2] Our paper provides novel evidence in this direction by showing that the Federal Reserve's Quantitative Easing (QE) program appears to have distorted prices in an important segment of the U.S. corporate bond market, viz., the 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 this 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

[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.

[2] See, among others, Financial Times, July 10, 2022 (link). An excerpt from the article: "*Some economists have always been uneasy with QE for a variety of reasons, including a concern that it leads to central banks having too large a footprint in financial markets, potentially distorting the process of how assets are priced. As well as expanding the monetary base, official asset purchases also crowd commercial investors out of the world's safest assets, and force them to support riskier parts of the economy that might otherwise struggle.*"

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.

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 these 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 this paper, we investigate these trends and provide evidence that they are—at least in part—a consequence of the QE programs on financial and real sectors. 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 long-term investors highly exposed to QE.[3] 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 (Caballero

[3] In practice, 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.

et al., 2008).[4]

We tease out this mechanism by combining various data sources at the issuer-level, bond-level, 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 holding-level data from eMAXX Bond Holders matched with security-level 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 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 during 2013–16. Crucially, this pattern—lower spreads for downgrade-vulnerable firms in a rating category—is

[4]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 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.

not present for other rating classes. This pattern is also not 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 $51 billion and $135 billion between 2009 and 2019.

Our empirical tests seek to identify the driving mechanisms behind the subsidy and are structured in three parts.[5] First, we show that investors exposed to QE drive the demand for corporate bonds issued by prospective fallen angels. 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.[6] 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, insurers 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 (the short-term probability of being downgraded to speculative grade is close to zero for prospective fallen angels that

[5] We also provide a conceptual framework in Appendix B.

[6] In addition to helping understand the mechanism behind the subsidy for prospective fallen angels, the *within- rm* 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.

conduct an M&A transaction). Announcements of these acquisitions suggest that they are value-destroying. However, announcements are usually accompanied by a promise 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 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 during 2013–16. Section 5 shows that this subsidy originates from QE-driven investor demand for IG bonds. 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 discusses the industry spillovers of the subsidy enjoyed by prospective fallen angels. 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 QE peaked but long rates were kept low for longer) 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., 2021; Altman, 2020).[7] 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

[7] 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 (2020) for an analysis of fragility and reaching-for-yield behavior in the leveraged loan market.

related to the literature on the misallocation of bank credit (Caballero et al., 2008; Acharya et al., 2020) 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 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. (2021); Darmouni et al. (2021)).[8] 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 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., 2020). Becker and Ivashina (2015) shows that, within rating categories, investors reaching-for-yield might tilt their portfolio toward 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

[8]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.

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 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 data construction (Section 3.1); (ii) introduce our definition of downgrade-vulnerable firms, presenting evidence of substantial and increasing "ratings inflation" for BBB-rated firms since 2009 (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 6,460 bond issues by 909 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 7,741 outstanding bonds issued by 1,146 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.[9] 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-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 8,505 investors, mostly property and casualty insurers (2,309), open-ended mutual funds (2,329), (other) life and health insurers (1,327), and insurers with annuities with minimum guarantees (754). 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:

$$Z'' = 6{:}56 \; \frac{Current\,Assets \quad Current\,Liabilities}{Total\,Assets} + 3{:}26\frac{Retained\,Earnings}{Total\,Assets} + 6{:}72\frac{EBIT}{Total\,Assets} + 1{:}05\frac{Book\,Value\,of\,Equity}{Total\,Liabilities}$$

[9]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).

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.[10] 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.[11]

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.[12] In addition, the right panel of Figure 1 shows that although downgrade-vulnerable firms are more likely to be downgraded

[10]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).

[11]We also document that the post-GFC to pre-COVID growth of the BBB market is driven by prospective 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 E.1).

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

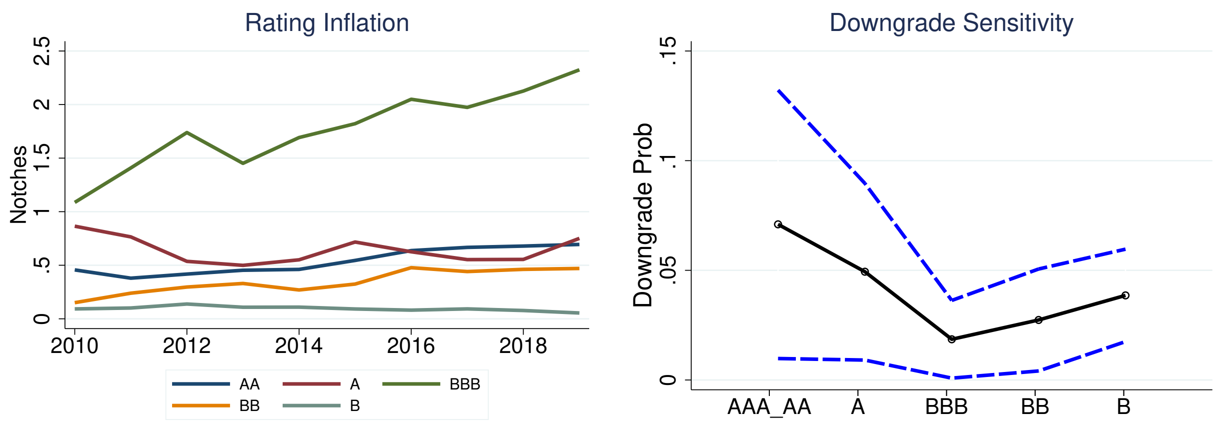

Figure 1: High and rising credit ratings inflation for BBB-rated issuers. This figure shows credit ratings inflation across rating categories. The left panel shows asset-weighted credit ratings inflation. Credit ratings inflation is equal to zero if an issuer has a Z"-score above the median Z"-score 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 vulnerable issuers relative to non-vulnerable issuers by rating category. Specifically, the figure shows the estimated coefficient, β_1, from the following regression specification estimated on 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.

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

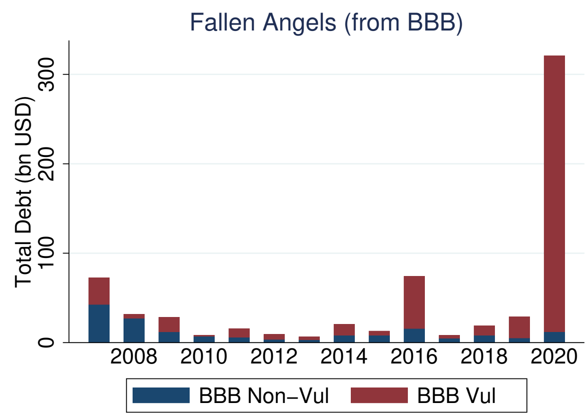

Figure 2: Risk materialization during COVID-19. This figure shows that the vulnerability of the BBB market materialized at the onset of the COVID-19 pandemic. The figure shows total debt downgraded from BBB to speculative-grade for (non-)downgrade-vulnerable firms from 2007 to 2020.

to fallen angels between March 22, 2020 and April 9, 2020.[13]

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-level controls and 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

[13]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.

	Δ Spread	Δ Spread
Ratings Inflation	15.804***	−1.178
	(3.529)	(5.822)
Sample	Vuln. BBB	Vuln. A-AAA
Industry FE	X	X
Firm Controls	X	X
Observations	751	391
R-squared	0.503	0.552

Table 1: Change in spreads of rating-inflated firms during COVID-19. This table presents estimation results from the bond-level regression (1) in the subsample of downgrade-vulnerable firms. The dependent variable is $\Delta\, Spread$, which is defined as the change in secondary market spread between January 2020 and March 2020 of a single bond. The independent variable is $RatingsInflation$ and is defined as the issuer rating at the start of 2020 minus the implied rating based on Altman Z"-score. We add a firm's total 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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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.

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 trend is particularly evident between 2013 and 2016, a period coinciding with the peaking of the Federal Reserve's balance sheet size as a result of its QE purchases and the Fed maintaining its balance sheet size roughly constant, while keeping long-term rates "lower for longer".

First, Figure 3 shows the difference in secondary market spreads between downgrade-vulnerable and non-downgrade-vulnerable BBB issuers as well as those rated AAA-A and with BB ratings. 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 2013 to 2016; and, (iii) almost always smaller than the same difference for AAA-A and BB segments

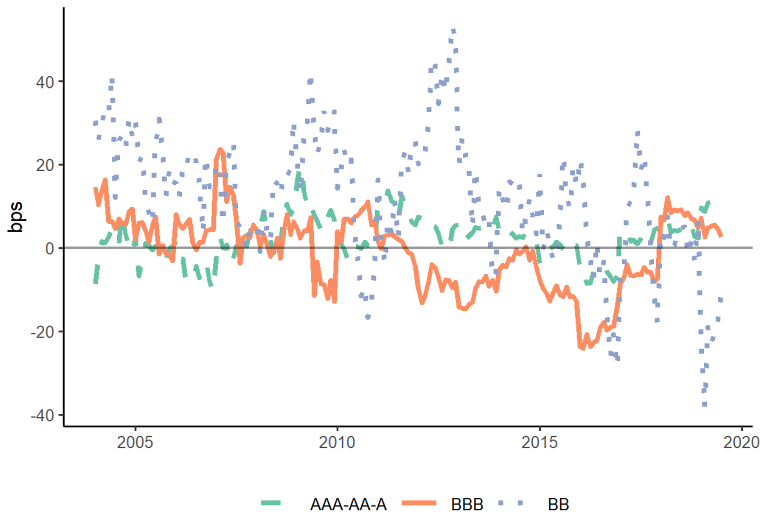

Figure 3: Bond spreads: downgrade-vulnerable minus non-downgrade-vulnerable firms. This figure shows the difference in secondary market spreads between downgrade-vulnerable and non-downgrade-vulnerable issuers for issuers rated AAA, AA and A (dashed line), BBB (solid line), and B (dotted line) controlling for year×month fixed effects.

between 2013 and 2016, which by and large tend to be positive.[14]

Second, we confirm the existence of this privilege for prospective fallen angel in bond markets using a formal test. In particular, we compare the bond spreads of downgrade-vulnerable and non-downgrade-vulnerable firms *within* a rating category by estimating the following specification:

$$\begin{aligned}\text{Spread}_{bit} = {}& {}_1\mathbf{Rating}_{it} + {}_2\text{Vulnerable}_{it} \times \mathbf{Rating}_{it} \\ & + \mathbf{X}_{bt} + \mathbf{Liquidity}_{bt} \times \mathbf{Rating}_{it} + {}_{ht} + \epsilon_{bit} \qquad (2)\end{aligned}$$

where Spread_{bit} is the spread (in basis points) of bond b issued by firm i in period t. We reiterate that we follow 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 also

[14] 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.

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 including 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.[15] $\mathbf{Rating}_{it}$ 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.[16] We also 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 including 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 $_{ht}$ 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. The first column shows the estimation results in the full sample period. As expected, the uninteracted ratings terms show that bond spreads increase as the ratings deteriorate. 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, CCC ratings) or statistically indistinguishable financing costs (A rating) compared with non-downgrade-vulnerable firms. Consistent with Figure 3, this pattern is reversed for BBB-rated firms as prospective fallen angels pay significantly *lower* financing costs than non-downgrade-vulnerable BBB firms.

[15] 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)'s estimates based on matched bonds from the same issuer.

[16] 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 vulnerable in year t.

	Spread	Spread	Offer Spread	Offer Spread
A	29.100***	30.471***	37.844	−10.718
	(8.495)	(8.087)	(35.806)	(28.191)
BBB	81.404***	79.464***	106.468***	62.556**
	(8.672)	(8.547)	(35.880)	(28.740)
BB	191.336***	182.127***	225.867***	200.985***
	(10.961)	(13.514)	(35.460)	(26.455)
B	337.734***	323.510***	310.352***	271.383***
	(17.427)	(26.301)	(35.608)	(29.504)
CCC	947.289***	1,049.530***	198.190**	356.475***
	(93.020)	(169.092)	(89.791)	(56.338)
Vulnerable × AAA-AA	12.235	19.194**	2.386	−45.703
	(8.768)	(9.079)	(37.643)	(30.406)
Vulnerable × A	2.091	−4.286	30.424**	41.941*
	(4.963)	(8.030)	(12.836)	(21.306)
Vulnerable × BBB	−9.680***	−18.423***	−23.579***	−25.001*
	(3.599)	(5.738)	(8.296)	(13.828)
Vulnerable × BB	14.121*	14.068	29.676*	7.081
	(7.473)	(11.776)	(16.316)	(28.776)
Vulnerable × B	86.094***	78.941**	43.206*	52.781
	(23.403)	(35.557)	(22.013)	(40.616)
Vulnerable × CCC	414.347**	363.544		
	(165.179)	(237.879)		
Industry-Year-Month FE	X	X	X	X
Bond-level controls	X	X	X	X
Sample	2009–19	2013–16	2009–19	2013–16
Observations	256,638	98,812	2,793	1,215
R-squared	0.651	0.626	0.836	0.824

Table 2: The exorbitant privilege of prospective fallen angels. This table shows the estimation results of specification (2). The dependent variable in columns (1)-(2) is the secondary market bond spread. The dependent variable in columns (3)-(4) is the primary 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 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.

The second column shows the estimation results in the subsample running from 2013 to 2016 when the Federal Reserve maintained a large and more or less constant balance sheet size. In this period, the funding privilege of prospective fallen angels increases in magnitude. The third and fourth columns show similar estimation results using primary market offering spreads as a dependent variable. The point estimates indicate that the vulnerable BBB funding subsidy is somewhat higher in primary bond markets. In Appendix D.3, we show

	EDF 2Y	EDF 5Y	Spread	Loan spread	CDS
BBB	0.598***	0.472***	18.943***	9.698	51.875***
	(0.086)	(0.068)	(4.730)	(18.914)	(5.117)
BB	1.493***	1.164***	87.178***	60.116***	178.520***
	(0.105)	(0.083)	(7.113)	(22.451)	(15.920)
B	2.769***	2.121***	162.085***	119.756***	385.052***
	(0.122)	(0.095)	(10.288)	(23.218)	(37.442)
CCC	4.129***	3.142***	359.317***	241.113***	659.209***
	(0.170)	(0.134)	(38.390)	(74.555)	(171.965)
Vulnerable × AAA-A	0.191*	0.146*	5.964*	−4.366	−6.370
	(0.102)	(0.084)	(3.293)	(25.558)	(3.902)
Vulnerable × BBB	0.208**	0.140**	10.053**	17.776*	−17.401***
	(0.090)	(0.068)	(4.752)	(9.359)	(5.476)
Vulnerable × BB	0.485***	0.349***	14.347**	18.360	45.797*
	(0.096)	(0.072)	(5.857)	(13.109)	(24.363)
Vulnerable × B	0.744***	0.561***	39.438**	49.392***	16.786
	(0.108)	(0.081)	(19.369)	(18.166)	(61.811)
Vulnerable × CCC	0.274	0.248	280.269***	−95.201	33.954
	(0.190)	(0.156)	(67.662)	(73.515)	(107.732)
Industry-Year-Month FE	X	X	X	X	X
Sample	2009–19	2009–19	2002–07	2009–19	2009–19
Observations	62,129	62,129	25,990	2,982	102,829
R-squared	0.767	0.789	0.776	0.715	0.743

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) are the log expected default frequencies at the 2-year and 5-year horizon, respectively, between 2009 to 2019. The dependent variables in column (3) is the secondary market bond spread in the pre-GFC period (2002–2007). The dependent variable in column (4) is the all-in-drawn spread for syndicated loans taken from DealScan. The dependent variable in column (5) is the spread on the CDS contract maturity matched to the corporate bonds sample in the first column 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. Columns (3) and (5) have the same controls as Table 2. Column (4) has loan-level controls, namely maturity, log amount, a dummy for dividend restrictions, and a dummy for agent consent in trading the loan. Standard errors are clustered at the firm and year-month level. *** p<0.01, ** p<0.05, * p<0.1.

that our baseline results are robust to using bond-level instead of issuer ratings as well as including additional controls for bond liquidity based on the frequency with which the bond trades and whether the bond is on- or off-the-run.

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 (EDF 2-Y) and 5-year (EDF 5-Y) horizons as dependent variables, respectively. While we confirm that the estimated coefficients on the uninteracted terms increase monotonically as ratings deteriorate, the funding advantage of prospective fallen angels disappears, suggesting that the exorbitant privilege is specific to the bond market. The third 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. The fourth column shows that prospective fallen angels did not enjoy a similar funding advantage in the syndicated loan market post 2010.[17] However, the fifth column of Table 3 suggests that credit default swap markets price 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. 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).

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

[17] 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.

D10.1 of the BIS Derivative Statistics), the same directional position as being long corporate bonds.

Taken together, these results suggest that the exorbitant privilege of prospective fallen angels is unique to corporate bonds (and replication CDS markets such as CDS) since 2009.

5 The origins of the exorbitant privilege

We now discuss the origins of this exorbitant privilege. Section 5.1 presents a conceptual framework that explains how the exorbitant privilege can arise in equilibrium due to a higher investor demand for BBB-rated corporate bonds. Consistent with its prediction, 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 of 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.

We present a more formal framework in Appendix B. Figure 4 outlines the intuition. 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.[18]

[18]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*

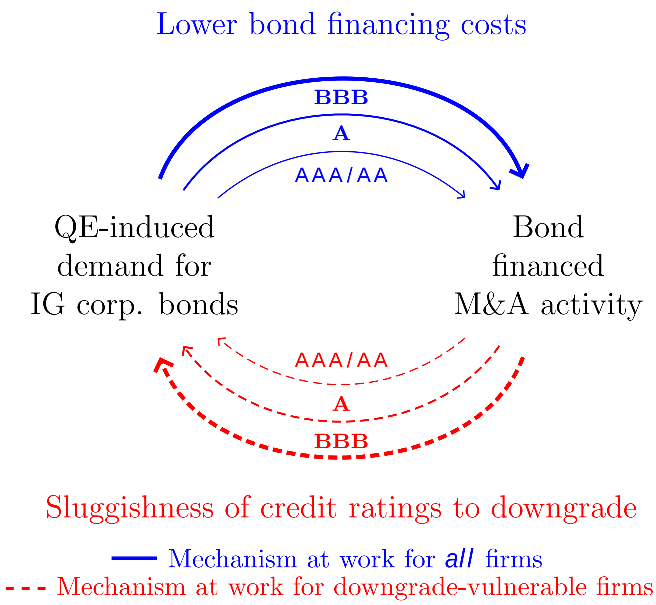

Figure 4: Scheme of intuition. This figure shows the intuition behind our framework. QE induces an increase in demand for IG corporate bonds causing, in turn, an increase in issuers' bond financing, largely to finance M&A. This effect (blue solid lines) is at work for all firms and stronger as we move down the rating categories within IG. Given that credit rating agencies are sluggish in downgrading firms (especially those at the IG threshold) post-M&A, the debt issuance by downgrade-vulnerable issuers (and especially by prospective fallen angels) is met again by the high demand of investors sensitive to credit ratings.

In response to the heightened demand from investors, issuers just above the IG cutoff take advantage of the low financing cost by issuing bonds, largely to finance M&A. This issuance serves two purposes: (i) it meets the large demand for IG-rated bonds (and in particular BBB-rated ones), and (ii) it ensures, given the sluggishness of credit ratings post-M&A, that issuers likely remain IG-rated in the few years post-M&A, prolonging their access to low financing costs. The post-M&A sluggishness of credit ratings is priced favorably by investors that care about the IG-rating status because of, for example, rating-based regulation and self-imposed limits in their asset allocations. While helping to preserve the IG status in the short-term, this M&A activity is risky, mostly due to the associated increase in firm leverage. This build-up of fragility explains why only firms at immediate risk of being downgraded (i.e., prospective fallen angels) engage in bond financed M&A.

from the world's central banks." Source: "Search for yield draws U.S. life insurers to risky places," Financial Times, February 21, 2019.

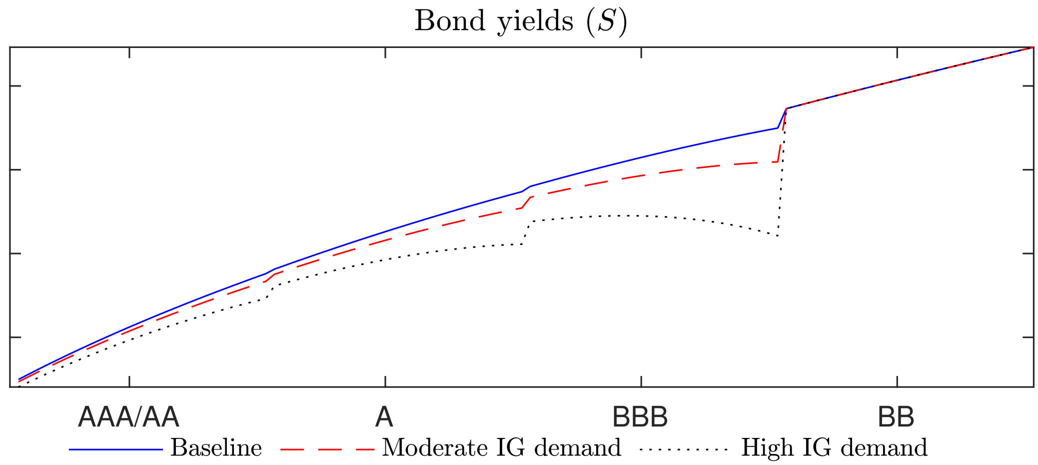

Figure 5: Corporate bond yields, illustration of our framework. This figure presents the corporate yield curve with yields on the y-axis and firms sorted by quality, and grouped in credit ratings, on the x-axis. The solid blue line, the red dashed line, and the black dotted line represent a baseline economy, an economy with moderate demand for IG-rated bonds, and an economy with high demand for IG-rated bonds.

To summarize how these forces affect credit spreads in equilibrium, Figure 5 illustrates the main results of the framework presented in Appendix B, where we assume that investors prefer and therefore subsidize (i) IG bonds relative to sub-IG bonds, and (ii) bonds issued by firms in the riskier part of each rating bucket. The first assumption captures the observation that capital requirements and investment restrictions are lighter for IG relative to sub-IG bonds. To the extent that riskier issuers pay higher bond yields, the second assumption captures the so-called "reach-for-yield" behavior. Further, to the extent that riskier issuers engage in actions (e.g., M&A) to delay downgrades, the second assumption also captures the value that investors attach to ratings—and, in particular, to the IG status.

The figure shows bond yields as a function of firm quality, with firms grouped by credit ratings. Firms are ordered by decreasing quality on the x-axis: (i) The blue line, corresponding to the baseline economy, shows that bond yields increase as firms deteriorate in quality. There is an additional jump at each rating cutoff, particularly pronounced at the IG cutoff. (ii) The dashed red line shows bond yields in an economy with a moderate demand for IG-rated bonds. The curve flattens and becomes more concave within each rating bucket, reflecting the equilibrium lower yields of downgrade-vulnerable firms. (iii) The black dotted line shows bond yields in an economy with a high demand for IG-rated bonds. The flattening and concavity of the yield curve is so pronounced that yields of bond of prospective fallen angels fall below those of non-downgrade-vulnerable BBB-rated issuers, generating the "exorbitant privilege" we documented empirically in Section 4.[19]

5.2 QE-driven demand by investment-grade investors

To establish a preference among IG investors for higher-risk bonds that drives the conceptual framework laid out above, we investigate the role of QE in affecting IG-investor holdings. In particular, we document 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 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).

We measure investor-level exposure to QE, merging our granular holdings-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:

$$\text{QE Exposure}_{kt} = \frac{\sum_b (Holdings_{bkt} \times SOMA_{bt})}{\sum_b Holdings_{bkt}} \tag{3}$$

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. Figure 6 shows the time-series evolution of average QE Exposure$_{kt}$.

[19]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.

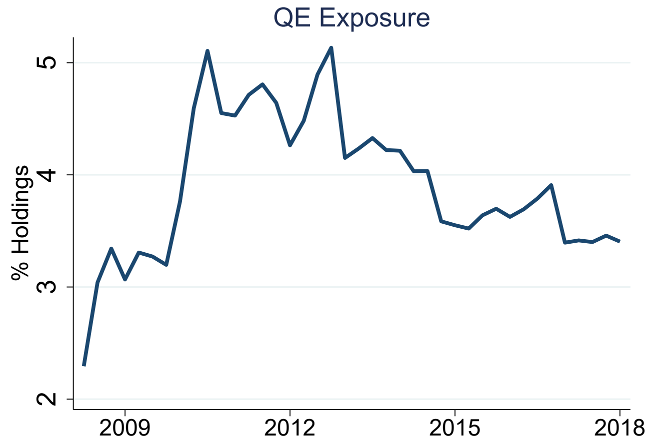

Figure 6: Investor exposure to QE. This figure shows the evolution of the cross-sectional mean of the QE Exposure$_{kt}$ variable at a quarterly frequency. This variable is defined as the share of investor total holdings that are held by the Federal Reserve in the SOMA Treasury portfolio, where holdings are weighted by the share of amounts outstanding held by the Federal Reserve.

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

$$Holdings_{ikt} = \beta_1 \text{QE Exposure}_{kt-1} \times Vulnerable_{it} + \eta_{kt} + \mu_{it} + \epsilon_{ikt} \tag{4}$$

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 investors less exposed to QE. 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 potential differential characteristics of downgrade-vulnerable and non-downgrade-vulnerable bonds (e.g., issuance volume) that might interact

Panel A	*Holdings*$_{ikt}$					
QE Exposure$_{kt-1} \times Vulnerable_{it}$	1.197***	1.292***	1.250***	1.346***	1.337***	1.342***
	(0.258)	(0.262)	(0.270)	(0.276)	(0.276)	(0.277)
Maturity$_{kt-1} \times Vulnerable_{it}$					−0.016**	0.001
					(0.008)	(0.015)
(Maturity)$^2_{kt-1} \times Vulnerable_{it}$						0.000
						(0.000)
Fixed Effects						
Issuer i	X	X				
Investor k	X		X			
Time t	X					
Investor k - Time t		X		X	X	X
Issuer i - Time t			X	X	X	X
Sample investors	Full	Full	Full	Full	Full	Full
Sample issuers	Full	Full	Full	Full	Full	Full
Observations	6,598,509	6,584,866	6,597,759	6,584,115	6,582,311	6,582,311
R-squared	0.542	0.599	0.558	0.615	0.614	0.614

Panel B	*Holdings*$_{ikt}$			
QE Exposure$_{kt-1} \times Vulnerable_{it}$	0.436	1.072**	1.811***	−0.165
	(0.703)	(0.463)	(0.410)	(0.463)
Fixed Effects				
Investor k - Time t	X	X	X	X
Issuer i - Time t	X	X	X	X
Sample investors	Full	Full	Full	Full
Sample issuers	AAA/AA	A	BBB	HY
Observations	399,373	1,392,209	2,324,449	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 (4). 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 (3). $Vulnerable_{it}$ 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.

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) issuers, respectively. The results show that the overall effect is driven by holdings of 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) implies a rise in demand for bonds issued by prospective fallen angels roughly coinciding with the greater privilege in borrowing costs for these firms during in 2013-16 (see Figure 3). In unreported results, we also confirm that these results are robust to (i) using a balanced sample of investors during our sample period, and (ii) using managing firms (instead of funds) to identify investors.

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 entirely 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

	$Holdings_{ikt}$				
QE Exposure$_{kt-1} \times Vulnerable_{it}$	0.497	0.586	2.360***	1.462**	2.380***
	(0.442)	(0.382)	(0.515)	(0.603)	(0.550)
Fixed Effects					
Investor k - Time t	X	X	X	X	X
Issuer i - Time t	X	X	X	X	X
Observations	420,315	469,522	1,434,185	777,588	656,422
R-squared	0.650	0.652	0.664	0.654	0.674
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	16%	17%	67%	29%	39%
Share of Life & Health Insurance	33%	18%	48%	23%	26%
Share of Property & Casualty Insurance	59%	22%	19%	6%	13%
Share of Open Ended Mutual Fund	30%	20%	51%	22%	28%

Table 5: Demand for bonds issued by prospective fallen angels, sample splits. This table presents estimation results from specification (4). 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 (3). $Vulnerable_{it}$ 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.

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.[20] 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

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

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.

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 it stays roughly constant for

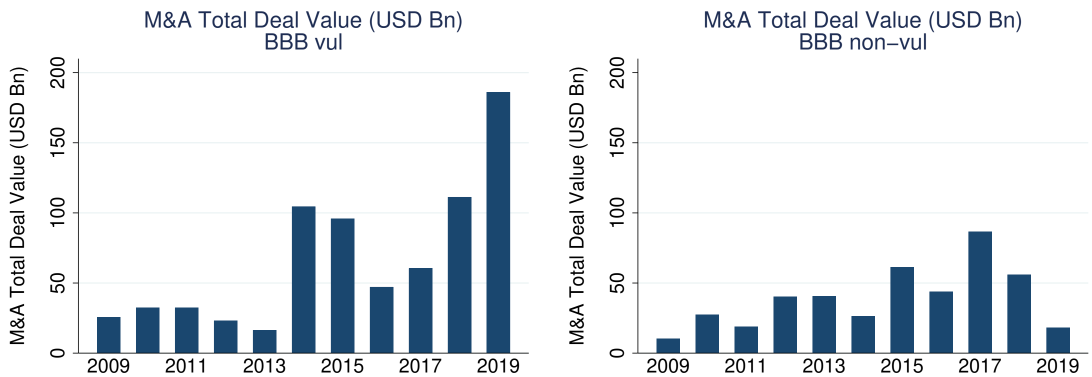

Figure 7: M&A activity, BBB-rated issuers. This figure shows the M&A activity by BBB-rated issuers. The left panel shows deal volume for downgrade-vulnerable issuers. The right panel shows deal volume for non-downgrade-vulnerable issuers.

non-downgrade-vulnerable BBB-rated firms.[21]

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:

$$Y_{it} = \beta_1 \text{BBB}_{it} + \beta_2 \text{M\&A}_{it} + \beta_3 \text{M\&A}_{it} \times \text{BBB}_{it} + \delta X_{it} + \eta_{ht} + \epsilon_{it} \tag{5}$$

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

[21]In the online appendix, we additionally show that the increase in M&A deal volume is more pronounced for prospective fallen angels compared with other downgrade-vulnerable IG-rated firms (Figure F.1), that we do not observe these dynamics in the speculative-grade market (Figure F.2), and that the substantial increase in investment-grade bond issuance since 2013–15 was in large part to fund M&A activity (Figure F.3).

	Ratings inflation	Ratings inflation
BBB_{it}	0.380**	0.016
	(0.188)	(0.288)
$\text{M\&A}_{it}$		−0.318
		(0.199)
$\text{M\&A}_{it} \times \text{BBB}_{it}$		0.566*
		(0.302)
Industry-Year FE	X	X
Controls	X	X
Sample	Vulnerable	Vulnerable
Observations	2,750	2,750
R-squared	0.381	0.386

Table 6: The role of M&A in prolonging ratings inflation. This table presents estimation results from specification (5) 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.

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 angels enjoy an additional 0.4 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

No M&A

From \ To	AAA/AA	A	BBB	BB
AAA/AA	97.2	2.8	**0**	0
A	0	91	**8.9**	0
BBB	**0**	**4.4**	**92.1**	**3**
BB	0	0	**4.2**	92.1

Post-M&A

From \ To	AAA/AA	A	BBB	BB
AAA/AA	94.5	5.5	**0**	0
A	1.8	88.3	**10**	0
BBB	**0**	**1.6**	**97.8**	**0.1**
BB	0	0	**5.8**	93.4

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 M&A transaction within the last 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. Sources: Thomson Reuters and Compustat.

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.[22] 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

[22] Figure F.4 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..."*

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 undertook an M&A in year t:

$$\begin{aligned} Y_{it} &= \alpha + \beta_1 BBB_{it} + \beta_2 Vulnerable_{it} + \beta_3 Vulnerable_{it} \times BBB_{it} \\ &+ \gamma \times X_{it} + \eta_{ht} + \epsilon_{it}, \end{aligned} \tag{6}$$

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 (in year $t+1$), 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 M&A deal size of prospective fallen angels is larger. The second column shows that as a result, net debt to EBITDA rises after prospective fallen angels undertake 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 BBB to speculative-grade in 2020 was almost entirely driven by prospective fallen angels that

	$Relative\ Deal\ Size_{it}$	$Net\ Debt/EBITDA_{it+1}$	$CARs_{ijt}$
BBB	−0.045***	−0.222*	0.001
	(0.013)	(0.125)	(0.003)
Vulnerable	−0.033**	−0.263	0.003
	(0.015)	(0.183)	(0.004)
Vulnerable × BBB	0.055**	0.373*	−0.010*
	(0.025)	(0.212)	(0.005)
Controls	X	X	X
Industry-Year FE	X	X	X
Sample	M&A Rated	M&A Rated	M&A Rated
Level	Firm	Firm	Deal
Observations	1,840	2,625	2,412
R-squared	0.261	0.470	0.197

Table 7: M&A and risk-taking by prospective fallen angels. This table presents estimation results from specification (6) in the sample of firms that undertook 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 in the year after the M&A announcement. 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 acquiror, 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 acquiror from -210 to -11 days. A t-test shows that on average the CARs of BBB vulnerable firms are -1 percent. 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.

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.[23]

[23] A similar pattern is evident when looking at the number of issuers downgraded, not weighted by debt volume (Figure F.5). In Appendix F.2, we also show that the low bond financing costs of prospective fallen angels is particularly pronounced for issuers engaging in M&A activity.

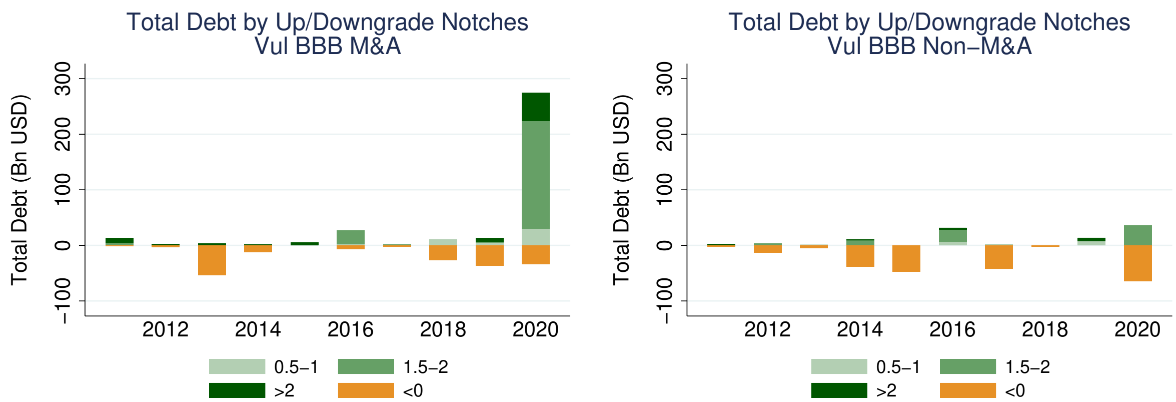

Figure 9: Downgrade materialization of (prospective) fallen angels. This figure shows the total debt of vulnerable BBB-rated firms that has been upgraded and downgraded in the years 2011 to 2020. The downgraded debt is grouped according to their downgrade severity. The downgrade severity is measured 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.

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 one of its indirect economic cost via spillovers to 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 \$51 to \$135 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.[24] 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 third column of Table 2.[25] The sum of the two components results in a subsidy of 143 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 143 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 over the years 2009–19. This calculation results in a subsidy estimate of $135 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 $51 billion to $135 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 79 basis points, resulting in a total dollar subsidy of around $75 billion. The second approach assumes that actual firm risk

[24] 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).

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

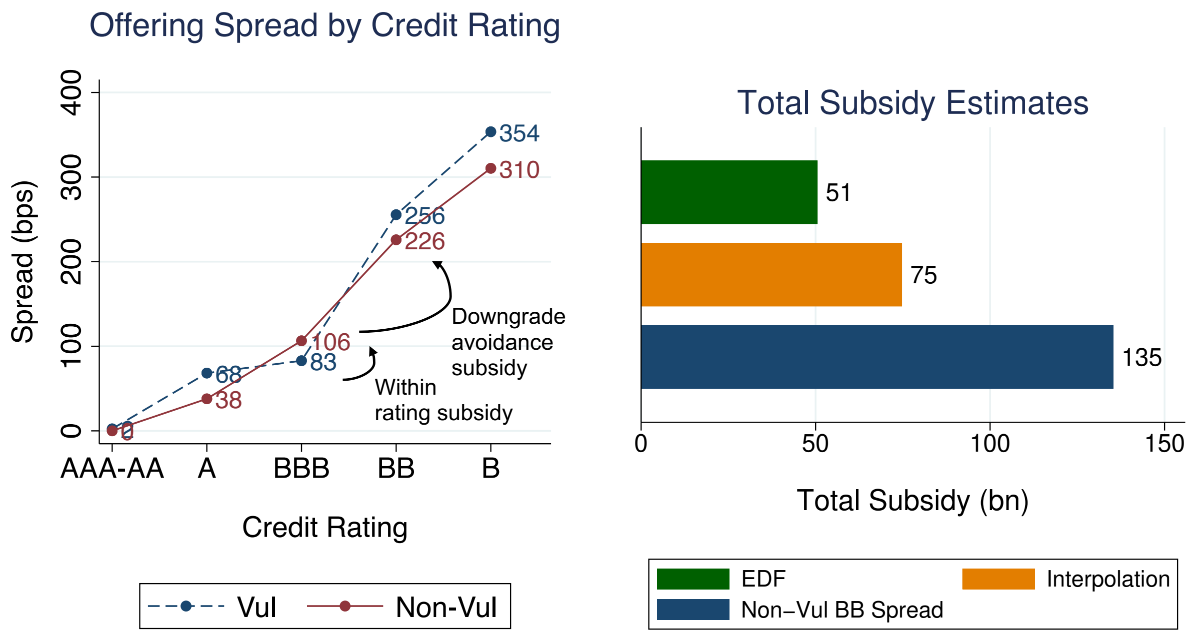

Figure 10: Prospective fallen angel subsidy. The left panel plots the offering spreads by credit rating from the third column of Table 2 for downgrade-vulnerable and non-downgrade-vulnerable issuers, and shows the downgrade avoidance and within-rating subsidy components for prospective fallen angels. 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 in Table 3. Interpolation: counterfactual spread based on linear interpolation between spreads of downgrade-vulnerable A and downgrade-vulnerable BB rated firms from Table 2 Column 3. Non-downgrade-vulnerable BB spread: counterfactual spread equal to the offering spreads of non-downgrade-vulnerable firms estimated in Table 2 Column 3. 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.

is evident in equity prices and thus captured by the EDF. Taking the log 2-year EDF of prospective fallen angels from Table 3 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 53 basis points subsidy and a total dollar subsidy of $51 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

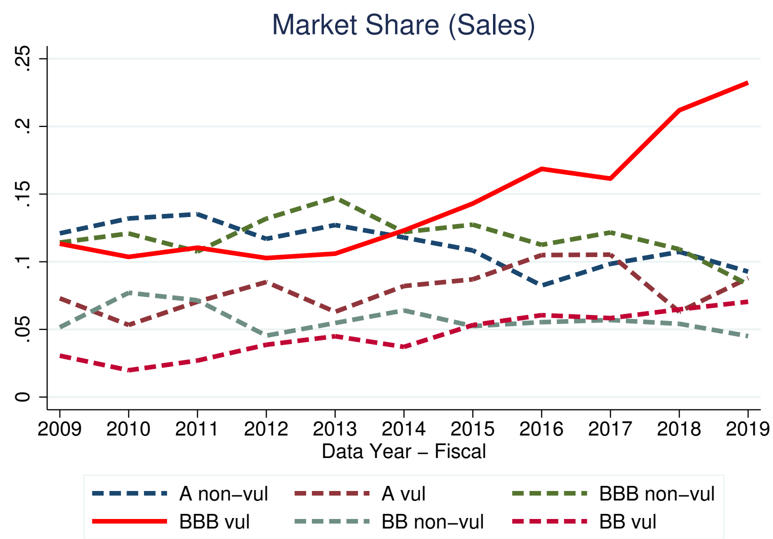

Figure 11: The increase in market share of prospective fallen angels. This figure shows the evolution of firm market share (share of sales in an industry, weighted by the relative size of the respective industry). Firms are grouped by credit rating from A to BB and further distinguished between downgrade-vulnerable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

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 driven by prospective fallen angels.[26]

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:

$$\begin{aligned} Y_{it} &= \beta_1 \text{Non-Vulnerable}_{it} \\ &+ \beta_2 \text{Non-Vulnerable}_{it} \times \text{Share Vulnerable BBB}_{ht\ \ 1} + \eta_{ht} + \epsilon_{it}, \end{aligned} \tag{7}$$

[26]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.6).

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 (0.144). This increase implies that non-downgrade-vulnerable investment-grade firms face a 1.3pp lower employment growth, 2.1pp lower investment, and a 1.4pp lower sales growth.

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

	Emp Growth	CAPX	Sales Growth	Markup
Panel A: Rated Firms - Vulnerable IG				
Non-vulnerable IG_{it}	0.018**	0.031***	0.005	0.633**
	(0.009)	(0.010)	(0.008)	(0.296)
Non-vulnerable IG_{it} × Share Vulnerable BBB_{ht-1}	−0.091**	−0.149***	−0.099**	−1.925**
	(0.039)	(0.048)	(0.040)	(0.890)
Observations	6,923	7,113	7,121	7,121
R-squared	0.112	0.318	0.278	0.256
Panel B: Rated Firms - Placebo				
Non-vulnerable IG_{it}	0.033*	0.021**	0.022	0.293
	(0.017)	(0.011)	(0.015)	(0.231)
Non-vulnerable IG_{it} × Share $Vulnerable_{ht-1}$	−0.039	−0.023	−0.038	0.289
	(0.030)	(0.021)	(0.028)	(0.367)
Observations	6,923	7,113	7,121	7,121
R-squared	0.112	0.318	0.278	0.256
Panel C: All Firms				
$Non\text{-}vulnerable_{it}$	0.040***	0.042***	0.040***	0.372**
	(0.010)	(0.011)	(0.012)	(0.179)
$Non\text{-}vulnerable_{it}$ × Share Vulnerable BBB_{ht-1}	−0.064**	−0.101**	−0.073**	−0.900**
	(0.030)	(0.046)	(0.031)	(0.432)
Observations	26,009	27,471	26,978	26,872
R-squared	0.042	0.191	0.045	0.133
Industry-Year FE	X	X	X	X
Firm-level Controls	X	X	X	X

Table 8: Negative spillovers on other firms. This table presents estimation results from specification (7). 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.

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, present since the Global Financial Crisis, peaked during 2013-16 when the Federal Reserve balance-sheet itself reached its pre-COVID peak of $4.5 trillion. 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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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 shows that the existence of a bond financing privilege by prospective fallen angels is empirically robust. Appendix E presents additional figures and tables. 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

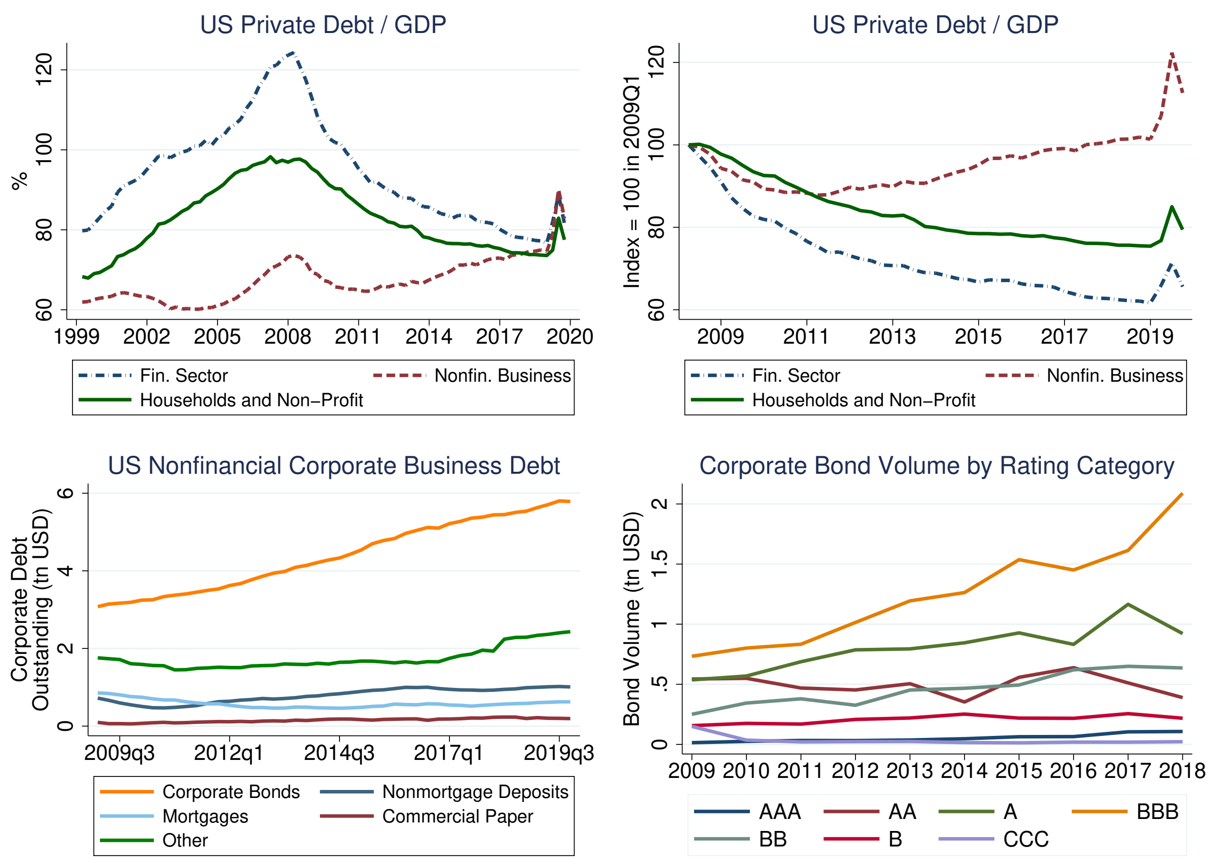

Figure A.1: The growth of the U.S. non-financial corporate debt. This figure shows the growth of the U.S. non-financial corporate debt and, in particular, of the U.S. corporate bond market. The top left panel shows the evolution of the financial sector debt, non-financial sector debt, and household debt, 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.

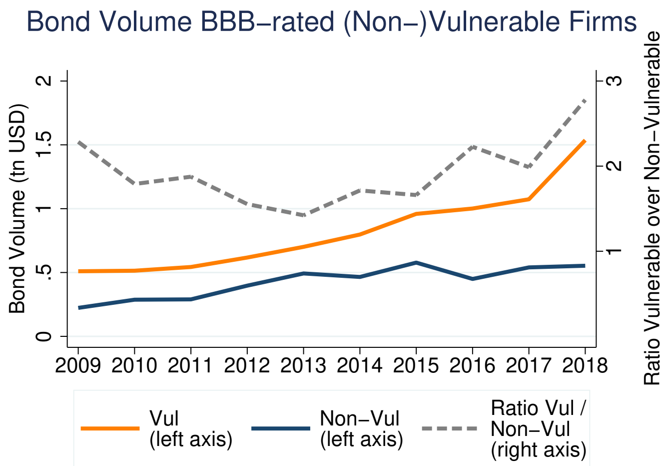

Figure A.2: Increased downgrade-vulnerability of BBB-rated firms. This figure shows the increased downgrade-vulnerability of BBB-rated firms. The figure shows, within the BBB rating category, the share of bonds outstanding issued by vulnerable and non-vulnerable BBB-rated firms. The dashed line is the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

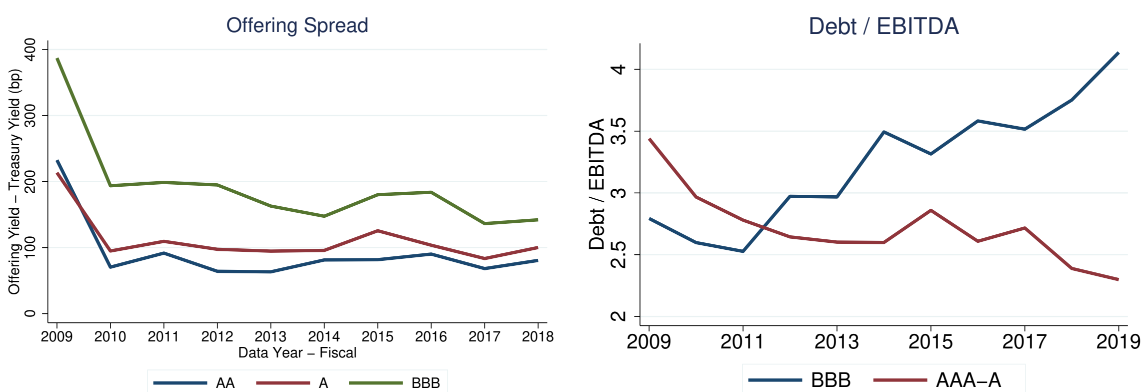

Figure A.3: Increased fragility and lower bond financing costs for BBB-rated firms. This figure shows the increasing fragility and the declining bond financing costs for BBB-rated firms. The left panel shows the offering spread (primary market bond yields minus the Treasury yield with a similar maturity) for newly issued bonds. The right panel shows the asset-weighted debt over EBITDA for BBB and other IG-rated firms. Figure E.1 provides further non-parametric evidence that the bond financing cost of BBB firms dropped significantly, more than the financing costs of other IG issuers.

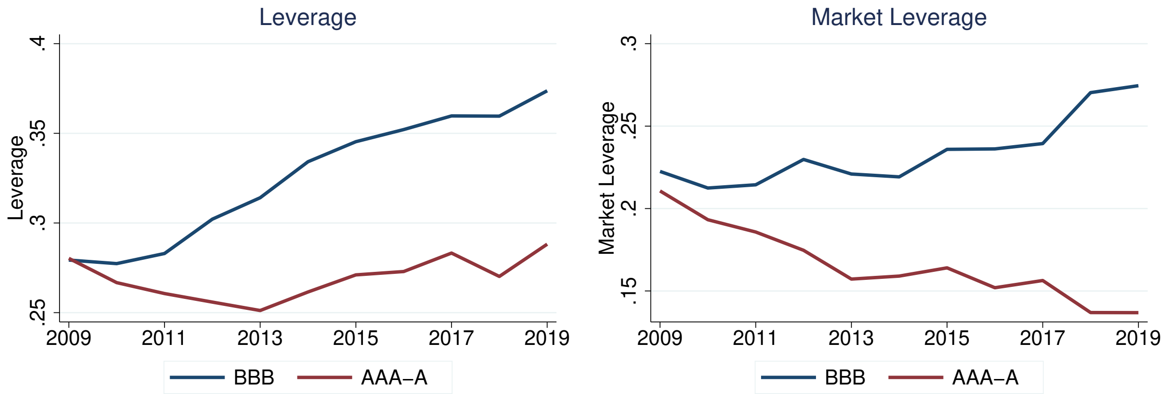

Figure A.4: Leverage over time. This figure shows the leverage evolution for BBB and IG-rated firms over the years 2009 to 2019. The left panel shows the asset-weighted book leverage, which is defined by a firm's total debt over assets. the right panel shows the asset-weighted market leverage, which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

Appendix B Theoretical framework

In this appendix, we present a simple model to explain how the exorbitant privilege of prospective fallen angels can arise in equilibrium. This model adds a subsidy for debt financing to an environment similar to the one in John and John (1993).

Setup There are two dates, $t = 0$ and $t = 1$, and universal risk neutrality. A firm with debt F can invest in a safe investment and a risky investment. The safe investment pays off I with probability 1 at $t = 1$. The risky investment pays off H with probability q and L with probability $1 - q$, where $H > I > L$ and $q \sim U[0, 1]$. The debt provides a tax shield (the tax rate is τ) and there is limited liability. The timing works as follows: (i) The firm chooses F; (ii) The probability q is realized; and (iii) The firm makes its investment decision.

Firm risk The firm invests in the risky project if and only if $q \geq \widetilde{q}$. We refer to $\widetilde{q}$ as the risk of the firm (for illustrative purposes, we will refer to $1 - \widetilde{q}$ as firm risks when presenting the results). Depending on the level of firm debt F, there are three cases:

1. A "low debt case" with $F \leq L$. Firms choose the first-best risk $\widetilde{q} = \frac{I\;\;L}{H\;\;L}$. There is no agency cost of debt.

2. A "moderate debt case" with $F \in (L, I)$. Firms choose the second-best risk $\widetilde{q} = \frac{I\;\;F}{H\;\;F}$, where $\frac{d\widetilde{q}}{dF} = -\frac{H\;\;I}{(H\;\;F)^2} < 0$, namely firms take more risk (lower $\widetilde{q}$) as their debt increases.

3. A "high debt case" with $F \geq I$. Firms choose the highest level of risk ($\widetilde{q} = 0$) as they always take the risky project.

Fairly priced debt The firm chooses the level of debt F that maximizes firm value $V(F)$. The debt is fairly priced. There are three states of the world that depend on the realization of the probability q.

1. The firm chooses to undertake the riskless project. This state of the world has an unconditional probability of $\widetilde{q}$.

2. The firm chooses to undertake the risky project and the risky project fails. This state of the world has an unconditional probability of $(1 - \widetilde{q})^2$.

3. The firm might chooses to undertake the risky project and the risky project succeeds. This state of the world has an unconditional probability of $(1 - \widetilde{q}^2)$.

Hence, firms solve:

$$
\begin{aligned}
max_F \quad & V(F) \qquad \text{where} \\
& V(F) = \frac{1}{2}(1 - \widetilde{q}^2)((1 - \tau)H + \tau min\{H, F\}) \\
& \qquad + \widetilde{q}((1 - \tau)I + \tau min\{I, F\}) \\
& \qquad + \frac{1}{2}(1 - \widetilde{q})^2((1 - \tau)L + \tau min\{L, F\})
\end{aligned}
$$

Firms trade-off the tax benefit of debt with the agency cost of debt. Given the tax shield, firms never choose a debt $F < L$. Hence, firms can either have "moderate debt" or "high debt". In most of our analysis, we focus on the former as the latter is always characterized by maximum risk-taking ($\widetilde{q} = 0$).

Non-fairly priced debt We compare the economy presented above with an economy where debt is not fairly priced. More specifically, the value of debt now includes a subsidy α. Firms now solve:

$$
\begin{aligned}
max_F \quad & \widehat{V}(F) \qquad \text{where} \\
& \widehat{V}(F) = V(F) + \alpha F
\end{aligned}
$$

The subsidy induces firms to take on more debt and thus more risk (lower $\widetilde{q}$). This subsidy can be rationalized by a high demand for debt.

Mapping the model to data The tax rate τ, the primitive driving the firm debt choice and thus its risk profile, is firm quality. We map intervals in τ to credit ratings. The cost of debt $S = F/D(F)$ is the bond yield. Firm risk $1 - \widetilde{q}$ is the risk-taking behavior of firms, for example through risky M&A. The subsidy parameter α is the strength of the demand for bonds. We increase the demand for bonds within each rating bucket as τ increases, capturing the idea that investors demand more bonds of firms in the bottom part of each rating bucket. This behavior can be explained by rating-based regulation or implicit and explicit limits that investment managers face in their asset allocation across ratings. To the extent that riskier issuers offer higher bond yields, the higher demand for bonds issued by riskier firms might also capture the so-called "reach-for-yield" behavior. To the extent that riskier issuers engage in actions (e.g., M&A) that allow them to delay downgrades, the higher demand for bonds issued by these firms might reflect the value that investors attach to ratings—and, in particular, the IG status.

Applications We now show two applications to interpret our empirical findings through the lenses of the framework just presented. Figure B.1 shows firm risk choice and bond yields as a function of firm quality. The x-axes feature increasing tax rates τ, grouped in rating categories. We compare three cases: an economy with normal demand for IG bonds (blue solid line), an economy with moderate demand for IG bonds (red dashed line), and an economy with high demand for IG bonds (black dotted line). As discussed above, the subsidy increases as firm quality deteriorates within each rating bucket. Within each rating bucket, the subsidy induces higher risk-taking, and more so as we approach the BBB-rated market. The subsidy both flattens and introduces a convexity in bond yields.

Figure B.2 shows average bond yields and firm risk-taking within each rating bucket for the three cases discussed above: normal demand for IG bonds, moderate demand for IG bonds, and high demand for IG bonds.

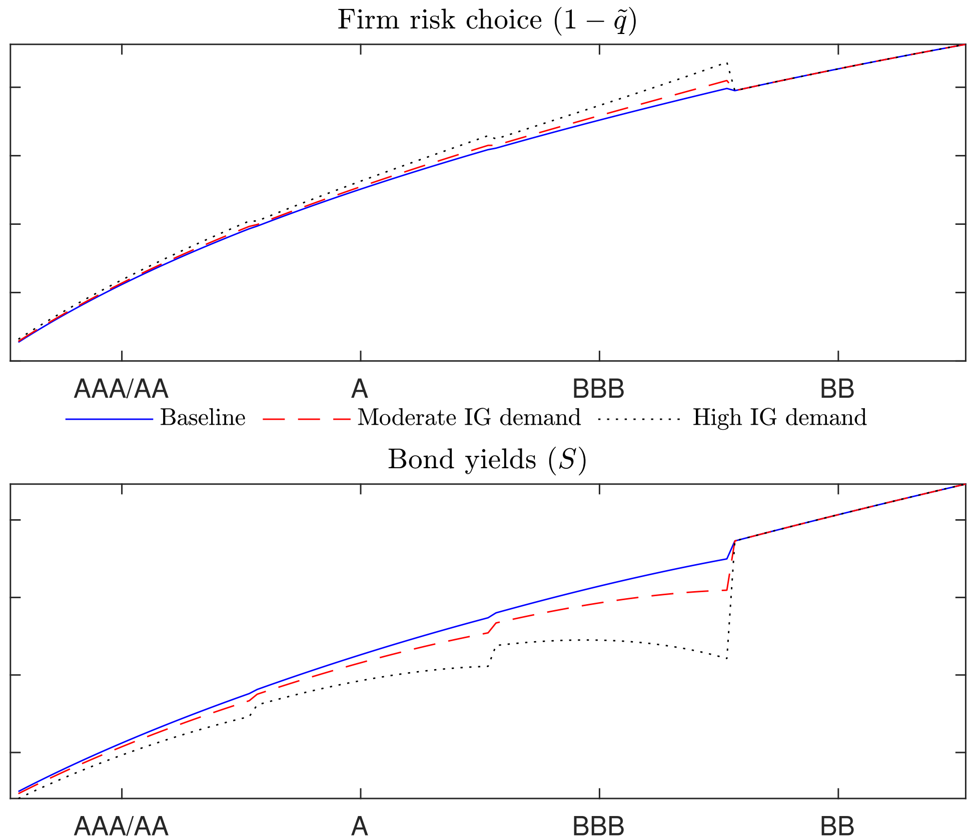

Figure B.1: Firm risk-taking and bond yields. This figure shows firm risk choice (top panel) and firm bond yields (bottom panel) as a function of firm quality. The x-axes show progressively higher tax rates, grouped in rating categories. The blue line corresponds to the baseline economy. The red dashed line corresponds to an economy with moderate demand for IG-rated bonds. The black dotted line corresponds to an economy with high demand for IG-rated bonds. Demand for bonds issued by firms in the bottom part of each rating bucket is modeled through an increase in α within each rating group in the investment-grade market. The increase is more pronounced as we approach the BBB market from the AAA/AA market.

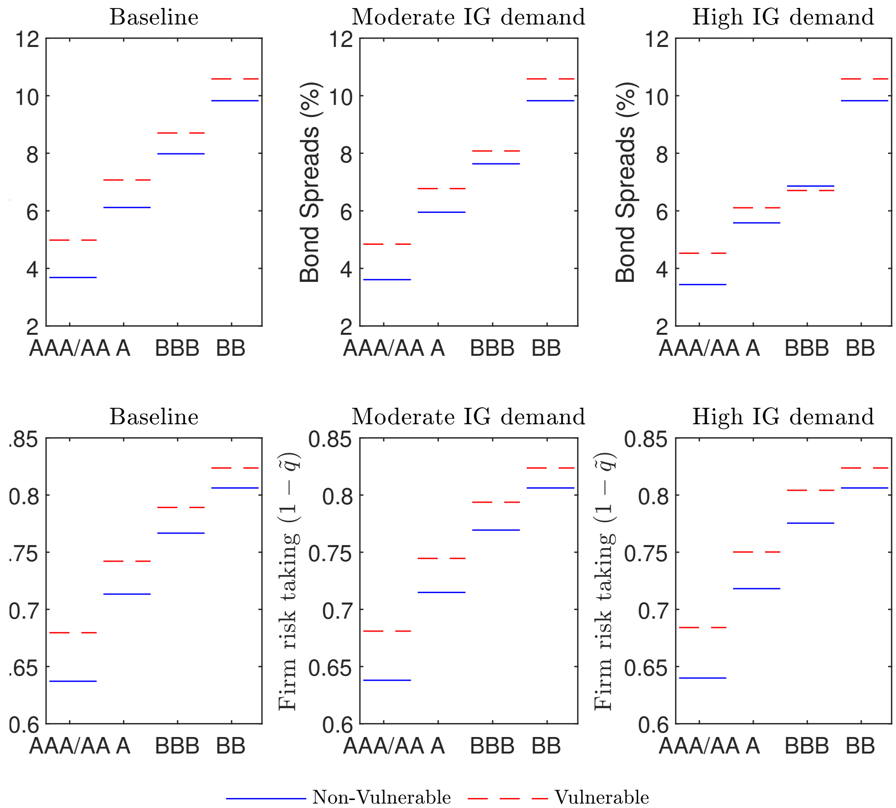

Figure B.2: Firm risk-taking and bond yields. This figure shows bond spreads (top panel) and firm risk choice (bottom panel) as a function of firm quality. The x-axes show progressively higher tax rates, grouped in rating categories. The blue lines show averages within a rating group for non-downgrade-vulnerable issuers. The red lines show averages within a rating group for downgrade-vulnerable issuers. The two left panels correspond to the baseline economy. The two middle panel correspond to an economy with moderate demand for risk. The two right panels correspond to an economy with high demand for IG-rated bonds. Demand for IG-rated bonds is modeled through an increase in α within each rating group in the investment-grade market. The increase is more pronounced as we approach the BBB market from the AAA/AA market.

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[27] 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.[28]

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.

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.

[27] 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.

[28] 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.

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).

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 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), bringing our data set to 14.1 million observations, corresponding to 8,505 funds, 1,635 issuers, and 12,686 securities. We then collapse our data set at the issuer-investor-quarter level. Our data runs quarterly from 2009Q1 to 2018Q4 and features 8,505 investors and 1,635 corporate bond issuers. Out of the 8,505 funds, 775 are annuities, 1,327 are life and health insurance, 2,309 are property and casualty insurance, and 2,791 are mutual funds, at some point during the sample period. Out of the 1,635 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.

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).

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:

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

	Downgrade-vulnerable	Non-downgrade-vulnerable	Difference
Total Assets	24,114	10,988	13,126***
Leverage	0.403	0.354	0.049***
EBITDA/Assets	0.104	0.132	−0.028***
Interest Coverage	7.747	13.114	−5.367***
Sales Growth	0.038	0.056	−0.017***
CAPX	0.188	0.225	−0.037***
Employment Growth	0.008	0.036	−0.027***
Net Worth	0.183	0.248	−0.066***

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***	0.043**	0.021***	0.018***
	(0.018)	(0.018)	(0.005)	(0.005)
Size		0.017**		0.003*
		(0.007)		(0.002)
Leverage		0.131**		0.016
		(0.055)		(0.015)
IC Ratio		−0.010***		−0.000**
		(0.001)		(0.000)
Industry-Year FE	X	X	X	X
Observations	9,056	8,973	9,431	9,341
R-squared	0.118	0.150	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.

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 $t+1$. 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:

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

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.

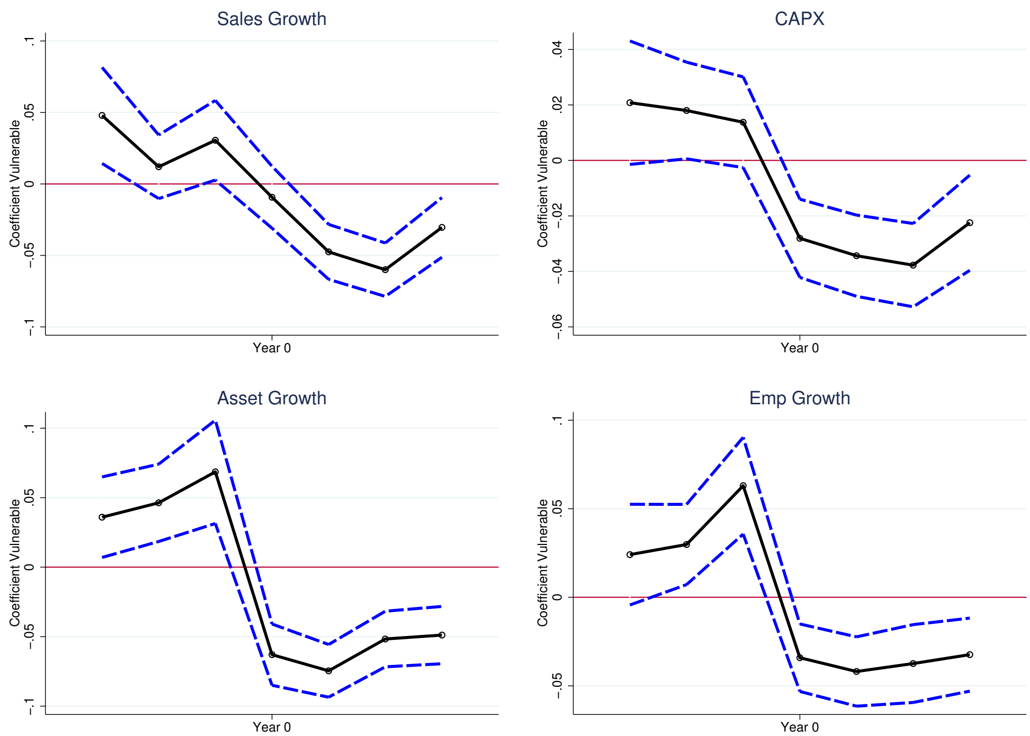

Figure D.1: Firm performance after being classified as downgrade-vulnerable. This figure shows the evolution of the estimated coefficient β_q from Specification (D1) three years before and after a firm becomes downgrade-vulnerable. Year zero corresponds to the first year a firm is classified as downgrade-vulnerable. 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 6.7 and 6.6 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,

Panel A: Bond-level descriptive statistics

Variable	Vulnerable	Mean	StDev	p25	p50	p75
Remaining maturity	No	9.7	8.5	3.9	6.7	9.9
Remaining maturity	Yes	10.3	9.0	3.8	6.8	15.1
log(offering amount)	No	13.2	0.6	12.8	13.1	13.5
log(offering amount)	Yes	13.4	0.7	12.9	13.3	13.8
Senior bond	No	0.7	0.4	0.0	1.0	1.0
Senior bond	Yes	0.7	0.4	0.0	1.0	1.0
Callable bond	No	0.9	0.3	1.0	1.0	1.0
Callable bond	Yes	0.9	0.3	1.0	1.0	1.0
Spread	No	136.0	150.8	59.4	97.5	161.4
Spread	Yes	132.1	163.6	58.3	95.4	151.1

Panel B: Bond spreads by rating

Rating	Vulnerable	Mean	p25	p50	p75	Std Dev
AAA-AA	No	40.5	16.9	31.3	53.4	32.4
AAA-AA	Yes	42.1	21.8	36.4	55.9	26.8
Di erence		*1.6*	*4.9*	*5.1*	*2.5*	
A	No	60.0	35.3	52.9	73.8	34.7
A	Yes	65.5	41.2	58.6	82.1	33.7
Di erence		*5.4*	*5.9*	*5.6*	*8.4*	
BBB	No	110.1	72.3	99.7	134.4	54.0
BBB	Yes	106.7	67.7	93.2	129.9	56.8
Di erence		*−3.4*	*−4.6*	*−6.5*	*−4.5*	
BB	No	223.1	167.8	216.4	270.1	93.5
BB	Yes	253.1	179.3	239.3	308.0	115.6
Di erence		*30.0*	*11.4*	*22.9*	*37.9*	
B	No	358.8	246.5	327.7	431.0	175.9
B	Yes	500.2	326.1	429.6	580.0	325.7
Di erence		*141.4*	*79.6*	*101.9*	*149.0*	
CCC	No	1104.4	557.9	769.7	1451.0	793.7
CCC	Yes	1277.1	699.1	975.6	1502.3	880.7
Di erence		*172.7*	*141.2*	*205.8*	*51.3*	

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.

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.

D.3 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.4 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 2013–16 period both in secondary and primary markets.

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 first two columns of Table D.5 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 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 (3) to (6) we examine if the age of the bond affects our results. Columns (3) and (5) confirm the fallen angel privilege in both on-the-run bonds that were issued over the past twelve months as well as in older bonds, with both regressions having almost identical estimates of around 11 basis points. Columns (4) and (6) confirm that spreads were higher in the 2013–16 period, with slightly higher point estimates in the on-the-run sample.

	Spread	Spread	Offer Spread	Offer Spread
A	18.069	26.892***	28.153*	22.757
	(12.203)	(8.225)	(14.229)	(19.417)
BBB	69.378***	78.467***	88.911***	87.631***
	(12.875)	(9.086)	(14.233)	(16.806)
BB	170.350***	170.273***	191.808***	171.639***
	(14.117)	(14.204)	(15.421)	(20.990)
B	269.201***	277.771***	254.082***	255.729***
	(17.462)	(20.429)	(16.062)	(26.260)
CCC	513.016***	510.402***	310.965***	293.466***
	(48.641)	(85.702)	(24.983)	(42.128)
Vulnerable × AAA-AA	−2.882	9.253	−0.389	−12.441
	(11.601)	(8.397)	(17.815)	(22.726)
Vulnerable × A	1.143	−0.451	−0.861	−10.215
	(4.718)	(7.356)	(5.910)	(12.099)
Vulnerable × BBB	−9.273***	−15.229***	−12.604**	−26.295***
	(3.367)	(4.970)	(4.924)	(7.547)
Vulnerable × BB	15.636*	34.854**	9.886	14.347
	(8.455)	(14.388)	(9.419)	(17.007)
Vulnerable × B	73.552***	90.564**	54.012***	55.764***
	(24.499)	(35.794)	(12.709)	(16.988)
Vulnerable × CCC	319.958**	447.016***	49.794	40.469
	(127.525)	(157.206)	(30.458)	(52.759)
Industry-Year-Month FE	X	X	X	X
Bond-level controls	X	X	X	X
Sample	2010–19	2013–16	2010–19	2013–16
Observations	217,106	91,431	4,493	1,902
R-squared	0.639	0.630	0.822	0.787

Table D.4: 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 spreads. 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 on the latter are allowed to vary by rating. The specification also includes dummy variables for 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.

	Spread_{it}	Spread_{it}	Spread_{it}	Spread_{it}	Spread_{it}	Spread_{it}
A	29.242***	29.069***	21.395***	29.302***	27.681***	28.767***
	(7.069)	(8.010)	(5.789)	(4.682)	(8.420)	(9.464)
BBB	77.156***	74.784***	66.478***	73.602***	80.202***	80.073***
	(7.228)	(8.216)	(6.046)	(5.800)	(8.754)	(9.982)
BB	177.345***	169.624***	180.852***	192.978***	183.090***	177.533***
	(8.751)	(11.138)	(8.354)	(10.578)	(11.220)	(15.293)
B	301.157***	299.086***	290.967***	284.286***	322.081***	332.645***
	(13.080)	(21.378)	(13.407)	(22.557)	(17.305)	(29.418)
CCC	965.367***	1,204.623***	722.061***	820.932***	983.977***	1,102.156***
	(108.813)	(182.198)	(101.199)	(151.244)	(123.193)	(217.426)
Vulnerable × A	0.049	−5.771	−3.044	−13.153	2.118	−1.984
	(4.618)	(7.558)	(5.349)	(9.085)	(5.019)	(8.664)
Vulnerable × BBB	−10.644***	−17.789***	−11.049**	−23.131***	−11.830***	−19.293***
	(3.294)	(5.183)	(4.367)	(6.802)	(3.604)	(6.034)
Vulnerable × BB	12.280*	12.398	18.967**	15.879	12.442	11.922
	(7.454)	(11.578)	(8.490)	(13.485)	(8.207)	(13.030)
Vulnerable × B	70.596***	62.849**	62.587**	73.735**	80.738***	80.900**
	(21.153)	(31.946)	(24.364)	(36.235)	(24.674)	(39.599)
Vulnerable × CCC	382.004**	297.260	309.406*	243.458	402.316*	367.686
	(184.720)	(253.627)	(177.172)	(217.371)	(203.185)	(288.044)
Vulnerable × AAA-AA	12.812*	17.325**	11.364**	14.760**	11.130	19.551*
	(6.849)	(7.923)	(5.584)	(5.590)	(8.500)	(10.556)
Trades × AAA	0.009	−0.017				
	(0.013)	(0.015)				
Trades × AA	0.035***	0.028***				
	(0.008)	(0.011)				
Trades × A	0.029***	0.026**				
	(0.007)	(0.011)				
Trades × BBB	0.036***	0.036***				
	(0.008)	(0.012)				
Trades × BB	0.055***	0.074***				
	(0.009)	(0.012)				
Trades × B	0.109***	0.171***				
	(0.022)	(0.039)				
Trades × CCC	−0.023	−0.440***				
	(0.114)	(0.166)				
Industry-Year-Month FE	X	X	X	X	X	X
Bond-level controls	X	X	X	X	X	X
Sample	2010–19	2013–16	2010–19	2013–16	2010–19	2013–16
Bond age	All	All	< 12 months	< 12 months	>12 months	>12 months
Observations	240,380	98,812	44,913	20,532	194,465	77,916
R-squared	0.650	0.637	0.734	0.705	0.642	0.622

Table D.5: Additional bond liquidity controls. This table shows the estimation results of specification (2), with tests for bond liquidity. The first two columns 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 third and fifth columns, the sample is restricted to bonds that have been issued within the past 12 months, while in the fourth and sixth columns only include bonds issued at least 12 months ago and greater. In all regressions, the dependent variable in each column is the secondary market bond spreads. 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 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. Additional dummy variables for convertible bonds, covenant bonds, and senior bonds are also included in the estimation. 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   Additional figures and tables

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 E.1, 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 E.2, we show that the 2013–16 is characterized by a substantial monetary easing by the Federal Reserve.

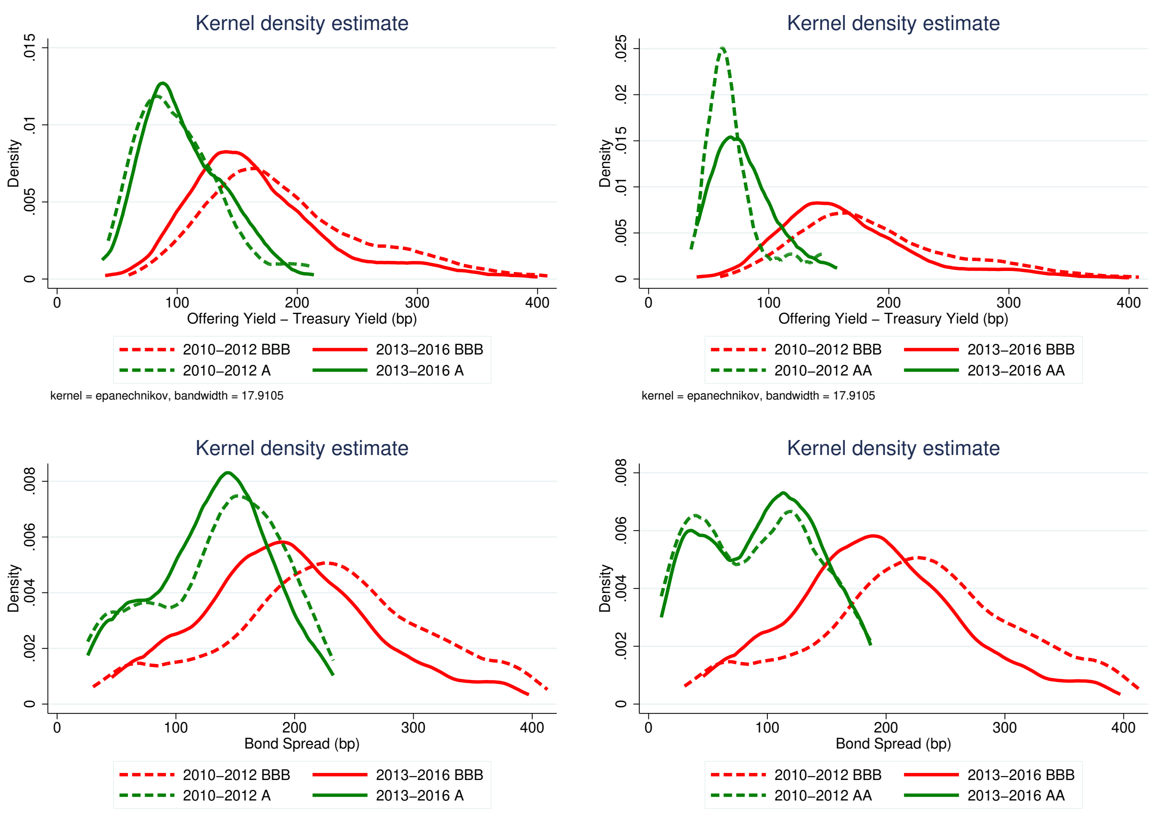

Figure E.1: Shift in bond spread distributions from 2010–12 to 2013–16. This figure shows how bond spreads distributions changed from 2010–12 (dashed lines) to 2013–16 (solid lines). The top panels show the distribution of offering spreads for newly issued bonds. The bottom two panels show the distribution 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.

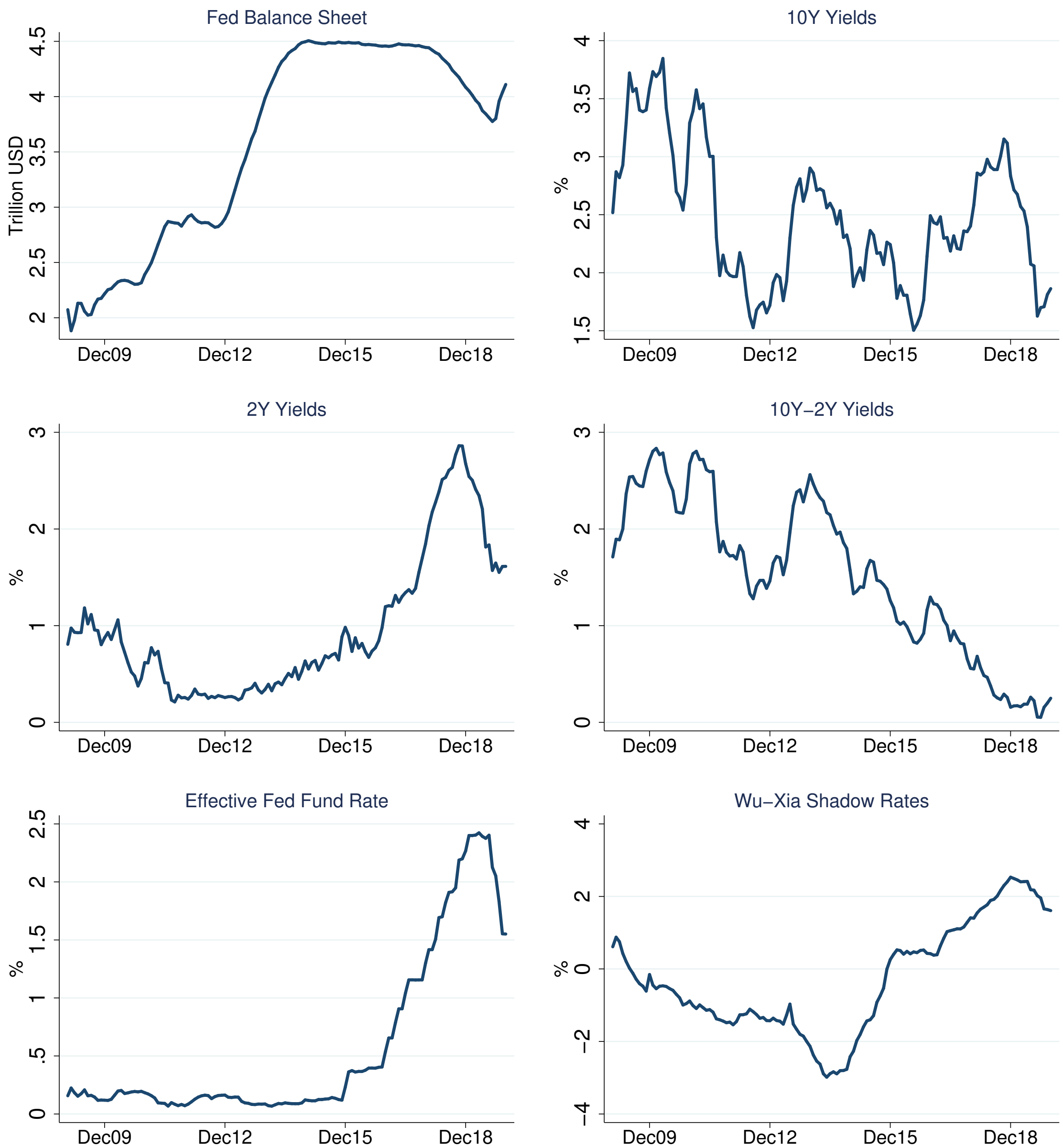

Figure E.2: Monetary policy stance. This figure shows the monetary policy stance in the U.S. during our sample period. The six panels show the size of the Fed balance sheet (trillion dollars), the 10-year Treasury yields (%), the 2-year Treasury yields (%), the difference between the 10-year and the 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.

	N_k^{09q1}	N_k^{13q1}	N_k^{17q1}	$Hold_k^{09q1}$	$Hold_k^{13q1}$	$Hold_k^{17q1}$
Annuities	489	439	447	$42.65	$98.54	$108.56
Life & Health Insurance	1036	1145	942	$317.35 b	$573.67 b	$658.66 b
Property & Casualty Insurance	1944	2041	1782	$77.74 b	$125.28 b	$130.46 b
Open Ended Mutual Funds	1078	1358	1533	$236.11 b	$631.19 b	$908.23 b

QE Exposure$_{kt}$	mean	stdev	p25	p50	p75
Annuities	0.028	0.005	0.027	0.029	0.031
Life & Health Insurance	0.013	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	0.023	0.024	0.027

Corporate and Treasury Bond Portfolio Maturity$_{kt}$	mean	stdev	p25	p50	p75
Annuities	14.612	9.839	8.641	9.457	18.531
Life & Health Insurance	11.428	2.440	10.468	10.762	11.282
Property & Casualty Insurance	7.088	3.703	5.836	5.934	6.266
Open Ended Mutual Funds	14.118	9.911	8.347	8.579	17.955

Treasury Bond Portfolio Maturity$_{kt}$	mean	stdev	p25	p50	p75
Annuities	13.676	7.414	9.111	9.606	16.853
Life & Health Insurance	9.429	3.087	8.367	8.549	9.209
Property & Casualty Insurance	6.546	3.519	5.457	5.499	5.661
Open Ended Mutual Funds	14.419	9.704	8.757	9.139	17.752

Share of IG Corporate and Treasury Bonds$_{kt}$	mean	stdev	p25	p50	p75
Annuities	0.550	0.058	0.497	0.548	0.604
Life & Health Insurance	0.723	0.025	0.700	0.733	0.743
Property & Casualty Insurance	0.788	0.015	0.778	0.788	0.799
Open Ended Mutual Funds	0.559	0.025	0.537	0.559	0.576

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

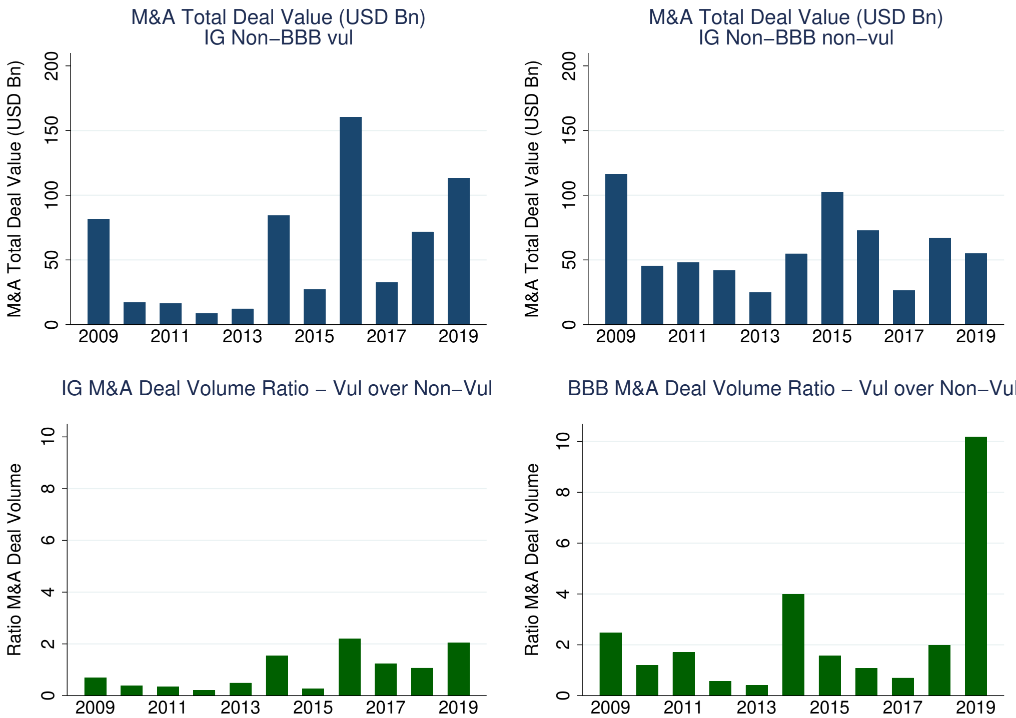

Figure F.1: M&A activity, IG-rated issuers. This figure shows the M&A activity by downgrade-vulnerable and non-downgrade-vulnerable A/AA/AAA-rated issuers. The first row shows deal volume for downgrade-vulnerable (left) and non-downgrade-vulnerable (right) A/AA/AAA-rated firms. The second row shows the ratio of the total M&A deal volume of downgrade-vulnerable firms over the total M&A deal volume of non-downgrade-vulnerable firm in the AAA/AA/A (left) and BBB (right) rating categories.

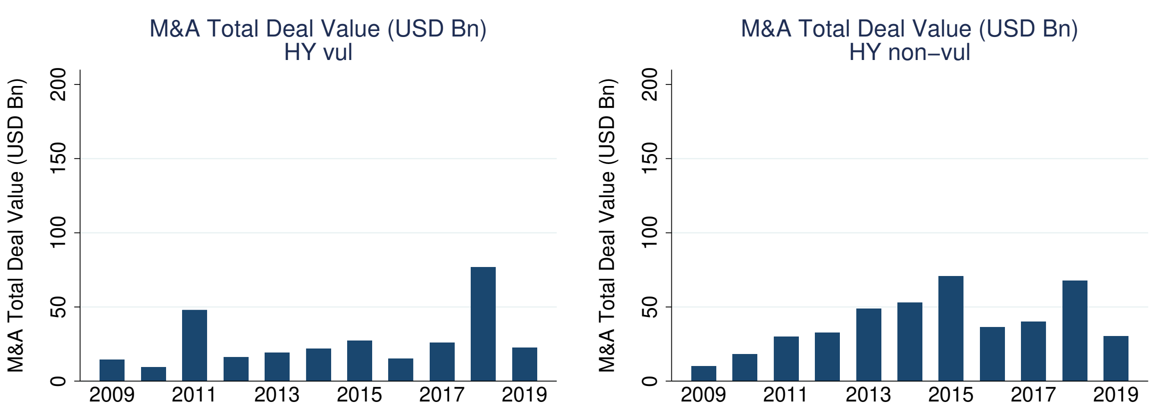

Figure F.2: M&A Total Deal Volume. This figure shows the total M&A deal volume for downgrade-vulnerable and non-downgrade-vulnerable firms in the high-yield (speculative-grade) category.

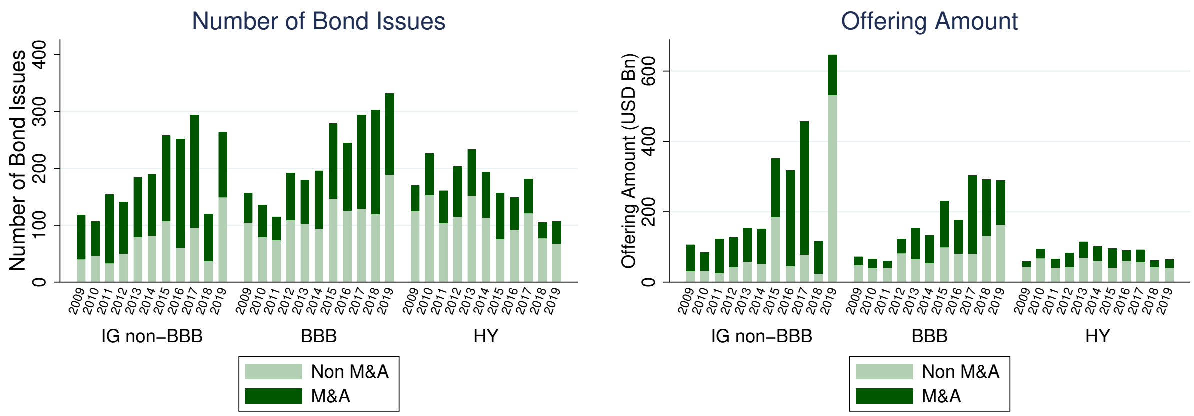

Figure F.3: Bond issuance and volume. This figure shows the number of bond issues and the bond issuance volume for high-yield, BBB-rated, and A/AA/AAA-rated firms from 2009 to 2019. The left panel shows the total number of bond issues, separated by M&A and non-M&A bond issues. The right panel shows the 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.

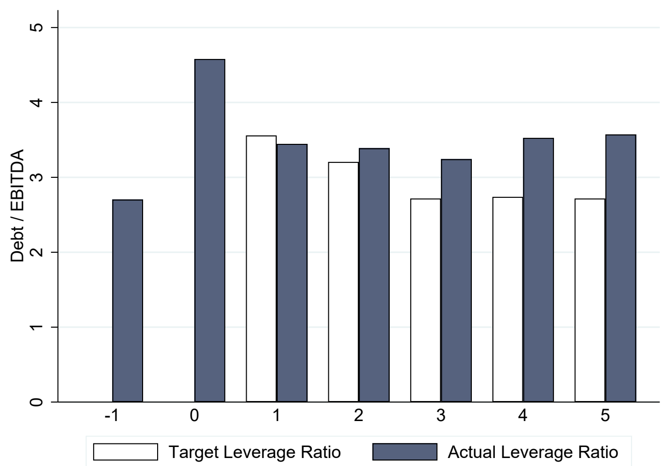

Figure F.4: Broken promises about debt reduction after M&A. This figure compares the year-by-year promised path of debt reduction with observed debt after firm M& A. The x-axis shows the years since transaction. The y-axis is debt divided by EBITDA. We assume that debt reduction plans (e.g., leverage 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.

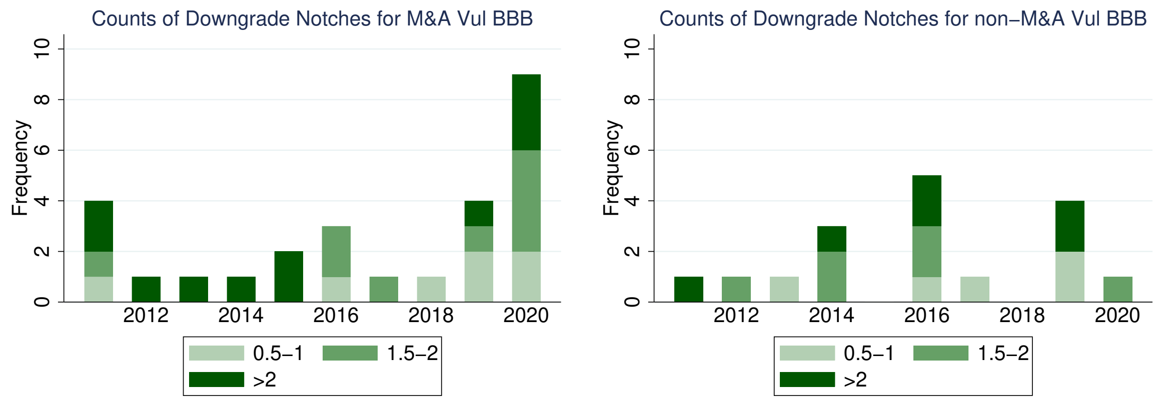

Figure F.5: Downgrade materialization of (prospective) fallen angels. This figure shows the number of downgrades that downgrade-vulnerable BBB-rated firms have experienced in the years 2011 to 2020, and groups them according to their downgrade severity. The downgrade severity is measured by the number 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.

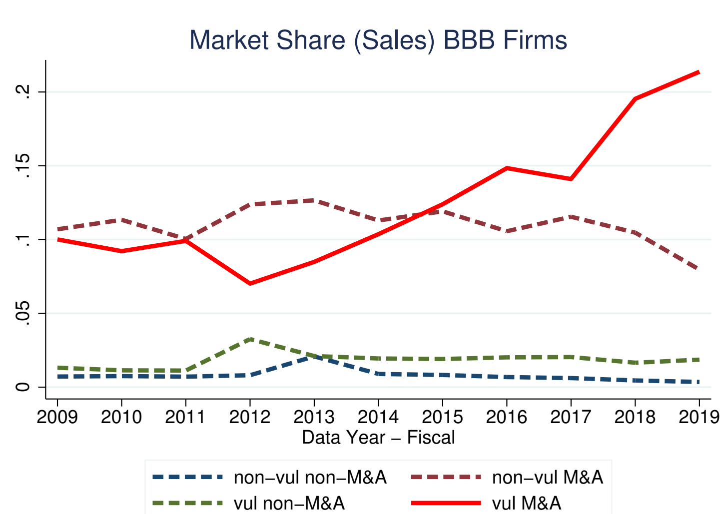

Figure F.6: M&A and the increase in market share of prospective fallen angels. This figure shows the evolution of firm market share (share of sales, weighted by the relative size of the respective industry)) for BBB-rated issuers, broken down by downgrade-vulnerability and whether a firm engages in an M&A transaction during our sample period.

F.2 Exorbitant privilege largely driven by M&A

In this section, we document that the low bond financing costs of prospective fallen angels is particularly pronounced for issuers engaging in M&A activity.

We revisit our bond pricing analysis and show that the bond financing privilege of prospective fallen angels is largely driven by M&A. To do so, we modify specification (2) to examine the change in bond spreads around M&A announcements by estimating the following specification which includes interactions with an M&A variable:

$$\begin{aligned}\Delta_{12}Spread_{bit} = {} & \beta_1 \text{M\&A}_{it\quad 11} \times \text{Vulnerable}_{it\quad 11} \times \textbf{Rating}_{it\quad 11} \\ & + \quad {}_{\mathbf{2}}\text{Vulnerable}_{it\quad 11} \times \textbf{Rating}_{it\quad 11} \\ & + \quad {}_{\mathbf{3}}\text{M\&A}_{it\quad 11} \times \textbf{Rating}_{it\quad 11} + \quad \boldsymbol{X}_{bt\quad 11} + \quad {}_{rht} + \epsilon_{bit}\end{aligned} \tag{F1}$$

where $\Delta_{12}Spread_{bit}$ is the change in the secondary market spread on bond b issued by firm i between month $t-12$ and t, $\text{M\&A}_{it}$ is an indicator variable equal to one if issuer i announces an M&A deal in month t, and $\textbf{Rating}_{it}$ is a vector of dummy variables corresponding to the credit rating of firm i in month t. We also include the same bond-level controls as in specification (2) $\boldsymbol{X}_{bt}$ and rating-industry-year-month fixed effects $\quad_{rht}$.

Table F.1 shows the estimation results. The significant triple interaction terms of M&A $\times$ Vulnerable $\times$ BBB confirm that secondary market spreads on bonds issued by prospective fallen angels decline around M&A announcements relative to bonds issued by prospective fallen angels that did not announce an M&A. The second column shows that the privilege was larger during the period of large QE purchases. Consistent with the privilege being only present for prospective fallen angels, downgrade-vulnerable firms in other ratings segments do not experience a decline in spreads after M&A announcements.

	$\Delta_{12}Spread$	$\Delta_{12}Spread$
Vulnerable$_{it\ \ 11}$ × AAA-AA$_{it\ \ 11}$	−4.197***	−4.018***
	(0.899)	(0.265)
Vulnerable$_{it\ \ 11}$ × A$_{it\ \ 11}$	0.294	1.474
	(1.320)	(2.481)
Vulnerable$_{it\ \ 11}$ × BBB$_{it\ \ 11}$	0.553	−1.976
	(0.964)	(1.740)
Vulnerable$_{it\ \ 11}$ × BB$_{it\ \ 11}$	1.897	4.984
	(5.183)	(6.577)
Vulnerable$_{it\ \ 11}$ × B$_{it\ \ 11}$	21.853*	23.897*
	(13.078)	(13.176)
M&A$_{it\ \ 11}$ × Vulnerable$_{it\ \ 11}$ × AAA-AA$_{it\ \ 11}$	6.229**	8.295***
	(2.462)	(0.860)
M&A$_{it\ \ 11}$ × Vulnerable$_{it\ \ 11}$ × A$_{it\ \ 11}$	1.146	1.941
	(1.503)	(2.148)
M&A$_{it\ \ 11}$ × Vulnerable$_{it\ \ 11}$ × BBB$_{it\ \ 11}$	−2.369	−6.399**
	(2.063)	(3.147)
M&A$_{it\ \ 11}$ × Vulnerable$_{it\ \ 11}$ × BB$_{it\ \ 11}$	29.558***	40.129***
	(10.957)	(14.127)
M&A$_{it\ \ 11}$ × Vulnerable$_{it\ \ 11}$ × B$_{it\ \ 11}$	−7.472	47.515
	(40.912)	(57.013)
Rating × industry × year-month FE	X	X
Rating × M&A controls	X	X
Sample period	Entire	2013–16
Observations	66,000	33,170
R-squared	0.790	0.778

Table F.1: Prospective fallen angels subsidy and M&A activity. This table presents estimation results from specification (F1). The dependent variable is the change in the spread of bond b issued by firm i between month $t-12$ and t. Vulnerable is a dummy equal to 1 if firm i is vulnerable to a downgrade at date t and zero otherwise. M&A is a dummy variable equal to one if issuer i announces an M&A acquisition in month t and zero otherwise. The interactions between the M&A dummy and issuer ratings are included in the estimation but not reported for brevity. The specification also includes dummy variables for callable bonds, bonds with a 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. Dummy variables for convertible bonds, covenant bonds, and senior bonds are included in the estimation but not reported for brevity. Standard errors clustered at the firm level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix G Quantifying the subsidy

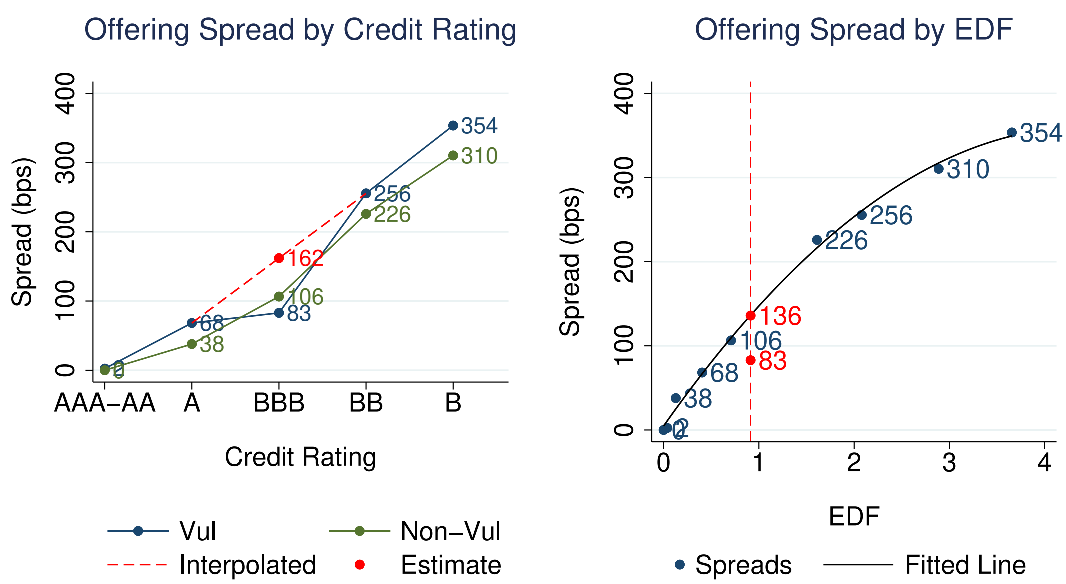

Figure G.1: Subsidy alternative calculations. The left panel shows in red the counterfactual vulnerable BBB rated spread, based on the spread interpolation between the downgrade-vulnerable rating categories. The right panel plots the relationship between the 2-year expected default frequencies and offering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