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

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Abstract

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

JEL Codes: E31, E44, G21.
Keywords: Capital misallocation, corporate bond market, investment-grade bonds, BBB rating, large-scale asset purchases (LSAP), credit ratings.

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1 Introduction

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

By way of motivation, we start with some striking observations (documented in Figure 1) about the corporate bond market. Its size doubled since the GFC, resulting in non-financial sector debt being the fastest-growing component of private-sector debt (including household and financial sector debt). This growth was largely driven by the BBB-rated segment, namely firms just above the IG cutoff which face prospects of becoming "fallen angels" upon a downgrade and experiencing a steep increase in their cost of borrowing. In particular, between 2008 and 2020, the amount outstanding of BBB-rated bonds more than tripled to \$3.5 trillion, representing more than 40% of all non-financial corporate debt, up from less than 25% 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 as well as market leverage rose. These dynamics are unique to the BBB rating. 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.

In many respects, the growth in issuance of risky investment-grade bonds could be considered a desired outcome of monetary policy easing after the GFC. In particular, QE

[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 at the "COVID-19 and the economy" Brookings webinar (link).

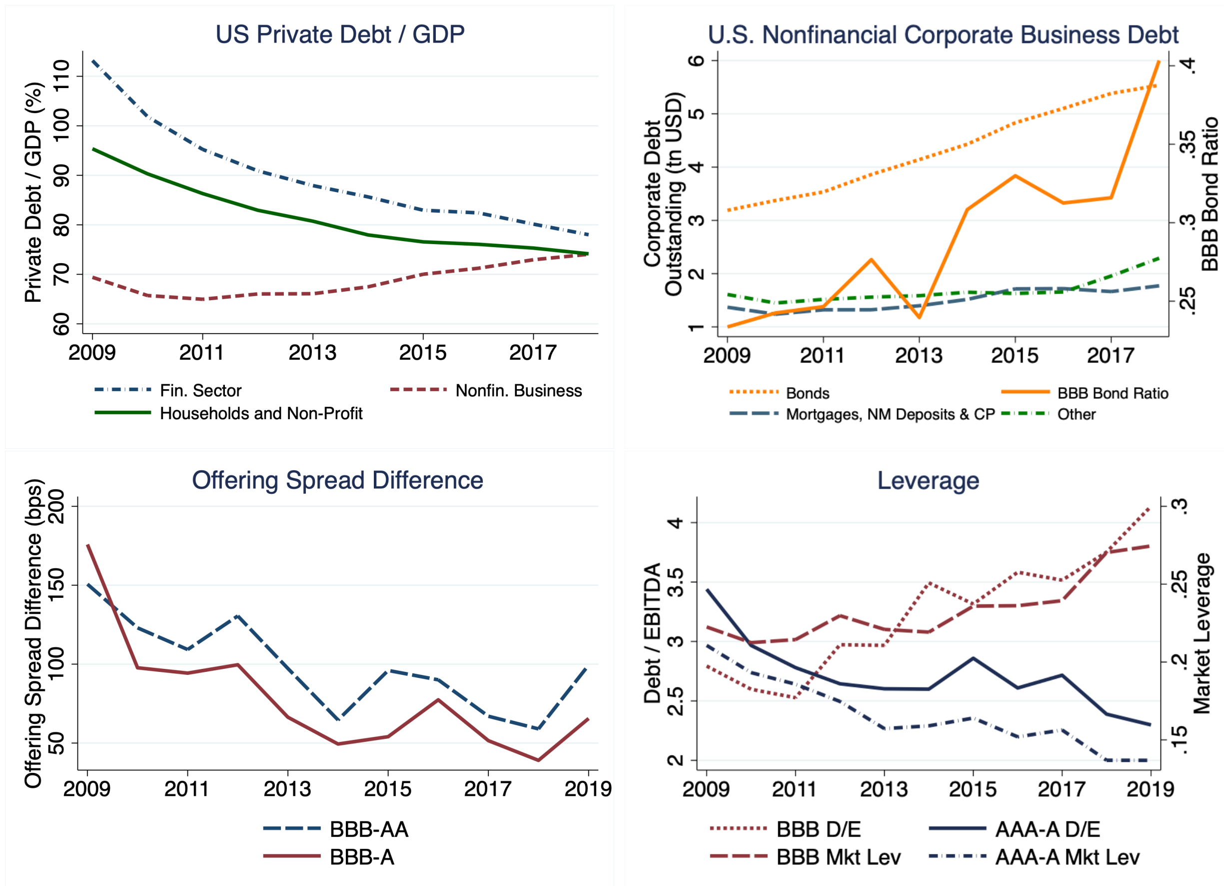

Figure 1: The growth of the BBB-rated segment of the U.S. corporate bond market. This figure shows the growth of U.S. non-financial corporate debt and, in particular, of the U.S. BBB-rated corporate bond market. The top left panel shows the evolution of financial sector debt, non-financial sector debt, and household debt, normalized by GDP. The sources are series dodfs, tbsdodns, and cmdebt from FRED. The top right panel shows the evolution on the left y-axis of (i) corporate bonds, (ii) mortgages, non-mortgage deposits (includes loans from banks, credit unions, and savings and loans associations), and commercial paper, (iii) other loans (loans from non-bank institutions, excluding mortgages, and industrial revenue bonds), and on the right y-axis of (iv) BBB-rated corporate bonds as a ratio of total corporate bond volume. The sources are series cblbsnncb, mlbsnncb, ncbilia027n, cplbsnncb, and olalbsnncb from FRED, Capital IQ, and Thomson Reuters. The bottom left panel shows the differences in offering spread (primary market bond yields minus Treasury yields with similar maturity) for newly issued bonds. The bottom right panel shows the asset-weighted debt over EBITDA (left y-axis) and market leverage (right y-axis) for BBB-rated and other IG-rated firms.

is aimed at pushing investors into riskier assets by lowering the yields on government and mortgage-backed bonds (Gagnon et al., 2011), and lowering in turn the yields on other long-term riskier assets (Krishnamurthy and Vissing-Jorgensen, 2011). However, the growing issuance in the riskiest IG bucket also comes with a buildup of vulnerabilities which materialized at the onset of the COVID-19 pandemic. The volume of debt downgraded from BBB to speculative grade in a few weeks at the beginning of 2020 was more than twice the volume of similar downgrades during the *entire* GFC, leading, together with other market-wide stresses, to the Federal Reserve stepping in to stabilize the corporate bond market in the second half of March and into April 2020.

In this paper, we investigate these trends, provide detailed evidence that they are—at least in part—a consequence of the QE programs on financial and real sectors, and document their financial and real spillovers. Specifically, we document the existence of a bond market subsidy for "prospective fallen angels", i.e., downgrade-vulnerable BBB-rated firms which are on the cusp of the IG cutoff. The subsidy originates from a demand for riskier BBB-rated bonds by yield-hungry IG-focused investors highly exposed to the QE-induced compression of long-term premia in fixed-income securities. In particular, as the quantity of the Fed QE purchases expands, financial institutions such as insurance companies earn lower term premia on securities purchased by the Fed such as Treasuries, Agency MBS, and Agency debt securities, and simultaneously hold more and more of securities such as corporate bonds which incur relatively higher capital requirements. This combination of term-premia compression and portfolio rebalancing induces in these investors a preference for IG bonds, which incur a relatively lower capital charge, but within IG bonds those that have higher yields and yet are the least likely to be downgraded.

In response to the subsidy, 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 at least 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 on other firms negative externalities that are similar to the congestion effects created by zombie firms on healthier firms (Caballero et al., 2008).

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

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

Using this measure, we define a "prospective fallen angel" as a BBB-rated firm that is vulnerable to being downgraded. We show that during 2009 to 2019 prospective fallen angels benefit from a reduction in bond spreads relative to the rest of the BBB segment—a relative pattern between downgrade-vulnerable and non-downgrade-vulnerable firm borrowing costs not present for other rating classes. Moreover, when replacing bond spreads with equity-market-based measures of expected default, 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 during 2009 to 2019 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 $43 billion and $120 billion over this period.

Our empirical tests seek to identify the mechanisms leading to this subsidy and its consequences and are structured in three parts. First, we show that investors exposed to QE drive the demand for corporate bonds issued by prospective fallen angels as they rebalance their portfolio away from Treasuries—a dynamic reflected in bond prices. 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 corporate 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. We find that the within-firm correlation between investor exposure to QE and investor bond holdings is more pronounced for bonds issued by prospective fallen angels. This is the case especially for long-duration investors that invest mostly in IG bonds, in particular, insurance companies with minimum guarantee variable annuities and open-ended debt mutual funds focused on IG bond investments. To verify the special role played by investors' demand in driving the subsidy, we also document that the yields of bonds issued by prospective fallen angels are reduced by the QE exposure of investors holding the bonds.

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

Third, we find that across rating classes, BBB-rated firms also have the highest market share by sales over our sample period. Moreover, this share increased over the last decade, and the increase was 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 adverse 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. At the industry-level, we find that the presence of prospective fallen angels is associated with higher contemporaneous industry-level credit risk and concentration, and eventually higher markups as prospective fallen angels keep growing together with the industry concentration.

Overall, we conclude that quantitative easing led to a capital misallocation via a corporate bond market subsidy for prospective fallen angels, an exorbitant privilege that they exploited with greater issuance and M&A activity at the expense of competitors, but fragility at the time of the COVID-19 outbreak. 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)). Our paper documents QE-induced capital misallocation 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 IG bonds.

Second, we contribute to the literature on fragility in corporate borrowing markets. The documented vulnerability of the IG bond market since 2009 is consistent with warning signs from academics and practitioners about the BBB market (Altman, 2020; S&P Global, 2020a; Çelik et al., 2020; Blackrock, 2020; Morgan Stanley, 2018a,b) and partly explains the large price drop of IG corporate bonds at the onset of the COVID-19 pandemic (Haddad et al., 2021; Boyarchenko et al., 2022; Altman, 2020). 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).

Third, we contribute to the literature on the real effects of frictions in investor portfolio choice. Consistent with the framework in Vayanos and Vila (2021), a few recent papers document the role of bond investors in the transmission of monetary policy (e.g., Ahmed et al. (2022); Darmouni et al. (2021)).[2] 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., 2022). Becker and Ivashina (2015) shows that, within ratings, investors reaching-for-yield might tilt their portfolio towards riskier assets. Goldstein and Huang (2020) shows that this behavior might, in equilibrium, induce credit rating agencies to inflate their ratings. Finally, our paper is also related to Aktas et al. (2021) that shows that investment-grade firms are concerned about acquisition-related downgrades in their M&A activity. However, we find that such concern appears to be muted in the case of prospective fallen angels due to QE-induced demand for their bonds and the sluggishness of credit rating agencies in downgrading after M&A.

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

The remainder of the paper is structured as follows. Section 2 presents the data and our measure of downgrade vulnerability. Section 3 documents that prospective fallen angels benefited from a bond financing subsidy during QE. Section 4 shows that this subsidy originates from investors rebalancing their bond portfolios. Section 5 discusses the sizable increase in M&A activity of prospective fallen angels. Section 6 quantifies the subsidy enjoyed by prospective fallen angels and discusses its industry spillovers. Section 7 concludes.

[2] 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.

2 Identifying prospective fallen angels

In this section, we (i) describe our data sources and construction (Section 2.1); (ii) introduce our definition of downgrade-vulnerable firms, showing the sluggishness of credit rating agencies in downgrading BBB-rated firms to speculative grade (Section 2.2); and, (iii) document the realized fragility of BBB-rated downgrade-vulnerable firms during COVID-19 (Section 2.3).

2.1 Data

Our main data set consists of firm-level, bond-level, and investor-level data from 2009 to 2019, described in detail in Appendix OA.2. 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 ratings into numerical values (see Table OA.2). Lastly, we use ThomsonOne for mergers and acquisitions data. Combining these various data sources, we analyze 6,145 firms. Our sample consists of firms that are incorporated in the U.S. and excludes financial firms that have a SIC-code between 6000-6999.

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 6,329 bond issues by 886 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 6,116 outstanding bonds issued by 863 firms. To compute primary and secondary market corporate bond spreads, we follow Gilchrist and Zakrajšek (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. This data set—used by, among others, Becker and Ivashina (2015), Bretscher et al. (2022), and Cai et al. (2019)—shows security-level holdings by individual investors at a quarterly frequency. We match eMAXX 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 7,253 investors, mostly property and casualty insurers (28%), open-ended mutual funds (25%), (other) life and health insurers (16%), and insurers with annuities with minimum guarantees (9%). The investor-level data covers around 20%-25% (depending on the date and rating category) of the stock of corporate bonds outstanding.

2.2 Downgrade-vulnerable firms

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

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

Specifically, we classify a firm as downgrade-vulnerable if its Z"-score is lower than the historical median Z"-score of the next lowest rating category.[3] 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 several ways. First, we show that downgrade-vulnerable firms are more likely to be downgraded and to be assigned a negative

[3]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).

	Negative Watch	Negative Watch	Downgrade	Downgrade
Vulnerable	0.102***	0.046***	0.024***	0.018***
	(0.017)	(0.017)	(0.006)	(0.006)
Size		0.011*		0.003*
		(0.007)		(0.002)
Leverage		0.350***		0.020
		(0.056)		(0.015)
IC Ratio		−0.000		−0.000
		(0.001)		(0.000)
Profitability		−1.654***		−0.112**
		(0.171)		(0.050)
Industry-year FE	✓	✓	✓	✓
Observations	8,506	8,426	9,431	9,341
R-squared	0.251	0.295	0.095	0.098

Table 1: Credit rating actions after being classified as downgrade-vulnerable. This table presents the estimation results from specification (1) 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. 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 downgrade-vulnerable in period t. Firm-level control variables are size (log of total assets), leverage, IC ratio, and profitability. Standard errors clustered at the firm-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

credit watch relative to non-downgrade-vulnerable firms. Second, we show that BBB-rated downgrade-vulnerable firms appear to be treated favourably by rating agencies compared to other downgrade-vulnerable firms. In addition, (i) in Table A.1, we show that the probability of being downgraded is higher for downgrade-vulnerable firms compared with non-downgrade-vulnerable firms in various sub-periods of our sample period, and (ii) in Appendix OA.3, we show that 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) and firms' performance deteriorates after becoming downgrade-vulnerable (decline in sales growth, investments, firm size, and employment).

First, for the analysis of the probability of being downgraded or placed on a negative watch, we estimate the following specification:

$$Y_{it+1} = \beta_1 \text{Vulnerable}_{it} + \beta_2 X_{it} + \mu_{ht} + \epsilon_{it+1} \tag{1}$$

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 a downgrade event in $t+1$. To qualify as

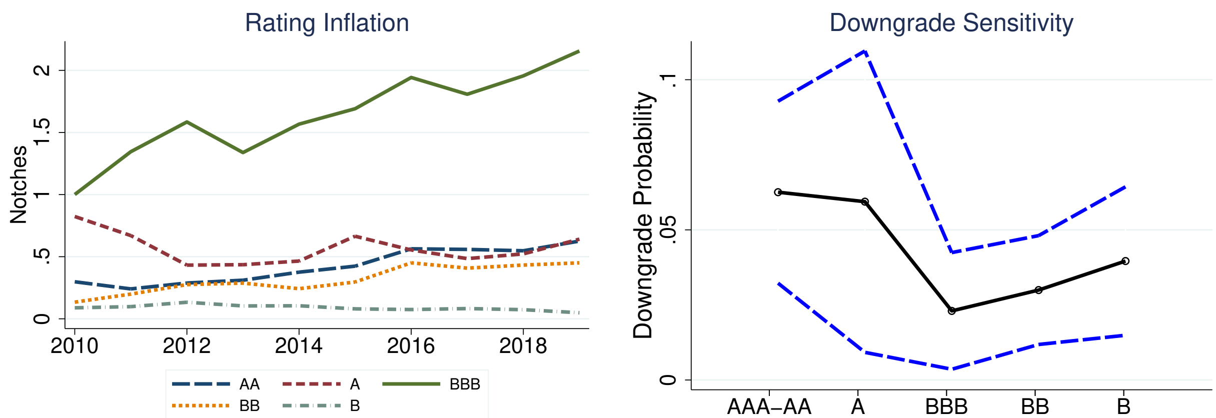

Figure 2: High and rising credit ratings inflation for BBB-rated issuers. This figure shows credit ratings inflation across rating categories. The left panel shows asset-weighted credit ratings inflation. Credit ratings inflation is equal to zero if an issuer has a Z”-score above the median Z”-score of firms in the next lower rating category, otherwise credit ratings inflation is calculated as the number of notches between the issuer's credit rating notch (e.g., AA+, AA, AA-, A) and the credit rating notch implied by its Z”-score. The right panel shows the sensitivity of downgrades of downgrade-vulnerable issuers relative to non-downgrade-vulnerable issuers by rating category. Specifically, the figure shows the estimated coefficient, β_1, from the following regression specification estimated in each rating category separately: $Y_{it+1} = \beta_1 Vulnerable_{it} + \beta_2 X_{it} + \mu_{ht} + \epsilon_{it+1}$, where i is a firm, h an industry, t a year, Y_{it+1} is a dummy equal to one in the case of a downgrade event in $t+1$, $Vulnerable_{it}$ is a dummy equal to one if a firm is downgrade-vulnerable in period t, μ_{ht} are industry-year fixed effects, and X_{it} is a vector of controls (log of total assets, leverage, and interest coverage ratio). Dashed lines delimit 95 percent confidence intervals, with standard errors clustered at the firm-level.

a 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 are industry-year fixed effects. X is a vector of controls, namely the logarithm of total assets, leverage, and the interest coverage ratio.

Table 1 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.

Second, we document a substantial and increasing ratings inflation for BBB-rated issuers which increased markedly after 2009 (Figure 2, 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. This evidence is consistent with Bruno

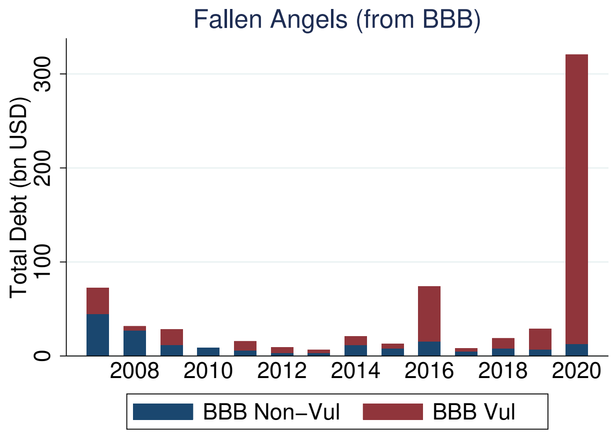

Figure 3: Risk materialization during COVID-19. This figure shows total debt downgraded from BBB to speculative grade split by non-downgrade-vulnerable issuers (blue) and downgrade-vulnerable issuers (red). The vulnerability of the BBB market materialized at the onset of the COVID-19 pandemic and was concentrated in downgrade-vulnerable issuers.

et al. (2016) that shows that Moody's avoids downgrading issuers of corporate bonds that are close to losing their investment-grade status. In addition, the right panel of Figure 2 shows that although downgrade-vulnerable firms are more likely to be downgraded in each rating bucket compared to their non-downgrade-vulnerable peers, this correlation is the weakest for BBB-rated issuers. These findings are consistent with other studies and anecdotal evidence on the sluggishness of rating agencies in downgrading BBB-rated firms to speculative grade.

2.3 Prospective fallen angels during COVID-19

The downgrade vulnerability of BBB-rated firms, and especially prospective fallen angels, manifested itself during the COVID-19 pandemic. 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 3 shows that, in 2020, the total debt of fallen angels amounted to an unprecedented \$320 billion of which the vast majority was debt of firms classified as prospective fallen angels before the COVID shock. This wave of fallen angels only stopped when the Federal Reserve expanded its corporate buying program on April 9, 2020 to include those issuers downgraded from BBB to fallen angels between March 22, 2020 and April 9, 2020. Some examples of firms eligible for the program are Ford Motor, Macy's, and Occidental Petroleum (S&P Global,

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

Table 2: Change in spreads at the onset of COVID-19. This table presents estimation results from the bond-level regression (2) in the subsample of downgrade-vulnerable firms. The dependent variable is the change in secondary market spread between January 2020 and March 2020 of a single bond. Ratings Inflation is the issuer rating at the start of 2020 minus the implied rating based on Altman Z"-score. The regression also includes log assets of the firm and industry fixed effects. In the first column, the subsample consists of BBB-rated firms. In the second column, the subsample consists of non-BBB-rated investment-grade firms. Standard errors are clustered at the firm-level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

2020b), all of which are classified as prospective fallen angels in our data.

Furthermore, a formal test shows that BBB-rated firms with more inflated credit ratings experienced sharper increases in spreads in 2020. Specifically, we relate the degree of ratings inflation in 2020:Q1 with the change in firms' bond spreads using the following specification:

$$\Delta\text{Spread}_{bi} = \beta_1 \text{Ratings Inflation}_i + \beta_2 X_i + \phi_h + \epsilon_{bi}, \tag{2}$$

where the dependent variable is the change in secondary market spread between January 2020 and March 2020 of bond b of firm i, Ratings Inflation is the difference between the issuer rating at the start of 2020 and the implied rating based on Altman Z"-score, X are firm (log) assets, and ϕ are industry fixed effects. Table 2 presents our results. The first column shows that for downgrade-vulnerable BBB firms, issuers with higher ratings inflation experienced a greater widening of their spreads in the first months of the pandemic. In particular, a one-notch inflated issuer rating is on average associated with a 16 basis points increase in bond spreads for prospective fallen angels. In contrast, the second column shows that no such relationship exists for the other downgrade-vulnerable investment-grade 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.

3 The exorbitant privilege

In this section, we document the extraordinarily low bond financing costs of prospective fallen angels—BBB-rated downgrade-vulnerable firms—since 2009, which we call the "exorbitant privilege". We find that this subsidy emerges with QE and diminishes with the withdrawal of monetary stimulus through Quantitative Tightening (QT).

Non-parametric evidence. To describe the time-series evolution of the exorbitant privilege, Figure 4 plots the difference in secondary market spreads between downgrade-vulnerable and non-downgrade-vulnerable BBB-rated issuers as well as those rated AAA-A and BB. The difference in the spread between downgrade-vulnerable and non-downgrade-vulnerable BBB-rated firms is (i) generally positive until the GFC; (ii) largely *negative* during the QE-to-QT period; and, (iii) almost always smaller than the same difference for the AAA-A and BB segments, which by and large tends to be positive.

Table OA.5 shows non-parametrically that, within each rating category, secondary market spreads of bonds issued by downgrade-vulnerable firms are higher than those issued by non-downgrade-vulnerable firms across the rating distribution. The one exception is the BBB segment where downgrade-vulnerable firms have *lower* spreads in 2009-19.

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

$$\begin{aligned}\text{Spread}_{bit} =& \boldsymbol{\beta_1}\mathbf{Rating}_{it} + \boldsymbol{\beta_2}\text{Vulnerable}_{it} \times \mathbf{Rating}_{it} \\ &+ \boldsymbol{\delta}\mathbf{X}_{bt} + \boldsymbol{\gamma}\text{Liquidity}_{bt} \times \mathbf{Rating}_{it} + \boldsymbol{\mu}_{ht} + \epsilon_{bit} \end{aligned} \tag{3}$$

where Spread is the spread (in basis points) of bond b issued by firm i in period t. We reiterate that we follow (i) Gilchrist and Zakrajšek (2012) and compute spreads relative to the yield on a synthetic Treasury with the same cash flows as the corporate bond and (ii) Faust et al. (2013) to further adjust the spreads of callable bonds to account for the influence of risk-free rates on the option value of these bonds. As Becker et al. (2021) shows, changes

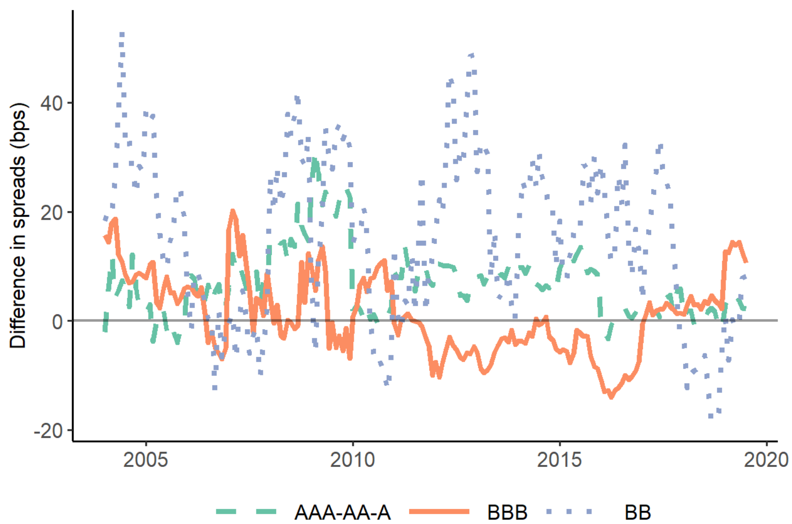

Figure 4: Bond spreads: downgrade-vulnerable minus non-downgrade-vulnerable issuers. This figure shows the difference in secondary market spreads between downgrade-vulnerable and non-downgrade-vulnerable issuers for issuers rated AAA, AA and A (dashed line), BBB (solid line), and B (dotted line), controlling for year-month fixed effects and bond-level controls for remaining maturity, offering amount, coupon, and dummy variables for convertible, senior, callable bonds, bonds with a price above par but below a price of 105, and the interaction between the latter two variables to account for changes in credit quality affecting spreads on callable bonds.

in credit quality can also influence the spread on bonds with a call option. Hence, we include control variables to absorb the influence of changes in credit quality on callable bond spreads by adding an indicator variable for callable bonds, another for bonds which are trading above par but below a price of 105 as well as the interaction of the two.[4] **Rating** is a vector of dummy variables corresponding to firm i's rating in period t and Vulnerable 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.

We also include (i) a vector $\mathbf{X}$ 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, in addition to the controls for callable bonds described above) and (ii) control variables to capture the influence of bond liquidity on spreads

[4]As shown in Table OA.5, around 90% of bonds in our sample are callable. Since 2010, this share has remained relatively constant. Our estimated regression coefficient suggests that, when trading close to the call barrier, callable bonds trade at a 40 basis point discount to non-callable bonds, an estimate not far from the one in Becker et al. (2021).

Panel A	Secondary market spread			Primary market spread		
Vulnerable × AAA-AA	10.471**	11.964**	4.769	22.980	15.854	0.000
	(4.129)	(5.197)	(4.600)	(19.691)	(19.602)	(0.000)
Vulnerable × A	4.975	7.376*	−1.259	17.736*	24.365**	9.739
	(3.477)	(3.761)	(4.805)	(10.090)	(11.865)	(25.317)
Vulnerable × BBB	−5.457**	−7.752**	2.032	−19.273**	−19.928*	−15.252
	(2.632)	(3.067)	(3.338)	(9.246)	(11.701)	(9.148)
Vulnerable × BB	19.056***	22.620***	10.066	48.487***	50.241***	18.476
	(5.534)	(6.152)	(9.164)	(15.515)	(17.170)	(27.200)
Vulnerable × B	25.102***	33.684***	−44.704*	63.488**	64.010**	0.000
	(8.925)	(8.572)	(23.693)	(24.905)	(25.407)	(0.000)
Sample period	Full sample	QE1-QT	QT	Full sample	QE1-QT	QT
Industry-year-month FE	✓	✓	✓	✓	✓	✓
Bond-level controls	✓	✓	✓	✓	✓	✓
Observations	243,162	179,527	53,721	2,481	2,026	455
R-squared	0.731	0.730	0.760	0.866	0.870	0.867

Panel B	Δ Secondary market spread			
Vulnerable × Flattening Shock × AAA	0.162**	0.091	0.121*	1.186
	(0.080)	(0.091)	(0.060)	(0.781)
Vulnerable × Flattening Shock × AA	−0.061	−0.106	0.068***	0.017
	(0.051)	(0.099)	(0.012)	(0.056)
Vulnerable × Flattening Shock × A	0.029	0.039	0.020	−0.001
	(0.030)	(0.034)	(0.035)	(0.062)
Vulnerable × Flattening Shock × BBB	−0.060**	−0.075**	−0.115***	0.015
	(0.029)	(0.031)	(0.017)	(0.037)
Vulnerable × Flattening Shock × BB	0.023	0.081	−0.013	−0.084
	(0.081)	(0.099)	(0.105)	(0.196)
Vulnerable × Flattening Shock × B	0.155	0.105	−0.057	−0.667
	(0.459)	(0.448)	(0.309)	(0.384)
Sample period	Full sample	QE1-QT	QE events	QT
Industry-year-month FE	✓	✓	✓	✓
Bond-level controls	✓	✓	✓	✓
Observations	157,451	132,599	26,742	22,028
R-squared	0.191	0.189	0.205	0.257

Table 3: The exorbitant privilege of prospective fallen angels. Panel A shows the estimation results from specification (3). Panel B shows the estimation results of specification (4). The dependent variables in Panel A are the secondary market bond spread (first three columns) and the primary market bond spread (last three columns). The dependent variable in Panel B is the one-day change in the secondary market spread. Bond spreads are measured in basis points. Vulnerable is a dummy variable equal to 1 if issuer i is downgrade-vulnerable in date $t-1$ and t. Flattening Shock is the change in the slope of the yield curve multiplied by minus one (i.e., 2-year minus 10-year yield on Treasury futures contracts) in a 30-minute event window around monetary policy announcements. The specific periods are: Full sample, January 2009 to December 2019; QE1-QT, January 2009 to September 2017; QT, October 2017 to September 2019. QE events are defined as monetary policy announcements containing specific information about QE purchases (see Table OA.9 for details on the specific dates). Additional bond-level controls are residual maturity, log of amount outstanding, and bid-ask spreads. Coefficients on the latter are allowed to vary by rating. The specification also includes dummy variables for bonds with covenants, convertible bonds, senior bonds, callable bonds, bonds with a price above par but below a price of 105, and the interaction between the latter two variables to account for changes in credit quality affecting spreads on callable bonds. These control variables are included in the estimation but not reported for brevity. Also omitted for brevity are the coefficients on the uninteracted ratings. Standard errors are double clustered at the firm and year-month level. *** p<0.01, ** p<0.05, * p<0.1.

by adding bid-ask spreads which we allow to vary by rating bucket, Liquidity × **Rating**. Finally, industry-year-month fixed effects μ absorb the unobserved time-variation in spreads within an industry. Due to the few bonds having a rating of AAA, we combine AAA-rated and AA-rated firms into one category.

Table 3 presents the estimation results. The first three columns of Panel A show the estimation results for secondary market spreads. The first column shows results estimated over the full sample period. The interaction terms between ratings and the downgrade-vulnerable firm dummy variable show that in all rating categories, *except* BBB, downgrade-vulnerable firms have either higher financing costs (AAA-AA, BB, B ratings) or statistically indistinguishable financing costs (A rating) compared with non-downgrade-vulnerable firms. In Table OA.6, we show the estimates of the uninteracted rating variables. These results are robust to using bond instead of issuer ratings (Table OA.7) and to further controling for bond liquidity with the number of times a bond is traded within a month or whether the bond is a newly issued on-the-run bond, or a seasoned off-the-run issue (Table OA.8).

The second column shows that, in the subsample covering the QE era from QE1 to QT (January 2009 to September 2017), the Vulnerable × BBB coefficient is negative, statistically significant, and larger compared to the full sample (2009-19). The third column shows that the privilege disappears from secondary markets in the QT period (October 2017 to September 2019). In additional tests, we find that the difference in the Vulnerable × BBB coefficients in the QE1-to-QT period is significantly different from that in the QT period.

The final three columns of Panel A present the estimation results using primary market offering spreads as the dependent variable. Notwithstanding the smaller sample of observations relative to secondary market spreads, the estimates again indicate a downgrade-vulnerable BBB funding subsidy. By contrast, downgrade-vulnerable firms in other rating buckets have higher spreads. In the QT period, the subsidy of prospective fallen angels diminishes in magnitude and becomes statistically insignificant.

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

$$
\begin{aligned}
\Delta\,\text{Spread}_{bit} =& \boldsymbol{\beta_1}\textbf{Rating}_{it} + \boldsymbol{\beta_2}\text{Vulnerable}_{it} \times \textbf{Rating}_{it} + \boldsymbol{\beta_3}\textbf{Rating}_{it} \times \text{Flattening Shock}_t \\
&+ \boldsymbol{\beta_4}\text{Vulnerable}_{it} \times \textbf{Rating}_{it} \times \text{Flattening Shock}_t \\
&+ \boldsymbol{\delta}\mathbf{X}_{bt} + \boldsymbol{\gamma}\text{Liquidity}_{bt} \times \textbf{Rating}_{it} + \mu_{ht} + \epsilon_{bit} \qquad (4)
\end{aligned}
$$

where Δ Spread is the one-day change in the corporate bond spread (in basis points). To capture the influence of QE events, we compute the variable Flattening Shock, defined as the change in the slope of the yield curve multiplied by minus one (i.e., 2-year minus 10-year yield on Treasury futures contracts)—capturing the QE-induced drop in long-term yields. This shock to the yield curve is computed within a −15 to +15 minute event window around monetary policy announcements or, for press conferences and release of minutes, with a slightly longer window, from −15 to +90 minutes, as these communications are more extensive and contain broader information which may take longer for investors to process. The monetary policy announcement dates are from Cieslak and Schrimpf (2019), updated up until end 2019.

Panel B of Table 3 presents the event study estimates. The negative and significant coefficient on the Vulnerable × BBB × Flattening Shock variable in the first column shows that bond spreads of downgrade-vulnerable BBB-rated firms declined relative to non-downgrade-vulnerable BBB-rated firms when the yield curve flattened around monetary policy announcements. In quantitative terms, a 100 basis point flattening of the yield curve leads to a 6 basis point decline in the bond spreads of BBB downgrade-vulnerable issuers. The second column shows that this effect was larger for the QE period.

The third column of Panel B further confirms the specific influence of QE. It does so by constraining the event study to only monetary policy announcements with specific information about QE purchases. We classify 33 out of the 171 monetary policy announcements between 2009 and 2019 as being "QE-specific" (see Table OA.9 for details on the specific events). Just focusing on these events results in a 50% increase in the point estimate of the Vulnerable × BBB × Flattening Shock coefficient, with the statistical significance increasing to a p-value<0.001. By contrast, the fourth column shows that, during QT, shocks to the yield curve slope did not have significant effects on the spread between downgrade-vulnerable and

	EDF 2Y	EDF 5Y	Loan spread	Spread	CDS
BBB	0.623***	0.494***	7.350	22.146***	50.358***
	(0.082)	(0.065)	(16.390)	(4.722)	(5.038)
BB	1.528***	1.190***	51.534**	88.018***	183.299***
	(0.104)	(0.082)	(19.590)	(8.113)	(14.513)
B	2.851***	2.188***	114.606***	155.357***	435.137***
	(0.126)	(0.099)	(20.325)	(11.485)	(33.402)
CCC	4.211***	3.209***	216.636***	306.994***	951.977***
	(0.219)	(0.167)	(70.905)	(62.100)	(175.963)
Vulnerable × AAA-A	0.303**	0.236**	−4.242	8.898**	−3.275
	(0.125)	(0.102)	(24.623)	(3.683)	(5.071)
Vulnerable × BBB	0.220**	0.138*	15.367	9.221*	−1.773
	(0.100)	(0.075)	(10.106)	(5.422)	(5.180)
Vulnerable × BB	0.472***	0.339***	34.985**	13.405*	97.160***
	(0.113)	(0.085)	(14.396)	(7.282)	(23.784)
Vulnerable × B	0.661***	0.506***	46.086**	29.766	105.954
	(0.128)	(0.095)	(18.966)	(23.898)	(92.551)
Industry-year-month FE	✓	✓	✓	✓	✓
Observations	56,675	56,675	3,009	23,144	145,145
R-squared	0.755	0.780	0.713	0.780	0.740

Table 4: The exorbitant privilege is unique to the corporate bond market post-2009. This table shows the estimation results of specification (3). This table provides robustness checks on the downgrade-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 variables in the first two columns are the log 2-year and log 5-year expected default frequency between 2009 to 2019. The dependent variable in the third column is the the all-in-drawn spread for syndicated loans from DealScan. The dependent variable in the fourth column is the secondary market bond spread in the pre-GFC period (2002-07). The dependent variable in the fifth column is the spread on the CDS contract maturity matched to the corporate bond sample in Panel A of Table 3. 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). The first two columns are at the firm-level, so we do not include bond-level controls but control for firm size. Loan-level controls included in the third column are maturity, loan size, and dummy variables for dividend restrictions and for agent consent in trading the loan. Controls included in the fourth column are residual maturity, amount outstanding, coupon, firm size, bid-ask spreads; coefficients on the latter variable are allowed to vary by rating. The specification also includes dummy variables for bonds with covenants, convertible bonds, senior bonds, callable bonds, bonds with a price above par but below a price of 105, and the interaction between the latter two variables to account for changes in credit quality affecting spreads on callable bonds. The last column includes maturity controls. These control variables are included in the estimation but not reported for brevity. Standard errors are double clustered at the firm and year-month level. *** p<0.01, ** p<0.05, * p<0.1.

non-downgrade-vulnerable BBB-rated firms. Taken together, the results in Table 3 suggest that the exorbitant privilege of prospective fallen angels emerged with QE and diminished with the Federal Reserve's withdrawal of unconventional monetary stimulus.

Exorbitant privilege uniquely a bond market phenomenon. Table 4 shows that this privilege is unique to the corporate bond market in the QE era. The first two columns use, as dependent variables, the (log) expected default frequency (EDF) derived from equity markets at the 2-year and 5-year horizon, respectively. While the estimated coefficients on the uninteracted terms increase monotonically as ratings deteriorate, downgrade-vulnerable BBB-rated firms have significantly higher EDFs compared to their non-downgrade-vulnerable BBB-rated peers, as shown by the positive and significant Vulnerable $\times$ BBB coefficient. This result suggests that the exorbitant privilege is not present in equity markets. Rather, equity markets view downgrade-vulnerable BBB-rated firms as riskier than their non-downgrade-vulnerable peers. Note that, given the limited number of observations in the AAA and AA rating buckets (especially in the syndicated loan market data), we combine AAA-A ratings into a single rating category.

The third column shows that prospective fallen angels did not enjoy a similar funding advantage in the syndicated loan market during this period. The Vulnerable $\times$ BBB coefficient is positive (although not statistically significant), suggesting that loan markets tended to perceive these firms to be riskier than non-downgrade-vulnerable BBB-rated firms. The fourth column shows that, in the last business cycle before the GFC (2002-07), prospective fallen angels did not benefit from a funding privilege in the corporate bond market. If anything, they paid higher spreads in this period, in line with other rating categories. That being said, it is possible that, in this period, corporate bond investors might have reached for yield in other asset classes, such as MBS.

However, the fifth column suggests that credit default swap markets may have priced a similar, though smaller, privilege for prospective fallen angels. The point estimate of the Vulnerable $\times$ BBB interaction term is negative at around a fifth of the magnitude of our baseline specification in Table 3 Panel A. This result is 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).[5]

[5] 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 Treasury. Two pieces of evidence suggest 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

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

4 The origins of the exorbitant privilege

We now discuss the origin of the exorbitant privilege and the role of QE. Section 4.1 explains how the exorbitant privilege can arise in equilibrium due to the sluggishness of credit ratings and the presence of an IG threshold—and especially during the QE-induced rebalancing of investors' portfolios. Consistent with the prediction of the proposed mechanism, (i) Section 4.2 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; and (ii) Section 4.3 shows that this demand is priced in the corporate bond yields of prospective fallen angels.

4.1 Theoretical framework

Our explanation for the origin of the exorbitant privilege relies on the interplay between two 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 issuers, especially from IG to speculative grade, after M&A. The intuitive discussion in this section is based on a formal model presentend in Appendix OA.1.

Consider the portfolio choice of an investor that is subject to a regulatory capital requirement. Its optimal portfolio allocation trades-off discounted expected cash flows with their capital requirements. More practically, a particularly appealing asset is one with high

significantly higher capital requirements for speculative-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 (Table D10.1) also show that insurance companies have been consistent net sellers of CDS protection on non-financial corporates to dealers between 2009 and 2019, the same directional position as being long corporate bonds.

discounted expected cash flows and a low regulatory capital requirement. In the context of the corporate bond market, capital requirements are predominantly driven by credit ratings: as the credit ratings of its bond holdings deteriorate, an investor needs to comply with increased capital requirements. For several types of investors, this dynamic is highly non-linear at the investment-grade threshold. Some investors (e.g., insurance companies) face substantially higher capital requirements for holding speculative-grade compared with investment-grade bonds. Some other investors (e.g., investment-grade mutual funds), while not facing substantially higher capital requirements, voluntarily restrict their holdings to IG-rated bonds only. These investors are thus forced to sell bonds issued by firms that become fallen angels, bearing the associated liquidation costs.

By lowering yields on government bonds and mortgage-backed securities, and especially at the long end of the curve ("flattening shock"), QE induces in these "IG-focused" investors a preference for a particular type of IG bond, namely the one rated BBB. In particular, investors such as life insurers seek out a greater quantity of high-yield, yet IG-rated, assets (BBB-rated bonds) 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 (Gagnon et al., 2011; Krishnamurthy and Vissing-Jorgensen, 2011). This mechanism is consistent with anecdotal evidence. For example, the Financial Times on February 21, 2019, reports that *"insurance companies such as AIG and MetLife hold huge investment books, mainly consisting of bonds, to back the promises they make to their customers. Over the past decade, they have increasingly moved into riskier assets, according to Fitch, as yields in safer categories have fallen under aggressive easing policies from the world's central banks."*

This QE-induced demand for higher yield and capital-efficient BBB bonds is met, in equilibrium, by an increased issuance, mostly with the goal of financing M&A, by BBB-rated firms at risk of being downgraded. These large issuance volumes serve two purposes. On the one hand, issuers benefit from the low financing costs—possibly the intended consequence of QE. On the other hand, by engaging in M&A, these issuers delay a potential downgrade, thus maintaining their precious IG status. This effect is rooted in an often overlooked friction, namely the sluggishness of credit rating agencies in downgrading issuers, especially to speculative grade, after M&A. In a way, even if value-destroying, M&A is a technology that issuers can use to ensure that their issuance is met by the *continued* high demand for BBB-rated bonds, as the post-M&A sluggishness of credit ratings lowers investors' expected capital charge over their holding period. The net effect of these factors at play is that QE results in a bond market subsidy—heightened demand or lower equilibrium spreads (relative to risk)—for prospective fallen angels.

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 nonperforming 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.

4.2 QE-driven demand by investment-grade investors

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

The left panel of Figure 5 shows that investors substituted holdings of Treasuries with holdings of corporate bonds during QE until the withdrawal of monetary accommodation with QT. The solid line shows the size of the Fed balance sheet and the dashed line shows investors' holdings of corporate bonds as a share of the entire bond portfolio (Treasuries and corporate bonds). The share of corporate bonds held by investors increases markedly during QE, before decreasing at the time of QT from 2017 onward.

To formally analyze the preference for bonds issued by high-yield, yet IG, corporate bonds,

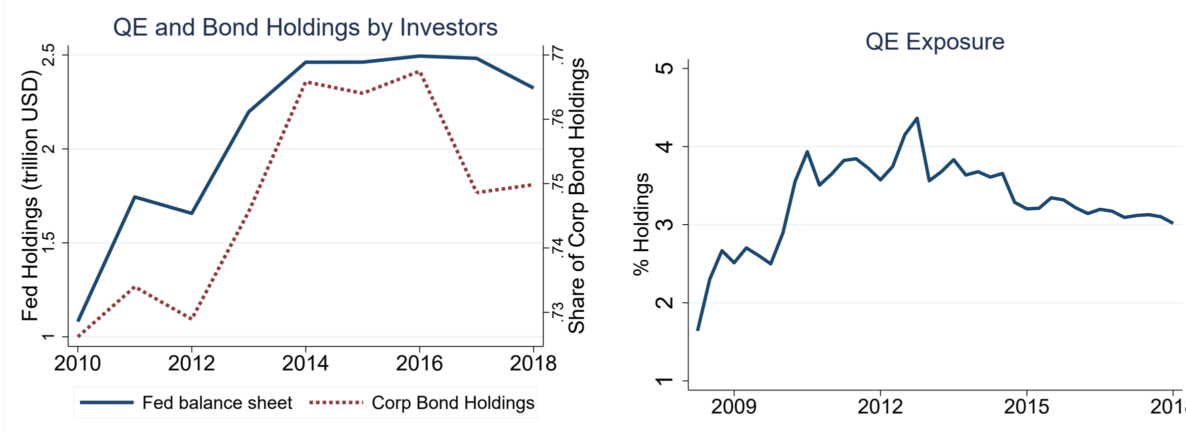

Figure 5: Investors' holdings and QE. This figure analyzes the interaction between investors' bond holdings and QE using a balanced sample of investors. The left panel shows the size of the Fed balance sheet (solid line) and investors' holdings of corporate bonds as a share of corporate bonds and Treasuries (dashed line). The right panel shows the evolution of the cross-sectional mean of the QE Exposure variable. This variable is defined as the share of investors' total holdings of bonds that are also 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.

we measure investor-level exposure to QE. To this end, we merge 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 investors' total holdings of bond issues that are also 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 larger share of their security holdings in bonds that are also held by the Federal Reserve at time t are the ones more affected by QE. Formally, we define the variable QE Exposure as follows:

$$\text{QE Exposure}_{kt} = \frac{\sum_b (\text{Holdings}_{bkt} \times \text{SOMA}_{bt})}{\sum_b \text{Holdings}_{bkt}} \tag{5}$$

where b is a security, k is an investor, and t is a date. SOMA is the share of Treasury security b outstanding held by the Federal Reserve at date t. Holdings are the holdings of security b held by investor k at time t. This variable is calculated at a quarterly frequency. The right panel of Figure 5 shows the time-series evolution of average QE Exposure.

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

$$\text{Holdings}_{ikt} = \beta_1 \text{QE Exposure}_{kt-1} \times \text{Vulnerable}_{it} + \eta_{kt} + \mu_{it} + \epsilon_{ikt} \quad (6)$$

where k is an investor, i is an issuer, and t is a quarter. The dependent variable is holdings (thousands of dollars) 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 and Vulnerable, a dummy equal to one if issuer i is downgrade-vulnerable in year t. Following Cohn et al. (2022), we estimate a fixed-effects Poisson model.

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

Table 5 shows the estimation results. In Panel A, the estimated coefficient β_1 is positive and significant, suggesting that investors more exposed to QE 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' time-varying bond portfolio maturity and maturity squared, respectively. Our coefficient of interest is stable and significant. This result 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

Panel A	Holdings					
QE Exposure × Vulnerable	2.942***	2.803***	2.905***	2.729***	2.715***	2.715***
	(0.818)	(0.785)	(0.873)	(0.819)	(0.817)	(0.817)
Maturity × Vulnerable					−0.026***	−0.024
					(0.008)	(0.023)
(Maturity)^2 × Vulnerable						−0.000
						(0.000)
Fixed Effects						
Issuer	✓	✓				
Investor	✓		✓			
Time	✓					
Investor-time		✓		✓	✓	✓
Issuer-time			✓	✓	✓	✓
Sample investors	Full	Full	Full	Full	Full	Full
Sample issuers	Full	Full	Full	Full	Full	Full
Observations	6,594,994	6,571,075	6,593,753	6,569,837	6,569,799	6,569,799
Pseudo R-squared	0.773	0.795	0.784	0.805	0.805	0.805

Panel B	Holdings			
QE Exposure × Vulnerable	0.588	2.589**	3.310***	−0.406
	(0.808)	(1.041)	(1.127)	(0.928)
Fixed Effects				
Investor-time	✓	✓	✓	✓
Issuer-time	✓	✓	✓	✓
Sample investors	Full	Full	Full	Full
Sample issuers	AAA/AA	A	BBB	HY
Observations	397,259	1,387,882	2,316,423	1,343,930
Pseudo R-squared	0.892	0.846	0.812	0.820

Table 5: Demand for bonds issued by prospective fallen angels. This table presents Poisson Pseudo Maximum Likelihood estimation results from specification (6). The unit of observation is investor k-issuer i-date t. The dependent variable is holdings by investor k in year t of corporate bonds issued by issuer i (thousands dollars). QE Exposure is defined in (5). Vulnerable is a dummy equal to 1 if issuer i is downgrade-vulnerable at date t. Maturity 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 and QE exposure 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-level and issuer-level reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

estimation is run in the sub-sample of AAA/AA, A, BBB, and speculative-grade issuers, respectively. The results show that the overall effect is more pronounced in BBB-rated bonds.

Table 6 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

	Holdings				
QE Exposure × Vulnerable	0.647	2.248***	3.653***	2.425***	3.736***
	(0.902)	(0.792)	(1.231)	(0.811)	(1.335)
Fixed Effects					
Investor-time	✓	✓	✓	✓	✓
Issuer-time	✓	✓	✓	✓	✓
Observations	417,289	454,540	1,444,113	780,214	663,726
Pseudo R-squared	0.825	0.813	0.810	0.796	0.838
Sample issuers	BBB	BBB	BBB	BBB	BBB
Sample investors (portfolio duration)	< 5Y	(5Y,7Y)	> 7Y	> 7Y	> 7Y
Sample investors (portfolio IG rating share)	Full	Full	Full	< 0.75	> 0.75
Share of investors (by type) with a given portfolio duration and IG rating share in 2016					
Share of Annuities	17%	17%	66%	26%	40%
Share of Life & Health Insurance	35%	17%	48%	22%	25%
Share of Property & Casualty Insurance	57%	21%	21%	6%	15%
Share of Open Ended Mutual Fund	28%	17%	55%	22%	33%

Table 6: Demand for bonds issued by prospective fallen angels, sample splits. This table presents Poisson Pseudo Maximum Likelihood estimation results from specification (6). The unit of observation is investor k-issuer i-date t. The dependent variable is holdings by investor k in year t of corporate bonds issued by issuer i (thousands dollars). QE Exposure is defined in (5). Vulnerable is a dummy equal to 1 if issuer i is downgrade-vulnerable at date t. The uninteracted Vulnerable and QE exposure terms are included in the estimation but not reported for brevity. All the regressions are estimated in the subsample of BBB-rated issuers. In the first three columns, the results are estimated in the subsample of investors with a portfolio maturity below five years, between five and seven years, and above seven years, respectively. In the fourth column, 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 the fifth column, 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-level and issuer-level reported in parentheses. The bottom panel shows, for each investor type, the share 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.

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 5 are driven by investors holding a long-maturity portfolio and predominantly investment-grade securities. These findings are consistent with QE reducing long-term yields and the BBB threshold affecting primarily those investors that mostly hold IG bonds.

The investors most represented in our sample are property and casualty insurers (28%), open-ended mutual funds (25%), (other) life and health insurers (16%), and insurers with annuities with minimum guarantees (9%). As shown at the bottom of Table 6, variable annuities with minimum guarantees hold the longest maturity portfolio—in addition to being extremely exposed to QE. Other life and health insurers also hold a long maturity portfolio but are less exposed to QE as their liabilities do not induce as much preference for risk as variable annuities do. Property and casualty insurers are highly exposed to QE but hold a somewhat short-term portfolio, mostly made of IG securities.[6] These observations are related to (i) Koijen and Yogo (2021, 2022) that document the fragility of such products in a low interest rate environment and how the minimum return guarantees have changed the primary function of life insurers from traditional insurance to financial engineering, and (ii) Fringuellotti and Santos (2022) that shows that insurance companies have almost nonupled their investments in CLOs post-GFC, largely driven by IG-rated mezzanine debt tranches of CLOs. Finally, open-ended mutual funds have a moderate exposure to QE, while also holding a long-term portfolio not too concentrated in the IG market. It is interesting to note that during the COVID-19 outbreak, debt mutual funds experienced significant redemptions and contributed to corporate bond fire sales (see, among others, Haddad et al. (2021) and Falato et al. (2021a)).

4.3 QE exposure and the exorbitant privilege

Having shown that investors exposed to QE increased their holdings of bonds issued by prospective fallen angels, we now go back to bond prices and show that the yields of these bonds are affected by the QE exposure of the investors holding them.

To this end, we define a measure of *indirect* QE exposure at the issuer-quarter level. In each quarter t and for each issuer i, we calculate the weighted average of the exposure to QE of i's investors, where the weights are the holdings that each investor owns in i, namely:

$$\text{QE Exposure}_{it} = \frac{\sum_k \text{QE Exposure}_{kt}\text{Holdings}_{ikt}}{\sum_k \text{Holdings}_{ikt}}$$

We then add this measure as an independent variable in specifications (3) and (4). Figure A.1 documents the increasing indirect QE exposure of BBB-rated firms during our period.

Table 7 shows that the exorbitant privilege of prospective fallen angels is explained by their indirect exposure to QE. Panel A shows the estimation results based on adding the issuers'

[6]See Table OA.10 for summary statistics by investor type for the main types of investors in our data.

Panel A	Secondary market spread			Primary market spread		
Vulnerable × AAA-AA	10.471**		9.008**	22.980		17.260
	(4.129)		(3.996)	(19.691)		(19.431)
Vulnerable × A	4.975		6.649*	17.736*		22.197**
	(3.477)		(3.489)	(10.090)		(10.464)
Vulnerable × BBB	−5.457**		−3.872	−19.273**		−15.886*
	(2.632)		(2.567)	(9.246)		(9.377)
Vulnerable × BB	19.056***		17.854***	48.487***		45.641***
	(5.534)		(5.529)	(15.515)		(14.876)
Vulnerable × B	25.102***		24.049***	63.488**		62.992**
	(8.925)		(8.839)	(24.905)		(24.954)
QE Exposure		−13.345***	−11.980***		−22.730***	−19.369***
		(2.248)	(2.253)		(6.950)	(6.919)
Industry-year-month FE	✓	✓	✓	✓	✓	✓
Bond-level controls	✓	✓	✓	✓	✓	✓
Observations	243,162	243,162	243,162	2,481	2,481	2,481
R-squared	0.731	0.730	0.733	0.866	0.862	0.867

Panel B	Δ Secondary market spread		
Vulnerable × Flattening Shock × AAA	0.162**		0.178***
	(0.080)		(0.043)
Vulnerable × Flattening Shock × AA	−0.061		−0.061
	(0.051)		(0.044)
Vulnerable × Flattening Shock × A	0.029		0.043***
	(0.030)		(0.005)
Vulnerable × Flattening Shock × BBB	−0.060**		−0.039
	(0.029)		(0.024)
Vulnerable × Flattening Shock × BB	0.023		0.008
	(0.081)		(0.078)
Vulnerable × Flattening Shock × B	0.155		0.131
	(0.459)		(0.322)
QE Exposure × Flattening Shock		−0.193**	−0.187**
		(0.074)	(0.076)
QE Exposure		0.058	0.073
		(0.188)	(0.189)
Industry-year-month-day FE	✓	✓	✓
Bond-level controls	✓	✓	✓
Observations	157,451	132,599	26,742
R-squared	0.191	0.189	0.205

Table 7: Issuers' QE exposure and the exorbitant privilege of prospective fallen angels. Panel A shows the estimation results of specification (3). Panel B shows the estimation results of specification (4). Both specifications also include a the QE Exposure variable as an independent variable. The dependent variables in Panel A are the secondary market bond spread (first three columns) and the primary market bond spread (last three columns). The dependent variable in Panel B is the one-day change in the secondary market spread. Bond spreads are measured in basis points. Vulnerable is a dummy variable equal to 1 if issuer i is downgrade-vulnerable in date $t-1$ and t. QE Exposure is defined as the weighted average of the exposure to QE of j's investors, where the weights are the holdings that each investor owns in j. In Panel B, Flattening Shock is the change in the slope of the yield curve multiplied by minus one (i.e., 2-year minus 10-year yield on Treasury futures contracts) in a 30-minute event window around monetary policy announcements. QE specific events are defined as monetary policy announcements containing specific information about QE purchases (see Table OA.9). 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 bonds with covenants, convertible bonds, senior bonds, callable bonds, bonds with a price above par but below a price of 105, and the interaction between the latter two variables to account for changes in credit quality affecting spreads on callable bonds. These control variables are included in the estimation but not reported for brevity. Also omitted for brevity are the coefficients on the uninteracted ratings. Standard errors are double clustered at the firm and year-month level. *** p<0.01, ** p<0.05, * p<0.1.

indirect QE exposure to specification (3), where the dependent variable is the secondary market spread. For ease of comparison, the first column replicates the baseline full sample result presented in Table 3 Panel A, showing that downgrade-vulnerable BBB-rated issuers enjoyed a subsidy of around five basis points. The negative and significant coefficient on the QE exposure variable in the second column shows that issuers with greater QE exposure (via their investors) enjoyed, on average, lower secondary market bond spreads. In other words, QE-induced portfolio rebalancing is associated with a lowering of corporate bond spreads. The third column shows that, once we include the indirect QE exposure variable in specification (3), the coefficient on Vulnerable × BBB is no longer statistically significant and falls in magnitude by about 25% of its magnitude in Column (1).

The last three columns show similar results for primary market bond spreads. The fifth column shows that issuers with greater indirect QE exposure enjoyed, on average, lower primary market bond spreads. The last column shows that, once we include the indirect QE exposure variable in specification (3), the point estimate on the Vulnerable × BBB coefficient falls again by about 25% of its value in Column (4) and its statistical significance falls from the 5% to the 10% level.

Panel B confirms that the issuers' indirect QE exposure is priced in bond yields using the event study specification (4). Again, for ease of comparison, the first column replicates the baseline full sample result presented in the first column of Table 3 Panel B, where we show that bond spreads of downgrade-vulnerable BBB issuers declined when the yield curve flattened around monetary policy announcements. In Table 7, the second column examines how our measure of issuers' indirect QE exposure influenced the reaction of bond spreads to monetary policy announcements which flattened the yield curve. The negative and significant coefficient on the QE Exposure × Flattening Shock shows that firms with greater QE exposure experienced greater declines in bond spreads when the yield curve flattened around monetary policy announcements. The third column shows that the coefficient on the triple interaction of Vulnerable × BBB × Flattening Shock (which captures how monetary policy announcements lowered downgrade-vulnerable BBB-rated issuers bond spreads) becomes statistically insignificant once we control for QE exposure, while the coefficient on QE Exposure × Flattening Shock is virtually unaffected relative to Column (2).

Taken together, these results indicate that QE exposure of issuers via their investors' portfolios helps explain the exorbitant privilege of prospective fallen angels.

5 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 5.1 shows the increase in M&A activity by prospective fallen angels. Section 5.2 documents the sluggishness of credit rating agencies in downgrading post-M&A. Section 5.3 shows ex-ante evidence linking M&A and the increased vulnerability of prospective fallen angels. Section 5.4 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.

5.1 The increase in M&A

Prospective fallen angels drive the surge in M&A activity in the BBB market. The left panel of Figure 6 shows that M&A deal volumes of prospective fallen angels increased substantially. This increase coincides with the rise in the share of corporate bond holdings in investors' portfolios (Figure 5). The right panel shows that the increase is less pronounced for the non-downgrade-vulnerable BBB-rated firms. In Figure OA.7, we additionally show that the substantial increase in investment-grade bond issuance was in large part to fund M&A activity.

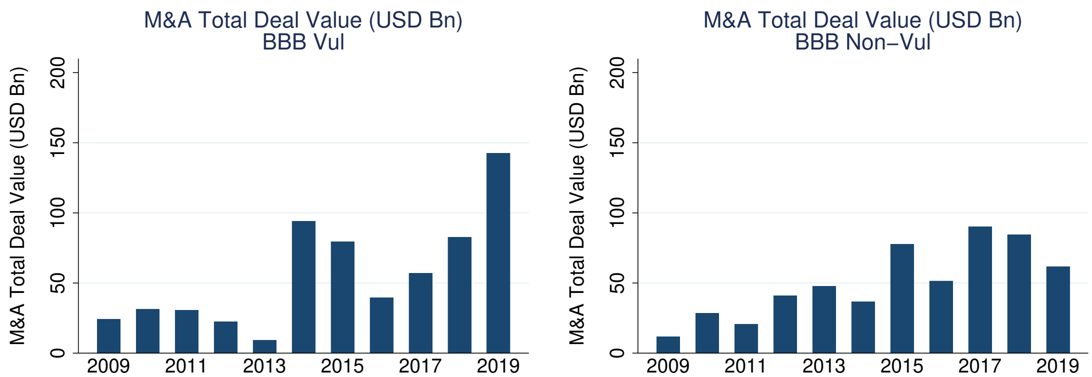

Figure 6: M&A activity, BBB-rated issuers. This figure shows M&A activity by BBB-rated issuers. The left panel shows deal volume for downgrade-vulnerable issuers. The right panel shows deal volume for non-downgrade-vulnerable issuers.

5.2 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:

$$Y_{it} = \beta_1 \text{BBB}_{it} + \beta_2 \text{M\&A}_{it} + \beta_3 \text{M\&A}_{it} \times \text{BBB}_{it} + \delta X_{it} + \eta_{ht} + \epsilon_{it} \tag{7}$$

where i is a firm, h an industry, and t a year. The dependent variable 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 and M&A, where M&A is a dummy equal to one in the year firm i has conducted an M&A deal and for the years thereafter. BBB is a dummy equal to one if firm i has a BBB rating in t. X represents a set of firm controls (log assets, leverage, net worth, and profitabiliy) and η are industry-year fixed effects.

Table 8 shows the estimation results. The first column suggests that prospective fallen angels enjoy an additional 0.5 notches in ratings inflation compared with downgrade-vulnerable issuers in other rating groups. The second column shows that, within downgrade-vulnerable firms, ratings inflation is largely driven by firms that have undertaken an M&A and is in fact

	Ratings inflation	Ratings inflation	Ratings inflation
BBB	0.443**	0.060	−1.900
	(0.202)	(0.283)	(1.191)
M&A		−0.357*	0.021
		(0.200)	(0.953)
M&A × BBB		0.666**	0.624**
		(0.306)	(0.302)
M&A × Size			−0.040
			(0.106)
BBB × Size			0.209*
			(0.121)
Size	0.164**	0.173**	0.127
	(0.072)	(0.073)	(0.091)
Industry-year FE	✓	✓	✓
Controls	✓	✓	✓
Sample	Vulnerable	Vulnerable	Vulnerable
Observations	2,424	2,424	2,424
R-squared	0.380	0.386	0.389

Table 8: The role of M&A in prolonging ratings inflation. This table presents estimation results from specification (7) 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 (log(total assets), leverage, net worth, and profitability). Standard errors are clustered at the firm-level. *** p<0.01, ** p<0.05, * p<0.1.

higher at 0.6 notches. This M&A ratings inflation is, however, only enjoyed by prospective fallen angels. The third column confirms this result is robust to including additional firm size interactions with the BBB rating and M&A variables.

An alternative way to examine post-M&A ratings sluggishness is to examine ratings transition matrices. These matrices confirm that M&A deals are associated with sluggishness of credit ratings. Figure 7 shows two ratings transition matrices, reporting the debt-weighted share of issuers transitioning across rating groups. The left matrix only covers firms without an M&A transaction in the past two years, while the right matrix only includes firms that have conducted an M&A transaction in the past two years. The left matrix shows that in the non-M&A sample, 8.9 percent of A-rated firms are typically downgraded to BBB and that 3.0 percent of BBB-rated firms are typically downgraded to BB and below. By contrast, the right matrix shows that after M&A, the downgrade probability of BBB rated firms falls to almost zero, but rises for all other IG-rating groups. Figure A.2 confirms that this sluggishness of credit ratings downgrades at the IG cutoff after M&A transactions is particularly pronounced

No M&A (From rows, To columns)

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 rows, To columns)

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

among downgrade-vulnerable firms.

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. 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..."* In sum, 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. Figure OA.8 shows that these promises are often broken, consistent with market participants' observations.

5.3 M&A and the vulnerability of prospective fallen angels

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

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

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

where i is a firm, h an industry, and t is the year of the M&A. Y measures either the relative deal size, net debt/EBITDA, or the cumulative abnormal return (CAR). The coefficient of interest, β_3, captures the 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 9 shows that the 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 announce an M&A. The same dynamic is not evident in M&A's of other downgrade-vulnerable firms. Finally, the third column shows that only M&A deals by prospective fallen angels are associated with negative CARs, suggesting that their M&A activity is value-destroying. Taken together, these findings suggest that M&A activity contributed to a buildup of vulnerabilities among prospective fallen angels.

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

This vulnerability of prospective fallen angels materialized 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 3 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 engaged in M&A. The green bar in the left panel of Figure 8 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

	Relative Deal Size	Net Debt/EBITDA	CARs
BBB	−0.043***	−0.124	0.001
	(0.013)	(0.116)	(0.003)
Vulnerable	−0.038**	−0.097	0.005
	(0.017)	(0.170)	(0.004)
Vulnerable × BBB	0.056**	0.365*	−0.012**
	(0.027)	(0.210)	(0.006)
Controls	✓	✓	✓
Industry-year FE	✓	✓	✓
Sample	M&A Rated	M&A Rated	M&A Rated
Level	Firm	Firm	Deal
Observations	1,829	2,950	2,412
R-squared	0.268	0.535	0.198

Table 9: M&A and risk-taking by prospective fallen angels. This table presents estimation results from specification (8) in the sample of rated firms that announced an M&A. The dependent variable in the first column 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 the second column is net debt/EBITDA. For the first two columns the firm-level controls consist of the log of assets, profitability, leverage, and tangibility. The third column presents the 5-day cumulative abnormal returns for the M&A deals performed by firms in our sample, for which we run the specification on a deal-level. The total return value-weighted index is used as benchmark over a -210 to -11 day period. Control variables include the logarithm of total assets, leverage, profitability, an indicator variable for whether the deal is at least partially financed with stock, an indicator variable for whether the target has the same 2-digit SIC code as the acquirer, an indicator variable for whether the deal is cross-border, an indicator variable for a publicly listed target, and the pre-deal buy-and-hold returns of the acquirer from -210 to -11 days. A t-test shows that on average the CARs of BBB-rated downgrade-vulnerable firms are -1 percent. In all columns, Vulnerable is a dummy variable equal to one if a firm is downgrade-vulnerable in period t. BBB is a dummy variable equal to one if a firm has a BBB rating in period t. All specifications are in the sample of firm-years with positive total transaction value and include industry-year fixed effects. Standard errors are clustered at the firm-level.

$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.

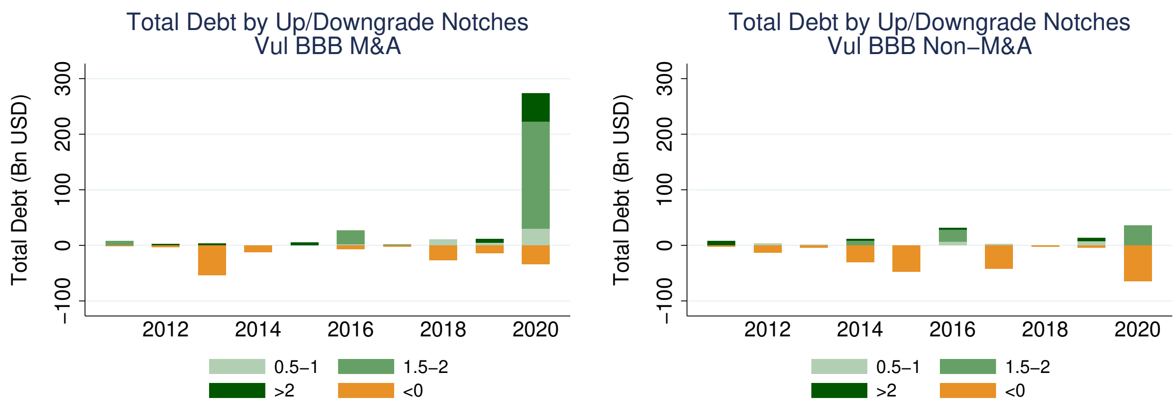

Figure 8: Downgrade materialization of (prospective) fallen angels. This figure shows the total debt of downgrade-vulnerable BBB-rated firms that has been upgraded and downgraded in the years from 2011 to 2020. The downgraded debt is grouped according to their downgrade severity. The downgrade severity is measured by the number of notches a firm is being downgraded by, and is subdivided into three broad categories: 0.5-1, 1.5-2, and >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 downgrade-vulnerable BBB-rated firms that have conducted an M&A since the year that they have become downgrade-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 downgrade-vulnerable.

6 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 now quantify the overall bond market subsidy (Section 6.1) and examine the indirect economic cost that arises from spillovers to competing firms (Section 6.2).

6.1 Quantifying the subsidy for prospective fallen angels

In this section, we quantify the subsidy enjoyed by prospective fallen angels. Our estimates range from around \$43 to \$120 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 3. The second "downgrade-avoidance" component originates from the fact that, by benefiting from delay to downgrades, prospective fallen angels avoid paying the much higher financing costs of speculative-grade issuers.[7] This second component is measured by the difference in spreads between a non-downgrade-vulnerable BBB-rated firm and a non-downgrade-vulnerable BB-rated firm. In the left panel of Figure 9, the black arrows indicate the two subsidy components for the downgrade-vulnerable BBB-rated firms, using the offering spreads in the third columns of Table 3 Panel A and Table OA.6.[8] The sum of the two components results in a subsidy of 141 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 141 basis points between the downgrade-vulnerable BBB-rated firms and non-downgrade-vulnerable BB-rated 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 \$120 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-rated 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 9, we provide an overview of our ballpark figures, which ultimately range from \$43 billion to \$120 billion. The first alternative 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 OA.10). Taking the yield differential between the prospective fallen angel spread and the linearly interpolated counterfactual spread implies a subsidy of 83 basis points, resulting in a total dollar subsidy of around \$70 billion. The second approach assumes that actual

[7]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 at https://content.naic.org/sites/default/files/inline-files/Master%20NAIC%20Designation%20and%20Category%20grid%20-%202020.pdf.

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

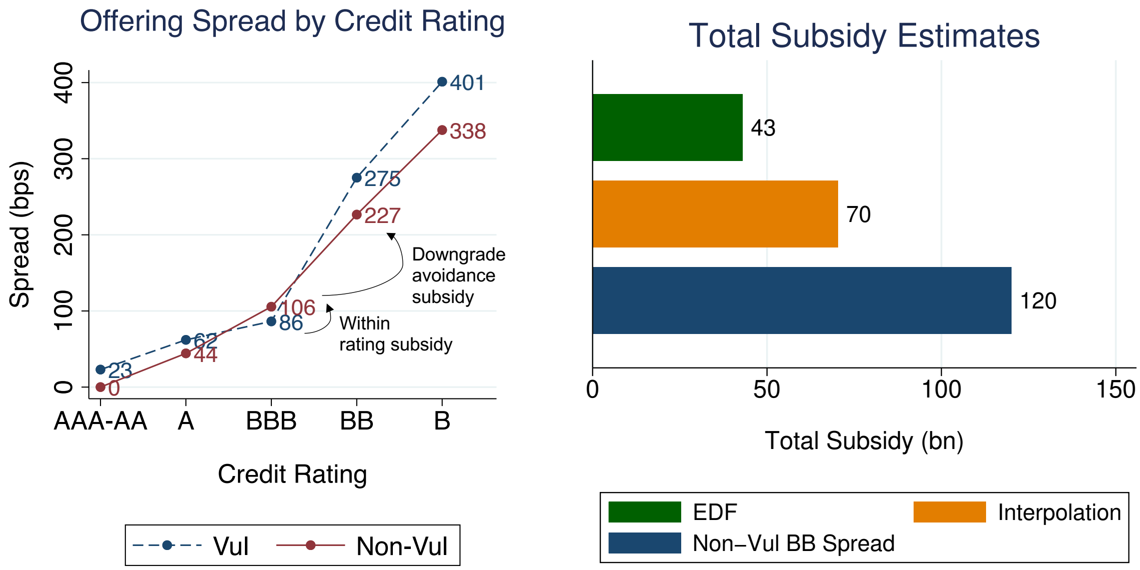

Figure 9: Quantifying the prospective fallen angel subsidy. The left panel plots the offering spreads by credit rating from the third column of Table 3 Panel A and Table OA.6 for downgrade-vulnerable and non-downgrade-vulnerable issuers, and shows the downgrade avoidance and within-rating subsidy components for prospective fallen angels. The right panel presents a range of estimates for the total subsidy of prospective fallen angels in dollar terms based on alternative counterfactual spreads of prospective fallen angels. EDF: counterfactual spread based on firm risk measured by the log of 2-year EDFs. Interpolation: counterfactual spread based on linear interpolation between spreads of downgrade-vulnerable A-rated and downgrade-vulnerable BB-rated firms. Non-downgrade-vulnerable BB spread: counterfactual spread based on the offering spreads of non-downgrade-vulnerable BB-rated firms. 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 and 2019.

firm risk is evident in equity prices and thus captured by the EDF. Using the log 2-year EDF of prospective fallen angels and then backing out the counterfactual spread based on the relationship between the EDFs and the offering spreads of all other ratings categories with a quadratic function, we find that downgrade-vulnerable BBB-rated firms receive a 51 basis points subsidy and a total dollar subsidy of $43 billion (see Figure OA.10).

6.2 Spillovers to competing firms

Finally, we examine real economy spillovers 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 is largely driven by M&A; and, (ii) that non-downgrade-vulnerable firms are negatively affected by the presence of prospective fallen angels in their market.

Figure 10 shows that the market share of prospective fallen angels increased in our sample

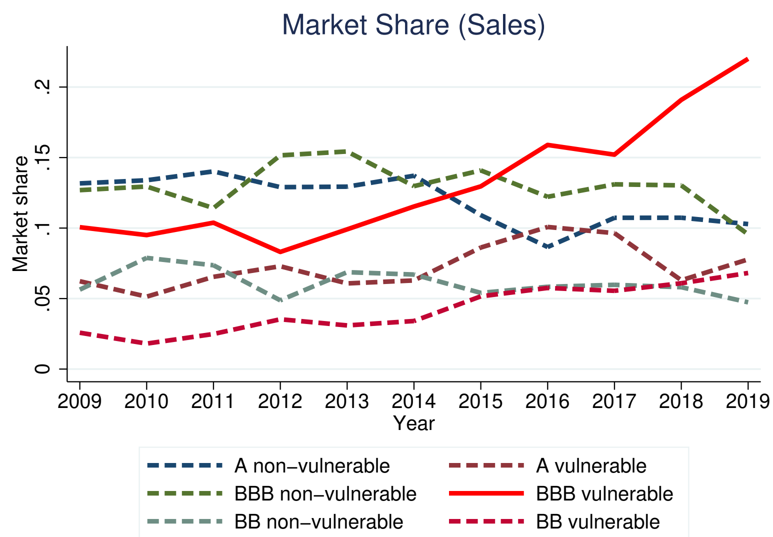

Figure 10: The increase in market share of prospective fallen angels. This figure shows the evolution of firm market shares (share of sales in an industry, weighted by the relative size of the respective industry). Firms are grouped by credit rating from A to BB and further distinguished between downgrade-vulnerable and non-downgrade-vulnerable within each rating.

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. Moreover, the increase in market share of BBB-rated firms has been driven largely by prospective fallen angels engaging in M&A (Figure OA.9).

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:

$$\begin{aligned} Y_{it} &= \beta_1 \text{Non-Vulnerable}_{it} \\ &+ \beta_2 \text{Non-Vulnerable}_{it} \times \text{Share Vulnerable BBB}_{ht-1} + \eta_{ht} + \epsilon_{it}, \end{aligned} \tag{9}$$

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.

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

Table 10: Negative spillovers on other firms. This table presents estimation results from specification (9). 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 2.2. 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 are log of total assets, leverage, and net worth. Standard errors clustered at the industry-level reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 10 reports the estimation results. Panel A shows that, in the sample of rated firms, non-downgrade-vulnerable IG firms are negatively affected by the presence of prospective fallen angels. More precisely, the first two columns show that, while non-downgrade-vulnerable firms have on average higher employment growth rates and invest more, both employment and investment are impaired by the presence of prospective fallen angels. Moreover, these firms face lower sales growth and lower markups compared with firms that do not compete with a large share of prospective fallen angels. To assess the economic magnitude of these spillover effects, consider a one standard deviation increase in the share of prospective fallen angels (0.136). This increase implies that non-downgrade-vulnerable investment-grade firms face a 1.1pp lower employment growth, 1.4pp lower investment, and a 1.2pp lower sales growth.

Panel B shows that these spillover effects are not present when we replace the share 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. Besides Caballero et al. (2008), these findings are also related to the recent literature on the misallocation of bank credit (Acharya et al., forthcoming; Blattner et al., 2023) and of other forms of financing (Midrigan and Xu, 2014; Whited and Zhao, 2021).

Panel C confirms our main results for the full sample of firms rather than just IG-rated firms. At the industry-level, Table A.2 shows that the presence of prospective fallen angels increases both industry-level credit risk and concentration, and, with some delay, markups. This evidence is consistent with industry-level markups eventually increasing as prospective fallen angels keep growing, along with industry-level concentration.

7 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 IG cutoff. This subsidy disappeared with the withdrawal of monetary stimulus and QT. We find the subsidy to be driven by QE-induced demand for IG bonds of 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 sluggishness 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 the IG bond segment may have been a desired consequence of QE, the resulting concentration of issuance in the *riskiest* IG (BBB) bucket also comes at a cost that may run counter to central bank objectives. First, the subsidized 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 pandemic. 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 the size of central bank balance sheets following the extraordinary magnitude of the COVID-19 related QE programs. Indeed, the 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 IG corporate bonds during the post-pandemic period is worthy of careful scrutiny in future research.

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Appendix

Additional figures and tables

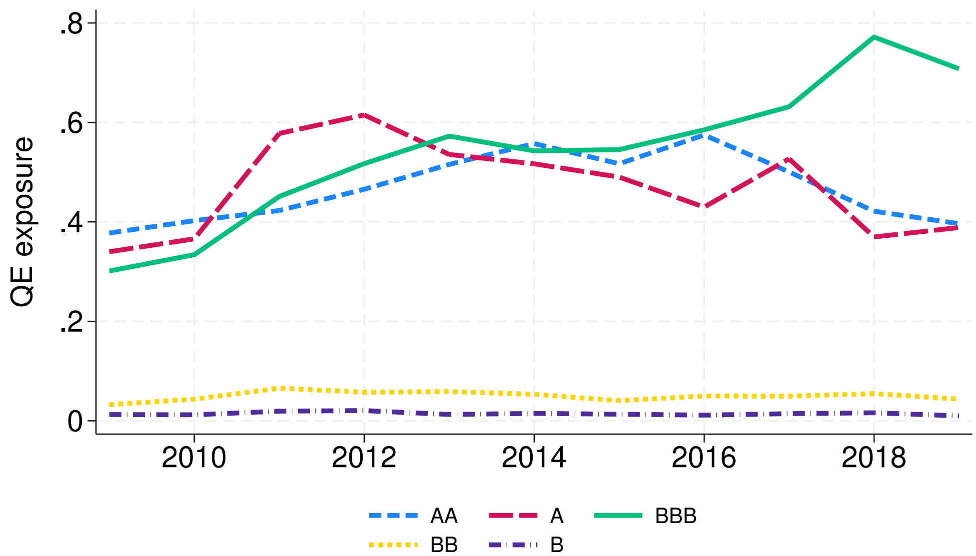

Figure A.1: Rising QE exposure of BBB-rated issuers. This figure shows the indirect QE exposure of issuers—indirectly through their investors—across rating categories, weighted by total assets of the issuers. For each issuer, the indirect measure of QE exposure is calculated as the weighted average of the exposure to QE of the issuer's investors, where the weights are the holdings that each investor owns of the issuer bonds. QE exposure by rating is then computed as the asset-weighted sum of issuers' QE exposures in a given rating bucket and year.

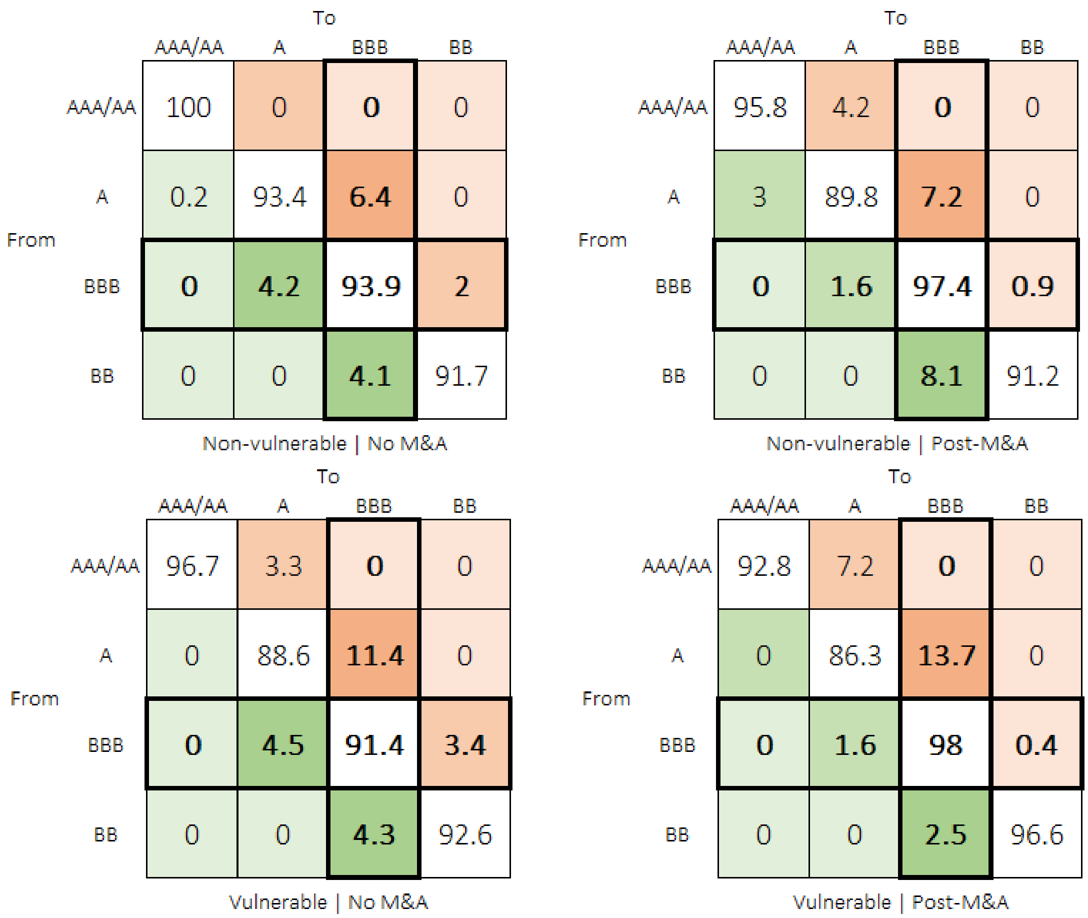

Figure A.2: The sluggishness of credit ratings post-M&A, downgrade-vulnerable and non-downgrade-vulnerable firms. This figure shows the debt-weighted share (in %) of firms transitioning across issuer rating groups (AAA/AA, A, BBB, and BB and below) in one calendar year. The left matrices include only firms without an M&A transaction within the past two years. The right matrices include only firms within a two-year period after an M&A transaction. The top matrices only include non-downgrade-vulnerable firms. The bottom matrices only include downgrade-vulnerable firms. 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.

	Downgrade	Downgrade	Downgrade	Downgrade	Downgrade	Downgrade
Vulnerable	0.031**	0.026*	0.032***	0.024**	0.018***	0.015**
	(0.014)	(0.014)	(0.011)	(0.012)	(0.007)	(0.007)
Size		0.009***		0.004		0.001
		(0.003)		(0.003)		(0.002)
Leverage		0.008		0.053*		0.005
		(0.033)		(0.028)		(0.020)
Interest Coverage		−0.017		0.025		−0.040**
		(0.023)		(0.022)		(0.019)
Profitability		−0.098		−0.158**		−0.037
		(0.075)		(0.072)		(0.065)
Sample Period	2009-2010	2009-2010	2011-2013	2011-2013	2014-2018	2014-2018
Industry-Year FE	✓	✓	✓	✓	✓	✓
Observations	1,654	1,633	2,518	2,494	5,259	5,214
R-squared	0.071	0.076	0.106	0.115	0.095	0.097

Table A.1: Credit rating actions after being classified as downgrade-vulnerable, subsample periods. This table presents the estimation results from specification (1) for our sample of rated firms, separately for different subsample periods: 2009-2010, 2011-2013, and 2014-2018. 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 downgrade-vulnerable in period t. Firm-level control variables are size (log of total assets), leverage, IC ratio, and profitability. Standard errors clustered at the firm-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Panel A	HHI	HHI	HHI	HHI	HHI
Share Vulnerable BBB_t	0.064***	0.054***	0.056***	0.064***	0.058***
	(0.022)	(0.018)	(0.019)	(0.020)	(0.019)
Share Vulnerable BBB_{t-1}		0.026	0.024	0.011	0.022
		(0.023)	(0.019)	(0.022)	(0.024)
Share Vulnerable BBB_{t-2}			0.012	0.017	0.002
			(0.016)	(0.020)	(0.020)
Share Vulnerable BBB_{t-3}				0.007	0.020
				(0.024)	(0.018)
Share Vulnerable BBB_{t-4}					−0.016
					(0.037)
Industry FE	✓	✓	✓	✓	✓
Observations	682	620	558	496	434
R-squared	0.918	0.923	0.932	0.935	0.937

Panel B	Markup	Markup	Markup	Markup	Markup
Share Vulnerable BBB_t	0.005	−0.044	0.001	−0.012	0.040
	(0.128)	(0.103)	(0.069)	(0.067)	(0.067)
Share Vulnerable BBB_{t-1}		0.020	−0.026	−0.019	−0.072
		(0.097)	(0.100)	(0.075)	(0.077)
Share Vulnerable BBB_{t-2}			−0.036	−0.143	−0.118
			(0.071)	(0.107)	(0.078)
Share Vulnerable BBB_{t-3}				0.205**	0.168**
				(0.089)	(0.068)
Share Vulnerable BBB_{t-4}					0.134
					(0.096)
Industry FE	✓	✓	✓	✓	✓
Observations	622	564	505	448	390
R-squared	0.896	0.898	0.906	0.915	0.930

Panel C	Altman Z”	Altman Z”	Altman Z”	Altman Z”	Altman Z”
Share Vulnerable BBB_t	−1.562***	−1.466***	−1.362***	−1.377***	−1.206**
	(0.313)	(0.331)	(0.414)	(0.384)	(0.484)
Share Vulnerable BBB_{t-1}		−0.476	−0.535*	−0.456	−0.591*
		(0.441)	(0.309)	(0.283)	(0.319)
Share Vulnerable BBB_{t-2}			−0.377	−0.654	−0.655**
			(0.432)	(0.461)	(0.307)
Share Vulnerable BBB_{t-3}				0.190	−0.019
				(0.297)	(0.222)
Share Vulnerable BBB_{t-4}					−0.022
					(0.329)
Industry FE	✓	✓	✓	✓	✓
Observations	660	600	540	480	420
R-squared	0.143	0.136	0.130	0.125	0.120

Table A.2: Industry-level HHI, markups, and Z” score. This table presents the estimation results for a specification run at the industry-year level, where the dependent variables (at the industry-year level) are sales HHI (Panel A), sales-weighted markups (Panel B), and asset-weighted Altman Z” scores (Panel C). The variable Share Vulnerable BBB is the asset-weighted share of downgrade-vulnerable BBB-rated firms in an industry-year. The industry is the SIC2 code. All specifications include industry fixed effects. Standard errors clustered at the industry-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Online Appendix

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

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November 2023

Structure

This online appendix is structured as follows. Appendix OA.1 presents our theoretical framework. Appendix OA.2 explains the data construction. Appendix OA.3 provides validation tests of our downgrade-vulnerability measure and additional robustness tests on the existence of the prospective fallen angel bond financing privilege. Appendix OA.4 presents additional tables. Appendix OA.5 presents additional figures.

OA.1 Theoretical framework

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

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

$$max_{\beta_i} \left(\mathbb{E}(C_i) - p_i\right)\beta_i - f\left(\sum_i \mathbb{E}(K)_i \beta_i\right) \tag{OA.1}$$

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

where i is an asset, p_i is the price of asset i, and β_i is the allocation chosen by the investor in asset i. The function $f(\cdot)$ captures the balance sheet costs of all the assets $i \in \mathcal{I}$ held by the investor. Note that the balance sheet cost term in each β_i optimization problem is based on the *entire* portfolio choice, i.e., the common portfolio effect on each first-order condition.[2]

$\mathbb{E}(K)_i$ is the balance sheet cost of asset i. It depends on (i) the probability q_i of being downgraded, (ii) the sluggishness θ_i of credit ratings, (iii) the capital requirement κ_i, and (iv) the additional balance sheet cost α_i. The parameter Δ is just a scaling parameter. Credit ratings are sluggish. In the good state, there are no downgrades (nor upgrades, for simplicity). In the bad state, asset i is downgraded with probability $1-\theta_i$, i.e., the rating is sluggish with a probability $\theta_i \in (0,1)$. In the case of a downgrade, the balance sheet cost of asset

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

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

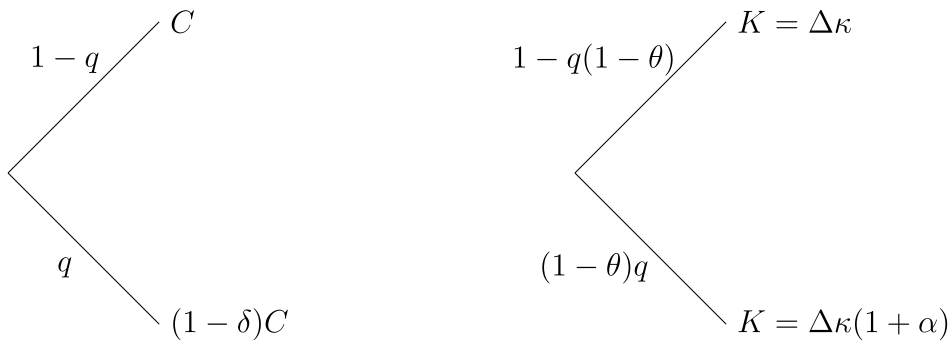

Figure OA.1: Cash flows and balance sheet costs in good and bad state. This figure shows the discounted cash flows (left) and the balance sheet costs (right) in the good and bad state of the world.

i is $\kappa_i(1+\alpha_i)$, where α_i captures the incremental cost associated with being downgraded. One example of this cost is the drop in bond prices caused by investors forced selling of downgraded bonds, particularly pronounced at the investment-grade threshold for insurance companies and high-yield mutual funds (see, e.g., Ellul et al. (2011)).

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

The first-order condition can be written as:

$$\begin{aligned} \mathbb{E}(C_i) - p_i - f'\left(\sum_i \mathbb{E}(K)_i\beta_i\right)\frac{\partial\left(\sum_i \mathbb{E}(K)_i\beta_i\right)}{\partial\beta_i} &= 0 \\ \Leftrightarrow\; p_i = \mathbb{E}(C_i) - f'\left(\sum_i \mathbb{E}(K)_i\beta_i\right)\frac{\partial\left(\sum_i \mathbb{E}(K)_i\beta_i\right)}{\partial\beta_i} & \end{aligned} \tag{OA.2}$$

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

$$p_i = \underbrace{\overline{C}_i(1-q_i\delta)}_{\mathbb{E}(C_i)} - \mathbb{E}(K)_i f'\left(\sum_i \mathbb{E}(K)_i S_i\right) \tag{OA.3}$$

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

$$\frac{dp_i}{dq_i} = -\overline{C}_i\delta - f'\left(\sum_i \mathbb{E}(K)_i S_i\right)\kappa_i\Delta\alpha q_i(1-\theta_i) \tag{OA.4}$$

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

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

$$p_i = \overline{C}_i(1 - q_i\delta) - \mathbb{E}(K)_i\bigg(\sum_i \mathbb{E}(K)_i S_i\bigg) \qquad \text{(OA.5)}$$

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

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

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

Calibration results In Figures OA.2-OA.5, we show the calibration results. Figure OA.2 shows the benchmark case with no credit rating sluggishness and no cost of downgrade. Figure OA.3 shows the case with cost of downgrade but no credit rating sluggishess. Figure OA.4 shows the case with cost of downgrade and credit rating sluggishness. Figure OA.5 shows the case with cost of downgrade, credit rating sluggishness, and a lower supply of AAA/AA/A-rated bonds and a higher supply of BBB/BB-rated bonds—mimicking the increased stock of lower-rated bonds outstanding from QE3 to QT. In each figure, we show eight panels. The two top panels are the corporate bond yields (defined as $\overline{C}/p_i - 1$) and the probability of downgrade ($q_i(1 - \theta_i)$). The third and fourth panels show the sluggishness

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

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

of credit ratings (θ_i) and the expected cash flow ($\overline{C}(1 - q_i\delta)$). The fifth and sixth panels show the aggregate balance sheet cost ($\mathbb{E}(K)_i \sum_i \mathbb{E}(K)_i S_i$) and the difference, within each rating, between the average bond yields paid by downgrade-vulnerable issuers and the average bond yields paid by non-downgrade-vulnerable issuers. Finally, the last two panels show the balance sheet cost of an individual bond and the exogenous supply of bonds.

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

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

(iii) Baseline. Figure OA.4 shows the baseline calibration results. As credit risk increases, the probability of downgrade generally increases, with the notable exception of bonds that are close to being downgraded, especially at the investment-grade cutoff. As in

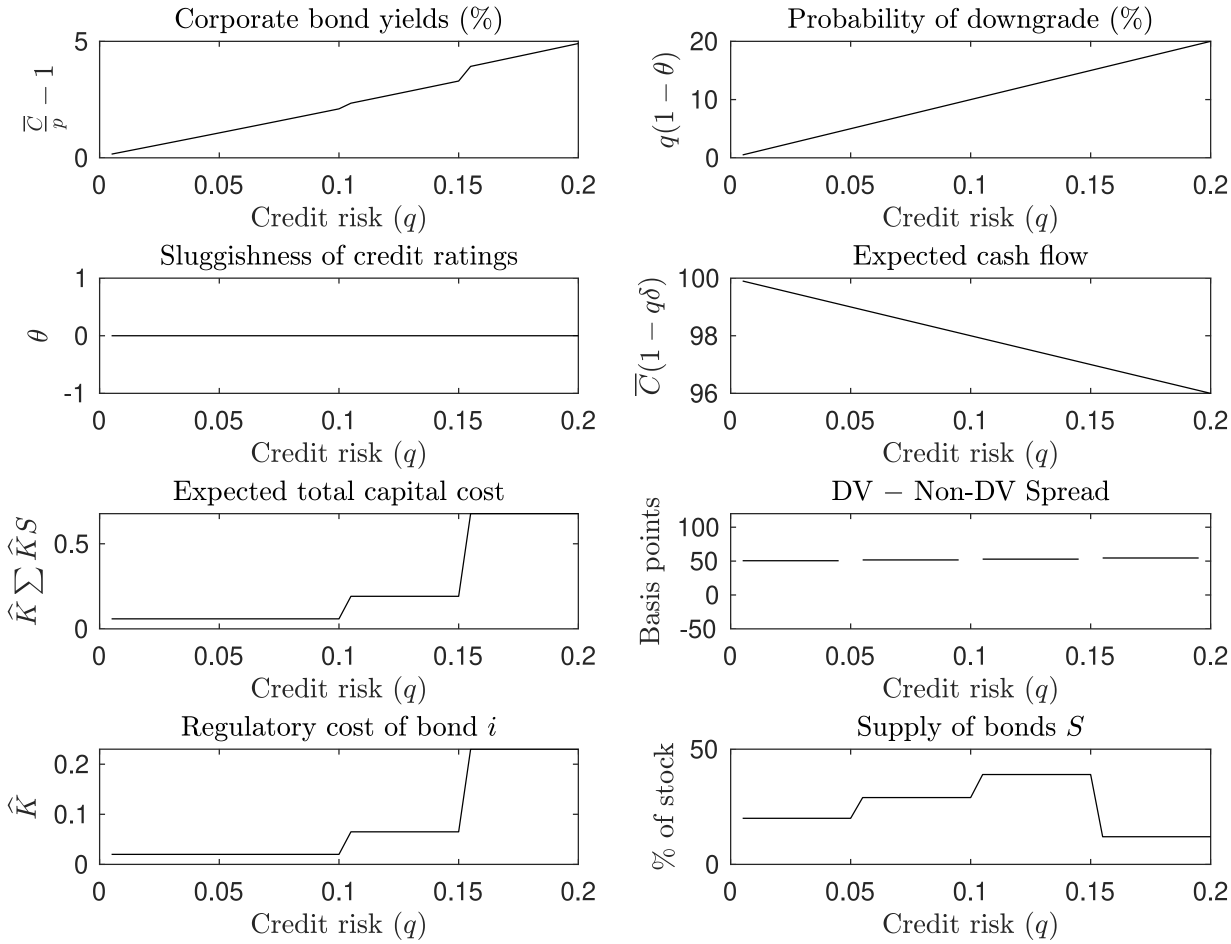

Figure OA.2: Model calibration results, no cost of downgrade and no credit rating sluggishness. This figure shows the model calibration results where the parameters are shown in Table OA.1 with the exception of $\alpha_i = \alpha = 0$ and $\theta_i = \theta = 0$.

the previous case, these bonds benefit from the sluggishness of credit ratings. The sluggishness—now interacting with the cost of downgrade—has a sizable effect on the balance sheet cost and, in turn, on corporate bond yields. In the sixth panel, we observe that, in the BBB rating category, downgrade-vulnerable issuers pay, on average, *lower* bond financing costs than non-downgrade-vulnerable issuers.

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

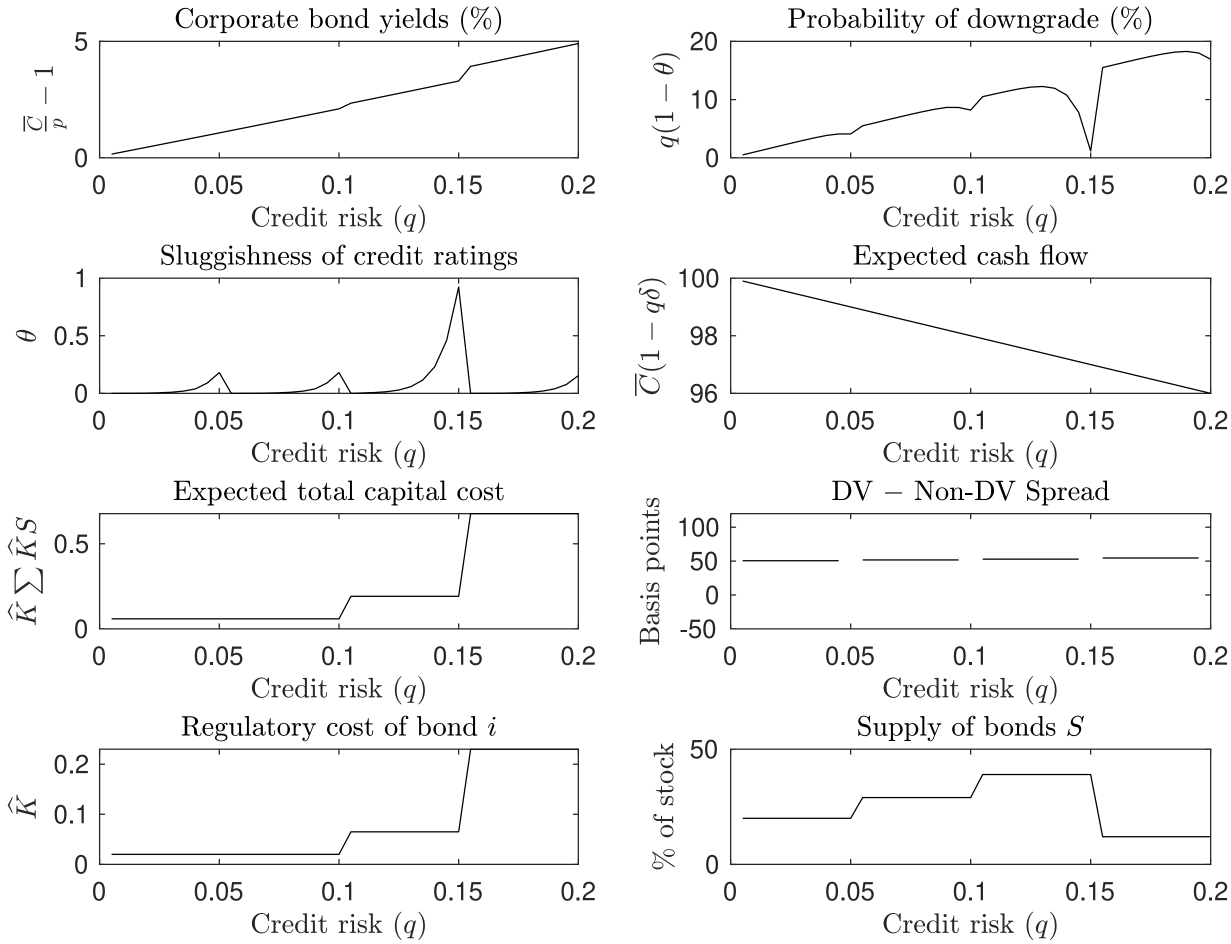

Figure OA.3: Model calibration results, no cost of downgrade. This figure shows the model calibration results where the parameters are shown in Table OA.1 with the exception of $\alpha_i = \alpha = 0$.

results are quantitatively larger than in the baseline case because QE causes the investor to hold more high balance sheet cost assets (BBB/BB-rated bonds) and fewer low balance sheet cost assets (AAA/AA/A-rated bonds).

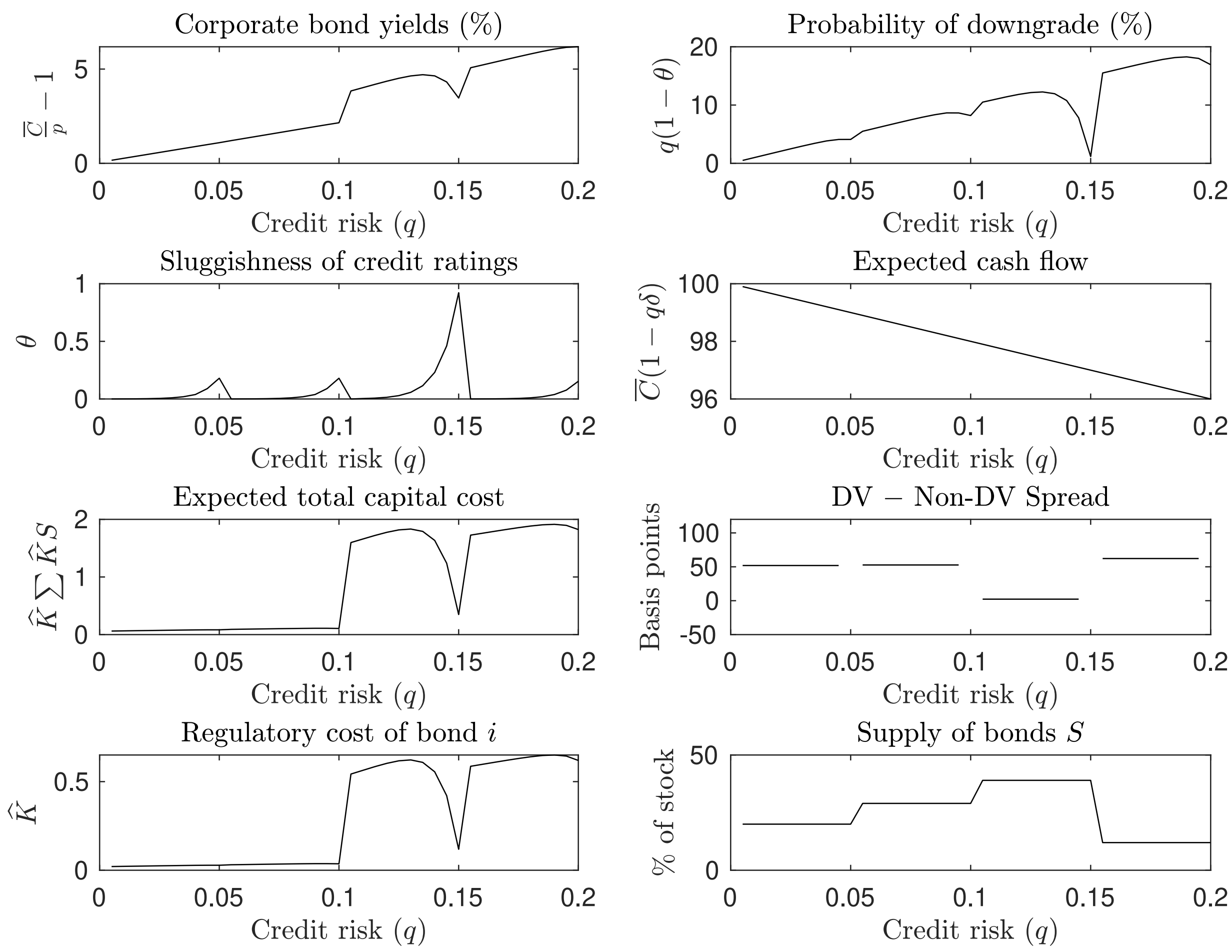

Figure OA.4: Model calibration results. This figure shows the model calibration results where the parameters are shown in Table OA.1.

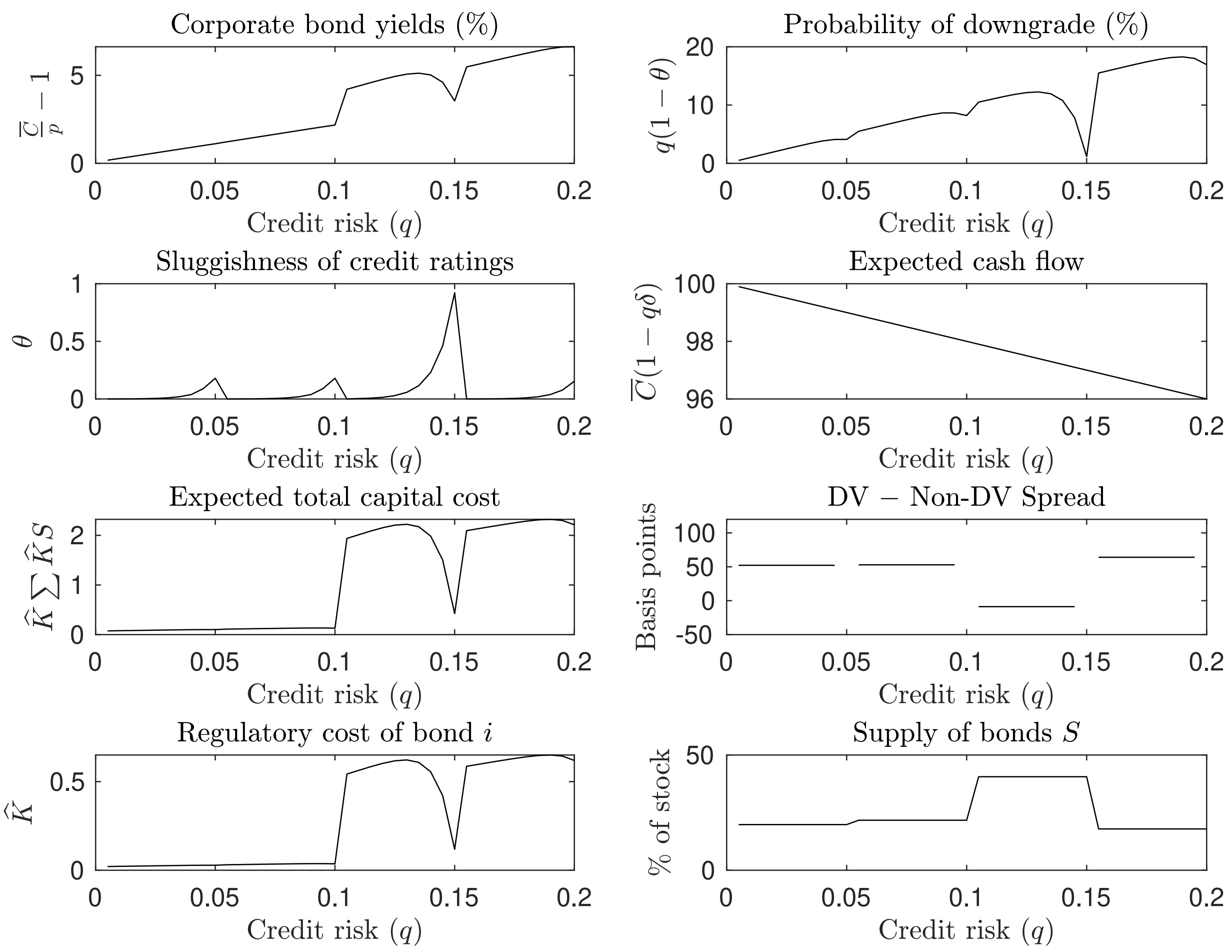

Figure OA.5: Model calibration results. This figure shows the model calibration results where the parameters are shown in Table OA.1 with the exception of $S_{AAA/AA} = S_A = 15000$ and $S_{BBB} = S_{BB} = 45000$.

OA.2 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[3] 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.[4]

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

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 OA.2: Rating classification. This table presents the rating mapping used in this paper, taken from Becker and Milbourn (2011).

[3]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.

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

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

Table OA.3: 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).

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 OA.2 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 6,329 bond issues and 886 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 6,166 outstanding bonds by 863 issuers, with bond b, firm j, year t as unit of observation. For the COVID analysis, we extend our data set to 2020.

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

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

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

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

Transferring ratings into numerical values Following Becker and Milbourn (2011), we transfer the ratings of S&P, Moody and Fitch into numerical values using Table OA.2. 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. See Table OA.3.

OA.3 Validating the downgrade-vulnerability measure

In this section, we show (i) how the balance sheet characteristics of downgrade-vulnerable firms differ from those of non-downgrade-vulnerable firms, (ii) how a firm's downgrade probability, balance sheet characteristics, and firm performance change after a firm is classified as downgrade-vulnerable. and (iii) that our measure of downgrade vulnerability predicts downgrades consistently over time.

In Table OA.4, 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.

We then examine how the balance sheet characteristics of downgrade-vulnerable firms change after the obtaining the vulnerability status. Following Banerjee and Hofmann (2022), 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:

$$Y_{it+q} = \beta_q \text{Enter Vulnerable}_{it} + \gamma_q \text{Vulnerable}_{it} + \eta_q X_{it+q} + \mu_{ht+q} + \epsilon_{it+q}, \quad \text{(OA.6)}$$

where i is a firm, h an industry, t a year, and $q \in \mathcal{Q}$, where $\mathcal{Q} = \{-3, -2, -1, 0, 1, 2, 3\}$.

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

Table OA.4: 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.

The dependent variable is asset growth, employment growth, sales growth, and capital expenditures in period $t+q$. Enter Vulnerable is a dummy equal to one if a firm becomes downgrade-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-downgrade-vulnerable firms. X is the logarithm of total assets and μ 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 OA.6 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.

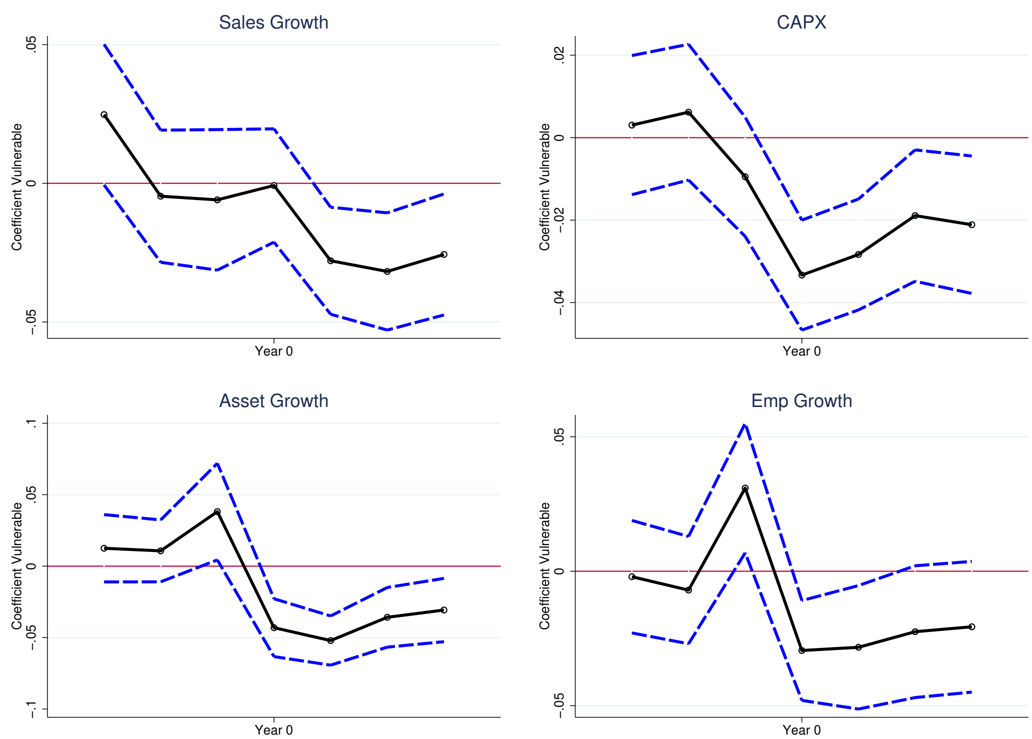

Figure OA.6: Firm performance after being classified as downgrade-vulnerable. This figure shows the evolution of the estimated coefficient β_q from specification (OA.6) three years before and after a firm becomes downgrade-vulnerable. Year zero corresponds to the first year a firm is classified as downgrade-vulnerable. The 95% confidence interval is reported, with standard errors clustered at the firm-level.

OA.4 Additional tables

Panel A of Table OA.5 shows that the characteristics of bonds issued by downgrade-vulnerable firms are similar to those issued by non-downgrade-vulnerable firms. The remaining maturities are similar, with a median remaining maturity of 6.4 and 6.3 years, respectively. The offering amounts are also similar as is the likelihood of bonds being classified as senior and also whether the bond is callable. On average, secondary market spreads on bonds issued by downgrade-vulnerable firms are *lower* than spreads of non-downgrade-vulnerable firms. Panel B, however, shows that this is driven by a composition effect across the sample. Within each rating category secondary market spreads of bonds issued by downgrade-vulnerable firms are *higher* than those of their non-downgrade-vulnerable peers across the distribution. The one exception is the BBB segment where bond spreads are lower than their non-downgrade-vulnerable peers.

Panel A: Bond-level descriptive statistics

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

Panel B: Bond spreads by rating

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

Table OA.5: 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.

Baseline results of the exorbitant privilege

	Secondary market spread			Primary market spread		
A	23.555***	25.419***	20.522***	44.292**	41.297**	−7.695
	(3.836)	(4.412)	(4.302)	(17.395)	(16.454)	(9.568)
BBB	66.432***	71.817***	53.817***	105.570***	107.667***	45.022***
	(4.055)	(4.733)	(4.600)	(17.627)	(16.528)	(7.872)
BB	144.969***	149.716***	133.270***	226.566***	228.232***	175.982***
	(5.683)	(6.817)	(6.391)	(20.407)	(20.731)	(23.012)
B	233.964***	237.547***	219.411***	337.640***	343.213***	274.192***
	(7.117)	(8.043)	(10.542)	(23.192)	(24.519)	(34.771)
Vulnerable × AAA-AA	10.471**	11.964**	4.769	22.980	15.854	
	(4.129)	(5.197)	(4.600)	(19.691)	(19.602)	
Vulnerable × A	4.975	7.376*	−1.259	17.736*	24.365**	9.739
	(3.477)	(3.761)	(4.805)	(10.090)	(11.865)	(25.317)
Vulnerable × BBB	−5.457**	−7.752**	2.032	−19.273**	−19.928*	-15.252
	(2.632)	(3.067)	(3.338)	(9.246)	(11.701)	(9.148)
Vulnerable × BB	19.056***	22.620***	10.066	48.487***	50.241***	18.476
	(5.534)	(6.152)	(9.164)	(15.515)	(17.170)	(27.200)
Vulnerable × B	25.102***	33.684***	−44.704*	63.488**	64.010**	
	(8.925)	(8.572)	(23.693)	(24.905)	(25.407)	
Sample period	Full sample	QE1-QT	QT	Full sample	QE1-QT	QT
Industry-Year-Month FE	✓	✓	✓	✓	✓	✓
Bond-level controls	✓	✓	✓	✓	✓	✓
Observations	243,162	179,527	53,721	2,481	2,026	455
R-squared	0.731	0.730	0.760	0.866	0.870	0.867

Table OA.6: The exorbitant privilege of prospective fallen angels, uninteracted rating variables. This tables shows the estimation results of specification (3). Dependent variables: secondary market bond spread and 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 bonds with covenants, convertible bonds, senior bonds, callable bonds, bonds with a price above par but below a price of 105 and the interaction between the latter two variables to account for changes in credit quality affecting spreads on callable bonds. These control variables are included in the estimation but not reported for brevity. Standard errors are double clustered at the firm and year-month level. *** p<0.01, ** p<0.05, * p<0.1.

Additional robustness tests of the exorbitant privilege

In this section, we provide additional tests examining the exorbitant privilege of downgrade-vulnerable BBB-rated firms. We first examine the sensitivity of our baseline results in Table 3 to the use of bond instead of firm-level ratings and additional controls for bond liquidity.

Table OA.7 shows that the downgrade-vulnerable BBB exorbitant privilege remains if we use bond-level ratings to define downgrade-vulnerability. The point estimates are almost unchanged compared with our baseline results. The results with bond-level ratings also confirm the finding of a larger exorbitant privilege in the QE period, with it disappearing with QT.

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 OA.8 additionally control for the number of times a bond is traded in a month. Similar to bid-ask spreads we allow the coefficients of the number of trades to vary by ratings category. These columns show that bonds which tend to trade more frequently have higher spreads. Nevertheless, the point estimates of the prospective fallen angel subsidy remains almost unchanged. In columns (3) to (6), we examine if the age of the bond affects our results. It is possible that the exorbitant privilege could be an artifact of lower liquidity in off-the run bonds. Column (3) and (4) confirm that this is not the case. On-the-run bonds of downgrade-vulnerable BBB-rated issues (i.e., only bonds issued over the past twelve months), continue to show the subsidy. As do those for off-the-run bonds in column (6) shows with an almost identical magnitudes. For other ratings buckets, downgrade-vulnerable firms have consistently higher spreads than their non-downgrade-vulernable peers across all specifications.

	Secondary market spread		
A	25.231***	29.125***	17.575***
	(5.427)	(6.180)	(5.868)
BBB	67.919***	74.561***	51.563***
	(5.754)	(6.581)	(6.283)
BB	143.842***	148.907***	131.397***
	(6.995)	(8.091)	(8.065)
B	208.597***	214.078***	186.746***
	(8.191)	(9.045)	(10.842)
Vulnerable × AAA-AA	4.680	5.157	−0.299
	(5.959)	(7.134)	(5.353)
Vulnerable × A	3.498	5.920*	−1.263
	(2.969)	(3.316)	(3.999)
Vulnerable × BBB	−5.913**	−8.094***	2.948
	(2.334)	(2.639)	(3.250)
Vulnerable × BB	18.212***	20.855***	6.455
	(4.867)	(5.441)	(9.219)
Vulnerable × B	26.932***	27.319***	9.616
	(8.516)	(8.129)	(25.367)
Sample period	Full sample	QE1-QT	QT
Industry-Year-Month FE	✓	✓	✓
Bond-level controls	✓	✓	✓
Observations	239,229	183,019	49,965
R-squared	0.725	0.719	0.753

Table OA.7: The exorbitant privilege of prospective fallen angels, bond-level ratings. This table shows the estimation results of specification (3), where bond-level ratings are used instead of issuer-level ratings. The dependent variable in each column is the secondary market bond spread. Bond spreads are measured in basis points. Vulnerable is a dummy variable equal to 1 if issuer i is downgrade-vulnerable in date $t-1$ and t, based on bond ratings. Additional bond-level controls include residual maturity, amount outstanding and bid-ask spreads. Coefficients on the latter variable are allowed to vary by rating. The specification also includes dummy variables for bonds with covenants, convertible bonds, senior bonds, callable bonds, bonds with a price above par but below a price of 105 and the interaction between the latter two variables to account for changes in credit quality affecting spreads on callable bonds. These control variables are included in the estimation but not reported for brevity. These specifications include industry-year-month fixed effects (2-digit SIC). Standard errors are double clustered at the firm and year-month level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

	Secondary market spread					
A	24.830***	25.336***	15.586***	14.929***	26.511***	30.429***
	(4.469)	(5.159)	(3.344)	(3.527)	(5.010)	(5.670)
BBB	66.740***	69.734***	56.376***	58.055***	71.737***	79.135***
	(4.421)	(5.104)	(3.382)	(3.623)	(5.249)	(6.083)
BB	142.313***	146.078***	151.949***	155.365***	147.346***	153.107***
	(5.631)	(6.451)	(5.758)	(6.338)	(6.702)	(7.943)
B	230.269***	232.665***	236.125***	240.320***	238.262***	242.899***
	(6.929)	(7.789)	(7.141)	(7.699)	(8.230)	(9.191)
Vulnerable × AAA-AA	8.658*	9.687*	10.331***	10.095***	8.672	11.673*
	(4.418)	(5.535)	(3.284)	(3.634)	(5.454)	(6.689)
Vulnerable × A	5.819*	8.209**	5.255	7.547*	7.170*	9.475**
	(3.348)	(3.681)	(4.148)	(4.518)	(3.695)	(3.972)
Vulnerable × BBB	−6.003**	−7.640**	−6.543**	−9.561***	−6.130**	−7.744**
	(2.589)	(3.033)	(3.187)	(3.574)	(2.690)	(3.099)
Vulnerable × BB	18.074***	20.520***	17.117**	23.149***	18.818***	21.140***
	(5.649)	(6.324)	(7.967)	(7.698)	(5.581)	(6.405)
Vulnerable × B	25.365***	29.779***	20.002*	19.156*	28.573***	37.294***
	(9.417)	(9.249)	(10.488)	(10.856)	(10.291)	(9.684)
Trades × AAA	0.005	−0.010				
	(0.010)	(0.013)				
Trades × AA	0.023***	0.017***				
	(0.005)	(0.006)				
Trades × A	0.016***	0.014***				
	(0.004)	(0.004)				
Trades × BBB	0.026***	0.030***				
	(0.005)	(0.005)				
Trades × BB	0.041***	0.041***				
	(0.007)	(0.007)				
Trades × B	0.056***	0.065***				
	(0.009)	(0.011)				
Sample period	Full sample	QE1-QT	Full sample	QE1-QT	Full sample	QE1-QT
Bond age	All	All	< 12 months	< 12 months	>12 months	>12 months
Industry-Year-Month FE	✓	✓	✓	✓	✓	✓
Bond-level controls	✓	✓	✓	✓	✓	✓
Observations	238,044	181,000	46,679	37,145	190,325	143,021
R-squared	0.740	0.739	0.814	0.821	0.730	0.727

Table OA.8: The exorbitant privilege of prospective fallen angels, additional bond liquidity controls. This table shows the estimation results of specification (3), with tests for bond liquidity. The dependent variable in all columns is the secondary market bond spread. 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 fourth columns, the sample is restricted to bonds that have been issued within the past 12 months, while the fifth and sixth columns only includes bonds issued at least 12 months earlier. 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 bonds with covenants, convertible bonds, senior bonds, 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 double clustered at the firm and year-month level. *** p<0.01, ** p<0.05, * p<0.1.

Date	Event	Details
25 November 2008	Unscheduled press release	Fed announces purchases of $100 billion in GSE debt and up to $500 billion in MBS.
1 December 2008	Speech	Chairman Bernanke mentions that the Fed could purchase long-term Treasuries in a speech to the Greater Austin Chamber of Commerce.
28 January 2009	FOMC decision	The Federal Reserve announces that it will use measures that are likely to keep the size of the Federal Reserve's balance sheet at a high level. It will continue to purchase large quantities of agency debt and mortgage-backed securities and is also prepared to purchase longer-term Treasury securities.
18 March 2009	FOMC decision	Purchase $300 billion in Treasuries, $750 billion of agency MBS, increase holdings of agency debt to $200 billion
12 August 2009	FOMC decision	The Committee decides to gradually slow the pace of Treasury purchases and anticipating that the full amount will be purchased by the end of October.
23 September 2009	FOMC decision	The Committee announces that it will gradually slow the pace of purchases in order to promote a smooth transition in markets. It anticipates that they will be executed by the end of the first quarter of 2010. Purchase of $300 billion will be completed by end October.
4 November 2009	FOMC decision	The amount of agency debt purchases, while somewhat less than the previously announced maximum of $200 billion, is consistent with the recent path of purchases and reflects the limited availability of agency debt. To smooth transition in markets, the Committee announces that it will gradually slow the pace of its purchases of both agency debt and agency mortgage-backed securities and anticipates that these transactions will be executed by the end of the first quarter of 2010.
16 December 2009	FOMC decision	Mentions phasing out of purchases as previously indicated.
27 January 2010	FOMC decision	Mentions phasing out of purchases as previously announced.
10 August 2010	FOMC decision	To help support the economic recovery in a context of price stability, the Committee announces that it will keep constant the Federal Reserve's holdings of securities at their current level by reinvesting principal payments from agency debt and agency mortgage-backed securities in longer-term Treasury securities. The Committee will continue to roll over the Federal Reserve's holdings of Treasury securities as they mature.
27 August 2010	Jackson Hole speech	Chairman Bernanke states that the Committee is prepared to provide additional monetary accommodation through unconventional measures if it proves necessary, especially if the outlook were to deteriorate significantly.
21 September 2010	FOMC decision	Announcement to maintain reinvestment policy.
15 October 2010	Boston Fed speech	Chairman Bernanke states that the FOMC is prepared to provide additional accommodation if needed to support the economic recovery and to return inflation over time to levels consistent with our mandate.
3 November 2010	FOMC decision	Announcement for purchases of a further $600 billion of longer term Treasuries.
26 August 2011	Jackson Hole speech	Chairman Bernanke hints that the US Federal Reserve will do more to support the stalling US economy. Will extend its September monetary policy meeting to allow for a fuller discussion.
21 September 2011	FOMC decision	Maturity extension program (MEP) announced using $400 billion Treasury securities.
20 June 2012	FOMC decision	MEP extended until end-2012.
31 August 2012	Jackson Hole speech	Chairman Bernanke states that balance sheet tools are effective and recovery is far from satisfactory due to head winds.
13 September 2012	FOMC decision	Monthly purchases of $40 billion in mortgage-backed securities and long-maturity Treasury securities holdings at $45 billion per month announced.
12 December 2012	FOMC decision	Expansion of purchases by US Treasuries in addition to agency debt.
22 May 2013	Bernanke testimony	Taper tantrum begins following Bernanke's statement at the Congress Joint Economic Committee.
19 June 2013	FOMC decision	Taper tantrum continues; FOMC statement offers no clarification to the Chairman's May speech.
18 September 2013	FOMC decision	Tapering postponed.
9 October 2013	Minutes released	Minutes released following decision to postpone QE tapering.
30 October 2013	FOMC decision	Further postponement of QE tapering.
18 December 2013	FOMC decision	QE tapering announced. Cut monthly purchases of MBS and Treasuries to $35 billion and $40 billion per month.
29 January 2014	FOMC decision	Announced cut of monthly purchases of MBS and Treasuries to $30 billion and $35 billion per month.
19 March 2014	FOMC decision	Announced cut of monthly purchases of MBS and Treasuries to $25 billion and $30 billion per month.
30 April 2014	FOMC decision	Announced cut of monthly purchases of MBS and Treasuries to $20 billion and $25 billion per month.
18 June 2014	FOMC decision	Announced cut of monthly purchases of MBS and Treasuries to $15 billion and $20 billion per month.
9 June 2014	FOMC minutes	Federal Reserve announces that it will end its QE3 programme of asset purchases in October if the economy progresses as the Committee expects. It will keep reinvesting income into their asset purchases until at or after the time that interest rates rise.
30 July 2014	FOMC decision	Cut monthly purchases of MBS and Treasuries to $10 billion and $15 billion per month.
17 September 2014	FOMC decision	Cut monthly purchases of MBS and Treasuries to $5 billion and $10 billion per month.
14 June 2017	FOMC decision	Publishes addendum to FOMC's policy normalisation principles and plans alongside normal press release. Document provides additional details on the FOMC's approach to reduce the Federal Reserve's holdings of Treasury and agency securities.
20 September 2017	FOMC decision	In October, the Committee will initiate the balance sheet normalization program described in the June 2017 Addendum to the Committee's Policy Normalization Principles and Plans.

Table OA.9: QE specific monetary policy announcements.

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

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

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

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

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

Table OA.10: 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.

OA.5 Additional figures

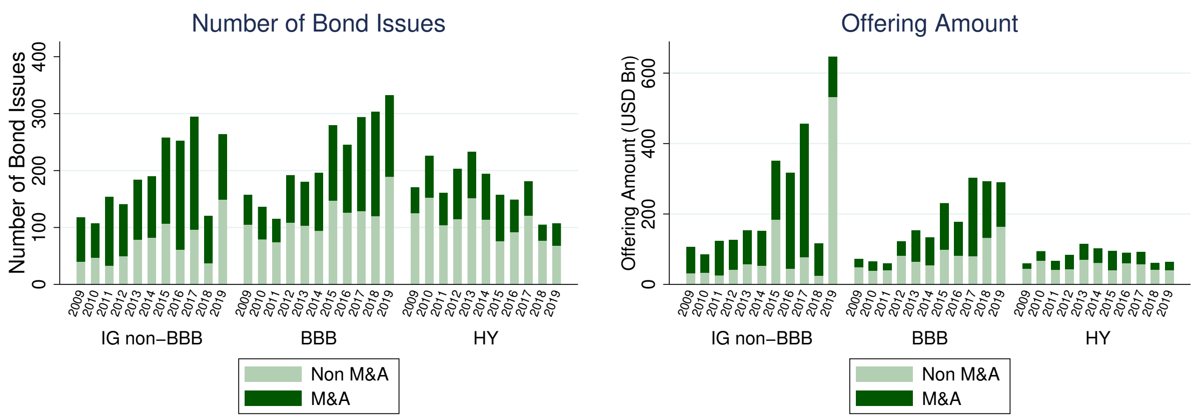

Figure OA.7: Bond issuance and volume. This figure shows the number of bond issues and the bond issuance volume for high-yield, BBB-rated, and A/AA/AAA-rated firms from 2009 to 2019. The left panel shows the total number of bond issues, separated by M&A and non-M&A bond issues. The right panel shows 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.

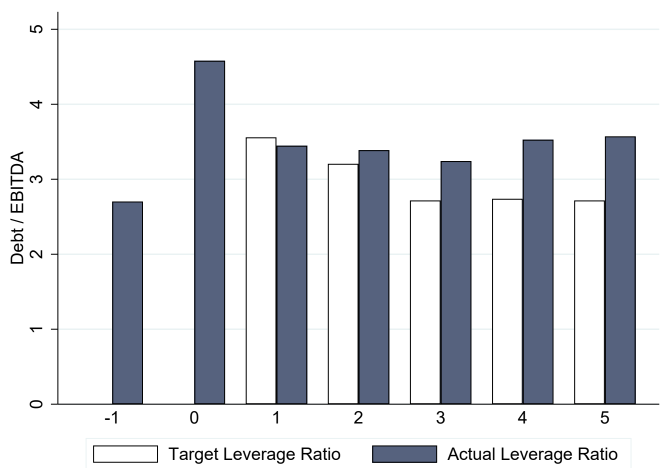

Figure OA.8: Broken promises about debt reduction after M&A. This figure compares the year-by-year promised path of debt reduction with observed debt after firm M&A. The x-axis shows the years since transaction. The y-axis is debt divided by EBITDA. We assume that debt reduction plans (e.g., leverage 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.

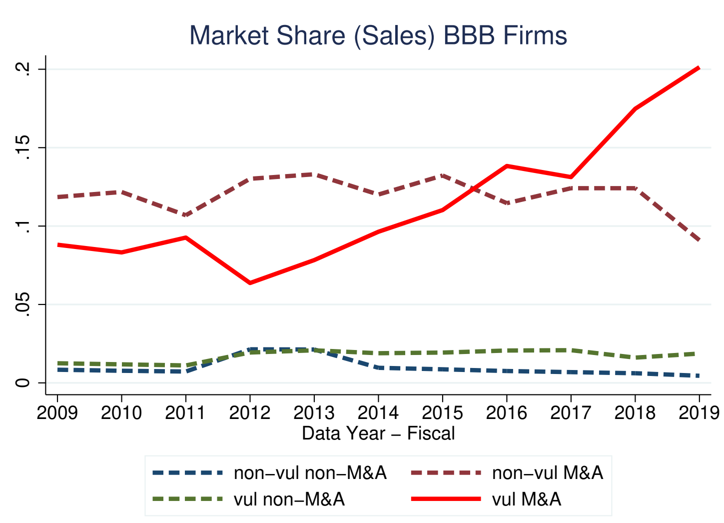

Figure OA.9: M&A and the increase in market share of prospective fallen angels. This figure shows the evolution of firm market share (share of sales, weighted by the relative size of the respective industry)) for BBB-rated issuers, broken down by downgrade-vulnerability and whether a firm engages in an M&A transaction during our sample period.

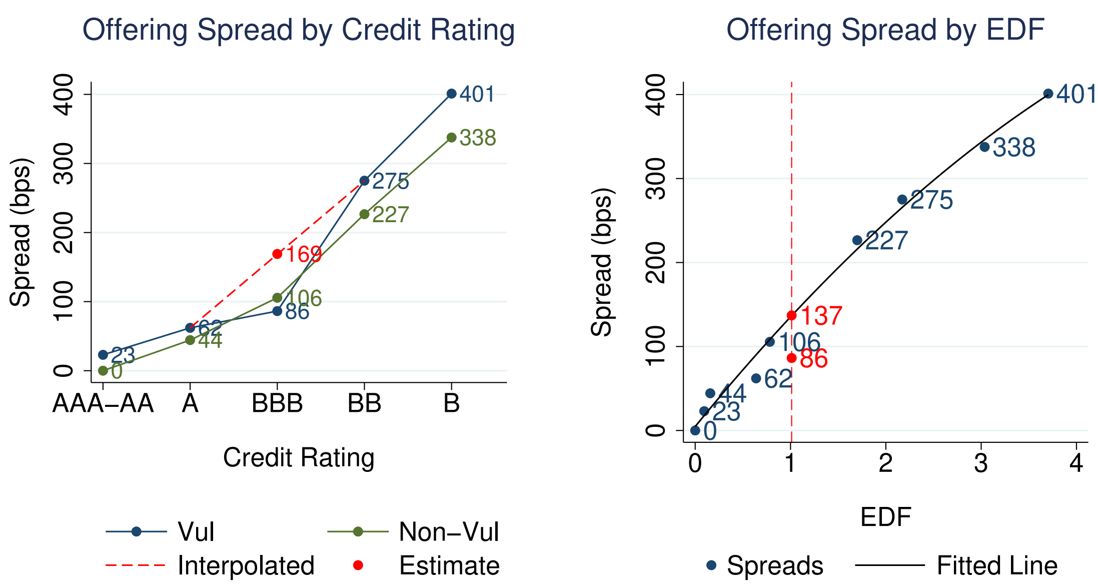

Figure OA.10: Quantifying the prospective fallen angel subsidy, alternative calculations. The left panel shows in red the counterfactual vulnerable BBB rated spread, based on the spread interpolation between the downgrade-vulnerable rating categories. The right panel plots the relationship between the 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.