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

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Abstract

We document capital misallocation in the U.S. investment-grade (IG) corporate bond market, driven by quantitative easing (QE). Prospective fallen angels—risky firms just above the IG rating cutoff—enjoyed subsidized bond financing since 2009, especially when the scale of QE purchases peaked and from IG-focused investors that held more securities purchased in QE programs. The benefiting firms used this privilege to fund risky acquisitions and increase market share, exploiting the reluctance of credit rating agencies to downgrade post-M&A and adversely affecting competitors' employment and investment. Eventually, these firms suffered more severe downgrades at the onset of the pandemic.

JEL Codes: E31, E44, G21.
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1 Introduction

Risky firms just above the investment-grade (IG) cutoff face the prospect of becoming "fallen angels" upon a downgrade. Despite this risk, the BBB segment of the bond market has been the fastest growing investment-grade rating category since the Global Financial Crisis. Between 2008 and 2020, the amounts outstanding of BBB-rated bonds have more than tripled in size to $3.5 trillion, representing 55% of all investment-grade debt, up from 33% in 2008. During the same period, BBB bond spreads dropped from from around 400 basis points to around 150 basis points and the profitability of BBB-rated firms did not keep up with their increased indebtedness (see Figure 2). These dynamics are unique to the BBB market. Other IG bond spreads did not fall as much during the same period and other IG-rated issuers actually improved their debt-to-profitability ratio.

In many respects, the growth of risky investment-grade bonds may be a desired outcome of crisis-related monetary policy easing. In particular, the Federal Reserve Quantitative Easing (QE) has aimed to push investors into riskier assets riskier assets by lowering the yields on government and mortgage-backed bonds (see Gagnon et al. (2011) or an early reference to this portfolio rebalancing channel of the Federal Reserve thinking). However, the growing concentration of issuance in the riskiest investment-grade bucket also comes with a buildup of vulnerabilities in the corporate sector. The fragility of the BBB market materialized at the onset of the COVID-19 crisis. The volume of assets downgraded from BBB in a few weeks at the beginning of 2020 was five times larger than the volume of similar downgrades during the entire Global Financial Crisis. Materialization of this vulnerability likely led to the Federal Reserve stepping in to stabilise the U.S. corporate bond market in the wake of the COVID-19 shock.[1]

In this paper, we examine the causes and consequences of an exorbitant privilege in the form of a bond market subsidy for "prospective fallen angels", i.e., firms on the cusp of the investment-grade cutoff. We classify prospective fallen angels as BBB-rated firms that

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[1]See Gilchrist et al. (2020) for details on the impact of the Federal Reserve's intervention on fallen angels.

are vulnerable to downgrades, and show that BBB bond growth has largely been driven by such firms. Our analysis shows that prospective fallen angels have benefited from investors subsidizing their bond financing since 2009, especially at the peak of quantitative easing.

Importantly, investors highly exposed to the Federal Reserve QE drive the demand for bonds issued by prospective fallen angels. Prospective fallen angels meet this demand by issuing bonds, largely to finance risky acquisitions. In conjunction, rating agencies appear to inflate ratings and delay downgrades for these firms that engage in M&A transactions. We show, however, that such downgrades eventually materialized at outbreak of the pandemic in March 2020, with prospective fallen angels that had engaged in M&A experiencing more severe downgrades. Finally, we find that prospective fallen angels exert negative externalities on more prudent firms similar to the congestion effect created by zombie firms (Caballero et al., 2008).

In summary, our paper documents a decade of capital misallocation in the U.S. corporate bond market, driven by QE-induced demand for IG bonds. Our empirical analysis combines various data sources at the issuer-level, bond-level, and investor-level. We use firm-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 pricing data from Mergent and secondary market pricing data from TRACE. Finally, for a crucial part of our analysis that highlights the demand for risky bonds as arising from IG-focused investors, we use investor holding-level data from eMAXX Bond Holders matched with security-level holdings in the Federal Reserve System Open Market Account (SOMA) portfolio.

We begin our empirical analysis by introducing a measure of downgrade-vulnerability based on the Altman Z"-score (Altman, 2020b). Built with balance sheet and income statement information, this measure captures whether an issuer is at risk of being downgraded. We confirm the validity of our measure by documenting that downgrade-vulnerable firms (i) look worse along various observable firm characteristics, such as leverage, profitability, net worth, and interest coverage ratio; (ii) exhibit lower employment growth, investment, sales, and asset growth once they become vulnerable; and, (iii) are more likely to be downgraded or put
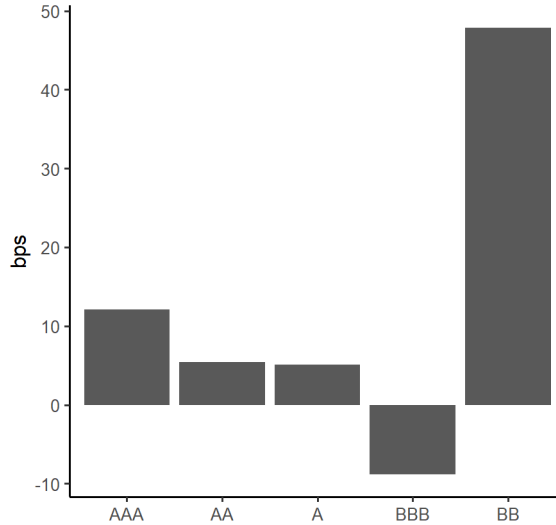
Figure 1: The privilege of prospective fallen angel subsidy. This figure shows the difference in basis points (bps) between the median secondary market spread of firms defined as being vulnerable to a downgrade and the median spread of non-vulnerable firms in the same ratings category. We classify a firm as vulnerable if its estimated Z"-score is lower than the Altman Z"-score benchmark of the next lowest rating category.

on negative watchlist/outlook than non-downgrade-vulnerable firms.[2]

Using this measure, we show that prospective fallen angels benefit from ratings inflation; this ratings inflation has been substantially increasing since 2009. Next, we document that there has been a reduction in bond spreads in the BBB segment, primarily driven by downgrade-vulnerable firms (prospective fallen angels). In other words, these firms are able to obtain cheaper funding than their safer, i.e., non-downgrade vulnerable counterparts in the BBB rating class (Figure 1). Crucially, this pattern is only present for BBB-rated firms. We do not find analogous evidence in other rating categories. Moreover, such subsidy in borrowing cost is not observed in corporate bond markets pre-2009. When replacing the bond spread with an equity market based measure of expected default, spreads in syndicated loan markets, or bond spreads before the global financial crisis, we find that across all rating categories (including BBB-rated firms), downgrade-vulnerable firms have higher—not lower—funding costs.

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[2]In 2018, the corporate bond volume of BBB-rated downgrade-vulnerable firms, the prospective "fallen angels," amounted to $1.5 trillion ($0.5 trillion in 2009), compared to the $0.5 trillion of BBB non-downgrade-vulnerable firms ($0.25 trillion in 2009).

We argue, and provide a theoretical sketch in Appendix C, that such an exorbitant privilege in the form of a bond-market subsidy can arise in equilibrium due to an investor demand for IG corporate bonds, such as that induced by QE. This high demand induces prospective fallen angels to take on more debt and increase their risk-taking. In conjunction, since there appears to be a reluctance of credit rating agencies to downgrade issuers to the speculative-grade market, downgrades of prospective fallen angels are less likely in normal times, increasing the demand for their bonds by QE-exposed investors.

Our empirical tests that tease out this chain of logic are structured in three parts. First, we show that investors exposed to QE drive the demand for downgrade-vulnerable IG corporate bonds. We define investor-level time-varying QE exposure as the share of investor total holdings that are held by the Federal Reserve. Exploiting the granularity of our bond holdings data, we compare, in each quarter, holdings of bonds issued by the *same* firm that are held by investors with a different exposure to QE. The correlation between the firm's bond holdings and QE-exposed investors is more pronounced for bonds issued by prospective fallen angels and more pronounced for investors such as insurance companies that focus on the IG market.[3] In addition to helping understand the mechanism behind the subsidy for prospective fallen angels, the within-firm test based on QE-exposure of different investors clarifies that it is unlikely that the bond-market subsidy we uncover is driven by a BBB-firm-level "error" in Altman Z"-score rendering it mistakenly as a downgrade-vulnerable firm. We show next that the resulting bond market subsidy has the flavor of an "exorbitant privilege" in that it leads to capital misallocation in the corporate bond market.

Second, we show that downgrade-vulnerable firms, and prospective fallen angels in particular, meet the QE-induced demand by IG investors by supplying bonds largely for the purpose of financing risky acquisitions. These M&A deals allow downgrade-vulnerable issuers, and prospective fallen angels in particular, to prolong their rating inflation and substantially increase their market share. The high and increasing ratings inflation of prospective fallen

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[3]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 (link).

angels appears to be driven by their M&A activity: announcements of acquisitions are usually accompanied by rosy forecasts about synergies and growth, and, more importantly, a promise to reduce the debt taken on to finance the acquisition, but data indicate that these end up being broken promises. In sum, prospective fallen angels exploit their funding privilege and the leniency of credit rating agencies to fund M&A and increase their market share. Again, the demand for bonds of M&A-undertaking prospective fallen angels stems from QE-exposed IG-focused investors. The resulting buildup of vulnerability over the extended period of QE led to an unprecedented wave of fallen angels at the onset of the COVID-19 pandemic, almost entirely among those firms that engaged in M&A and which got downgraded by more notches than other firms.

Third, we show that the privilege of prospective fallen angels, and the related increase in market share, adversely affects competing firms. Non-downgrade-vulnerable firms operating in an industry with a larger share of prospective fallen angels have lower employment growth rates, lower investment levels, lower sales growth rates, and lower markups compared with non-downgrade-vulnerable firms operating in an industry with a lower share of prospective fallen angels. Crucially, we do not find negative spillover effects when focusing on the overall share of downgrade-vulnerable firms, highlighting that the spillover effects arise only from prospective fallen angels which enjoy the exorbitant privilege in bond markets from QE-exposed investors.

Related literature Our findings contribute to three 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)). However, Fabo et al. (2021) document that only half of the academic papers find a statistically significant effect of QE on output. Our paper documents QE-induced capital misallocation, an important unintended consequence that might contribute to financial vulnerability, such as at the onset of the pandemic. In this vein, our paper is related to the 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 junk bond market, leveraged loan market, and real-estate investment trust (REIT) borrowings, our paper shows that distortions have materialized even in the space of downgrade-vulnerable investment-grade bonds.

Second, we contribute to the literature on misallocation and fragility in corporate borrowing markets. The documented vulnerability of the investment-grade bond market since 2009 is consistent with warning signs from practitioners about the BBB market (Altman, 2020b; S&P Global, 2020a; Blackrock, 2020; Morgan Stanley, 2018a,b) and explains the large price drop of investment-grade corporate bonds at the onset of the COVID-19 pandemic (Haddad et al., forthcoming; Boyarchenko et al., 2021; Altman, 2020a). The special role of the BBB market is consistent with the role of fire sale (cliff) risk documented in the literature (Falato et al., forthcoming, 2021; Gilchrist et al., 2020; Acharya and Steffen, 2020). More generally, our findings are related to the literature on the misallocation of bank credit (Caballero et al., 2008; Acharya et al., 2020) and of other forms of financing (Midrigan and Xu, 2014; Whited and Zhao, forthcoming) as well as the role of low interest rates on misallocation (Banerjee and Hofmann, 2018, 2020). Krishnamurthy and Muir (2020); Gilchrist and Zakrajsek (2012) discuss the behavior of credit spreads over the financial cycle, and Caballero and Simsek (2020) discuss the role of monetary policy as a driver of asset prices.

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

their bonds and rating agency leniency.

The remainder of the paper is structured as follows. Section 2 documents the rapid growth of the investment-grade corporate bond market, driven by BBB-rated issuers after the Global Financial Crisis. Section 3 presents the data, our measure of downgrade vulnerability, and the definition of prospective fallen angels. Section 4 documents that prospective fallen angels have benefited from a bond financing subsidy, especially since 2013–14. Section 5 shows that this subsidy originates in QE-driven investor demand for IG bonds paired with the leniency of credit rating agencies. Section 6 documents the costs that prospective fallen angels impose on other firms. Section 7 concludes.

2 Aggregate evidence

In this section, we present some aggregate facts. Section 2.1 documents the sizable growth of the U.S. corporate debt market, mostly driven by BBB-rated issuers, following the Global Financial Crisis. Section 2.2 shows that, during the same period, IG corporate issuers paid historically low bond yields while becoming considerably riskier—a dynamic particularly pronounced for BBB-rated issuers. Section 2.3 shows the unprecedented wave of fallen angels at the onset of COVID-19, before the Federal Reserve intervened to support this market.

2.1 The growth of non-financial corporate debt

After reaching $43 trillion in 2008, U.S. private debt decreased to $39 trillion in 2011 and then steadily increased reaching $51 trillion today, a dynamic accelerated by the COVID-19 pandemic. While the deleveraging in 2008–11 was mainly driven by the financial and household sectors, the subsequent private debt cycle has been predominantly driven by the *corporate* non-financial sector. See Appendix B.1 for a set of aggregate plots on the evolution of private debt, and corporate debt in particular, since the Global Financial Crisis.

The steady increase of non-financial business debt over the past 10 years has made it the largest private debt category, equivalent to 82% of GDP in 2020. The last cycle has been entirely driven by non-financial business debt, which increased from $10 trillion in 2008 to $17 trillion in 2020. The increase in non-financial corporate debt has been mostly driven

by corporate bonds, with the stock outstanding increasing from around $3 trillion in 2009 to around $6 trillion in 2020. This increase is almost entirely driven by bonds issued by BBB-rated firms, namely the lowest rated segment of the investment-grade bond market. This segment has tripled in size from around $0.7 trillion in 2009 to more than $2 trillion in 2018 and represents around 52% of all IG bonds outstanding up from 33%.

2.2   Firm risk and bond yields

The growth of the BBB segment of the bond market has been accompanied by a deterioration in the quality of BBB-rated firms and a substantial reduction in their bond financing costs. The deterioration of issuer quality has been discussed in industry pieces (Morgan Stanley, 2018a,b; Blackrock, 2020) and specialized papers (Çelik et al., 2020; Altman, 2020b; S&P Global, 2020a) that warned about the risk of a wave of "fallen angels," namely a large number of downgrades of BBB-rated firms to the sub-IG (or "speculative-grade") market.

In Figure 2, we document the deterioration in issuer quality and the drop in yields paid by BBB-rated firms since 2009. The top left panel shows the share of firms that are vulnerable to a downgrade based on the Altman Z"-score, a measure of credit risk calculated with income statement and balance sheet information (Altman, 2020a).[4] The figure shows that the share of firms that are vulnerable to a downgrade increased substantially in the BBB-market, but not in other markets, since 2013. The top right panel confirms that the growth of the BBB market is driven by these "prospective fallen angels." Since 2009, their stock of bonds outstanding tripled in size to $1.5 trillion in 2018. During the same period, the non-downgrade-vulnerable segment increased only from $0.2 to $0.5 trillion.

The bottom left confirms the deterioration in the quality of BBB-rated firms. The figure shows the debt-to-EBITDA ratio, a metric used by lenders and credit rating agencies to assess firms' ability to service their debt. For BBB firms, debt has steadily risen relative to EBITDA while it has declined for other investment-grade rated firms. A similar diverging

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[4]We explain this measure of downgrade vulnerability in more detail in Section 3.2.
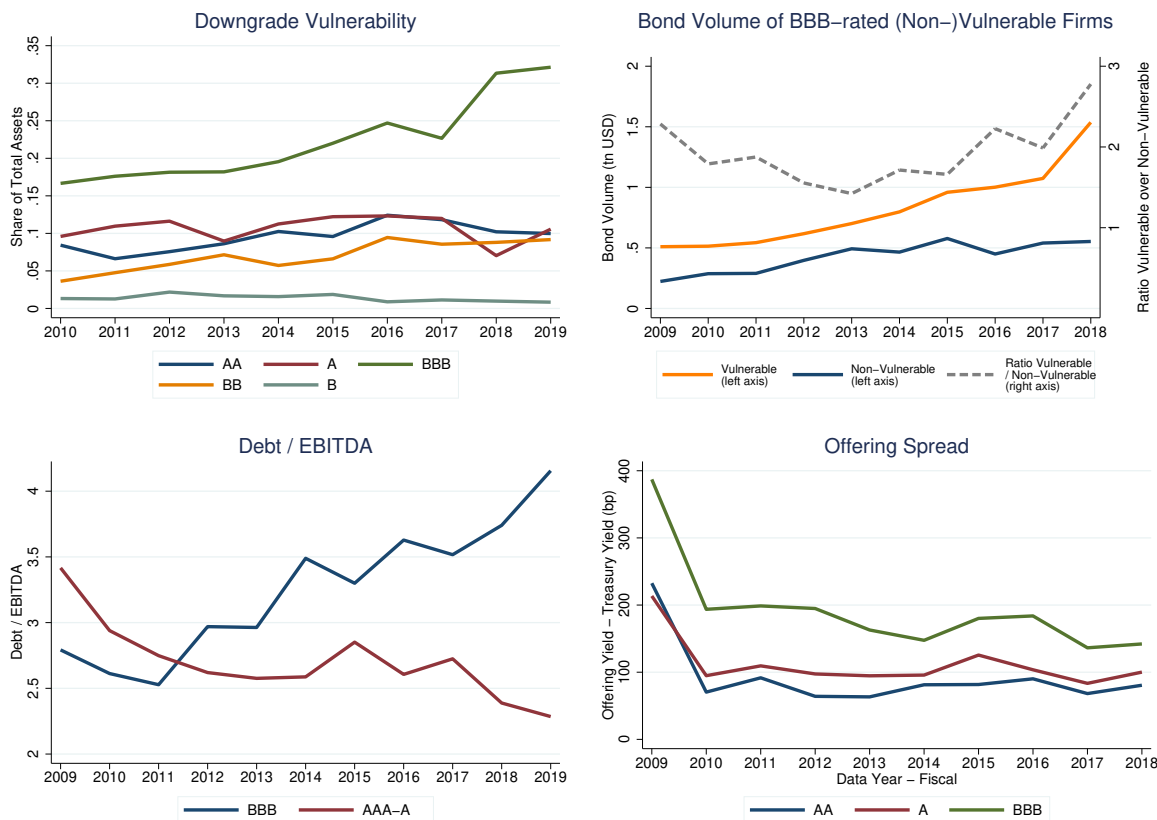
Figure 2: Downgrade vulnerability. This figure shows the deterioration of firm quality and the declining bond financing costs for BBB-rated firms. The top left panel shows the share of firms that are vulnerable to a downgrade based on the Z"-score by rating category, where firms are weighted by total assets. The top right panel shows, within the BBB rating category, the share of stock of bond debt issued by vulnerable and non-vulnerable BBB-rated firms. The dashed line is the ratio between these two series. The bottom left panel shows the asset-weighted debt over EBITDA evolution for BBB and other IG-rated firms. The bottom right panel shows the offering spread (primary market bond yields minus the treasury yield with a similar maturity) for newly issued bonds.

pattern can be observed for leverage, as shown in Figure B.4. The bottom right panel shows the evolution of offering spreads, namely the difference between primary market bond yields and the Treasury yields with a similar maturity. The offering spread of BBB issuers declined from around 400 basis points in 2009 to around 150 basis points in 2018, around 100 basis points more than either A or AA issuers. During this period, there is no evidence of a similar spread narrowing of A rating firms relative to those rated AA. Appendix B.2 provides further non-parametric evidence that the bond financing cost of BBB firms dropped significantly, more than the financing costs of other investment grade issuers.

2.3 Risk materialization during COVID-19

The onset of the COVID-19 crisis precipitated an unprecedented wave of fallen angels until the Federal Reserve stepped in and extended its investment-grade corporate bond purchase program to support recently fallen angels. We interpret this episode as ex-post evidence of the increased vulnerability of BBB-rated firms, and of prospective fallen angels in particular. The evidence presented here is non-parametric. We provide formal tests in Appendix B.4.

The volume of assets downgraded from BBB to speculative-grade in just a few weeks at the beginning of 2020 was five times larger than the volume of similar downgrades during the global financial crisis. The left panel of Figure 3 shows that, in 2020, the total balance sheet size of fallen angels amounted to an unprecedented $600 billion.

The right panel shows the monthly spreads of firms that were rated BBB in 2019, distinguishing between firms that were downgraded at the onset of the pandemic (fallen angels) and those who maintained their BBB rating. We observe a sudden increase in the spreads of fallen angels before the Federal Reserve expanded its corporate bond 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, 2020b), all of which are classified as prospective fallen angel in our data set, the definition of which we discuss in the next section.
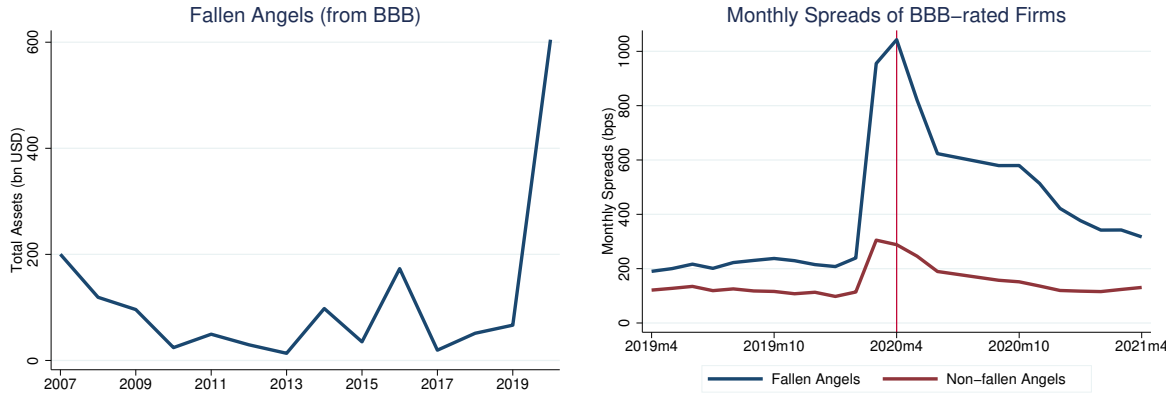
Figure 3: Risk materialization during COVID-19. This figure shows that the vulnerability of the BBB market materialized at the onset of the COVID-19 pandemic. The left panel shows total assets downgraded from BBB to speculative-grade from 2007 to 2020. The right panel shows monthly spreads of firms rated BBB in 2019. The blue line represents the spreads of fallen angels, namely firms downgraded during COVID-19. The red line represents the spreads of firms that maintained their investment-grade status.

3   Identifying prospective fallen angels

In this section, we describe our data and explain our strategy to identify downgrade-vulnerable firms, including prospective fallen angels. Section 3.1 describes our data sources and data construction. Section 3.2 introduces our definition of downgrade-vulnerable firms.

3.1   Data

Our main data set consists of firm-level, bond-level, and investor-level data from 2009 to 2019. See Appendix A for a detailed explanation of our data sources and data construction.

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

The bond-level data has information on prices in the U.S. corporate bond market. For

the primary market, we use data supplied by Mergent Fixed Income Securities Database (FISD), which is a fixed income database that includes issue details of publicly-offered U.S. bonds. We investigate 6,460 bond issues by 909 issuers. For the secondary market, we obtain data from TRACE, a database that constitutes of real-time secondary market information on transactions in the corporate bond market. This analysis is based on 7,741 outstanding bonds by 1,146 issuers. For the COVID analysis we extend our data set to 2020.

The investor-level data is from eMAXX Bond Holders data from Refinitiv, a detailed data set that documents security-level holdings by individual investors at a quarterly frequency. We match this data with the Fed security-level holdings in the SOMA portfolio (this data is publicly available on the website of the New York Fed). We also match this data with issuer- and security-level data set from the rest of our analysis and collapse holdings within an investor at the issuer level. The investor-level data has information on 2,750 investors, mostly property and casualty insurance policies (934), mutual funds (800), life and health insurance policies (590), and annuities (223) covering investments in 1,442 corporate bond issuers.

3.2 Downgrade-vulnerable firms

In this section, we explain how we identify downgrade-vulnerable firms and show evidence of substantial and increasing rating inflation for BBB-rated firms since 2009.

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

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

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.[5] For example, a BBB-rated firm

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[5]We thank Ed Altman for providing us with these median "benchmark" Z" scores for each rating category.

is classified as downgrade-vulnerable if its Z"-score is below the median Z"-score of BB-rated firms. A prospective fallen angel is a BBB-rated firm classified as downgrade-vulnerable.

We validate our measure of downgrade-vulnerability in Appendix B.3, where we show that (i) downgrade-vulnerable firms look worse along observables compared with non-downgrade-vulnerable firms (e.g., lower net worth, sales growth, investments, employment growth, interest coverage ratio, profitability, and higher leverage), (ii) downgrade-vulnerable firms are more likely to be downgraded and to be assigned a negative credit watch or outlook relative to non-downgrade-vulnerable firms, and (iii) firms' performance deteriorates after becoming downgrade-vulnerable (decline in sales growth, investments, firm size, and employment).

The Z"-score documents a substantial and increasing ratings inflation for BBB-rated issuers. Credit ratings inflation is defined as zero for issuers that have a Z"-score above the median Z"-score of firms in the next lower rating category and equal to the difference between the issuer credit rating notch (e.g., AA+, AA, AA-, A) and the credit rating notch implied by its Z"-score otherwise.[6] The left panel of Figure 4 shows that credit ratings inflation is highest for BBB-rated issuers, markedly increasing since 2009. The high ratings inflation for BBB-rated issuers is consistent with credit rating agencies' reluctance to downgrade BBB-rated firms to the speculative-grade market. The right panel of Figure 4 shows that downgrade-vulnerable firms are more likely to be downgraded in each rating bucket, but that this correlation is the lowest for BBB-rated issuers. This is consistent with other studies and anecdotal evidence.[7]

Panel A of Table 1 shows that the characteristics of bonds issued by downgrade-vulnerable firms are similar to those issued by non-downgrade-vulnerable firms. The remaining maturities

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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, 2020a). For a discussion on Z"-models, we refer to Altman (2018) and Altman et al. (2019).

[6]See Appendix A for additional details on the conversion of ratings notches to numerical values.

[7]For example, Bruno et al. (2016) show that Moody's avoids downgrading issuers of corporate bonds that are close to losing their investment-grade status. Investment bank analysts paint a similar picture of ratings inflation. For example in 2018 a research note by Morgan Stanley noted that, *"... where 55% of BBB debt would have a speculative-grade rating if rated based on leverage alone. Meanwhile, interest coverage has declined steadily since 2014, particularly for BBB issuers..."* (Morgan Stanley (2018a)).
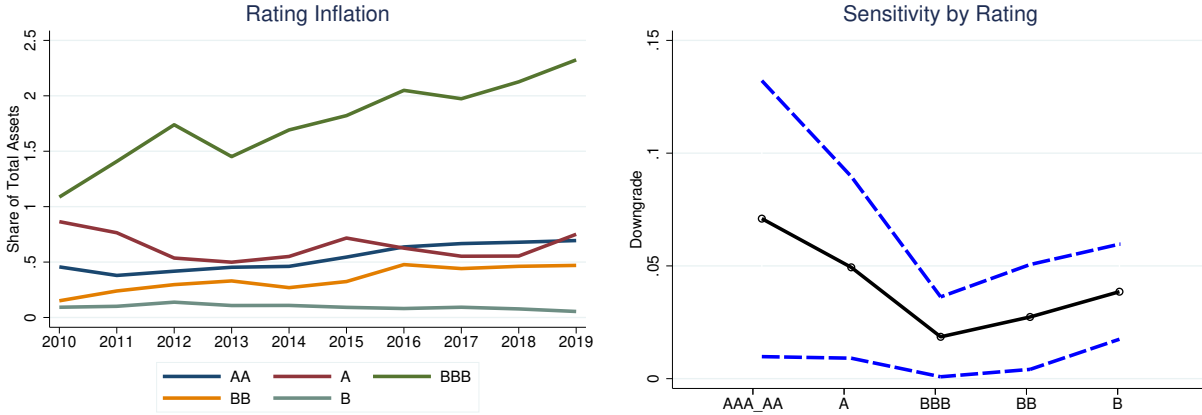
Figure 4: High and increasing credit ratings inflation for BBB-rated issuers. This figure shows credit rating inflation across rating categories. The left panel shows credit rating inflation based on firm Z"-score relative to Z"-scores of firms in lower ratings buckets. Credit rating inflation is equal to zero if an issuer has a Z"-score above the median Z"-score of firms in the next lower rating category, otherwise credit rating 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 figure shows asset weighted credit rating inflation in each year. The right panel shows how being classified as downgrade-vulnerable correlates with an actual downgrade across rating categories. The line shows, for each rating category, the estimated β_1 coefficient from the following regression specification: $Y_{iht+1} = \beta_1 Vulnerable_{iht} + \beta_2 X_{iht} + \mu_{ht} + \epsilon_{iht+1}$, where i is a firm, h an industry, t a year, Y_{iht+1} is a dummy equal to one in the case of a downgrade event in $t+1$ (to qualify as downgrade event, a firm must be downgraded by at least one rating category in year $t+1$, i.e. a firm that has a rating of A+, A, or A- is downgraded to at least BBB+), $Vulnerable$ is a dummy equal to one if a firm is downgrade-vulnerable in period t, μ_{ht} are industry-year fixed effects, and X_{iht} is a vector of controls (log of total assets, leverage, and interest coverage ratio). The error bars represent 95 percent confidence intervals, with standard errors clustered at the firm-level.

are similar, with a median remaining maturity of 6.7 years. The offering amounts are also similar as is the likelihood of bonds being classified as senior. On average, secondary market spreads on bonds issued by downgrade-vulnerable firms have *lower* spreads compared with non-downgrade-vulnerable firms on average. Panel B, however, shows that this is driven by a composition effect across the sample. Within each rating category, the mean and median secondary market spreads of bonds issued by downgrade-vulnerable firms are *higher* than those of their non-downgrade-vulnerable peers. The one exception is the BBB segment where the mean bond spread of downgrade-vulnerable issuers – prospective fallen angels – is around 4 basis points lower than their non-vulnerable peers, while the median spread is around 7 basis points lower. We analyse this anomaly in more detail in the next section.

Panel A: Bond-level descriptive statistics

Variable	Vulnerable	Mean	StDev	p25	p50	p75
Remaining maturity	No	9.6	8.5	4.0	6.7	9.9
Remaining maturity	Yes	10.0	9.0	3.7	6.7	12.8
log(offering amount)	No	13.2	0.6	12.6	13.1	13.5
log(offering amount)	Yes	13.4	0.7	12.9	13.3	13.8
Senior bond	No	0.7	0.4	0.0	1.0	1.0
Senior bond	Yes	0.7	0.4	0.0	1.0	1.0
Spread	No	223.4	206.4	117.7	170.4	265.4
Spread	Yes	217.0	219.9	107.9	166.0	246.0

Panel B: Bond spreads by rating

Rating	Vulnerable	Mean	StDev	p25	p50	p75
AAA	No	78.8	36.4	53.5	79.8	107.3
AAA	Yes	79.9	41.5	44.0	85.0	112.0
AA	No	89.8	51.7	42.2	87.5	133.8
AA	Yes	90.7	46.6	49.3	92.5	127.2
A	No	123.5	51.6	82.4	128.8	160.4
A	Yes	131.1	50.3	92.3	134.1	169.3
BBB	No	190.8	77.0	136.4	186.1	239.9
BBB	Yes	186.8	77.9	130.8	179.4	235.1
BB	No	338.1	129.6	257.8	340.7	417.1
BB	Yes	385.3	146.2	285.6	379.7	484.0
B	No	513.2	230.4	364.0	496.6	629.5
B	Yes	634.6	287.5	434.9	632.3	788.2
CCC	No	1496.1	901.5	783.2	1150.9	1955.2
CCC	Yes	1606.0	964.4	1047.7	1285.1	1895.8

Table 1: Bond-level summary statistics. This table reports summary statistics, Panel A shows shows descriptive statistics for all bonds in our sample. Panel B shows the secondary market spread by issuers' downgrade-vulnerability.

4   The exorbitant privilege

In this section, we document the extraordinarily low bond financing costs of prospective fallen angels since 2009. We show that these low bond financing costs were particularly evident between 2013 and 2016 which coincides with a period when the Federal Reserve's balance sheet grew strongly as a result of its QE purchases.

First, we show that the drop in BBB bond spreads documented above coincides with a marked decline of the spreads of downgrade-vulnerable issuers relative to non-downgrade-vulnerable issuers—a dynamic unique to the BBB market. Figure 5 shows secondary market
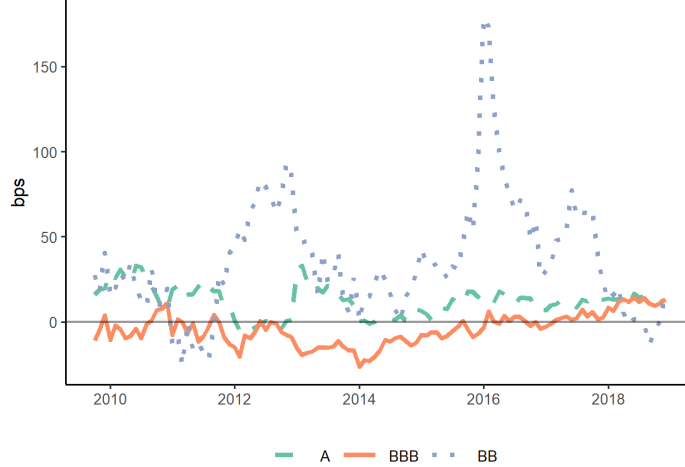
Figure 5: Bond spreads: downgrade-vulnerable – non-downgrade-vulnerable firms. This figure shows the difference in secondary market spreads between downgrade-vulnerable and non-downgrade-vulnerable issuers, separately for issuers rated A (dashed line), BBB (solid line), and B (dotted line).

spreads between downgrade-vulnerable and non-downgrade-vulnerable issuers rated A, BBB, and BB. The difference in the spread between downgrade-vulnerable and non-downgrade-vulnerable BBB-rated firms is (i) hovering around zero, (ii) *negative* from 2013 to 2016, and (iii) almost always smaller than the same difference in the A and BB markets.

Second, we confirm the existence of a privilege of prospective fallen angels using a formal test. We compare the bond spread of downgrade-vulnerable and non-downgrade-vulnerable firms within a rating category by estimating the following specification:

$$Spread_{bit} = \boldsymbol{\beta_1} \times \mathbf{Rating}_{it} + \boldsymbol{\beta_2} \times \mathbf{Rating}_{it} \times \text{Vulnerable}_{it} + \boldsymbol{\delta} \times \mathbf{X}_{bt} + \boldsymbol{\mu}_{ht} + \epsilon_{bit} \qquad (1)$$

where $Spread_{bit}$ is the spread (in basis points) of bond b issued by firm i in year t. Bond spreads are the difference between bond and treasury yields with a similar maturity. $\mathbf{Rating}_{it}$ is a vector of dummy variables corresponding to firm i rating in year t and Vulnerable$_{it}$ is an indicator variable equal to one if issuer i is classified as downgrade-vulnerable in year t. We also include a vector $\mathbf{X}_{bt}$ of bond-level characteristics in year t (residual maturity, liquidity, and a callable dummy) and industry-year fixed effects $\boldsymbol{\mu}_{ht}$. Due to a relatively low number of bonds with a AAA rating, we combine AAA- and AA-rated firms into one category.

Table 2 presents the estimation results. The first column shows the estimation results in the full sample period. As expected, the uninteracted terms show that bond spreads

are monotonically increasing as the ratings deteriorate. The interaction terms show that in all rating categories, except BBB, downgrade-vulnerable firms have either higher financing costs (AAA-AA, BB, B, CCC) or statistically indistinguishable financing costs (A) compared with non-downgrade-vulnerable firms. This correlation is reversed for BBB-rated firms as prospective fallen angels pay significantly *lower* financing costs than non-downgrade-vulnerable BBB firms. The second column shows the estimation results in the subsample running from 2013 to 2016. In this period of substantial monetary easing, the funding privilege of prospective fallen angels increases in magnitude.[8] The third and fourth columns show similar estimation results using primary market offering spreads as a dependent variable. Additionally, in Appendix B.5 we show that, consistent with an exorbitant privilege of prospective fallen angels, the sensitivity of bond spreads to changes in credit risk (measured with expected default frequencies) is the weakest for BBB-rated issuers.

Table 3 shows that this privilege is unique to the corporate bond market in the last decade.[9] The first two columns use the (log) expected default frequency derived from equity markets at the 2-year and 5-year horizons as dependent variables, respectively. While we confirm that the estimated coefficients on the uninteracted terms increase monotonically as ratings deteriorate, the funding advantage of prospective fallen angels disappears, suggesting that the exorbitant privilege is specific to the bond market. Second, the third column shows that between 2002 and 2007 (the last business cycle before the global financial crisis), downgrade-vulnerable BBB firms did not benefit from a similar privilege. In contrast, downgrade-vulnerable BBB firms paid higher spreads in this period, in line with other rating categories. Lastly, the fourth column shows that these firms did not have a similar funding advantage in the syndicated loan market. Taken together, these results suggest that the exorbitant privilege of prospective fallen angels is unique to bond markets since 2009.

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[8]See Appendix B.6 for evidence about the stance of monetary policy in our sample period.

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

	Spread	Spread	Offer Spread	Offer Spread
A	39.543***	49.667***	30.674**	12.506
	(8.489)	(8.624)	(14.738)	(8.150)
BBB	101.458***	111.983***	125.975***	103.315***
	(8.791)	(9.183)	(14.795)	(8.369)
BB	244.896***	244.390***	308.159***	260.369***
	(10.931)	(12.921)	(18.125)	(14.521)
B	395.971***	367.663***	485.593***	411.078***
	(16.245)	(26.416)	(21.700)	(22.242)
CCC	1,079.020***	1,068.282***	679.465***	453.226***
	(104.982)	(191.351)	(70.501)	(32.475)
Vulnerable × AAA-AA	23.464***	29.006***	8.094	-13.320
	(8.493)	(8.397)	(16.166)	(9.829)
Vulnerable × A	-3.902	-13.656	-6.086	-3.535
	(5.458)	(8.990)	(9.652)	(11.968)
Vulnerable × BBB	-18.186***	-33.213***	-27.477***	-36.186***
	(4.700)	(7.093)	(8.304)	(9.072)
Vulnerable × BB	30.919***	38.307***	34.649**	49.141**
	(10.585)	(12.909)	(14.559)	(23.501)
Vulnerable × B	79.032***	57.533*	54.550	57.205
	(26.524)	(32.964)	(33.141)	(58.371)
Vulnerable × CCC	447.860**	489.553*		
	(187.435)	(251.471)		
Industry-Year FE	✓	✓	✓	✓
Bond-level controls	✓	✓	✓	✓
Sample	Entire	2013–16	Entire	2013–16
Observations	19,322	9,015	3,133	1,160
R-squared	0.744	0.735	0.913	0.922

Table 2: The exorbitant privilege of prospective fallen angels. This table shows the estimation results of specification (1). The dependent variable in columns (1)-(2) is the secondary market bond spreads. The dependent variable in columns (3)-(4) is the primary market bond spread. Bond spreads, measured in basis points, are the difference between bond and treasury yields of the same maturity. Vulnerable is a dummy equal to one if a firm is downgrade-vulnerable. Bond-level controls are residual maturity, a callable dummy, and a liquidity measure. These specifications include industry-year fixed effects (2-digit SIC). Standard errors are clustered at the firm-level. *** p<0.01, ** p<0.05, * p<0.1.

	EDF 2Y	EDF 5Y	Spread	Spread
BBB	0.646***	0.567***	11.742	27.209*
	(0.084)	(0.065)	(14.271)	(14.827)
BB	1.580***	1.308***	65.479**	73.607***
	(0.101)	(0.079)	(28.847)	(15.741)
B	3.089***	2.470***	184.286***	160.509***
	(0.120)	(0.093)	(24.703)	(17.044)
CCC	4.640***	3.624***	245.292**	290.345***
	(0.192)	(0.166)	(103.430)	(54.476)
Vulnerable × AAA-A	0.484***	0.434***	10.737	28.072*
	(0.160)	(0.136)	(7.709)	(16.952)
Vulnerable × BBB	0.361**	0.283**	21.285*	13.721*
	(0.152)	(0.120)	(11.020)	(7.147)
Vulnerable × BB	0.713***	0.560***	23.706*	22.946***
	(0.166)	(0.129)	(13.454)	(7.094)
Vulnerable × B	0.817***	0.691***	53.516*	42.873***
	(0.180)	(0.140)	(27.960)	(12.400)
Vulnerable × CCC	0.360	0.416*	327.271***	17.238
	(0.284)	(0.240)	(65.169)	(71.769)
Industry-Year FE	✓	✓	✓	✓
Bond-level controls	✓	✓	✓	✓
Sample	Entire	Entire	2002-2007	Synd. loans
Observations	4,223	4,223	1,855	5,273
R-squared	0.780	0.804	0.715	0.516

Table 3: The exorbitant privilege is unique to the bond market post-2009. This table shows the estimation results of specification (1). This table provides robustness checks on mispricing in different markets and time periods. The dependent variable in columns (1)-(2) are the expected default frequencies at the 2-year and 5-year horizon, respectively. The dependent variable in column (3) is the secondary market bond spreads in the pre-global financial crisis period (2002–2007). The dependent variable in columns (4) is the all-in-drawn spread for syndicated loans taken from DealScan. The specifications include industry-year fixed effects (2-digit SIC). Standard errors are clustered at the firm-level. *** p<0.01, ** p<0.05, * p<0.1.

5   The origins of the exorbitant privilege

We now discuss the origins of the exorbitant privilege. Section 5.1 presents a theory that explains how the exorbitant privilege can arise in equilibrium. Section 5.2 to Section 5.4 provide empirical evidence supporting this theory.

5.1   Theoretical framework

The exorbitant privilege of prospective fallen angels can be rationalized by the interplay between four factors. First, a large demand for investment-grade bonds. Second, risk taking behavior of issuers. Third, leniency of credit ratings agencies to downgrades when firms undertake increased risk taking. In this section, we present the intuition behind the origin of the exorbitant privilege. We present our framework in more detail in Appendix C.

Figure 6 outlines the intuition. By absorbing large quantities of fixed income securities from the market, QE induces investors to rebalance their portfolios. This reallocation increases the demand for corporate bonds, an asset class that typically offers higher yields than other fixed income securities, such as Treasuries. The high demand for corporate bonds mechanically reduces the cost of bond financing, inducing issuers to take on more debt. More indebted issuers take on more risks, the outcome of a standard risk-shifting mechanism.

The extent of the increase in firms' risk taking, however, depends on whether issuers are vulnerable to a downgrade and the leniency of credit rating agencies. Non-downgrade-vulnerable issuers are *ex ante* unlikely to be downgraded and thus benefit less from the leniency of credit rating agencies, relative to any additional risks they may take. By contrast, downgrade-vulnerable issuers are *ex ante* more likely to be downgraded and thus benefit more from the leniency of credit rating agencies if they take additional risks. The intuition is similar to risk shifting incentives which depend on the distance to default.

Figure 7 illustrates the main results of the framework presented in Appendix C. The top panel shows bond yields as a function of firm quality, with firms grouped by credit ratings. Firms are ordered by decreasing quality on the x-axis. The blue line, corresponding to the baseline economy, shows that bond yields increase as firms deteriorate in quality. At each rating cutoff there is an additional jump, particularly pronounced at the investment-grade
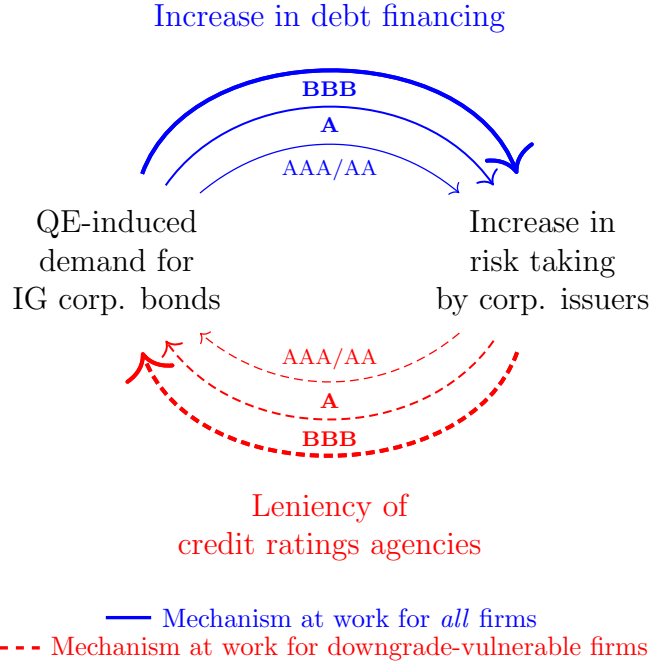
Figure 6: Scheme of model intuition. This figure shows the intuition behind the model. QE induces an increase in demand for investment-grade corporate bonds causing, in turn, an increase in issuers' debt financing. The now more indebted issuers take on more risk. This effect (blue solid lines) is at work for all firms and stronger as we move down the rating categories within the investment-grade space. Given that credit rating agencies are sluggish in downgrading firms (especially those close the investment-grade threshold), the increased risk taking by downgrade-vulnerable issuers is met again by high demand by investors sensitive to credit ratings. This effect (red dashed lines) is only at work for downgrade-vulnerable firms and stronger as we move down the rating categories within the investment-grade space.

cutoff between BBB-rated and BB-rated firms, capturing the importance of ratings (and of the investment-grade status in particular) for investors.

The dashed red line shows bond yields in an economy with a moderately higher demand for investment-grade bonds. As investors' demand increases, we observe two effects. First, the curve flattens as investors' demand throughout the IG market lowers the yield differential between high-quality and low-quality firms. Second, the curve becomes more convex within each rating bucket. This convexity is driven by lower yields of downgrade-vulnerable firms, namely firms located on the right of each rating category. These issuers benefit more from the leniency of credit rating agencies and are thus rewarded by lower bond yields. The leniency of credit rating agencies is stronger at the investment-grade rating cutoff, making the convexity for BBB-rated issuers more pronounced.

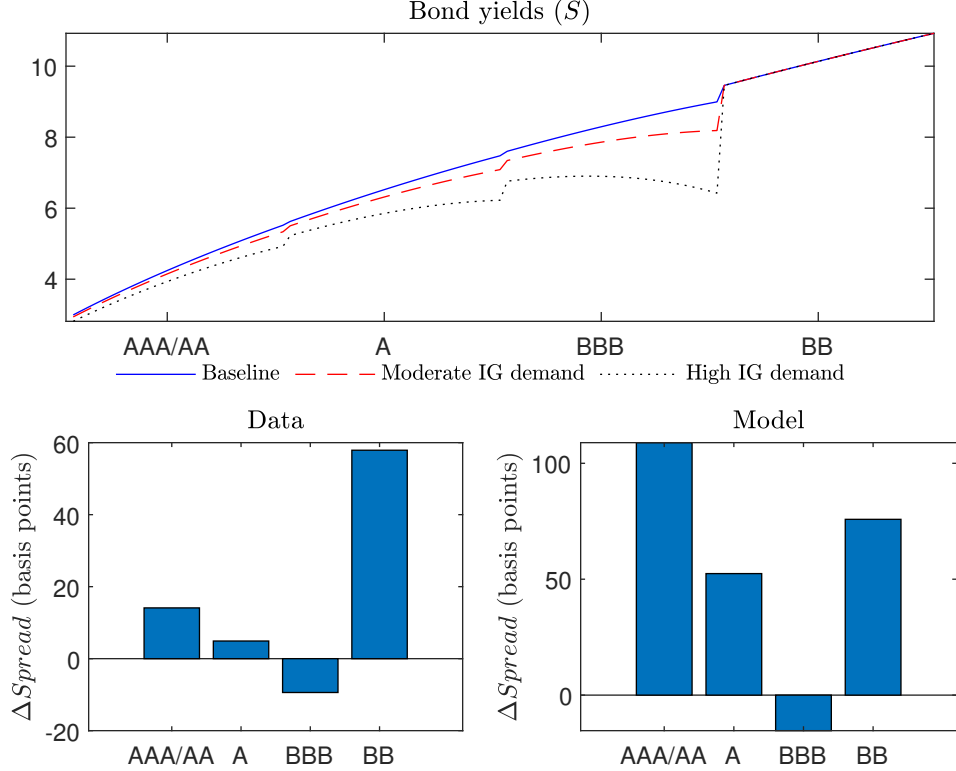With sufficiently high demand for investment-grade bonds, the black dotted line, the

Figure 7: Corporate bond yields, model and data. This figure shows corporate bond yields. The top panel presents the corporate yield curve with yields on the y-axis and firms sorted by quality, and grouped in credit ratings, on the x-axis. The solid blue line, the red dashed line, and the black dotted line represent a baseline economy, an economy with moderate demand for IG corporate bonds, and an economy with high demand for IG corporate bonds. The bottom panel shows, for each rating category, the yield spread between vulnerable and non-vulnerable issuers. The bottom left panel is the mean of this spread over the entire sample period. The bottom right panel is the model spread in the high IG demand case.

flattening and the convexity can become so pronounced that yields of bonds of prospective fallen angels can fall below that of non-downgrade-vulnerable BBB-rated issuers. The bottom panels compare the difference between the spread of downgrade-vulnerable firms and non-downgrade-vulnerable firms observed in the data in the full sample (left panel) and the one generated in our framework with a high demand for investment-grade bonds (right panel). Our framework generates the exorbitant privilege of prospective fallen angels.

The mechanism relies on two key frictions. First, credit rating agencies need to be somewhat reluctant to downgrade issuers, especially to the speculative-grade market. This leniency of credit rating agencies has been documented by Bruno et al. (2016), among others. Second, investors need to care about the investment-grade rating in their portfolio choice. A large empirical literature has discussed this friction, linking it to capital regulation and

agency problems between investment managers and investors.

The next three sections map the key elements in this framework to their empirical counterparts. Section 5.2 documents the role of QE in driving investors' demand for IG downgrade-vulnerable corporate bonds, especially those issued by prospective fallen angels. Section 5.3 documents that downgrade-vulnerable firms, and prospective fallen angels in particular, increase their bond financing to take on more risks, largely in the form of risky M&A. We document that this M&A critically exploits the leniency of credit rating agencies. Section 5.4 shows that bonds issued to finance M&A are in high demand and are largely responsible for the exorbitant privilege.

5.2 QE-driven demand by investment-grade investors

In this section, we document that investors exposed to the Federal Reserve QE programs drive the demand for IG corporate bonds, especially those issued by prospective fallen angels. This dynamic is entirely driven by investors that predominantly hold IG bonds.

Exploiting our granular holdings data, we measure investors' exposure to QE and observe investors' holdings of investment-grade bonds. We measure investor-level exposure to QE merging our holdings-level data with the Federal Reserve SOMA holdings data. Investor time-varying exposure to QE is defined as the share of investor total holdings that are held by the Federal Reserve in the SOMA Treasury portfolio, where holdings are weighted by the share of amounts outstanding held by the Federal Reserve.[10] The idea is that investors with a substantial share of their security holdings held by the Federal Reserve at time t are more affected by QE through its rebalancing channel (Gagnon et al., 2011). We classify an investor as an investment-grade investor if its mean holdings of investment-grade bonds in

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[10]Formally, we define the variable QE Exposure$_{kt}$ as follows:

$$\text{QE Exposure}_{kt} = \frac{\sum_i (Holdings_{ikt} \times SOMA_{it})}{\sum_i Holdings_{ikt}} \tag{2}$$

where i is a security, k is an investor, and t is a date. $SOMA_{it}$ is the share of Treasury security i held by the Federal Reserve at date t. $Holdings_{ikt}$ are the holdings of security i held by investor k at time t. This variable is calculated at a quarterly frequency.
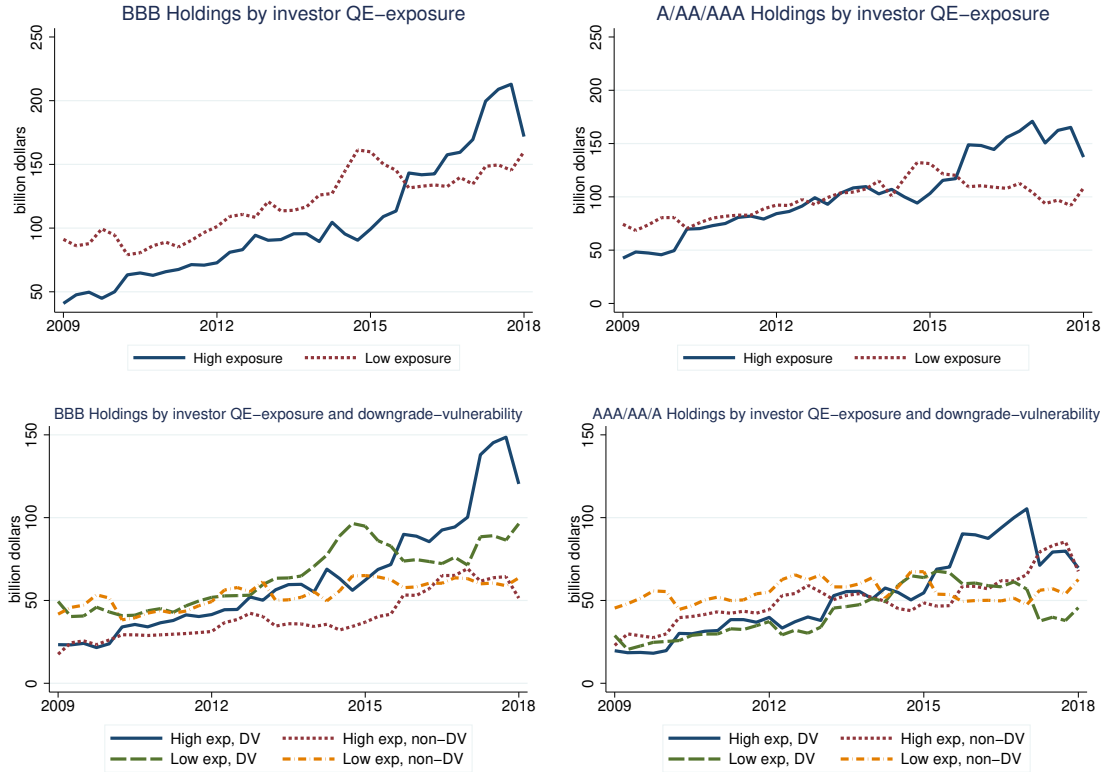
Figure 8: Investors' holdings of IG corporate bonds. This figure shows investors' holdings of investment grade corporate bonds, broken down by investor QE exposure and issuer rating and downgrade-vulnerability. The top panels show holdings of bonds issued by BBB-rated issuers (top left panel) and A/AA/AAA-rated issuers (top right panel) by high-exposure (blue solid line) and low-exposure (red dotted line) investors. High-exposure investors have an above median exposure to QE. The bottom panels show holdings of bonds issued by BBB-rated issuers (bottom left panel, broken down by downgrade-vulnerability) and A/AA/AAA-rated issuers (bottom right panel, broken down by downgrade-vulnerability) by high-exposure and low-exposure investors.

the entire sample period are at least 80% of its entire bond portfolio. We classify investors as non-investment grade if their holdings of investment-grade bonds are less than 60% of their portfolio.[11]

Figure 8 shows that high-exposure investors (above median QE exposure) increased their holdings of investment-grade corporate bonds compared with low-exposure (below median QE exposure) investors starting around 2014. This differential dynamic is particularly pronounced in the BBB market and, within the BBB market, for downgrade-vulnerable

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[11]Our results are robust to different thresholds. With these somewhat arbitrary thresholds, we split the sample in three terciles with roughly the same number of observations.

issuers. The top panel compares holdings by high-exposure and low-exposure investors in the BBB market (top left panel) and A/AA/AAA market (top right panel). High-exposure investors substantially increase their holdings starting in 2014 in both markets but more so in the BBB market. The two bottom panel further split holdings depending on whether bonds are issued by downgrade-vulnerable or non-downgrade-vulnerable firms. The substantial increase in holdings by high-exposure investors is almost entirely driven by holdings of downgrade-vulnerable firms. Again, this dynamic is more pronounced in the BBB market.

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

$$Holdings_{kjt} = \alpha + \beta_1 \text{QE Exposure}_{kt} \times Vulnerable_{jt} + \eta_{kt} + \mu_{jt} + \epsilon_{jkt} \tag{3}$$

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

The coefficient of interest β_1 captures whether investors more exposed to QE hold more or fewer bonds issued by downgrade-vulnerable issuers from 2009 to 2018 compared with investors less exposed to QE. In the most stringent specification, we are effectively comparing bonds, at time t, issued by the *same issuer* that are held by investors with a different QE exposure. In particular, we include investor-time and issuer-time fixed effects. Investor-time fixed effects 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 the QE-induced rebalancing channel. Issuer-time fixed effects control for the potential differential characteristics of downgrade-vulnerable and non-downgrade-vulnerable bonds (e.g., issuance volume) that might interact with the portfolio choice of high-exposure Vs. low-exposure investors for reasons, again, unrelated to the rebalancing channel.

Table 4 shows the estimation results. In the top panel, the first four columns show the coefficients estimated in the full sample. The estimated coefficient β_1 is positive and

PANEL A				$Holdings_{jkt}$		
QE Exposure$_{kt} \times Vulnerable_{jt}$	1.461***	1.328***	1.371***	1.271***	1.365***	-0.044
	(0.371)	(0.345)	(0.373)	(0.349)	(0.448)	(0.542)
Fixed Effects						
Issuer j	✓	✓				
Investor k	✓		✓			
Time t	✓					
Investor k - Time t		✓		✓	✓	✓
Issuer j - Time t			✓	✓	✓	✓
Sample investors	Full	Full	Full	Full	IG	non-IG
Observations	4,838,897	4,837,690	4,838,153	4,836,946	1,316,637	1,153,770
R-squared	0.505	0.556	0.524	0.575	0.605	0.547

PANEL B				$Holdings_{jkt}$		
QE Exposure$_{kt} \times Vulnerable_{jt}$	0.281	0.718*	1.939***	-1.024**	2.171***	-0.243
	(0.946)	(0.428)	(0.483)	(0.482)	(0.658)	(0.979)
Fixed Effects						
Investor k - Time t	✓	✓	✓	✓	✓	✓
Issuer j - Time t	✓	✓	✓	✓	✓	✓
Sample investors	Full	Full	Full	Full	IG	non-IG
Sample issuers	AAA/AA	A	BBB	HY	BBB	BBB
Observations	287,950	1,020,557	1,744,170	1,001,739	549,619	220,531
R-squared	0.726	0.673	0.616	0.537	0.621	0.644

Table 4: Demand for bonds issued by prospective fallen angels. This table presents estimation results from specification (3). The unit of observation is investor k-issuer j-date t. The dependent variable is $log(1 + Holdings_{jkt})$, where $Holdings$ are holdings by investor k in year t of corporate bonds issued by issuer j (thousands dollars). QE exposure$_{kt}$ is defined in (2). $Vulnerable_{jt}$ is a dummy equal to 1 if issuer j is downgrade-vulnerable to a downgrade in date t. The uninteracted $Vulnerable_{jt}$ and QE exposure$_{kt}$ terms are included in the estimation but not reported for brevity. In panel A, the first four columns are estimated in the full sample of investors and the last two columns are estimated in the subsample of investors with holdings of investment grade bonds greater than 80% and smaller than 60%, respectively. In panel B, the first four columns are estimated in the full sample of investors and in the subsample of issuers based on their rating and the last two columns are estimated in the subsample of BBB issuers for investment grade and non-investment grade investors respectively.. Standard errors double clustered at the investor k level and issuer j level reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

significant, suggesting that more exposed investors have a higher demand for bonds issued by downgrade-vulnerable issuers compared to less exposed investors. In the last two columns, we estimate the specification in the subsample of investment-grade and non-investment grade investors, respectively. The estimation results show that the demand of high-exposure investors for bonds issued by downgrade-vulnerable firms is stronger among investment-grade investors. The bottom panel shows other sample splits. In the first four columns, the estimation is run in the subsample of AAA/AA, A, BBB, and speculative-grade issuers. The results show that the overall effect is driven by BBB issuers. The last two columns show

results for the subsample of BBB issuers for investment grade and non-investment grade investors, respectively. The results confirm that the effects in the BBB segment are driven by investment-grade investors.

5.3 Issuers' risk taking and M&A activity

We now document how issuers meet the demand for corporate bonds discussed in the previous subsection. First, we show that downgrade-vulnerable issuers, and prospective fallen angels in particular, supply bonds largely for the purpose of financing acquisitions. Second, we show that these M&A deals allow downgrade-vulnerable issuers, and prospective fallen angels in particular, to substantially increase their market share and prolong their rating inflation—at the cost of increased fragility.

Figure 9 shows the substantial increase in investment-grade bond issuance since 2013–15, in large part to fund M&A activity. The figure shows the annual number of bond issues (left panel) and the offering amount (right panel) from 2009 to 2019, separately for high-yield (speculative-grade), BBB-rated, and A/AA/AAA-rated issuers. Both bond issues and offering amount markedly increase in the investment-grade market around 2013–15.[12] We do not observe a similar increase in the speculative-grade market. The figure further distinguishes between issuance for the purpose of funding an M&A deal and other issuance. While negligible in the speculative-grade space, issuance to fund M&A plays a progressively more important role in the IG market especially, again, since 2013–15.

Figure 10 shows that downgrade-vulnerable firms, and prospective fallen angels in particular, drive the increase in M&A activity since 2014 in the IG market. This is not the case in the speculative-grade market, as shown in Appendix B.7. The top panel and bottom panels focus on BBB-rated firms and A/AA/AAA-rated firms, respectively. The left and right panels focus on downgrade-vulnerable and non-downgrade-vulnerable firms, respectively. M&A deal volume increases substantially in 2014 for downgrade-vulnerable firms while stays

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[12]The spikes in the offering amount in 2015–17 and 2019 are explained by a few large issuances by Procter and Gamble (2015), Intl. Business Machines (2016), Walmart (2017), and Berkshire Hathaway (2019).
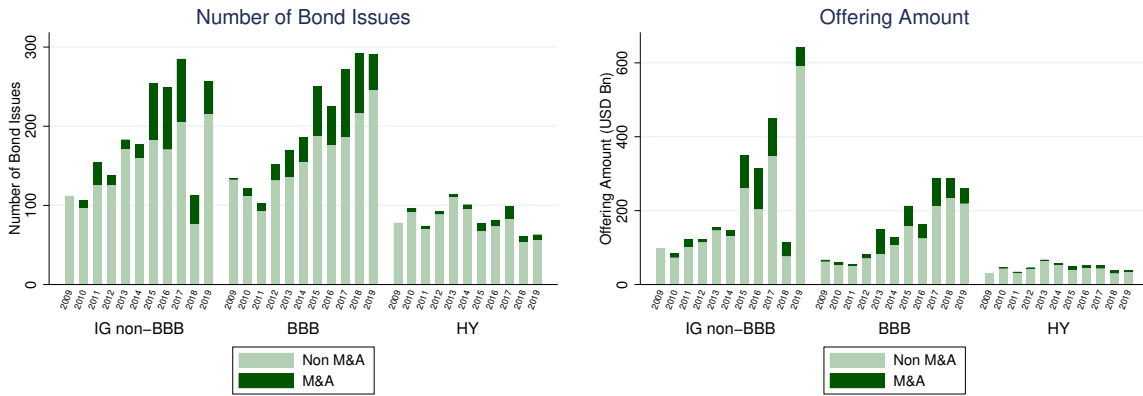
Figure 9: Bond issuance and volume. This figure shows the bond issues and bond volume for high-yield (speculative-grade), BBB-rated, and A/AA/AAA rated firms over time. The right panel shows the total number of bond issues, separated by M&A and non-M&A bond issues. The left panel shows the total offering amount, separated by M&A and non-M&A bond issues. An M&A bond issues is defined based on the bond purpose of the issue. Due to limited coverage of bond issue purposes, the M&A bond issues and issue volume likely represent a lower bound. The jumps in the offering amount can be explained by the large bond issuances that have been done by Procter and Gamble Co (2015), Intl Business Machines Corp (2016), Walmart Inc (2017) and Berkshire Hathaway (2019).
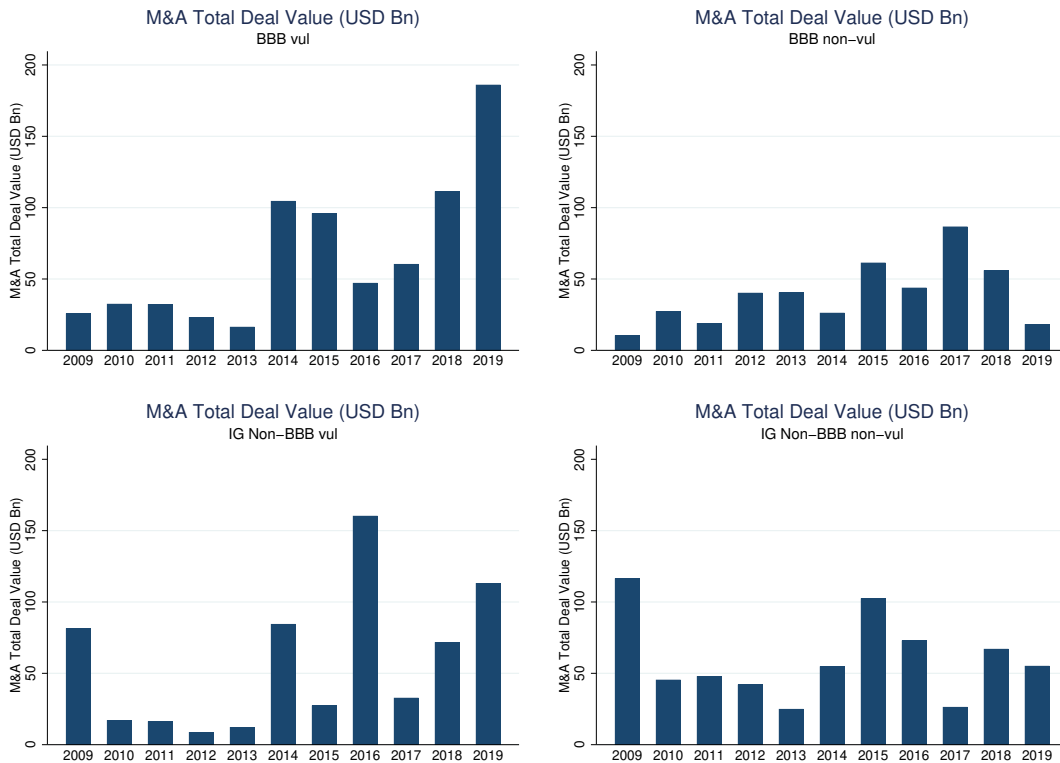

Figure 10: M&A deal volume. This figure shows the total M&A deal volume for vulnerable (left panel) and non-vulnerable (right panel) firms in the BBB rating category (top panel) and the A/AA/AAA rating category (bottom panel). Figure B.9 presents the same charts for speculative-grade firms.

roughly constant for non-downgrade-vulnerable firms. The increase is particularly noticeable for BBB-rated firms.

Having documented the increase in IG issuance to fund M&A and the increased M&A activity by downgrade-vulnerable firms, we now show that downgrade-vulnerable firms use M&A to prolong rating inflation and to increase their risk taking.

M&A to prolong rating inflation   Downgrade-vulnerable issuers engage in M&A to prolong their rating inflation. The announcement of an acquisition is almost always accompanied by rosy forecasts of synergies that will reduce costs and increase revenues and, even more importantly, a leverage-reduction plan. This plan is a promise to reduce the debt taken on to finance the acquisition in an, often successful, attempt to convince credit rating agencies about the issuer future prospects. We show in Appendix B.8 that this promise is often broken. This evidence is consistent with substantial anecdotal evidence from market participants. 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..."*

We have documented that ratings inflation is particularly high in the BBB market. We now show that this inflation is largely driven by M&A activity. Formally, we estimate the following specification in the subsample of downgrade-vulnerable firms:

$$Y_{ijt} = \beta_1 \times M\&A \times BBB_{ijt} + \beta_2 \times \text{BBB}_{ijt} + \beta_3 \times \text{M\&A}_{ijt} + X_{ijt} + \eta_{jt} + \epsilon_{ijt} \qquad (4)$$

where i is a firm, j is the industry, and t is year. The dependent variable Y_{ijt} 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 independent variable of interest is the interaction between $M\&A_{ijt}$, a dummy equal to one in the year firm i has conducted an M&A deal and for the years thereafter. BBB_{ijt} is a dummy equal to one if firm i has a BBB rating in t. X_{ijt} represents a set of firm controls (log assets, leverage and net worth) and η_{jt}

	Rating inflation	Rating inflation	Downgrade probability	Time to downgrade	Upgrade probability	Up/Downgrade intensity (Δ notch)
BBB	0.380**	-0.041	-0.069**	-0.677***	-0.026	0.003
	(0.188)	(0.290)	(0.032)	(0.244)	(0.019)	(0.082)
M&A $\times$ BBB		0.642**	-0.082**	-0.176	0.070**	-0.250***
		(0.302)	(0.038)	(0.290)	(0.033)	(0.093)
M&A		-0.318	0.043*	0.533*	-0.036*	0.104*
		(0.199)	(0.024)	(0.270)	(0.019)	(0.059)
Industry-Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Sample	Vulnerable Entire	Vulnerable Entire	Vulnerable Rating changes	Vulnerable Downgrades	Vulnerable Rating changes	Vulnerable Rating changes
Observations	2,750	2,750	255	143	255	255
R-squared	0.381	0.386	0.616	0.723	0.505	0.543

Table 5: The role of M&A in prolonging ratings inflation. This table presents firm-level regressions for vulnerable firms. In the left-hand panel, we focus on the entire sample. The dependent variable is rating 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. In the right-hand panel, we restrict our sample to all firm-years with rating changes (or downgrades). In these regressions M&A takes the value of one if - between rating changes - a firm has done an M&A deal while being vulnerable. The dependent variables include i) downgrade probability, which is a dummy variable equal to one in case of a downgrade by at least one rating category, ii) time to downgrade, which measures the time between the first time a firm is considered to be vulnerable after a rating change, up until the next rating change, iii) upgrade probability, which is a dummy variable equal to one in case of an upgrade by at least one rating category, and iv) downgrade intensity which measures the number of notches a firm is up- or downgraded. A positive number refers to a downgrade, and a negative number to an upgrade. The dependent variables are weighted by the total debt outstanding in a rating category in a given year. All specifications include industry-year fixed effects and firm-level controls (including log(total assets), leverage, net worth and tangibility (ppent / assets)). Standard errors are clustered at the firm level.

are industry-year fixed effects.

Table 5 shows the estimation results. The first column suggests that downgrade-vulnerable BBB issuers enjoy an additional 0.4 notches in ratings inflation compared with downgrade-vulnerable issuers in other ratings buckets. The second column shows that, within downgrade-vulnerable firms, ratings inflation is largely driven by firms that have undertaken an M&A. This M&A ratings inflation is, however, only enjoyed by BBB-rated issuers.

The last four columns further confirm the interplay between M&A and the leniency of credit rating agencies. In these columns, we restrict the sample to the firm-year pairs where we observe a rating change, namely either a credit rating upgrade or a downgrade. In columns (3) and (4), the independent variable is the probability of a downgrade and the time it takes a firm to get downgraded. In this test, the M&A dummy is equal to one in the case a downgrade-vulnerable firm has done an M&A deal. Column (3) shows that, while downgrade-vulnerable firms that undertake M&A have a higher probability of downgrade, prospective

fallen angels that undertake M&A have a *lower* probability of downgrade, consistent with a "wait-and-see" approach of credit rating agencies for BBB-rated issuers. In column (4), we further restrict the sample to include only downgrades. We find that, conditional on being downgraded, M&A extends the time-to-downgrade in all rating categories.

The inherent riskiness of M&A might be, ex-post, good news for the downgrade-vulnerable firm. The last two columns of the table likely capture these cases. Column (5) shows that, for prospective fallen angels, M&A provides an upside potential, estimated as an increased upgrade probability. This upside potential is confirmed in the last column, where the negative coefficient of the interaction term captures a higher upgrade intensity relative to other M&A firms. However, in the remainder of this section, we show that M&A causes a buildup in vulnerability, which materialized at the onset of the COVID-19 pandemic.

M&A as risk taking   Downgrade-vulnerable issuers engage in M&A to increase their risk-taking while being somewhat protected, as discussed above, from credit ratings downgrades. We now show that M&A allows downgrade-vulnerable firms, and prospective fallen angels in particular, to substantially increase their market share at the cost of increased fragility. This fragility materialized at the onset of the COVID-19 shock, leading to an unprecedented wave of fallen angels, almost entirely among those firms that engaged in M&A.

Figure 11 shows the substantial increase in market shares by prospective fallen angels. The top left panel shows the evolution of markets shares by issuer rating, highlighting the rapid increase in BBB-rated issuers' market share starting from around 2014. The top right panel further 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. The bottom panel only focuses on BBB-rated issuers. It shows that the increase in market share of BBB-rated firms from 2014 to 2019 has been driven by prospective fallen angels engaging in M&A.

The increased fragility of prospective fallen angels engaging in M&A materialized in March 2020, at the onset of the COVID-19 pandemic. Figure 12 shows that the yearly debt volume that has been downgraded (upgraded) from downgrade-vulnerable BBB firms to the next lower (higher) rating category. The two panels separate the debt volumes for the firms that
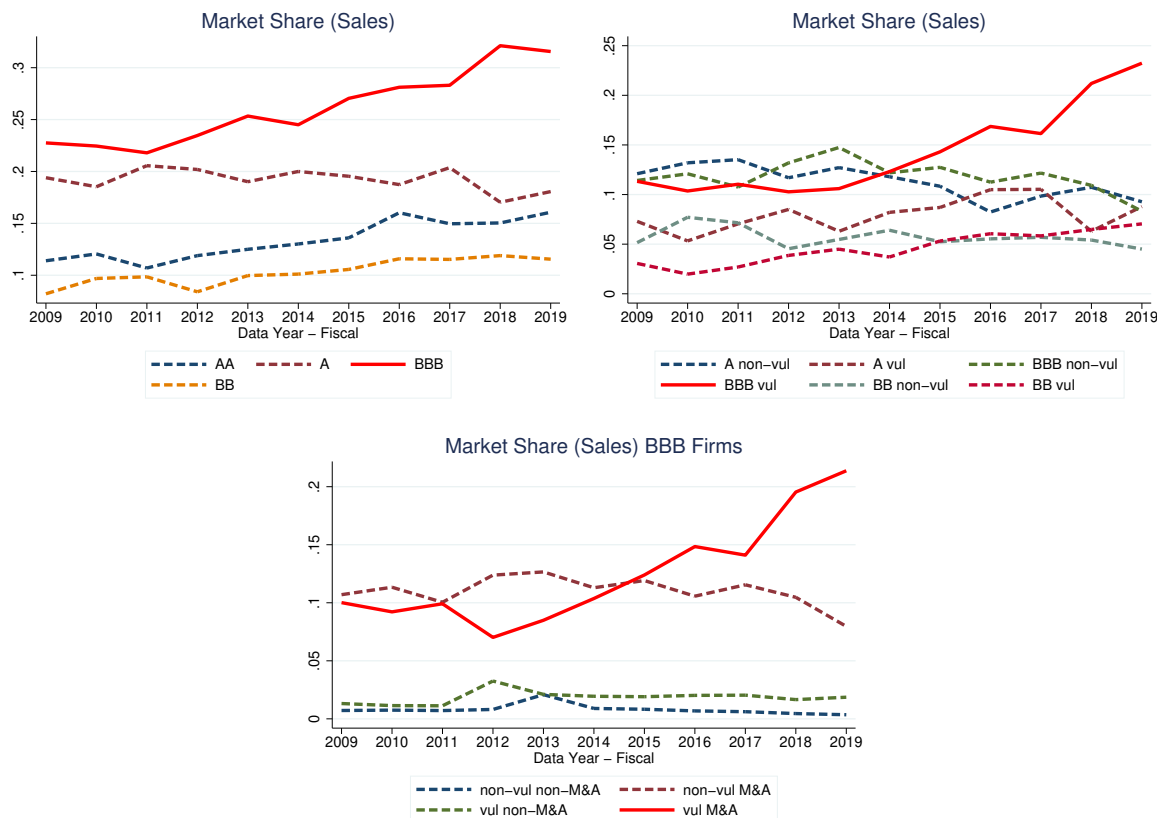
Figure 11: The increase in market share of prospective fallen angels. This figure shows the evolution of firm market share (share of sales). The top left panel includes all firms in Compustat, grouped by credit rating from AA to BB. The top right panel distinguishes between downgrade-vulnerable and non-downgrade-vulnerable firm within each rating. The bottom panel only includes BBB-rated issuers, broken down by downgrade-vulnerability and M&A activity.

engaged in M&A (left panel) and firms that did not engage in M&A (right panel). The green bar in Figure 12 shows that the debt downgraded from BBB to speculative-grade in 2020 was almost entirely driven by firms that engaged in M&A. The different shades indicate the severity of the downgrade (number of notches). The different pattern in 2020 is remarkable.[13] We complement this ex-post evidence with ex-ante evidence in Appendix B.11, where 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

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[13]Appendix B.10 shows a somewhat similar pattern when looking at the number of issuers downgraded, not weighted by debt volume.
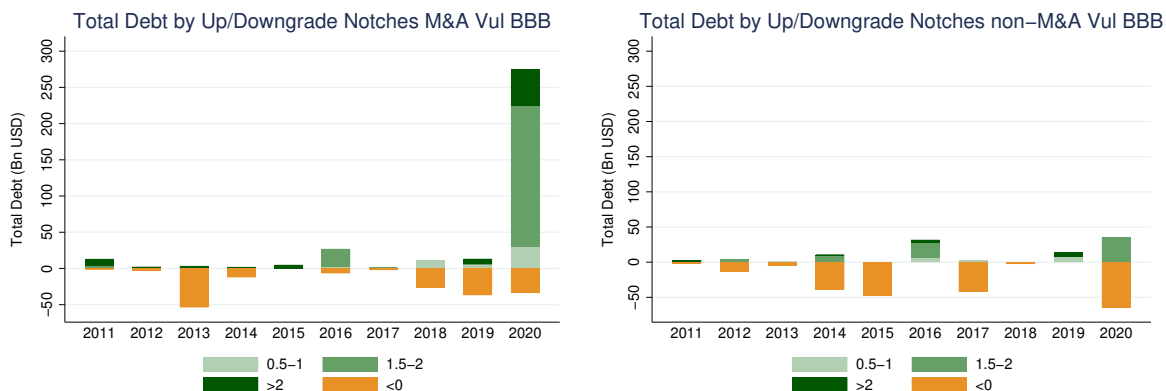
Figure 12: Downgrade materialization of (prospective) fallen angels. This figure shows the total debt of vulnerable BBB-rated firms that has been upgraded and downgraded in the years 2011 to 2020. The downgraded debt is grouped according to their downgrade severity. The downgrade severity is measured by the number of notches a firm is being downgraded, and is subdivided into three broad categories: 0.5-1, 1.5-2, >2 notches, as reflected by the green shades. The upgraded debt is shown by the orange bars, and is represented by the notches below zero. The left-hand panel plots the total amount of up/downgraded debt for vulnerable BBB firms that have conducted an M&A since the year that they have become vulnerable. The right-hand panel shows the total amount of up/downgraded debt for firms that have not conducted an M&A since the year that they have become vulnerable.

M&A announcement date (not the case for non-downgrade-vulnerable BBB-rated issuers).

More formally, Table 6 confirms that the COVID-19 shock affected in particular those prospective fallen angels that engaged in M&A. For this analysis, we augment specification (4) to include a triple interaction with a dummy variable equal to one in 2020. In Column (1), the sum of the coefficients of $M\&A$ and $M\&A \times 2020$ shows that undertaking M&A does not affect the probability of being downgraded in 2020. However, the incremental effect of $M\&A \times BBB$ and $M\&A \times BBB \times 2020$ shows that this is not the case for the BBB rating category. The downgrade risk of prospective fallen angels in 2020 is larger and materializes in an economic downturn. Importantly, Column (2) shows that while COVID had an effect on the downgrade probability of prospective fallen angels that engaged in M&A, it did not affect their upgrade probability in 2020.

In Column (3), we replace the probability of upgrades and downgrades by their intensity, measured by the number of notches a firm is upgraded or downgraded. A positive number refers to a downgrade, and a negative number to an upgrade. The sum of the coefficients $M\&A \times BBB$ and $M\&A$ show that, in the years prior to the COVID-shock, the downgrade-vulnerable BBB firms that conducted M&A deals have a greater upgrade intensity, echoing the results of Table 5. However, once the COVID-shock hits the economy, we see that the

	Downgrade probability	Upgrade probability	Up/Downgrade intensity (Δ notch)	Time to downgrade
M&A × BBB × 2020	0.233***	-0.051	0.441**	1.034*
	(0.068)	(0.050)	(0.170)	(0.566)
M&A × 2020	-0.065*	0.006	-0.022	-0.965**
	(0.037)	(0.032)	(0.125)	(0.437)
M&A × BBB	-0.124***	0.090**	-0.328***	-0.459
	(0.046)	(0.043)	(0.115)	(0.408)
BBB × 2020	-0.130**	-0.023	-0.273**	-0.512
	(0.052)	(0.032)	(0.123)	(0.435)
BBB	-0.056*	-0.025	0.023	-0.579**
	(0.032)	(0.020)	(0.082)	(0.245)
M&A	0.055**	-0.038*	0.109	0.772**
	(0.028)	(0.023)	(0.068)	(0.357)
Industry-Year FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Sample	Vulnerable firms Rating changes	Vulnerable firms Rating changes	Vulnerable firms Rating changes	Vulnerable firms Downgrades
Observations	255	255	255	143
R-squared	0.625	0.512	0.550	0.736

Table 6: Downgrade / Upgrade Results - Vulnerable firms. This table presents estimation results from the augmented specification (4). The dependent variables are downgrade probability, upgrade probability, time to downgrade and downgrade intensity, weighted by the total debt amount in a rating category in a given year. Downgrade / upgrade probability are dummy variables which take the value of one in case of a downgrade / upgrade. Downgrade intensity measures the number of notches a firm is downgraded, if downgraded by at least one rating category. Time to downgrade measures the time it took a firm to downgrade after obtaining the vulnerability status. Control variables include the log of total assets, leverage and tangibility (ppent / assets). For columns (1), (2), and (3), the sample consists of vulnerable firms that have experienced a rating change. Column (4) focuses on vulnerable firms that have been downgraded. Standard errors are clustered at the firm-level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

pattern reverses. In 2020, downgrade-vulnerable BBB firms have not only been downgraded more often, but have also been downgraded by more notches.

Finally, we turn to the question whether the downgrades of prospective fallen angels in 2020 can be linked to the leniency of credit rating agencies. To this end, we examine the time it took the downgrade-vulnerable firms to get downgraded in 2020. From Column (4) we observe that, if anything, it took longer for a downgrade-vulnerable BBB rated firm that did an M&A deal. These results hint to the fact that the highly-indebted BBB firms that fell off the cliff in 2020, got the benefit of the doubt by the credit rating agencies during the years without economic slowdowns. But, that once such economic downturn hit the economy, the credit rating agencies could no longer turn a blind eye. As previously shown in Figure 12, this resulted in a massive amount of debt being downgraded.

	$Holdings^{M\&A}_{jkt}$				$Holdings^{nonM\&A}_{jkt}$
QE Exposure$_{kt}$ × $Vulnerable_{jt}$	0.233	-0.133	2.009***	-0.593	1.191*
	(0.969)	(0.597)	(0.636)	(0.500)	(0.664)
Fixed Effects					
Investor k - Time t	✓	✓	✓	✓	✓
Issuer j - Time t	✓	✓	✓	✓	✓
Sample issuers	AAA/AA	A	BBB	HY	BBB
Observations	239,536	1,020,557	1,744,170	1,745,994	1,744,170
R-squared	0.635	0.477	0.512	0.566	0.522

Table 7: Demand for Bonds Issued by Prospective Fallen Angels to Fund M&A. This table presents estimation results from specification (3). The unit of observation is investor k-issuer j-date t. The dependent variable is $log(1 + Holdings_{jkt})$, where $Holdings$ are holdings by investor k in year t of corporate bonds issued by issuer j (thousands dollars). In the first four columns, the dependent variable are holdings of bonds issued to fund M&A. In the last column, the dependent variable is holdings of bonds issued for reasons other than funding M&A. QE exposure$_{kt}$ is defined in (2). $Vulnerable_{jt}$ is a dummy equal to 1 if issuer j is vulnerable to a downgrade at date t. Standard errors double clustered at the investor k and issuer j level reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.4 Investors' appetite for M&A bonds

In this section we analyse investors' appetite for bonds linked to vulnerable firm M&A and the roll of M&A in driving the bond market subsidy of prospective fallen angels. To this end, we first revisit our analysis of investors' demand for bonds, zooming in on bonds issued for M&As. Second, we examine whether bonds that are issued with an M&A purpose by vulnerable BBB firms have a higher propensity to be subsidized.

We analyze investors' demand for bonds issued by prospective fallen angels to fund M&A activity by estimating specification (3) separately for holdings of bonds issued to fund M&A and for holdings of other bonds. The results are presented in Table 8. In the first four columns, the dependent variable is holdings of bonds issued to fund M&A. The results in these columns show that high-exposure investors hold more bonds issued by prospective fallen angels to fund M&A activity compared with low-exposure investors. This correlation is unique to the BBB segment. In the last column, the dependent variable is holdings of other bonds. It shows that the demand by high-exposure investors for bonds issued by prospective fallen angels for non-M&A bonds is lower compared with the demand for M&A bonds.

Finally, we examine whether bonds that are issued with an M&A purpose by vulnerable BBB firms have a higher propensity to be subsidized. We do so by estimating the following

	Subsidy	Subsidy	Subsidy	Subsidy
M&A	-0.349	0.138**	0.161*	0.106
	(0.235)	(0.061)	(0.089)	(0.094)
Firm-Year FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Sample	Vulnerable BBB	Vulnerable BBB	Vulnerable BBB	Vulnerable BBB
	2009-2012	2013-2019	2013-2016	2017-2019
Observations	140	447	200	247
R-squared	0.593	0.674	0.765	0.621

Table 8: Subsidy for Bonds Funding M&A. This table presents estimation results from specification (5). The unit of observation is bond i-year t. The dependent variable is *Subsidy*, where *Subsidy* is a dummy variable which takes the value of one if a bond is subsidized - i.e. when the treasury spread of the bond is lower than the median treasury spread of non-vulnerable firms in the same rating category. *M&A* is a dummy variable which takes the value of one if the purpose of the bond is to fund M&A. Bond controls (log of offering amount, maturity, seniority and callability) as well as firm-year FE are included. Standard errors are clustered at the issuer j level, and reported in the parentheses. *** p<0.01, ** p<0.05, * p<0.1.

specification, in which we effectively compare bonds within the same firm-year:

$$Subsidy_{ijt} = \beta_1 \, \text{M\&A}_{ijt} + X_{ijt} + \theta_{jt} + \epsilon_{ijt} \qquad (5)$$

where i is a bond, j is an issuer, and t is time (yearly frequency). The dependent variable is a dummy variable which takes the value of one if a bond is subsidized - i.e. when the treasury spread of the bond is lower than the median treasury spread of non-vulnerable firms in the same rating category. The independent variable, M&A, is a dummy variable which takes the value of one if the purpose of the bond is to fund M&A. X_{ijt} represents a set of bond controls (log of offering amount, maturity, seniority and callability). θ_{jt} denotes the firm-year fixed effects.

Table 8 shows that within the set of bonds issued by vulnerable BBB issuers, those issued for the purposes of an M&A are more likely to benefit from the bond market subsidy. And that this tends to be during the period when QE purchases were large, but is less evident during the 2009-2012 and 2017-2019 periods.

6 Real effects of the exorbitant privilege

We have documented that the market share of prospective fallen angels increases substantially in our sample period, and especially since 2013–14, driven at least partially by M&A. In this

section, we show that non-downgrade-vulnerable firms are negatively affected by the presence of prospective fallen angels in their market.

This congestion effect is similar to the one documented in the context of zombie lending. Hence, we follow that (most notably Caballero et al. (2008)) and estimate the following regression at the firm-year level:

$$
\begin{aligned}
Y_{iht} \;=\;\; & \beta_1 \times \text{Non-Vulnerable}_{iht} \\
+\;\; & \beta_2 \times \text{Non-Vulnerable}_{iht} \times \text{Share Vulnerable BBB}_{ht-1} + \eta_{ht} + \epsilon_{iht},
\end{aligned}
\tag{6}
$$

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

Table 9 shows 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 downgrade-vulnerable BBB firms. 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 significantly 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 in their industry.

Panel B shows that these spillover effects are not present when we replace that share of prospective fallen angels with the overall share of downgrade-vulnerable rated firms. This result confirms the uniqueness of prospective fallen angels, also when it comes to driving negative spillover effects. Panel C confirms our main results for the full sample of firms (rated and unrated).

	Emp Growth	CAPX	Sales Growth	Markup
Panel A: Rated Firms - Vulnerable IG				
Non-vulnerable IG	0.013	0.029**	-0.003	0.570**
	(0.008)	(0.011)	(0.008)	(0.261)
Non-vulnerable IG × Share Vulnerable BBB	-0.090**	-0.112***	-0.089**	-1.555**
	(0.042)	(0.041)	(0.038)	(0.767)
Observations	6,923	7,113	7,121	7,121
R-squared	0.112	0.318	0.278	0.256
Panel B: Rated Firms - Placebo				
Non-vulnerable IG	0.023	0.019*	0.003	0.363
	(0.014)	(0.010)	(0.012)	(0.219)
Non-vulnerable IG × Share Vulnerable	-0.040	-0.009	-0.022	0.087
	(0.030)	(0.023)	(0.025)	(0.336)
Observations	6,923	7,113	7,121	7,121
R-squared	0.112	0.318	0.278	0.256
Panel C: All Firms				
Non-vulnerable	0.038***	0.040***	0.038***	0.395**
	(0.010)	(0.011)	(0.012)	(0.190)
Non-vulnerable × Share Vulnerable BBB	-0.068***	-0.094**	-0.074**	-0.873**
	(0.025)	(0.046)	(0.029)	(0.432)
Observations	26,009	27,471	26,978	26,872
R-squared	0.042	0.191	0.045	0.133
Industry-Year FE	✓	✓	✓	✓
Firm-level Controls	✓	✓	✓	✓

Table 9: Real effects, negative spillovers on other firms. This table presents estimation results from specification (6). The dependent variables are employment growth, CAPX/PPE, sales growth, and markups (defined as sales/cost of goods sold). Vulnerable/non-vulnerable is defined in Section 3.2. Panel A focuses on non-downgrade-vulnerable investment-grade firms and limits the sample to firms with a rating from at least one rating agency. Panel B focuses on all non-downgrade-vulnerable firms. Panel C focuses on non-downgrade-vulnerable firms, using the entire sample of firms. Share Vulnerable BBB measures the asset-weighted share of downgrade-vulnerable BBB firms in a two-digit SIC industry. Firm-level control variables include log of total assets, leverage, net worth, and an indicator variables for the rating bucket (AAA, AA, A, etc.). Standard errors are clustered at the industry-level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

7 Conclusion

We document an exorbitant privilege in the form of a bond market borrowing cost subsidy for prospective fallen angels, namely firms on the cusp of the investment-grade cutoff, and the costs that such privilege and corporate response to it impose on the economy. This subsidy, present since the Global Financial Crisis and driven by QE-induced demand for investment-grade bonds, induces prospective fallen angels to engage in risky M&A, exploiting the leniency of credit rating agency in order to increase their market share.

Our results suggest that although the growth of risky investment-grade bond segment may have been a desired consequence of QE, the growing concentration of issuance in the *riskiest* investment-grade (BBB) bucket also comes at a cost that may run counter to central bank objectives. First, the subsidised firms grow disproportionately large and become more fragile, as evidenced by the unprecedented wave of fallen angels that were downgraded by multiple notches at the onset of the COVID-19 crisis. Second, the resulting spillover effects force their competitors to reduce employment, investment, markups, and sales growth. This capital misallocation cost of QE has not been documented hitherto, to the best of our knowledge, and may need to be factored in while considering the desirability, scale, scope, and duration of QE interventions in the future.

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Appendix A   Data set 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[14] 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.[15]

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

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

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

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

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[14]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.

[15]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.

The data set from eMAXX has security level holdings at a quarterly frequency from 2008Q4. Securities are identified with cusip8 and the holdings amount are denominated in USD. There are two investors' identifiers: firmid (uniquely identifies a managing firm) and fundid (uniquely identifies a sub-account). This data has around 160 million observations corresponding to 4,244 unique firmid and 47,145 fundid. 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 cusip6 and gvkey. We end up with around 16 million observations, corresponding to 14,268 investors, 1,701 issuers, and 13,359 securities. At this stage, we match the data set with investor level characteristics from eMAXX Bond Holders and security-level characteristics (amount issued, issued date, maturity, M&A purpose dummy), bringing our data set to 13.8 million observations, corresponding to 13,577 investors, 1,494 issuers, and 11,231 securities. We then collapse our data set at the issuer-investor-quarter level. Our data runs quarterly from 2009 to 2019 and features 2,750 investors and 1,442 corporate bond issuers. Out of the 2,750 funds, 223 are annuities, 590 are life and health insurance, 934 are property and casualty insurance, and around 800 are mutual funds (the exact number depends on definition of mutual fund). Out of the 1,442 corporate bond issuers, 3 are rated AAA, 24 are rated AA, 137 are rated A, 360 are rated BBB, 390 are rated BB, and 345 are rated B.

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

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 A.1. This way we can estimate the median rating for each rated firm in our data set.

Ratings	Z-score 2006	Z-score 2013
AAA	7.91	8.80
AA	7.78	8.40
A	7.10	6.12
BBB	6.36	5.70
BB	5.65	5.07
B	3.68	3.74
CCC	1.62	1.72
CC	0.84	0.05

Table A.2: Z-Score cutoff points This table presents the Z-score values for each rating category from Altman (2020b).

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

Appendix B   Additional figures and results

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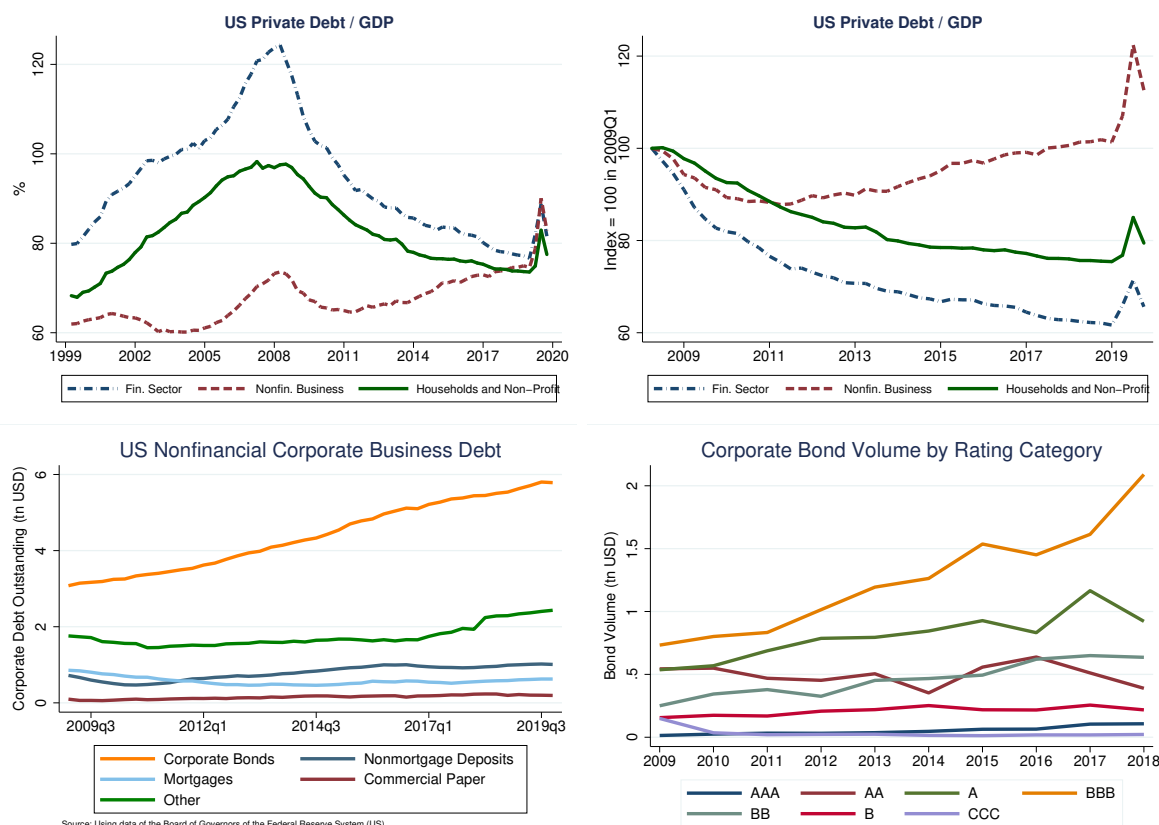
Figure B.1:   The growth of the U.S. non-financial corporate debt. This figure shows the growth of the U.S. non-financial corporate debt and, in particular, of the U.S. corporate bond market. The top left panel shows the evolution of the financial sector debt, non-financial sector debt, and household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

US Private Debt Outstanding

US Private Debt over GDP (%)
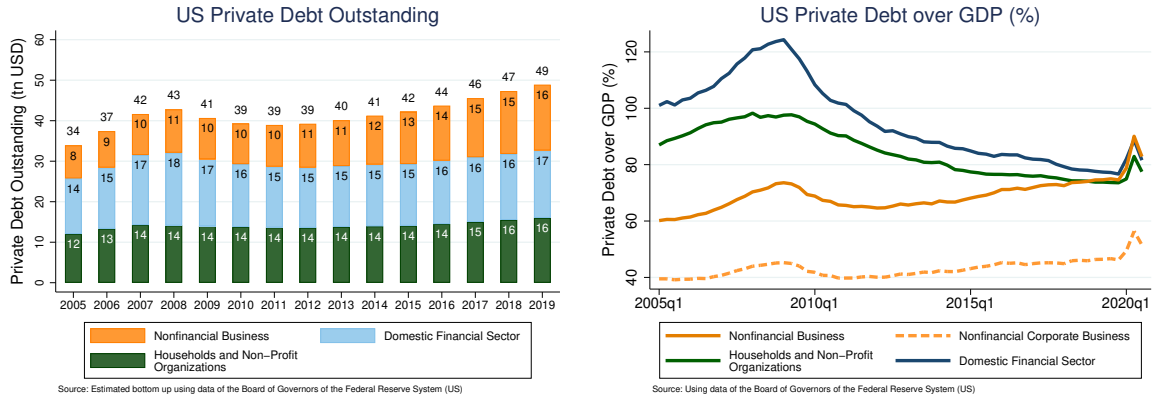
Figure B.2: U.S. private debt. This figure shows the aggregate figures for the private debt outstanding in the U.S. using data of the FRED. In Panel A, we show the breakdown in absolute numbers. In Panel B, we relate the different debt components to GDP.
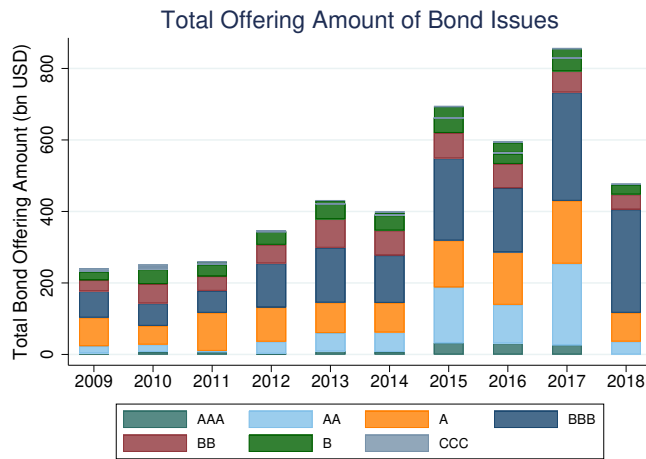

Total Offering Amount of Bond Issues

Figure B.3: Bond issues by rating. This figure shows the offering amounts over time by firm rating bucket.
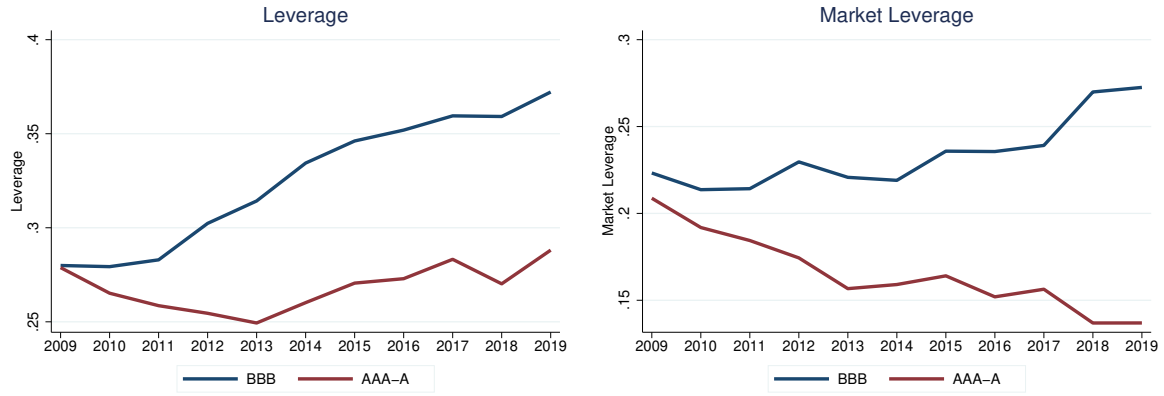
Figure B.4: Leverage over Time. This figure shows the leverage evolution for BBB and IG-rated firms over the years 2009 to 2019. In Panel A, we show the asset-weighted book leverage, which is defined by a firm's total debt over assets. In Panel B, we show the asset-weighted market leverage, which is defined by a firm's total debt over the market value of its assets (at-ceq+csho*prcc$_f$).

B.2 Compression of BBB spreads

We provide further evidence that the bond financing cost of BBB firms dropped significantly, and more than the financing costs of other investment grade issuers, since 2009. In Figure B.5, we show the compression of bond spreads by tracking the distribution of primary market spreads (top panel) and secondary market spreads (bottom panel) from 2010–12 (dashed lines) to 2013–16 (solid lines). The left panels compare the distribution of BBB bond spreads with the distribution of A bond spreads. The right panels compare the distribution of BBB bond spreads with the distribution of AA bond spreads. The four panels document a pronounced leftward shift of BBB spreads in the primary and the secondary market. If anything, we observe a slight *rightward* shift for A and AA spreads. In Figure B.8, we show that the 2013–16 is characterized by a substantial monetary easing by the Federal Reserve.
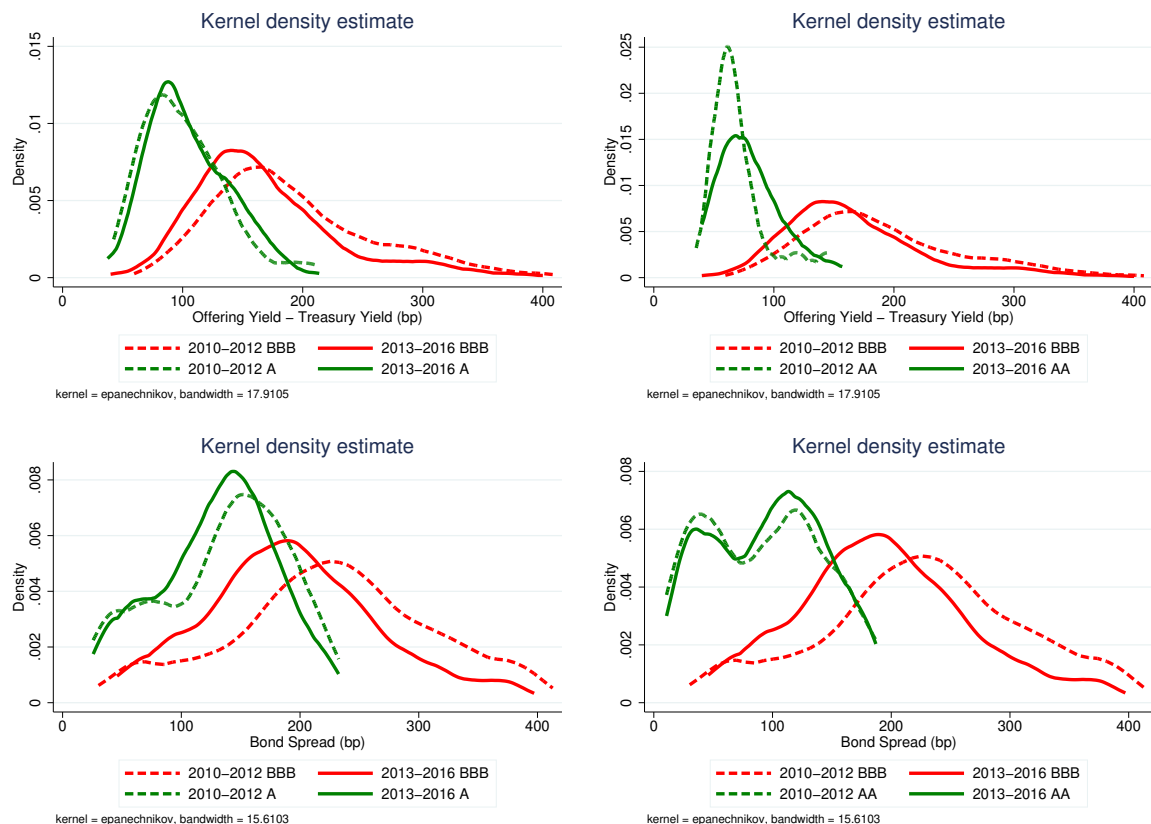
Figure B.5: Shift in bond spread distributions from 2010–12 to 2013–16. This figure shows how bond spreads distributions changed from 2010–12 (dashed lines) to 2013–16 (solid lines). The top panels show the distribution of offering spreads (offering yield−maturity adjusted treasury yield) for newly issued bonds. The bottom two panels show the distribution of secondary market spreads (bond yield−maturity adjusted treasury yield) for traded bonds. The left and right panels compare the distributions of BBB bond spreads (red lines) with the distributions of A bond spreads and AA bond spreads (green lines), respectively.

B.3 Validating the downgrade-vulnerability measure

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

In Table B.1, we present the descriptive statistics for the rated firms in our sample, separated for firms that are vulnerable and firms that are not vulnerable. The sample means highlight that vulnerable firms are larger and riskier along all dimensions. In particular, 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-vulnerable firms. The last column shows a test for the difference in means.

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

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

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

Table B.2 presents the estimation results. The first two columns show that a 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 vulnerable firm has a higher probability to be downgraded by at least one rating category in the next year.

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

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

	Negative Watch	Negative Watch	Downgrade	Downgrade
Vulnerable	0.078***	0.043**	0.021***	0.018***
	(0.018)	(0.018)	(0.005)	(0.005)
Size		0.017**		0.003*
		(0.007)		(0.002)
Leverage		0.131**		0.016
		(0.055)		(0.015)
IC Ratio		-0.010***		-0.000**
		(0.001)		(0.000)
Industry-Year FE	✓	✓	✓	✓
Observations	9,056	8,973	9,431	9,341
R-squared	0.118	0.150	0.094	0.097

Table B.2: Credit rating actions after being classified as vulnerable. This table presents the estimation results from Specification (B1) for our sample of rated firms. The dependent variable *Negative Watch* is a dummy variable equal to one if a firm is placed on negative credit watch or outlook in year t or $t+1$. The dependent variable *Downgrade* is a dummy variable equal to one if a firm is downgraded by at least one rating category in year $t+1$, i.e., a firm that has a rating of A+, A, or A- is downgraded to at least BBB+. *Vulnerable* is a dummy equal to one if a firm is vulnerable in period t. Firm level control variables are size (log of total assets), leverage and IC ratio. Standard errors clustered at the firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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

$$Y_{iht+q} = \beta_q Enter\,Vulnerable_{iht} + \gamma_q Vulnerable_{iht} + \eta_q X_{iht+q} + \mu_{ht+q} + \epsilon_{iht+q}, \quad \text{(B1)}$$

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

The coefficient of interest β_q measures a vulnerable firm's development, in the three years before and after the firm is classified as vulnerable, of sales growth, investments, asset growth, and employment growth. A positive (negative) coefficient implies that a vulnerable firm has a higher (lower) value of the respective dependent variable compared to a non-vulnerable firm. Figure B.6 shows the estimated β_q coefficients, documenting that firm performance deteriorates once it becomes vulnerable. Its sales growth and investment decline significantly, a dynamic also reflected in the drop in firm size and employment growth.
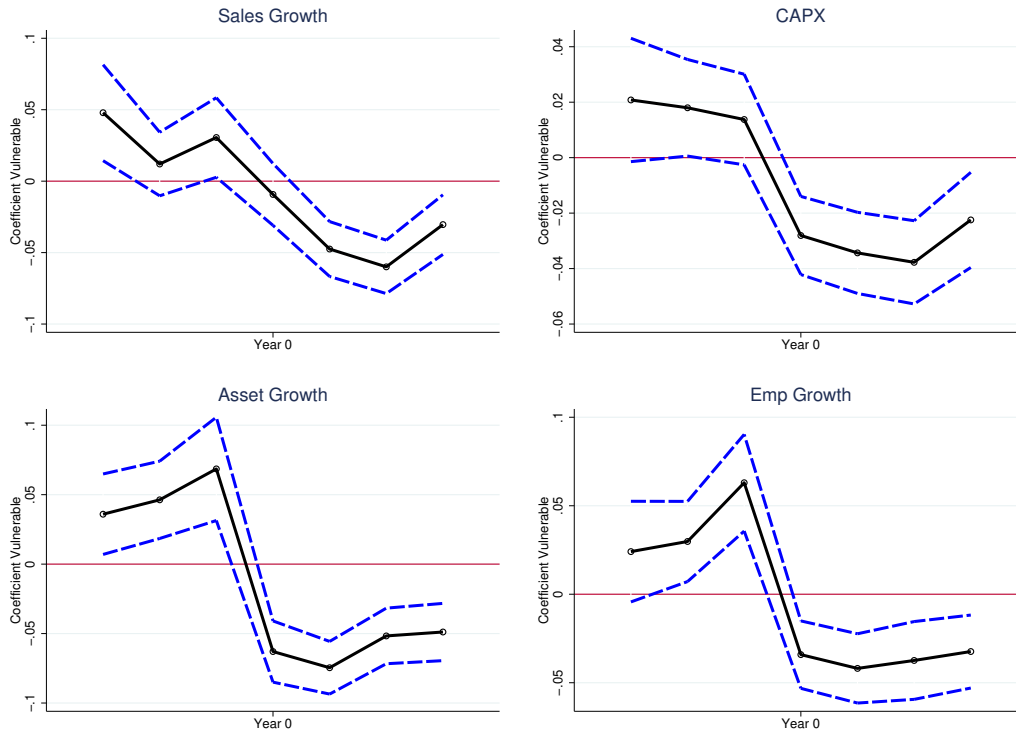
Figure B.6: Firm performance after being classified as downgrade-vulnerable. This figure shows the evolution of the estimated coefficient β_q from Specification (B1) three years before and after a firm becomes downgrade-vulnerable. Year zero corresponds to the first year a firm is classified as downgrade-vulnerable. The 95% confidence interval is reported, with standard errors clustered at the firm level.

B.4 Risk materialization with COVID-19

In this section, we provide parametric evidence that BBB firms with more inflated credit ratings experienced a sharper increase in spreads in 2020. Finally, we show non-parametrically that the vulnerable BBB-rated firms that engaged in M&A activity in the past had more (severe) downgrades than vulnerable BBB-rated firms that did not.

In a next step we provide more formal evidence for that riskier BBB firms experienced a sharper increase in bond spreads in March 2020. More precisely, we estimate the following specification in which we relate the degree of ratings inflation at the start of 2020 to the change in a firm's bond spreads:

$$\Delta Spread_{ijh} = \beta_1 \text{Rating Inflation}_{jh} + \gamma_{jh} + \phi_h + \epsilon_{ijh} \tag{B2}$$

$\Delta Spread_{ijh}$ is the change in secondary market spread between January 2020 and March 2020 of bond i of firm j in industry h, $Rating\ Inflation_{jh}$ is the difference between the issuer rating at the start of 2020 and the implied rating based on Altman Z"-score, and ϕ_h are industry fixed effects.

Table B.3 presents our results. In Column (1) we show that a greater difference between a vulnerable BBB rated firm's assigned rating and its implied rating leads to a greater change in spreads when the pandemic started. In particular, a one notch inflated issuer rating is on average associated with a 16 basis points increase in bond spreads for vulnerable BBB rated firms. In contrast the second columns shows that no such relationship exists for the other vulnerable investment grade rated firms.

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

Table B.3: Change in spreads of rating-inflated firms during COVID-19. This table presents estimation results from the bond-level regression (B2). The dependent variable is $\Delta Spread$, which is defined as the change in secondary market spread between January 2020 and March 2020 of a single bond. The independent variable is $RatingInflation$ and is defined as the issuer rating at the start of 2020 minus the implied rating based on Altman Z"-score. We add a firm's total assets as firm control, and a set of industry fixed effects. In the first column the sub-sample consists of BBB rated firms and in the second column of non-BBB investment grade rated firms. Standard errors are clustered at the firm j level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

B.5 Sensitivity of bond spreads to credit risk by ratings category

In this section, we show that, consistent with an exorbitant privilege of prospective fallen angels, the sensitivity of bond spreads to changes in credit risk is the weakest for BBB-rated issuers. To this end, we estimate the following specification:

$$Spread_{biht} = \beta_1 Rating_{iht} + \beta_3 EDF_{iht} + \beta_3 Rating_{iht} \times EDF_{iht} \qquad \text{(B3)}$$
$$+ \mathbf{\Gamma} X_{iht} + \mu_{ht} + \delta \times Z_b + \phi_i + \epsilon_{iht}$$

where $Spread_{biht}$ is the spread of bond b issued by firm i in industry h in period t, EDF_{iht} is the expected default frequency of firm i in period t, $Rating_{iht}$ is set of dummies for rating categories, μ_{ht} are industry-time fixed effects, and ϕ_i are firm fixed effects. As in the previous parametric test, we control for firm level and bond level characteristics. Figure B.7 presents the estimated sensitivities of bond spreads to EDFs within rating category, calculated as $\beta_2 \overline{EDF}_{iht} + \beta_3 Rating_{iht} \times \overline{EDF}_{iht}$, where $\overline{EDF}$ is the mean EDF in each rating category. The U-shaped pattern with a minimum at BBB shows that the sensitivity of bond spreads to equity-based EDFs is weakest for BBB-rated issuers.
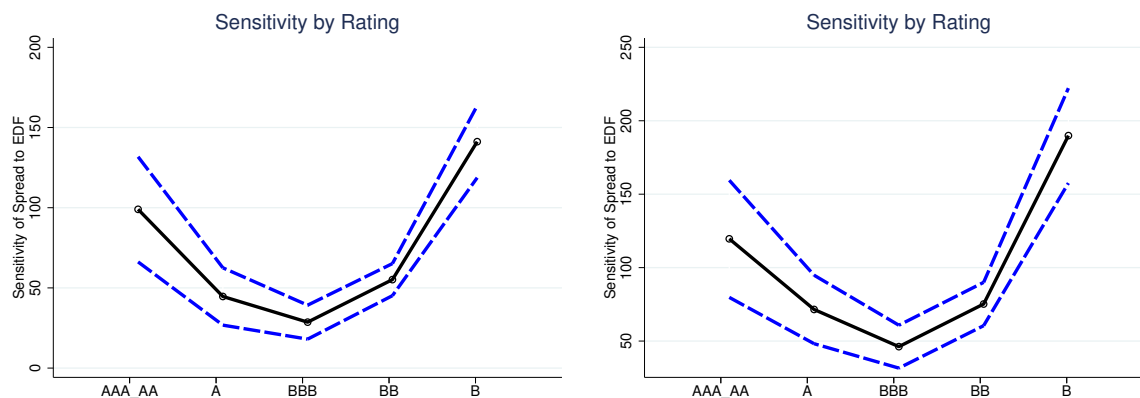

Figure B.7: Sensitivity of bond spreads to EDFs. This figure shows the sensitivity of bond spreads to 2-year EDFs (left panel) and 5-year EDFs (right panel). The points in the graph are obtained by calculating $\beta_2 \overline{EDF}_{iht} + \beta_3 Rating_{iht} \times \overline{EDF}_{iht}$, where the coefficients are estimated using Specification (B3) and $\overline{EDF}$ is the mean EDF in each rating category. The dashed blue lines represent 95% confidence intervals.
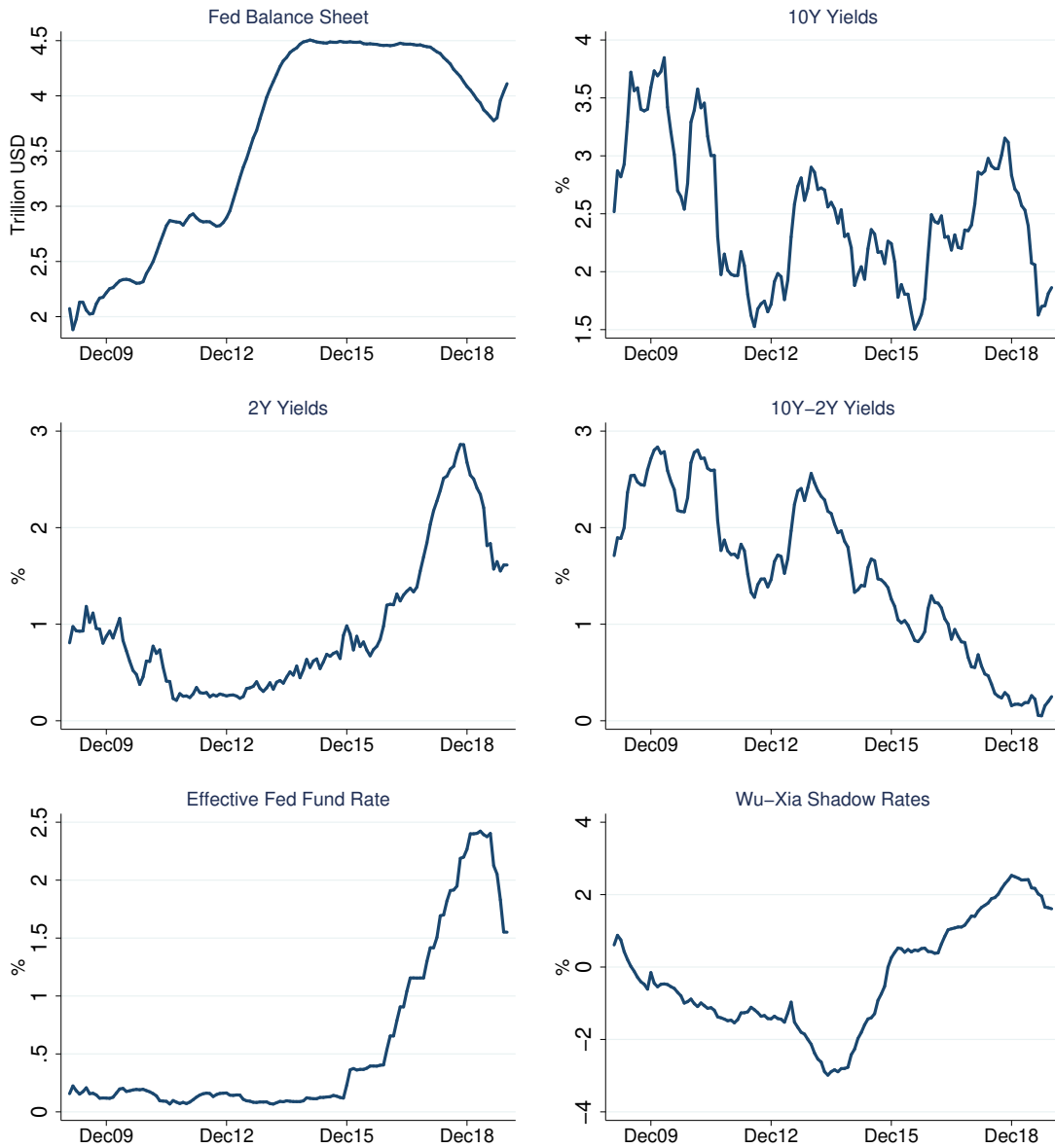
B.6 Monetary policy stance

Figure B.8: Monetary policy stance. This figure shows the monetary policy stance in the U.S. during our sample period. The six panels show the size of the Fed balance sheet (trillion dollars), the 10-year Treasury yields (%), the 2-year Treasury yields (%), the difference between the 10-year and the 2-year Treasury yields, the effective fed fund rate, and the shadow rate developed in Wu and Xia (2016). The series are plotted with observations at a monthly frequency. The 10-year yields, the 2-year yields, and the effective fed fund rate are monthly averages of daily data. The fed balance sheet size is the monthly average of weekly data.

B.7 M&A deal volume in the speculative-grade category
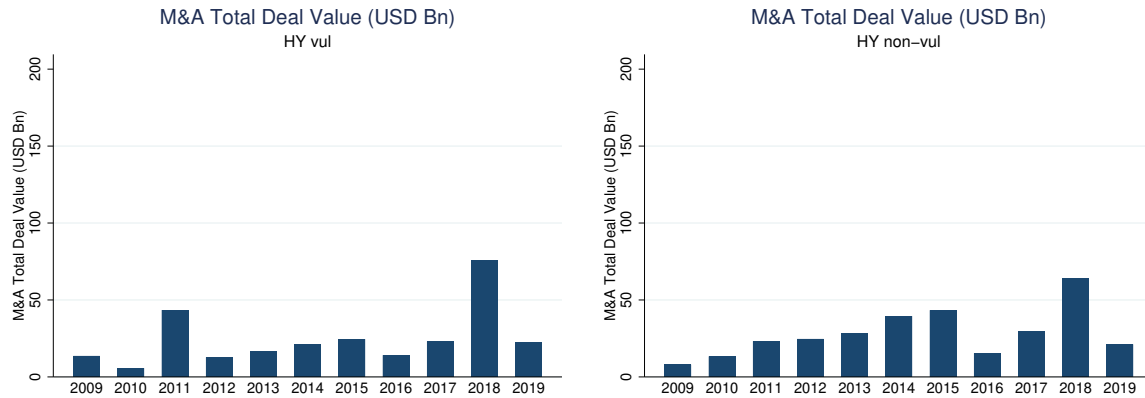
Figure B.9: M&A Total Deal Volume. This figure shows the total M&A deal volume for vulnerable and non-vulnerable firms in the high-yield (speculative-grade) category.

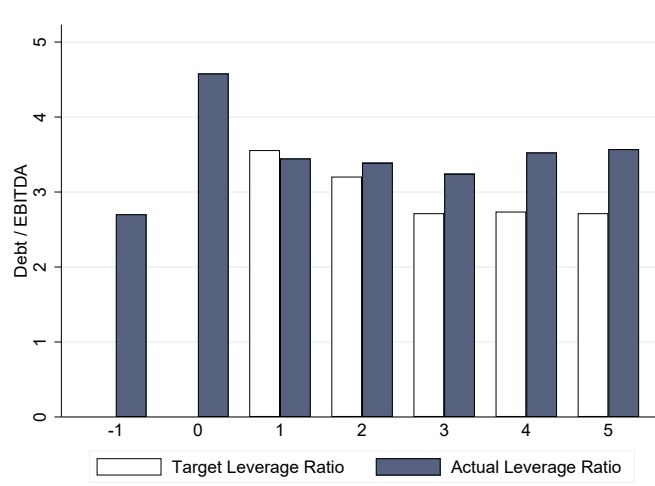## B.8 M&A's and broken promises

Figure B.10: 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.

B.9 M&A's and downgrades

Prospective fallen angels appear to engage in M&A to exploit the leniency of credit rating agencies following M&A. To assess the effect of M&A by downgrade-vulnerable firms on the propensity to be downgraded, we estimate the following probit local projection regression:

$$Pr(Downgrade_{i,t,t+h} = 1) = \Phi(\beta^h(M\&A_{i,t} = 1) \tag{B4}$$
$$+ \delta_1 log(Assets_{i,t-1}) + \delta_2 netlev_{i,t-1} + \delta_4 RoA_{it-1} + \alpha_t + \gamma_s$$

where the dependent variable $Downgrade_{i,t,t+h}$ is equal to one if firm i is downgraded between t and $t+h$, the function $\Phi(\cdot)$ is a normal distribution, $M\&A_{i,t}$ is a dummy equal to one if firm i undertakes an M&A in year t. The firm-level control variables $log(Assets_{i,t-1})$, $netlev_{i,t}$ and $RoA_{i,t}$, respectively log of total assets, net leverage, and the return on assets, are included to control for factors that predict selection into M&A. Finally, α_t and γ_s are time and two-digit SIC fixed effects, respectively.

Figure B.11 shows the estimation results. The central panel shows that for downgrade-vulnerable BBB firms that engage in M&A experience a decline in the downgrade probability relative to downgrade-vulnerable firms that did not engage in M&A for around three to four years. However, after around six years, M&As actually increase the downgrade probability for downgrade-vulnerable BBB firms. The point estimates indicate that an M&A increases the downgrade probability by around ten percentage points for a downgrade-vulnerable BBB firm after eight years. Figure B.12 shows that the downgrade intensity follows a similar time profile. Conditional on being downgraded, the average M&A downgrade-vulnerable BBB firm is initially downgraded by fewer notches. However, after six years the average rating of a downgrade-vulnerable BBB is around 0.5 ratings notch lower than those that did not engage in M&A. The ability of M&As to prolong ratings inflation appears limited to downgrade-vulnerable BBB-rated firms. The left and right panels of Figure B.11 do not show a similar relationship between M&As and subsequent downgrade probabilities for both downgrade-vulnerable A-rated and BB-rated firms.
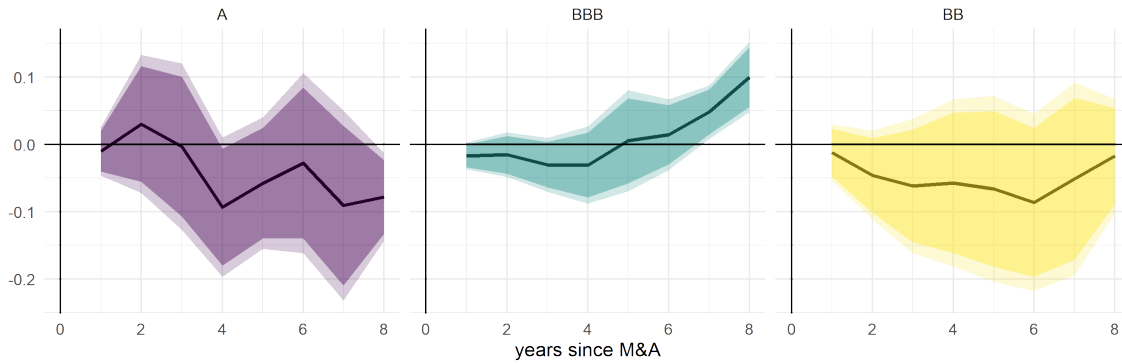
Figure B.11: M&As and downgrade probabilities among vulnerable firms. This figure shows the average marginal effect on the downgrade probability after a vulnerable firm undertakes an M&A in period 0. The figures present estimates results from specification (B4). The dependent variable is the probability of being downgraded to a lower rating bucket between period t and $t + h$, where $h = [1\ to\ 8]$ years, for a firm defined as vulnerable in t and undertakes an M&A in the same period. Control variables include the logarithm of total assets, net debt ratio and the return on assets ratio. The left panel shows the estimates for sample of A rated vulnerable firms, the centre panel for BBB rated vulnerable firms and the right panel for BB rated vulnerable firms. Shaded areas show the confidence intervals for the 90 and 95th percentiles. Standard errors are clustered at the two digit SIC level.
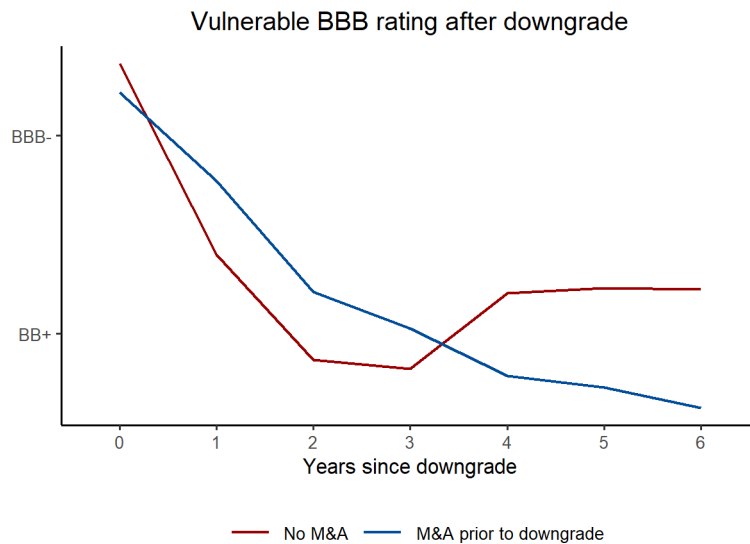

Figure B.12: Downgrade intensity of vulnerable BBB issuers. The mean rating of vulnerable BBB rated firms after six years. The red line shows the average rating if the issuer undertook an M&A in years t to $t - 2$ and was eventually downgraded to speculative-grade status in the years $t + 1$ to $t + 6$. The blue line shows the mean rating of firms that did not undertake an M&A in years t to $t - 2$ but was downgraded to speculative-grade status in the years $t + 1$ to $t + 6$.
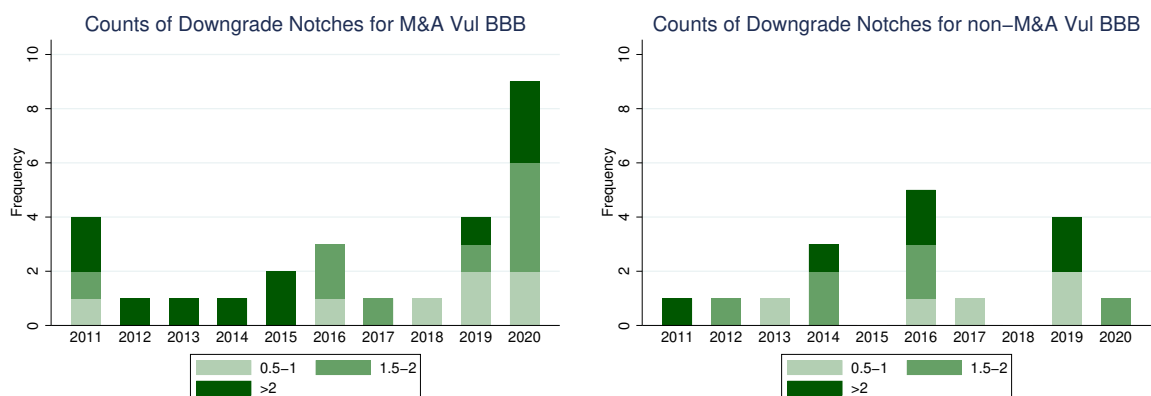
B.10 M&A's and the COVID-shock

Figure B.13: Downgrade Materialization of (prospective) fallen angels. This figure shows the number of downgrades that vulnerable BBB-rated firms have experienced in the years 2011 to 2020, and groups them according to their downgrade severity. The downgrade severity is measured by the number of notches a firm is being downgraded, and is subdivided into three broad categories: 0.5-1, 1.5-2, >2 notches. The left-hand panel plots the downgrade (notch) frequency for vulnerable BBB firms that have conducted an M&A since the year that they have become vulnerable. The right-hand panel shows the downgrade (notch) frequency for firms that have not conducted an M&A since the year that they have become vulnerable.

B.11 M&A risk taking

In this section, we show that vulnerable BBB firms conduct larger M&A transactions relative to their size, use higher leverage relative to their profitability level and have more negative CARs compared to non-vulnerable firms. More specifically, we estimate the following specification:

$$
\begin{aligned}
Y_{iht} =\ & \beta_1 Vulnerable_{iht} + \beta_2 BBB_{iht} + \beta_3 Vulnerable_{iht} \times BBB_{iht} \\
& +\ \gamma \times X_{iht} + \eta_{ht} + \epsilon_{iht},
\end{aligned}
\tag{B5}
$$

where i is a firm, h an industry, and t a year. Y_{iht} measures the relative deal size, net debt/EBITDA (adjusted to Y_{iht+1}) and CARs (adjusted to deal level). The coefficient β_1 captures the effect of a firm's vulnerable status on the dependent variable. The coefficient β_2 captures the effect of a firm's BBB rating on the dependent variable. The coefficient β_3 captures whether the effect of a firm vulnerable status on the dependent variable is different for BBB rated firms compared with non-BBB rated firms. We include industry-year fixed effects to absorb time-varying industry level heterogeneity (e.g., demand shocks) and time-varying firm level controls.

	Relative Deal Size	Net Debt/EBITDA	CARs
Vulnerable × BBB	0.056**	0.377*	-0.010*
	(0.025)	(0.212)	(0.005)
Vulnerable	-0.033**	-0.264	0.003
	(0.015)	(0.183)	(0.004)
BBB	-0.046***	-0.222*	0.001
	(0.013)	(0.125)	(0.003)
Controls	✓	✓	✓
Industry-Year FE	✓	✓	✓
Sample	M&A Rated	M&A Rated	M&A Rated
Level	Firm	Firm	Deal
Observations	1,837	2,622	2,412
R-squared	0.263	0.470	0.197

Table B.4: M&A Risk Taking. This table presents the risk taking of vulnerable BBB-rated firms in the year of (t) and after ($t + 1$) the announced M&A transaction. Column (1) shows the results for the relative deal size, which is measured by the total transaction value of a firm in a given year over its lagged assets. We restrict our sample to firm-years with total transaction value bigger than zero. Column (2) shows the net debt/EBITDA levels for the M&A rated firms in the year after the M&A announcement. For Column (1) and (2) the firm controls consist of the log of assets, profitability, leverage and tangibility. Column (3) presents the 5-day cumulative abnormal returns for the M&A deals performed by the rated firms in our sample, for which we run the specification on a deal level. The total return value-weighted index is used as benchmark over a -210 to -11 day period. Control variables include the logarithm of total assets, leverage, profitability, an indicator variable for whether the deal is at least partially financed with stock, an indicator variable for whether the target has the same 2-digit SIC code as the acquiror, an indicator variable for whether the deal is cross-border, an indicator variable for a publicly listed target and the pre-deal buy-and-hold returns of the acquiror from -210 to -11 days. A t-test shows that on average the CARs of BBB vulnerable firms are -1 per cent. All specifications include industry-year fixed effects. Standard errors are clustered at the firm level.

Appendix C   Theoretical framework

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

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

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

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

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

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

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

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

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

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

Hence, firms solve:

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

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

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

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

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

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

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

Figure C.2 shows average bond yields and firm risk taking within each rating bucket for the three cases discussed above: normal demand for IG bonds, moderate demand for IG bonds, and high demand for IG bonds.
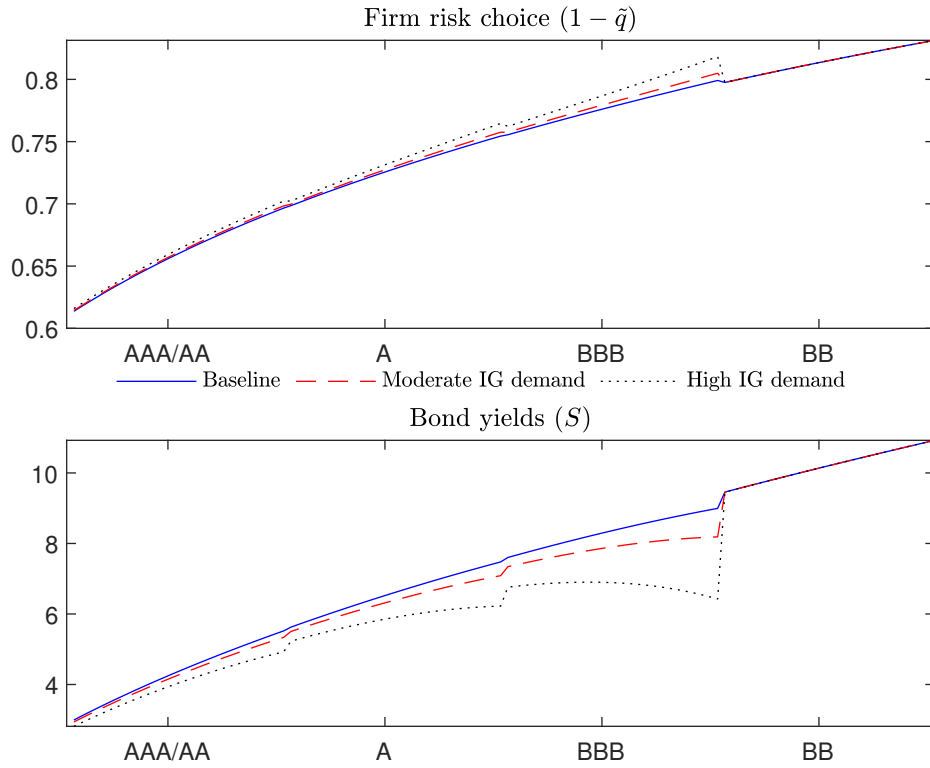
Figure C.1: Firm risk taking and bond yields. This figure shows firm risk choice (top panel) and firm bond yields (bottom panel) as a function of firm quality. The x-axes show progressively higher tax rates, grouped in rating categories. The blue line corresponds to the baseline economy. The red dashed line corresponds to an economy with moderate demand for risk. The black dotted line corresponds to an economy with high demand for risk. Demand for risk is modeled through an increase in *alpha* within each rating group in the investment-grade market. The increase is more pronounced as we approach the BBB market from the AAA/AA market.
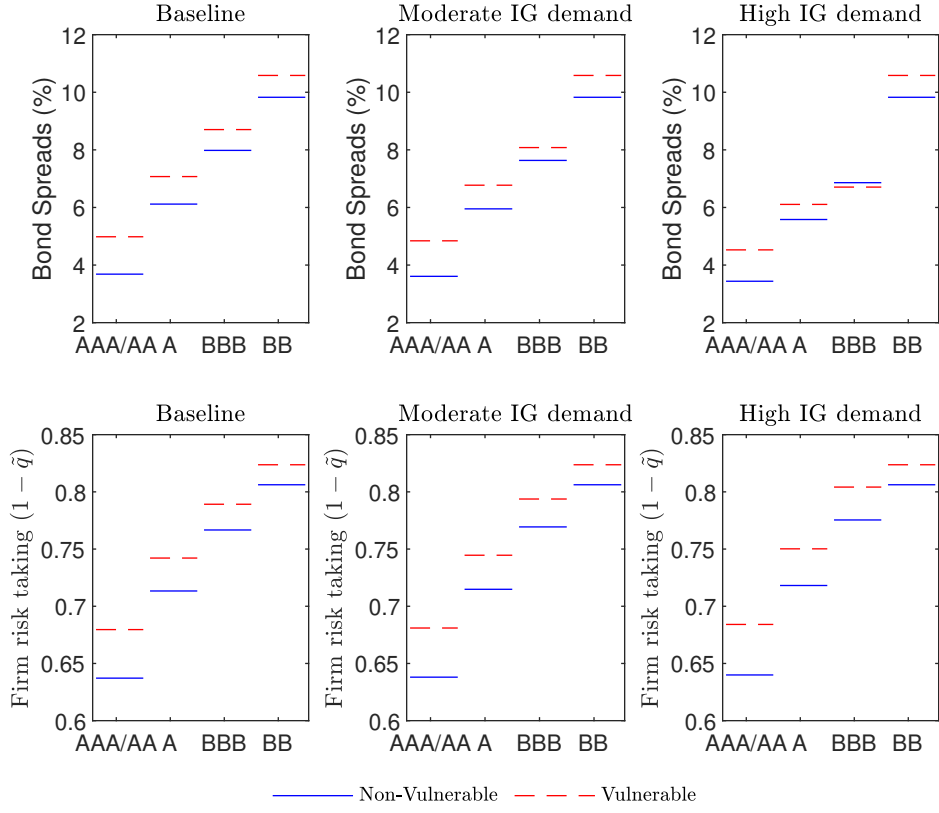
Figure C.2: Firm risk taking and bond yields. This figure shows bond spreads (top panel) and firm risk choice (bottom panel) as a function of firm quality. The x-axes show progressively higher tax rates, grouped in rating categories. The blue lines show averages within a rating group for non-downgrade vulnerable issuers. The red lines show averages within a rating group for downgrade vulnerable issuers. The two left panels correspond to the baseline economy. The two middle panel correspond to an economy with moderate demand for risk. The two right panels correspond to an economy with high demand for risk. Demand for risk is modeled through an increase in *alpha* within each rating group in the investment-grade market. The increase is more pronounced as we approach the BBB market from the AAA/AA market.