Exorbitant Privilege? The Bond Market Subsidy of Prospective Fallen Angels*

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Abstract

Risky firms just above the investment-grade rating cutoff face the prospect of becoming "fallen angels" upon a downgrade. We document that their bond issuance, especially during periods of monetary easing after the global financial crisis, enjoyed low borrowing costs relative to their non-rating based credit risk measures. This "exorbitant privilege" appears to originate in credit rating inflation, valued by yield-seeking investors. Prospective fallen angels increase their market share by acquiring firms and reducing markups, forcing their competitors to reduce employment, investment, markups, and sales, implying real effects and spillovers from their exorbitant privilege.

JEL Codes: E31, E44, G21.

Keywords: Corporate bond market, fallen angels, credit ratings, reach-for-yield.

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1 Introduction

Risky firms just above the investment-grade 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. In many respects, the growth of risky investment-grade bonds may be a desired outcome of crisis related monetary policy easing. In particular, large scale asset purchases have aimed to push investors into riskier assets through the portfolio rebalancing channel (see Gagnon et al. (2011) for an early reference on 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. Such vulnerabilities could well become important after a shock.

In this paper we examine the exorbitant privilege of prospective "fallen angels", i.e. firms on the cusp of the investment-grade cutoff, and the costs that such firms impose on the economy. We classify prospective fallen angels as BBB-rated firms that are vulnerable to downgrades, and show that BBB bond growth has largely been driven by such firms. Importantly our analysis shows that since the Global Financial Crisis, prospective fallen angels have benefited from investors subsidizing their bond financing, especially during periods of monetary easing. The subsidy appears to be driven by ratings agencies inflating their ratings when these firms engage in M&A. Even though these M&A transactions are value destroying, they are valued by bond investors because they delay downgrades of prospective fallen angels to the high-yield market. In particular, we document that yield-seeking investors drive the demand for bonds issued by prospective fallen angels. This dynamic is (i) driven by investors that predominantly hold investment grade bonds, therefore likely to be exposed to the fire sale risk related to an eventual downgrade and (ii) more pronounced for bonds issued by prospective fallen angels to fund M&A activity. Finally, we document that prospective fallen angels exert a negative externalities on more prudent firms similar to the congestion effect created by zombie firms (Caballero et al. (2008)).

Our empirical analysis combines various data sources at the firm-, bond-, 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. Moreover, our bond-level data consists of primary market pricing data from Mergent, and secondary market pricing data from TRACE. Finally, we use investor holding-level data from eMAXX Bond Holders. Our sample period covers the years 2009 to 2018.

First, we provide aggregate evidence on the developments in the U.S. debt market. We show that since 2009 corporate bond volume has steadily increased in dollar value to over $6 trillion today, largely driven by the increasing share of BBB-rated firms. We furthermore introduce a measure of downgrade-vulnerability based on the Altman Z"-score. This allows us to determine whether a firm is prone to be downgraded, based on firm fundamentals taken from balance sheet and income statement information. Using this measure, we show that in 2018, the corporate bond volume of the prospective "fallen angels" amounted to $1.5 trillion, compared to the $0.5 trillion of non-downgrade vulnerable firms. We confirm the validity of our downgrade-vulnerability measure by documenting that vulnerable firms (i) look worse along various observable firm characteristics, such as leverage, net worth, and interest coverage ratio, (ii) exhibit lower employment growth, investment, sales, and asset growth once they become vulnerable, and (iii) are more likely to be downgraded or put on negative watchlist/outlook than non-vulnerable firms.

Second, using information on bond spreads in primary and secondary markets, we document that BBB-rated firms benefited more from a sharper decrease in their bond spreads than other investment-grade rated firms. The difference in the offering spread between BBB and A or AA-rated firms narrowed from 150 bps in 2009 to just about 50 bps in 2018. Conversely, the difference in offering spreads between other investment-grade categories, e.g., AA vs A barely changed. This reduction in bond spreads in the BBB segment is primarily driven by downgrade-vulnerable BBB firms, who are able to obtain cheaper funding than their non-vulnerable counterparts (Figure 1). Crucially, this pattern is only present for BBB-rated firms and we do not find analogous evidence in other rating categories. Moreover, such underpricing is unique to corporate bond markets. When replacing the bond spread with an equity market based measure of expected default, we find that across all rating categories

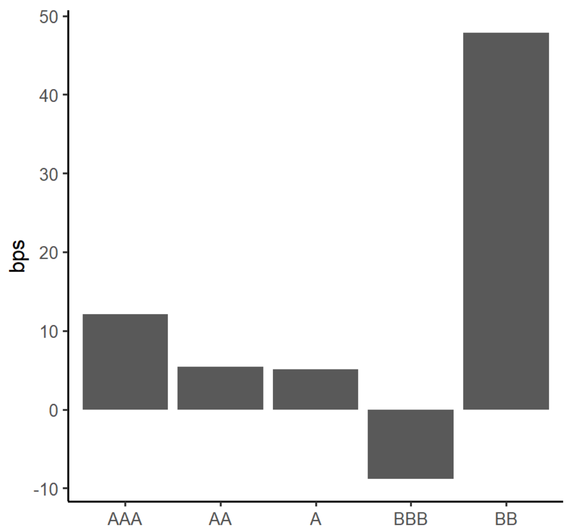

Figure 1: Prospective Fallen Angel Subsidy. This figure shows the difference between the median secondary market spread of firms defined as being vulnerable to a downgrade and the median spread of non-vulnerable firms in the same ratings category. We classify a firm as vulnerable if its estimated Z"-score is lower than the Altman Z"-score benchmark of the next lowest rating category.

(including BBB-rated firms), vulnerable firms have higher expected default frequencies.

Third, we document that credit rating inflation is particularly pronounced in the BBB segment of the bond market which in turn is closely associated with M&A activity by downgrade-vulnerable BBB firms. In particular, prospective fallen angels appear to engage in M&A activity to exploit the leniency of credit rating agencies following an M&A transaction. While these transactions are value destroying on average, we show that they might still be valued by bond investors because they delay the downgrade of prospective fallen angels to the high-yield market.

Fourth, using detailed data at the investor-security level, we show that the exorbitant privilege of prospective fallen angels is supported by the demand by yield-seeking investors, a dynamic more pronounced for investors that predominantly hold investment-grade bonds. In particular, we identify yield-seeking investors based on the residual maturity of the investor's portfolio as of 2009Q4 capturing the idea that investors with a long maturity of their bond portfolio at the end of 2009 likely suffered more from the subsequent reduction of long-term yields compared with shorter-duration investors. Moreover, we show that investors' demand for bonds issued by prospective fallen angels is driven by the large quantity of bonds issued to fund M&A activity, consistent with the idea that, exposed to the fire sale risk related to an eventual downgrade to the high-yield market, investment-grade investors value the leniency of credit rating agencies following M&A.

Finally, we investigate the real effects of the increased investor demand for risky BBB bonds. In aggregate, we find that BBB firms are able to significantly increase their market share. This gain in market share is largely driven by the downgrade-vulnerable firms in the BBB segment. At the firm-level, we show that vulnerable firms in general have lower employment growth and investment levels than non-vulnerable firms. This effect holds across all rating categories. Thus, despite their cheaper funding relative to other firms, vulnerable BBB firms neither invest more, nor hire more employees than other (vulnerable) firms. Importantly, we document that vulnerable BBB firms significantly increase their sales growth rate by charging lower markups on their products, likely contributing to their rapid increase in market share. This in turn negatively affects non-vulnerable firms competing with a larger share of vulnerable BBB firms in their industry. More precisely, non-vulnerable (investment-grade firms) operating in an industry with a larger share of vulnerable BBB firms have lower employment growth rates, lower investment levels, lower sales growth rates, and lower markups compared to non-vulnerable firms operating in an industry with a lower share of vulnerable BBB firms. This suggests that the relatively cheap funding of risky BBB firms indeed has negative spillover effects on higher quality competitors. Crucially, we do not find negative spillover effects when focusing on the overall share of downgrade vulnerable firms. This confirms once again the specialness of the BBB-rating segment.

Our findings contribute to two strands of literature. First, we contribute to the literature on misallocation and fragility in corporate debt 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, 2020; 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). More generally, our findings are related to the literature on the misallocation of bank credit (Caballero et al., 2008; Banerjee and Hofmann, 2020; Acharya et al., 2020) and source of financing more in general (Midrigan and Xu, 2014; Whited and Zhao, forthcoming). Krishnamurthy and Muir (2020); Gilchrist and Zakrajsek (2012) discuss the real effects of credit spreads. See, among others, Caballero and Simsek (2020) for a discussion of the role of monetary policy as a driver of asset prices.

Second, 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) shows that, within rating categories, investors reaching-for-yield might tilt their portfolio toward riskier assets. Goldstein and Huang (2020) shows that, this behavior might, in equilibrium, induce credit rating agencies to inflate their ratings. Credit rating inflation is discussed in, among others, Herpfer and Maturana (2020) that shows that credit rating agencies are less likely and slower to downgrade firms with "performance sensitive debt." Finally, our paper is also related to Aktas et al. (forthcoming) that shows that investment grade firms are concerned, in their M&A activity, about acquisition-related downgrades.

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 and our measure of rating inflation. Section 4 documents that prospective fallen angels have benefited from a subsidy in their bond financing after the Global Financial Crisis and shows that this subsidy is driven by credit ratings inflation and demand for BBB bonds by yield-seeking investors. Section 5 documents the real consequences of this subsidy. Section 6 concludes.

2 Aggregate Evidence

In this section, we present some aggregate facts. In Section 2.1, we document the sizable growth of the U.S. corporate debt market, mostly driven by BBB-rated issuers, following the Global Financial Crisis. In Section 2.2, we show that, during the same period, investment-grade corporate issuers paid historically low bond yields while becoming considerably riskier—a dynamic particularly pronounced for BBB-rated issuers.

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 sector, the subsequent private debt cycle has been predominantly driven by the corporate non-financial sector. The top left panel of Figure 2 shows the time-series evolution of private debt taken by the financial sector, the corporate non-financial sector, and the household and non-profit sector since 1999, as a share of GDP. The figure shows that the steady increase in the last ten years made the non-financial business debt the largest private debt category, equivalent to 82% of GDP in 2020. The top right panel normalizes these times series to 100 in 2009Q1, confirming that 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 bottom panel of Figure 2 shows that the increase in non-financial corporate debt has been mostly driven by corporate bonds. The figure in the bottom left shows that the stock of corporate bonds outstanding issued by non-financial firms increased 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 represents around 52% of all investment-grade bonds outstanding in 2020, up from 33% at the start of 2009. The bottom right panel shows the unprecedented rise in the size of the BBB-bond market, which tripled in size from around \$0.7 trillion in 2009 to more than \$2 trillion in 2018. Figure B.2 in the appendix shows the evolution of bond issuance by rating bucket.

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, 2020) that warned about the risk of a wave of "fallen angels," namely a large number

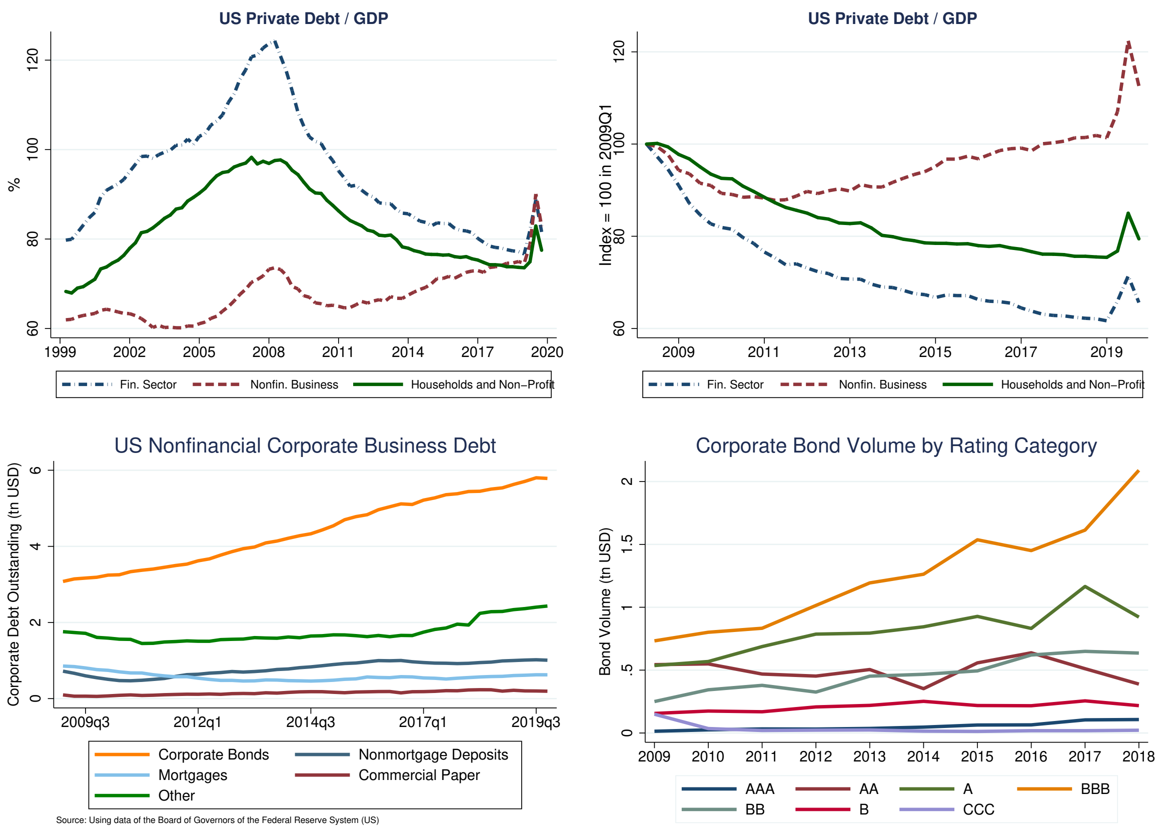

Figure 2: The Growth in U.S. Non-Financial Corporate Debt. This figure shows the growth in U.S. non-financial corporate debt and, in particular, bond markets. The top left panel shows the evolution of the financial sector debt, non-financial sector debt, and household debt, normalized by GDP. The sources 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 (consists of loans from non-bank institutions (excl. mortgages) and industrial revenue bonds). The sources are series cblbsnncb, mlbsnncbxxx, ncbilia027n, cplbsnncb and olalbsnncb from FRED. The bottom right panel shows the evolution of the stock outstanding of corporate bonds, grouped by rating category. The sources are Capital IQ and Thomson Reuters.

of downgrades of BBB-rated firms to the sub-investment grade, or high-yield, market.

In Figure 3, we document the deterioration in issuer quality and the drop in yields paid by BBB 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

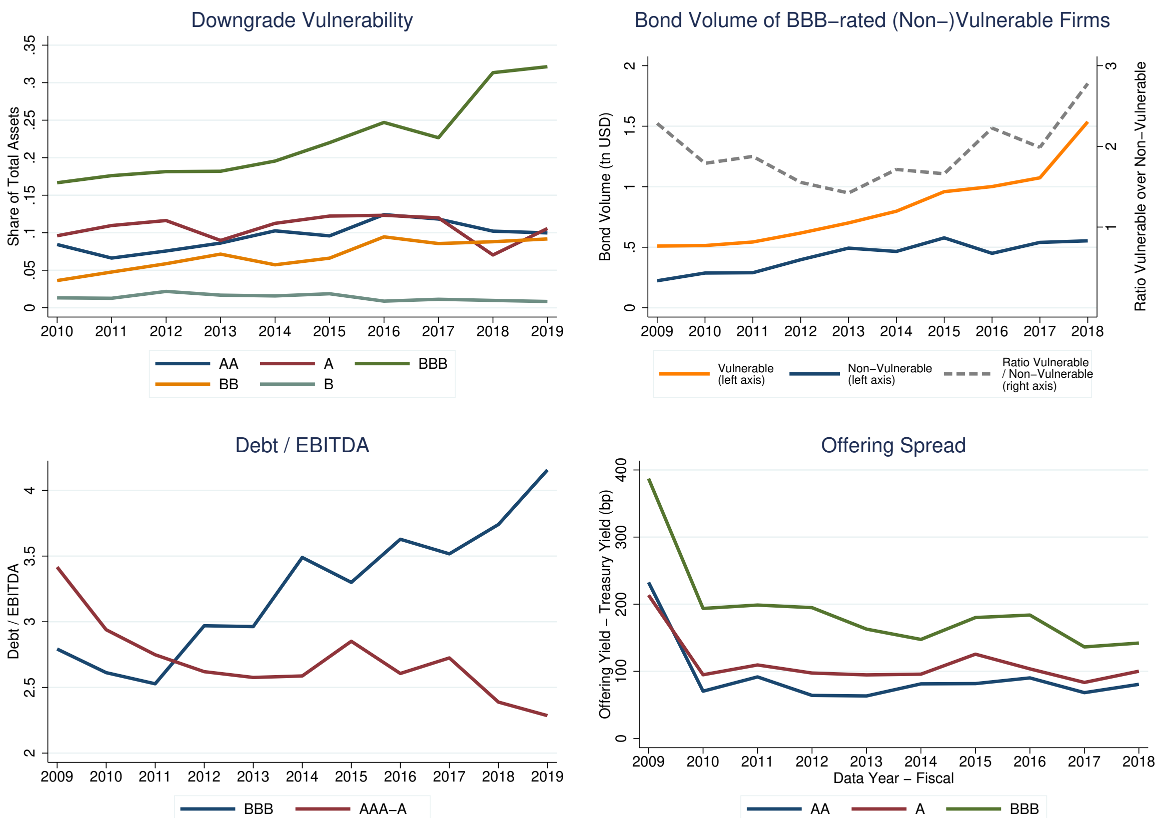

Figure 3: Downgrade Vulnerability. This figure shows the deterioration of firm quality and the declining bond financing costs for BBB-rated firms. The top left panel shows the share of firms that are vulnerable to a downgrade based on the Z"-score by rating category, where firms are weighted by total 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 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.

statement and balance sheet information (Altman, 2020a).[1] Specifically, we classify a firm as vulnerable if its Z"-score is lower than the historical median Z"-score of the next lowest rating category.[2] For example, a BBB-rated firm is classified as vulnerable if its Z"-score is below

[1] The Altman Z"-score is defined as:

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

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

the median Z"-score of BB rated firms. We explain this measure of downgrade vulnerability in great detail in Section 3.2. 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-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 and other investment-grade firms. 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. The figure also highlights that BBB offering spreads moved closer to AA and A offering spreads: the offering spread of BBB issuers declined by around 100 basis points relative to A and AA issuers. Over the same period, there is no evidence of a spread narrowing between A and AA firms.

3 Data and Empirical Work

In this section, we describe our data sources and explain our strategy to identify the prospective fallen angels. In Section 3.1, we describe our data sources and data construction. In Section 3.2, we describe our downgrade vulnerability measure, which we then use to show the increasing prevalence of prospective fallen angels since 2009.

3.1 Data

Our data set consists of firm-level, bond-level, and investor holding-level data from 2009 to 2018. 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. Lastly, rating information is obtained from Thomson Reuters, which provides worldwide coverage on ratings from S&P, Moody's and Fitch. We follow Becker and Milbourn (2011) in transferring ratings into numerical values. Combining the various data sources, we analyze 5,864 firms in total.

Second, we use bond-level data to investigate the pricing in the U.S. 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 3,140 bond issues by 910 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 7,700 outstanding bonds by 1,130 issuers, with bond b, firm j, year t as unit of observation.

Third, we examine bond investor holding level data using eMAXX Bond Holders data from Thomson Reuters Eikon, a detailed data set that documents security-level holdings by individual investors at a quarterly frequency. We collapse holdings within an investor at the issuer level so that our unit of observation is holdings at quarter t by investor k of bonds issued by issuer j. Our data set includes 2,127,296 observations spanning 37 quarters from 2009Q4 to 2018Q4. There are 892 unique issuers and 569 unique investors, mostly investment managers (268) and insurance companies (210).

3.2 Validating the Vulnerability Measure

In this section, we show (i) how vulnerable firms differ from non-vulnerable firms along observable characteristics and (ii) how firm balance sheet, firm performance, and firm downgrade probability change after the firm is classified as vulnerable.

In Table 1, we present some descriptive statistics for the rated firms in our sample, separately for firms that are vulnerable and firms that are not vulnerable to a downgrade. The sample means highlight that vulnerable firms are larger and riskier along all key 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

	Vulnerable	Non-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 1: Descriptive Statistics. 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.

are also significantly lower than those of non-vulnerable firms. The last column shows a test for the difference in means.

Next, we analyze how firms perform after being classified as vulnerable. 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:

$$Y_{iht+q} = \beta_q EnterVulnerable_{iht} + \gamma_q Vulnerable_{iht} + \eta_q X_{iht+q} + \mu_{ht+q} + \epsilon_{iht+q}, \quad (1)$$

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,

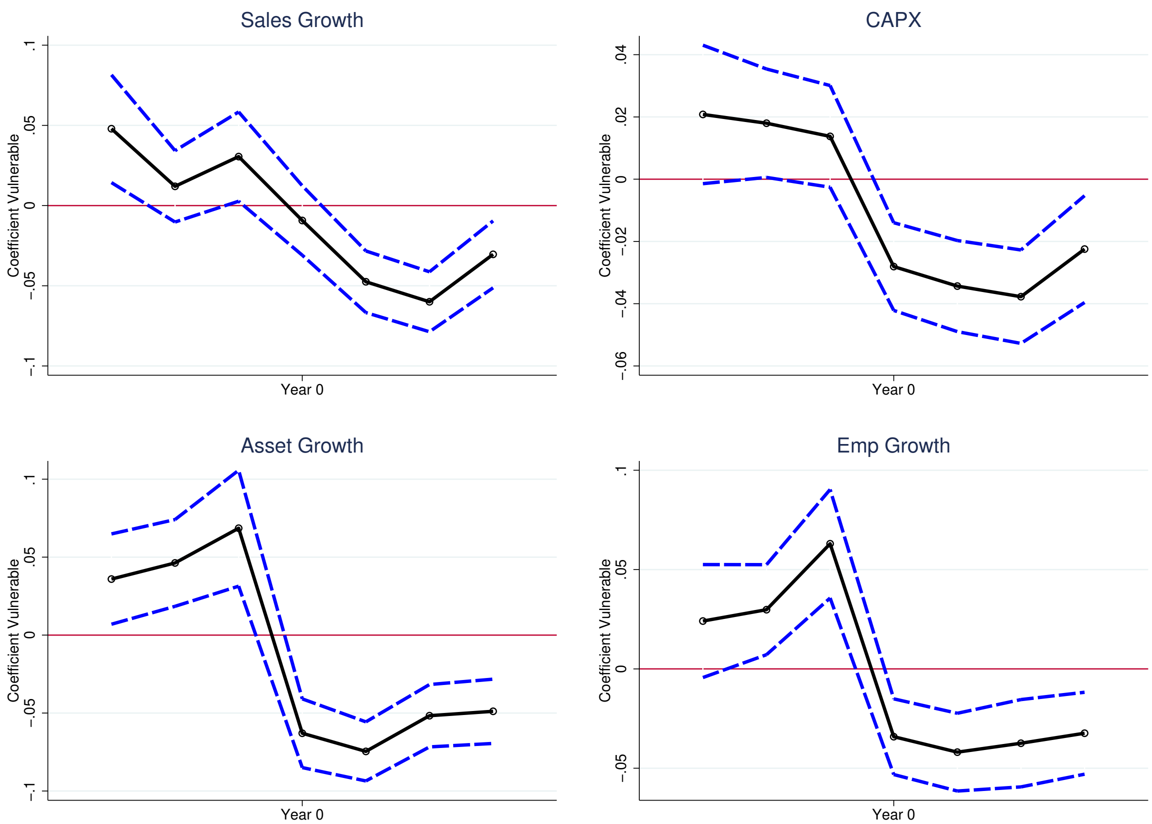

Figure 4: Firm Performance after Being Classified as Vulnerable. This figure shows the evolution of the estimated coefficient β_q from Specification (1) three years before and after a firm becomes vulnerable. Year zero corresponds to the first year a firm is classified as vulnerable. The 95% confidence interval is reported, with standard errors clustered at the firm level.

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 4 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.

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

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

where i is a firm, h an industry, and t a year. Our dependent variable Y is a dummy equal to

	Negative Watch	Negative Watch	Downgrade	Downgrade
Vulnerable	0.078***	0.043**	0.029***	0.021**
	(0.018)	(0.018)	(0.008)	(0.008)
Size		0.017**		0.006**
		(0.007)		(0.003)
Leverage		0.131**		0.070***
		(0.055)		(0.024)
IC Ratio		-0.010***		-0.000**
		(0.001)		(0.000)
Industry-Year FE	✓	✓	✓	✓
Observations	9,056	8,973	9,433	9,343
R-squared	0.118	0.150	0.110	0.114

Table 2: Credit Rating Actions after Being Classified as Vulnerable. This table presents the estimation results from Specification (2) 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 in year $t+1$. *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.

one in the case of a negative watch event in t or $t+1$ or a downgrade event in $t+1$. $Vulnerable$ 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 2 presents the estimation results. The first two columns show 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 when a vulnerable firm has a higher probability to be downgraded in the next year.[3]

4 The Exorbitant Privilege

In this section, we show that vulnerable BBB firms—prospective fallen angels—have benefited from extraordinarily low bond financing costs, supported by the leniency of credit rating agencies. In Section 4.1, we document the funding advantage, particularly large during

[3] In Figure B.3, we show the local projection for the downgrade propensity, showing its evolution over time.

periods of monetary easing, of prospective fallen angels. In Section 4.2 and Section 4.3, we show that this funding advantage originates, in equilibrium, from credit rating inflation and investors' demand for BBB-rated bonds.

4.1 The Funding Advantage

In this section, we document the funding advantage of prospective fallen angels with two non-parametric and two parametric tests.

First, 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 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.5, we show that the 2013–16 is characterized by a substantial monetary easing by the Federal Reserve.

Second, we show that the compression of BBB bond spreads coincides with a marked decline of the spreads of vulnerable issuers relative to non-vulnerable issuers—a dynamic unique to the BBB segment of the bond market. In Figure 6, we show secondary market spreads between vulnerable and non-vulnerable issuers rated A, BBB, and BB. We observe that the difference in the spread between vulnerable and non-vulnerable BBB rated firms is (i) almost always smaller than the difference for the A and BB segments, (ii) hovering around zero, and (iii) negative from 2013 to 2016.

Third, we document, in a formal test, the exorbitant privilege of prospective fallen angels, namely we show that the financing costs of vulnerable BBB firms are lower than the financing costs of non-vulnerable BBB-rated issuers. In particular, we compare the bond spread on vulnerable Vs. non-vulnerable firms within a rating category by estimating the following

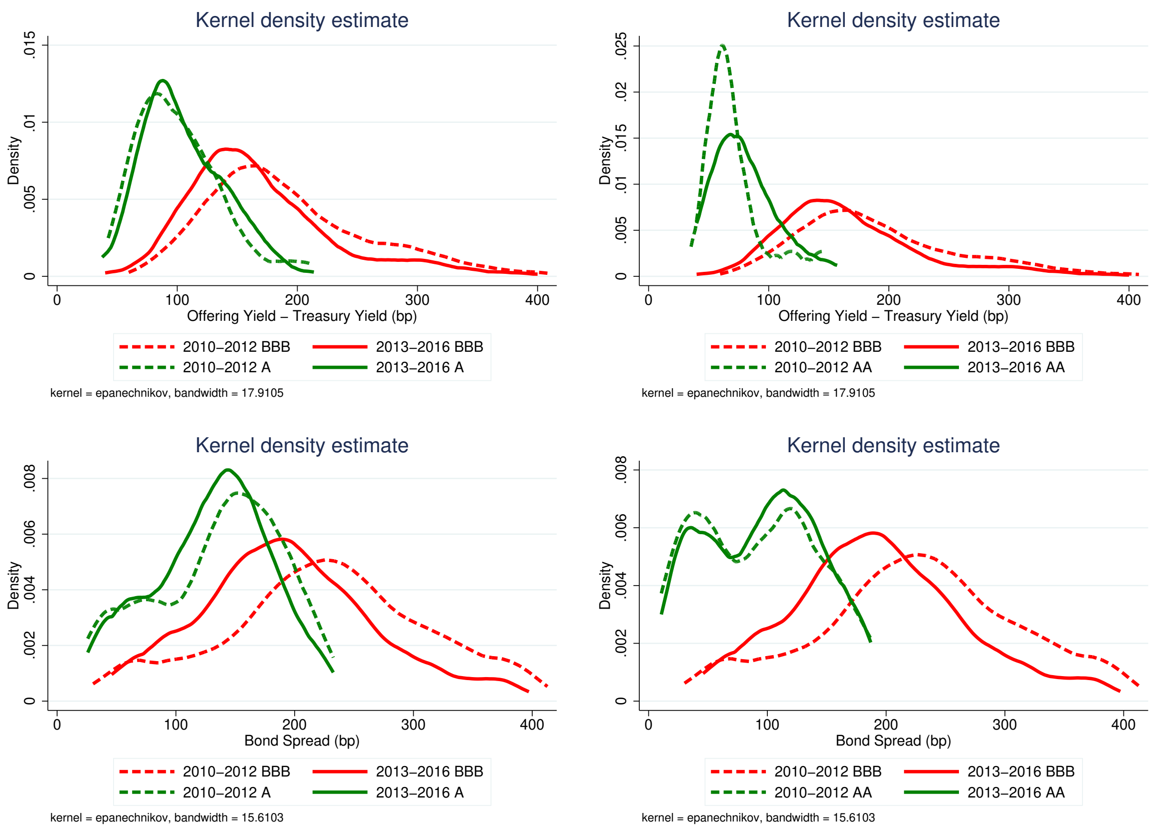

Figure 5: Shift in Bond Spread Distributions from 2010–12 to 2013–16. This figure shows how bond spreads distributions changed from 2010–12 (dashed lines) to 2013–16 (solid lines). The top panels show the distribution of offering spreads (offering yield−maturity adjusted treasury yield) for newly issued 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.

specification:

$$\begin{aligned} Spread_{biht} = & \beta_1 Rating_{iht} + \beta_2 Rating_{iht} \times Vulnerable_{iht} \\ & + \mathbf{\Gamma} X_{it-1} + \delta \times Z_{bt} + \mu_{ht} + \epsilon_{biht} \end{aligned} \tag{2}$$

where $Spread_{biht}$ is the spread (in basis points) of bond b issued by firm i in industry h in year t. Bond spreads are the difference between bond and treasury yields with a similar maturity. $Rating_{iht}$ is the firm rating and $Vulnerable_{iht}$ is an indicator variable equal to one if the issuer is classified as vulnerable in period t. We also include a vector X_{it} of firm level control variables, a vector Z_{bt} of bond level characteristics, and industry-year fixed effects μ_{ht}.

Table 3 presents the estimation results. The estimated coefficients of the uninteracted

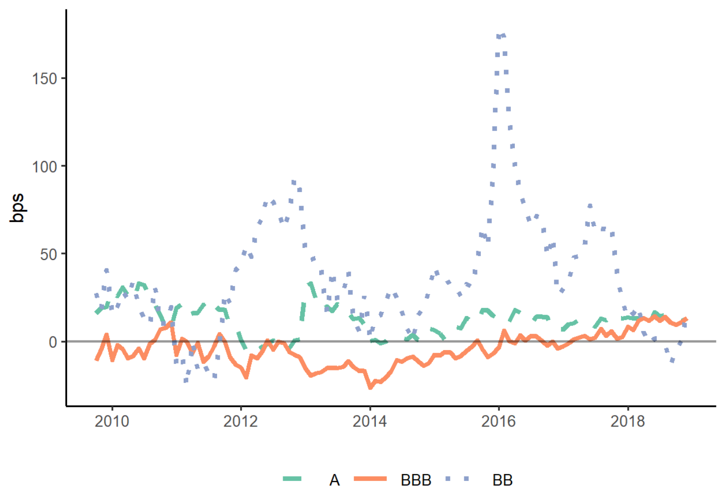

Figure 6: Secondary Market Spreads, Vulnerable Vs. Non-Vulnerable Issuers. This figure shows the difference in secondary market spreads between vulnerable and non-vulnerable issuers, separately for issuers rated A (dashed line), BBB (solid line), and B (dotted line).

terms in the first column show that bond spreads are monotonically increasing as the ratings deteriorate. The estimated coefficients of the interaction terms show that in all rating categories, except BBB, vulnerable firms have a higher financing cost than non-vulnerable firms. This correlation is reversed for BBB firms as prospective fallen angels pay *lower* financing costs than non-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 doubles in magnitude. The third and fourth columns show similar estimation results using primary market offering spreads as a dependent variable. In the last two columns, we use the (log) expected default frequency derived from equity markets at the 2-year and 5-year horizons as dependent variables. While we confirm that the estimated coefficients on the uninteracted terms increase monotonically as ratings deteriorate, the advantage of prospective fallen angels disappears, suggesting that the exorbitant privilege documented above is specific to the bond market.

Fourth, 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.

	Spread	Spread	Offer Spread	Offer Spread	EDF 2Y	EDF 5Y
AA	1.746	-17.597	16.091	-6.215	0.468*	0.239
	(13.065)	(21.188)	(21.738)	(8.670)	(0.265)	(0.183)
A	13.188	9.170	18.773	-8.315	0.586***	0.401***
	(8.817)	(13.644)	(21.545)	(10.791)	(0.133)	(0.099)
BBB	58.673***	56.923***	94.111***	61.258***	1.016***	0.762***
	(11.969)	(18.709)	(22.281)	(13.215)	(0.148)	(0.113)
BB	187.948***	174.870***	266.736***	232.979***	1.789***	1.328***
	(16.400)	(25.753)	(24.525)	(20.766)	(0.176)	(0.134)
B	347.962***	337.087***	386.862***	346.288***	3.141***	2.360***
	(24.574)	(39.757)	(26.699)	(29.786)	(0.201)	(0.150)
CCC	1,077.630***	1,141.733***	388.735***	44.463	4.719***	3.574***
	(134.709)	(247.433)	(45.244)	(172.345)	(0.242)	(0.191)
Vulnerable × AAA	22.965***	19.383*	5.825	-9.696	0.639**	0.362***
	(7.451)	(10.401)	(21.962)	(15.681)	(0.258)	(0.129)
Vulnerable × AA	22.230*	39.289**	4.293	-11.001	0.177	0.250
	(12.535)	(19.453)	(13.240)	(15.747)	(0.275)	(0.189)
Vulnerable × A	-6.707	-13.110	-7.641	-10.587	0.226*	0.174*
	(6.695)	(10.993)	(9.519)	(13.156)	(0.129)	(0.102)
Vulnerable × BBB	-11.135**	-23.924***	-15.572**	-23.096**	0.261***	0.176***
	(5.180)	(7.934)	(7.736)	(10.090)	(0.090)	(0.067)
Vulnerable × BB	34.636***	43.936***	30.039**	41.139	0.567***	0.432***
	(10.148)	(14.124)	(13.213)	(25.042)	(0.108)	(0.077)
Vulnerable × B	54.908**	33.364	19.991	4.313	0.626***	0.470***
	(25.505)	(32.282)	(19.190)	(53.462)	(0.124)	(0.089)
Vulnerable × CCC	246.180	164.243			-0.017	0.001
	(193.113)	(288.661)			(0.225)	(0.180)
Industry-Year FE	✓	✓	✓	✓	✓	✓
Firm-Level Controls	✓	✓	✓	✓	✓	✓
Bond-Level Controls	✓	✓	✓	✓		
Sample	Entire	2013–16	Entire	2013–16	Entire	Entire
Observations	20,106	9,514	3,140	1,163	4,353	4,606
R-squared	0.733	0.709	0.925	0.915	0.778	0.797

Table 3: Bond Spread of Vulnerable and Non-Vulnerable Firms by Firm Ratings. This table shows the estimation results of Specification (2). 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. The dependent variable in columns (5)-(6) are the expected default frequencies at the 2-year and 5-year horizon, respectively. 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 vulnerable. Firm level controls are the log of total assets, leverage, and the interest coverage ratio. Bond level controls are residual maturity, a callable dummy, and a liquidity measure. All 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.

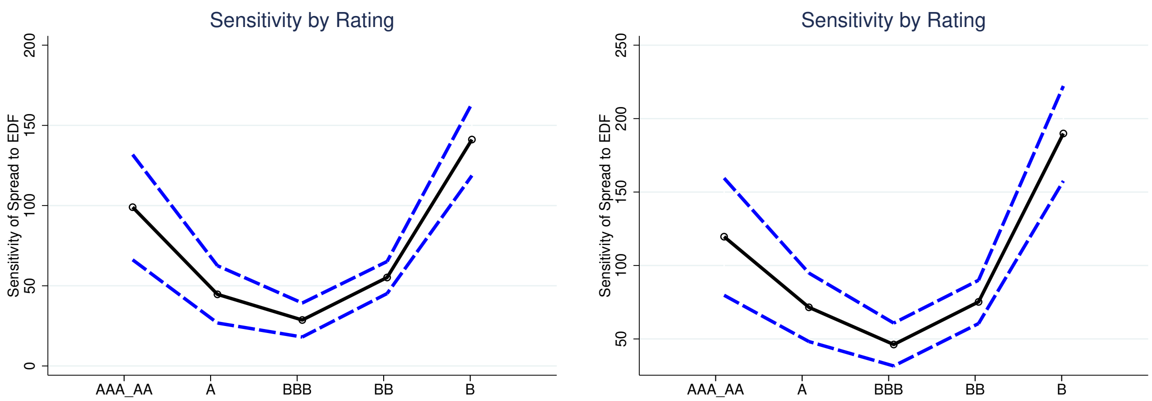

Figure 7: Sensitivity of Bond Spreads to EDFs. This figure shows the sensitivity of bond spreads to 2-year EDFs (left panel) and 5-year EDFs (right panel). The points in the graph are obtained by calculating $\beta_2 \overline{EDF}_{iht} + \beta_3 Rating_{iht} \times \overline{EDF}_{iht}$, where the coefficients are estimated using Specification (3) and $\overline{EDF}$ is the mean EDF in each rating category. The dashed blue lines represent 95% confidence intervals.

To this end, we estimate the following specification:

$$\begin{aligned} Spread_{biht} = & \beta_1 Rating_{iht} + \beta_3 EDF_{iht} + \beta_3 Rating_{iht} \times EDF_{iht} \\ & + \mathbf{\Gamma} X_{iht} + \mu_{ht} + \delta \times Z_b + \phi_i + \epsilon_{iht} \end{aligned} \tag{3}$$

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 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.

4.2 Credit Rating Inflation

In this section, we document that credit rating inflation is particularly pronounced, and increasing, in the BBB segment of the bond market. In addition, we show that M&A activity is closely associated with ratings inflation for prospective fallen angels such that prospective fallen angels engage in M&A activity to exploit the leniency of credit rating agencies following

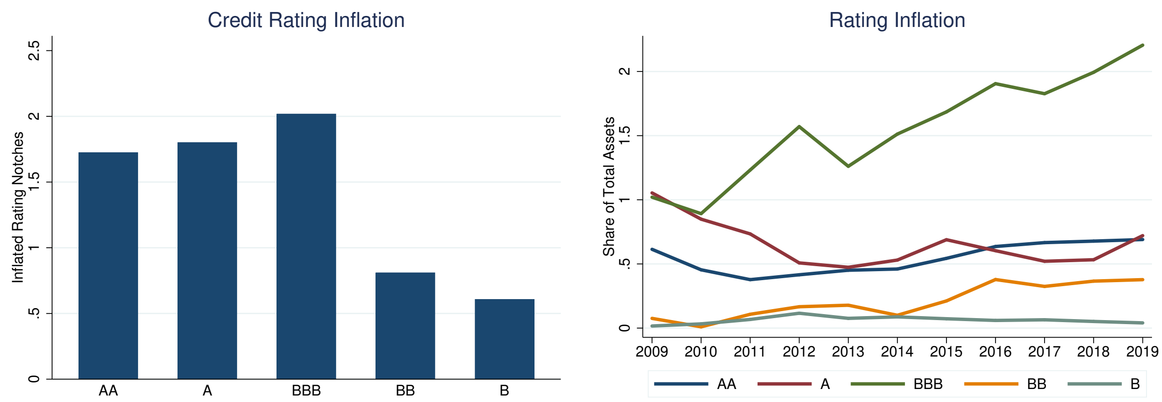

Figure 8: Credit Rating Inflation. This figure shows credit rating inflation based on the firm's Z"-score relative to Z"-scores of firms in lower ratings buckets. Credit rating inflation is equal to zero if an issuer has a Z"-score above the median Z"-score of firms in the next lower rating category, 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 left-hand panel shows average level of credit rating inflation across our sample by rating's category. The right-hand panel shows asset weighted credit rating's inflation in each year.

an M&A transaction. While these transactions are value destroying, we show that they are valued by bond investors because they delay downgrades of prospective fallen angels to the high-yield market.

We first show that credit rating inflation is particularly high, and increasing since 2009, for BBB-rated issuers in Figure 8. The left panel shows that credit rating inflation is highest for BBB-rated issuers where credit rating 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. The bar chart shows that credit rating inflation is the highest for BBB rated issuers, consistent with credit rating agencies' reluctance to downgrade BBB-rated firms to the high-yield market. The right panel presents the evolution of rating inflation and shows that the rating inflation of BBB-rated issuers has been steadily increasing from 2009 to 2019 in contrast to other rating buckets.

The presence of particularly pronounced ratings inflation among BBB issuers is consistent with other studies and anecdotal evidence. For example, Bruno et al. (2016) show that Moody's avoids downgrading issuers of corporate bonds that are close to losing their investment grade certification. Investment bank analysis paints a similar picture of ratings inflation. For example in 2018 a research note by Morgan Stanley noted that, "... where 55% of BBB debt

	Rating Inflation	Rating Inflation	Rating Inflation
Vulnerable × BBB	0.960***		
	(0.234)		
Vulnerable	5.454***		
	(0.163)		
BBB	-0.559***	0.380**	-0.041
	(0.141)	(0.188)	(0.290)
M&A × BBB			0.642**
			(0.302)
M&A			-0.318
			(0.199)
Controls	✓	✓	✓
Industry-Year FE	✓	✓	✓
Cluster	Firm	Firm	Firm
Sample	Rated	Vulnerable	Vulnerable
Observations	7,159	2,750	2,750
R-squared	0.725	0.381	0.386

Table 4: Rating Inflation. This table presents firm-level regressions where 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. All specifications include industry-year fixed effects and firm-level controls (log(total assets), leverage, net worth). Standard errors are clustered at the firm level.

would have a hig-yield rating if rated based on leverage alone. Meanwhile, interest coverage has declined steadily since 2014, particularly for BBB issuers..." (Morgan Stanley (2018a)).

Parametric tests in Table 4 confirm ratings inflation in the BBB ratings bucket. Moreover, these regressions show that ratings inflation is driven by vulnerable BBB firms, and importantly, that this is closely related to M&A activity. Column (1) shows that vulnerable issuers benefit from ratings inflation. Within vulnerable firms, the results in Column (2) suggestion that vulnerable BBB issuers enjoy on average an additional 0.4 notches in ratings inflation compared to vulnerable issuers in other ratings buckets. Finally, column (3) shows that within 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 issuers. Rather, M&A by issuers in other ratings buckets tends to result in a reduction in ratings inflation on average.

Value creating M&A by BBB vulnerable issuers could potentially justify the M&A related ratings inflation. However, M&A by BBB vulnerable issuers has instead been value destroying. In particular, Table 5 shows that the cumulative abnormal returns around M&A transactions by vulnerable BBB issuers have been negative. By contrast, for non-vulnerable BBB issuers

	(1) CARs (-2 to 2)	(2) CARs (-2 to 2)	(3) CARs (-2 to 2)
Vulnerable $\times BBB$	-0.013***	-0.014***	-0.019**
	(0.005)	(0.005)	(0.008)
Vulnerable	0.004	0.005	0.008
	(0.004)	(0.004)	(0.006)
BBB	-0.002	-0.000	-0.001
	(0.002)	(0.002)	(0.004)
Controls		✓	✓
Industry FE	✓	✓	✓
Year FE	✓	✓	✓
Sample	Rated	Rated	Rated
Observations	2,566	2,565	1,264
R-squared	0.057	0.080	0.112

Table 5: Cumulative Abnormal Returns. This table presents the 5-day cumulative abnormal returns for the M&A deals performed by the rated firms in our sample. The total return value-weighted index is used as benchmark over a -210 to -11 day period. Control variables in Column 2 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. Apart from the controls in Column 2, we also add the relative transaction size defined by the value of the transaction over the acquiror's lagged assets in Column 3. All specifications include industry and year fixed effects. Standard errors are clustered at the firm level. A t-test shows that on average the CARs of BBB vulnerable firms are -1 per cent.

as well as vulnerable firms in other ratings buckets, M&A has not been significantly correlated with negative abnormal returns. In Table 6, we also show that for vulnerable BBB rated firms the Tobin's Q and productivity drop in the year following the announced M&A transaction, and that net debt over EBITDA rises. This is in contrast to BBB non-vulnerable firms which show the reverse pattern. Again, this finding is consistent with anecdotal evidence from investment bank research notes regarding risky M&A, for example, "...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..." (Morgan Stanley (2018a)) Similarly, in the same year another research note noted, "...forward-looking assumptions often assume all goes well and earnings growth is strong. In reality, issuers have been slow to actually delever..." (Morgan Stanley (2018b)).

Even though M&A by BBB vulnerable firms is value destroying, somewhat surprisingly, it does appear to postpone ratings downgrades. Indeed, prospective fallen angels appear to engage in M&A activity to exploit the leniency of credit rating agencies following an M&A

	(1) Tobin's Q	(2) Productivity	(3) Net Debt/EBITDA
Vulnerable $\times BBB$	-0.234**	-0.140**	0.376*
	(0.093)	(0.067)	(0.212)
Vulnerable	-0.036	0.026	-0.263
	(0.073)	(0.048)	(0.183)
BBB	0.117*	0.088*	-0.222*
	(0.071)	(0.047)	(0.125)
Controls	✓	✓	✓
Industry-Year FE	✓	✓	✓
Sample	M&A Rated	M&A Rated	M&A Rated
Observations	2,621	2,540	2,622
R-squared	0.441	0.563	0.470

Table 6: Value Destruction. This table presents the value destruction of vulnerable BBB-rated firms in the year after the announced M&A transaction. The dependent variables at $t+1$ include Tobin's Q, productivity (log(sale) - 2/3*log(emp)- 1/3*log(ppent)) and net debt over EBITDA. The sample consists of all firms that are rated and have an announced M&A transaction in year t. Firm controls include the log of assets, profitability, leverage and tangibility. All specifications include industry-year fixed effects. Standard errors are clustered at the firm level.

transaction, allowing them to kick the downgrade can down the road. To assess the impact of M&A by vulnerable firms on the propensity to be downgraded, we calculate Kaplan-Meier (Kaplan and Meier, 1958) survival rate estimates. The Kaplan-Meier survival rate estimates are given by:

$$\hat{S}_t = \prod_{t_i < t} \left(1 - \frac{d_i}{n_i}\right) \tag{4}$$

where t_i is duration of being at particular credit rating at point i, d_i is the number of downgrades up to point i and n_i is the number of issuers at risk just prior to t_i. S estimates the probability that an issuer survives at its current rating category at the end of the time interval. We estimate the survival probability of vulnerable firms splitting them into two groups depending on whether they have conducted an M&A at their current rating bucket.

The left-hand panel of Figure 9 shows that the downgrade probabilities are indeed lower for vulnerable BBB issuers that have conducted an M&A compared with their vulnerable BBB peers that have not done so. After five years, only 8% of vulnerable BBB M&A issuers were downgraded. This compares with around 25% of vulnerable BBB issuers that did not undertake an M&A. The right-hand panel shows the cumulative downgrade probabilities of vulnerable issuers, conditional on them being downgraded during our sample period. Conditional on being eventually downgraded, M&As still appear to delay the point at which

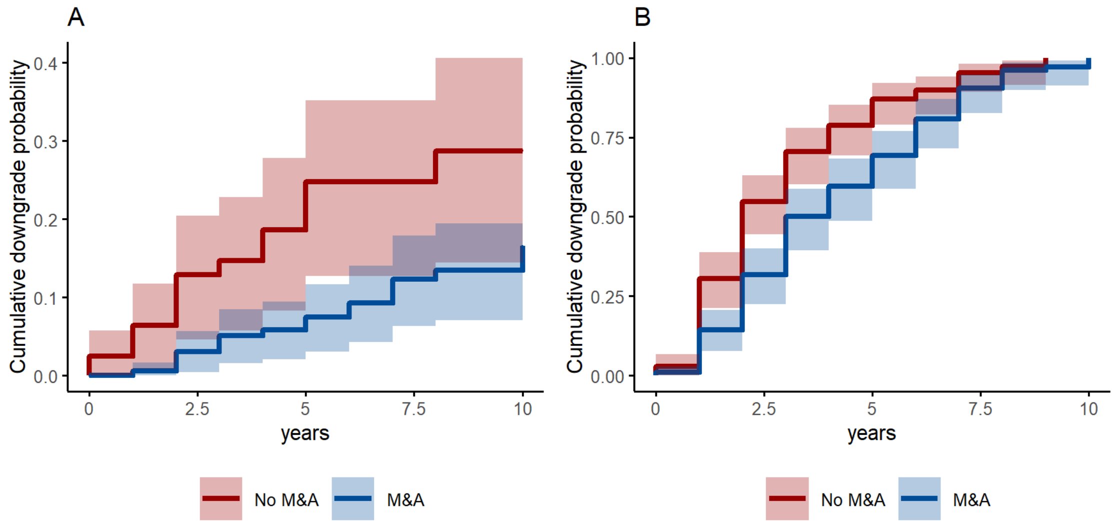

Figure 9: Cumulative Downgrade Probabilities of Vulnerable Firms. This figure shows the cumulative downgrade probabilities derived from Kaplan-Meier survival estimator together with 95% confidence bands. Panel A plots the cumulative downgrade probability of vulnerable BBB firms grouped by whether the firm did or did not conduct an M&A whilst being rated BBB. Panel B shows cumulative downgrade probabilities of vulnerable firms conditional on the firm eventually being downgraded in our sample.

credit rating agencies downgrade issuers, shown by the less steep curve.

Thus, the vulnerable BBB segment is characterized by high and increasing credit rating inflation. Moreover, the funding advantage of these prospective fallen angels is driven by their ability to exploit rating inflation related to value destroying M&A. Even though this M&A is value destroying on average, it delays the point at which credit ratings agencies downgrade the issuer. We now turn to the investor perspective in the next section.

4.3 The Role of Yield-Seeking Investors

In this section, we show that the exorbitant privilege of prospective fallen angels is supported by the demand by yield-seeking investors. First, we document that yield-seeking investors drive the demand for bonds issued by prospective fallen angels, a dynamic more pronounced for investors that predominantly hold investment-grade bonds. Second, we show that this demand is driven by the large quantity of bonds issued to fund M&A activity, consistent with the idea that, exposed to the fire sale risk related to an eventual downgrade to the high-yield market, investment-grade investors value the leniency of credit rating agencies following M&A.

Exploiting our investor holdings data, we find whether an investor is yield-seeking and whether it has an implicit or explicit mandate to hold only in investment-grade bonds. We identify yield-seeking investors defining an investor level variable based on the residual maturity of the investor's portfolio as of 2009Q4. The idea is that investors with a long maturity of their bond portfolio at the end of 2009 likely suffered more from the subsequent reduction of long-term yields compared with shorter-duration investors. We identify investors that have a mandate to hold only investment-grade bonds based on the share of their bond holdings rated investment-grade. Specifically, we classify an investor as an investment-grade investor if its mean holdings of investment-grade bonds in the entire sample period are at least 85% of its entire bond portfolio.

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

$$Holdings_{kjt} = \alpha + \beta_1 Duration_k^{09} \times Vulnerable_{jt} + \eta_{kt} + \mu_{jt} + \epsilon_{jkt} \tag{5}$$

where k is an investor, j is an issuer, and t is a year. 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 $Duration_k^{09}$, the duration of investor k's portfolio as of 2009Q4 (in years), and $Vulnerable_{jt}$, a dummy equal to one if issuer j is vulnerable in year t.

The coefficient of interest β_1 captures whether yield-seeking investors hold more or fewer bonds issued by vulnerable issuers from 2009 to 2018. In the most stringent specification, we are effectively comparing bonds issued by the same issuer that are held by investors with a different duration of their portfolio in 2009Q4. 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-duration investors, with respect to vulnerable and non-vulnerable bonds, for reasons unrelated to reaching-for-yield. Issuer-time fixed effects control for the potential differential characteristics of vulnerable and non-vulnerable bonds (e.g., issuance volume) that might interact with the portfolio choice of high-duration Vs. low-duration investors for reasons, again, unrelated to yield-seeing.

Table 7 shows the estimation results. The first three columns show the coefficients

	$Holdings_{jkt}$					
$Duration_k^{09} \times Vulnerable_{jt}$	0.328**	0.318**	0.300**	0.462**	0.883***	0.111
	(0.130)	(0.151)	(0.130)	(0.183)	(0.270)	(0.237)
Fixed Effects						
Issuer j	✓					
Investor k		✓				
Investor k - Time t	✓		✓	✓	✓	✓
Issuer j - Time t		✓	✓	✓	✓	✓
Sample	Full	Full	Full	BBB	BBB	BBB
Sample Investors	Full	Full	Full	Full	IG	non-IG
Observations	1,228,981	1,229,229	1,228,830	448,933	257,056	191,867
R-squared	0.534	0.495	0.554	0.585	0.586	0.589

Table 7: Demand for Bonds Issued by Prospective Fallen Angels. This table presents estimation results from specification (5). The unit of observation is investor k-issuer j-year 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). $Duration_k$ is the duration of investor k's portfolio (in years) as of 2009Q4. $Vulnerable_{jt}$ is a dummy equal to 0.01 (for legibility) if issuer j is vulnerable to a downgrade in year t. The uninteracted $Vulnerable_{jt}$ term in the first column is included in the estimation but not reported for brevity. The first two columns are estimated in the full sample of issuers. The first three columns are estimated in the full sample of investors. The last three columns are estimated in the subsample of issuers rated BBB. The last two columns are estimated in the subsample of investment grade and non-investment grade investors, respectively. Standard errors are clustered at the investor k level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

estimated in the full sample. The estimated coefficient β_1 is positive and significant, suggesting that high-duration investors have a higher demand for bonds issued by vulnerable issuers. In the last three columns, we estimate the specification (i) in the subsample of BBB bonds, (ii) in the subsample of BBB bonds and investment grade investors, and (iii) in the subsample of BBB bonds and non-investment grade investors. The estimation results show that the demand of yield-seeking investors for bonds issued by vulnerable firms is stronger in the BBB market, particularly when considering only investment grade investors. The last column shows that there is no correlation between yield-seeking and holdings in the BBB market by non investment grade investors.

Second, we analyze investors' demand for bonds issued by prospective fallen angels to fund M&A activity by estimating Specification (5) separatey 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 two columns, the dependent variable is holdings of bonds issued to fund M&A. In the last two columns, the dependent variable is holdings of other bonds. The first and third column are estimated in the full sample. The second and fourth column are estimated in the

	M&A $Holdings_{jkt}$		non-M&A $Holdings_{jkt}$	
$Duration_k^{09} \times Vulnerable_{jt}$	1.039***	1.225***	-0.261*	0.783**
	(0.239)	(0.341)	(0.156)	(0.330)
Fixed Effects				
Investor k - Time t	✓	✓	✓	✓
Issuer j - Time t	✓	✓	✓	✓
Sample	Full	BBB	Full	BBB
Sample Investors	Full	IG	Full	IG
Observations	172,758	52,742	1,228,839	257,056
R-squared	0.800	0.804	0.510	0.511

Table 8: Demand for Bonds Issued by Prospective Fallen Angels to Fund M&A. This table presents estimation results from specification (5). The unit of observation is investor k-issuer j-year 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 two columns, the dependent variable are holdings of bonds issued to fund M&A. In the last two columns, the dependent variable are holdings of bonds except those issued to fund M&A. $Duration_k$ is the duration of investor k's portfolio (in years) as of 2009Q4. $Vulnerable_{jt}$ is a dummy equal to 0.01 (for legibility) if issuer j is vulnerable to a downgrade in year t. Standard errors are clustered at the investor k level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

subsample of investment-grade investors and BBB-rated issuers. The estimated coefficients show that yield-seeking investors drive their holdings of bonds issued to fund M&A.

5 Real Effects of the Exorbitant Privilege

We have documented that vulnerable BBB firms benefit from a funding privilege in their corporate bond funding. In this section, we explore the real effects of this funding advantage. In Section 5.1, we show that BBB vulnerable firms increased their sales and lowered their markups but did not invest more or employed more workers during our sample period. In Section 5.2, we show that non-vulnerable firms are negatively affected by the presence of vulnerable BBB firms.

5.1 Direct Effects

How do BBB vulnerable firms take advantage of their cheap bond financing? The first observation from raw data is a sizable increase in the market shares of BBB vulnerable firms from 2009 to 2018, and in particular from 2013 onward. We present the data in Figure 10. The left panel shows the market shares of firms in each rating category. The right panel shows the market shares by rating category separately for vulnerable and non-vulnerable

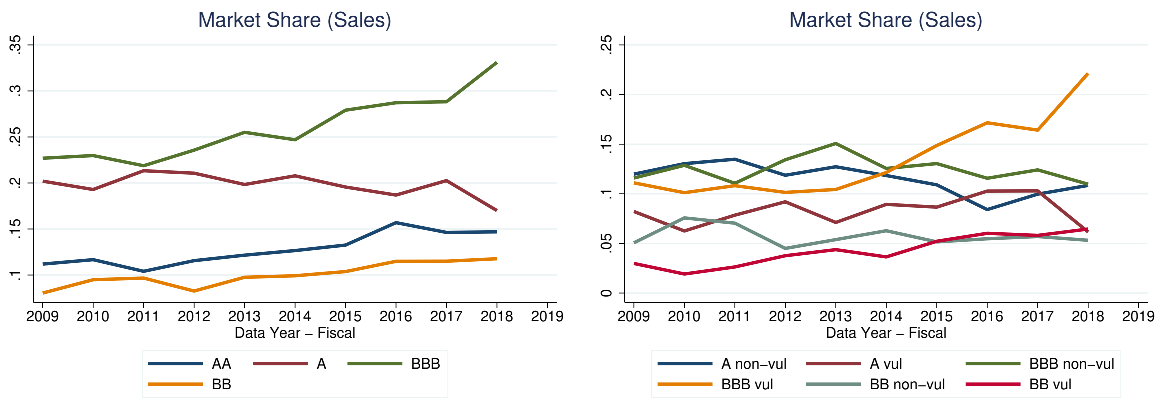

Figure 10: Market Shares. This figure shows the market share (share of sales) of firms in each rating category in the sample of Compustat Firms. The left panel shows a sample split based on rating category. The right panel shows a sample split based on rating category and firm downgrade vulnerability.

firms. These figures show that BBB firms increased their market share from around 25% in 2013 to around 33% in 2018, driven by vulnerable BBB firms that more than doubled their market share from around 10% in 2013 to around 22% in 2018.

Having documented the large increase in market shares, we now show that BBB vulnerable firms increased their sales and lowered their markups, but, despite their funding advantage, did not increase their investment or employment. Also, we show that BBB vulnerable firms increase their M&A activity. More specifically, we estimate the following specification:

$$\begin{aligned} Y_{iht+1} &= \beta_1 Vulnerable_{iht} + \beta_2 Vulnerable_{iht} \times BBB_{iht} \\ &+ \gamma \times X_{iht} + \eta_{ht} + \mu_i + \epsilon_{ihjt}, \end{aligned} \tag{6}$$

where i is a firm, h an industry, and t a year. Our dependent variables are employment growth, investment, sales growth, markups, relative deal size and a dummy for an M&A transaction in a given year. The coefficient β_1 captures the effect of a firm vulnerable status on the independent variable. The coefficient β_2 captures whether the effect of a firm vulnerable status on the independent 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), firm fixed effects to control for time-invariant firm characteristics, and time-varying firm level controls.

We show the estimation results in Table 9. Several results are noteworthy. First, consistent

	(1) Emp Growth	(2) CAPX	(3) Sales Growth	(4) Markup	(5) Deal Size	(6) M&A Indicator
Vulnerable $\times BBB$	0.020	0.012	0.047***	-0.101**	0.032**	0.062*
	(0.014)	(0.008)	(0.015)	(0.043)	(0.013)	(0.034)
Vulnerable	-0.027**	-0.016**	-0.014	0.031	-0.024***	-0.052**
	(0.011)	(0.006)	(0.010)	(0.026)	(0.008)	(0.022)
Industry-Year FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Observations	7,613	7,815	7,857	7,856	8,408	9,314
R-squared	0.360	0.745	0.475	0.930	0.284	0.423

Table 9: Real Effects - Direct Effects This table presents estimation results from Specification (6). The dependent variables are employment growth, CAPX/PPE, sales growth, markup (defined as sales/cost of goods sold), deal size (defined as the total transaction value in a given year divided by lagged assets) and an M&A indicator for a deal in a given year. Relative deal size and the M&A indicator are measured contemporaneously. Vulnerable is defined in Section 2.2. Firm level control variables include log of total assets, leverage, net worth, and indicator variables for the rating bucket (AAA, AA, A etc.). Standard errors are clustered at the firm-level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

with our evidence in Section 3.2, vulnerable firms have lower employment growth rates and invest less. The employment and investment outcomes of vulnerable BBB firms do not differ significantly from those of other vulnerable firms. These estimation results suggest that, despite their funding advantage, BBB vulnerable firms did not invest significantly more or hired significantly more employees. Second, we find a positive and significant effect on sales growth and significantly lower markups for vulnerable BBB firms. Consistent with the substantial increase in the market share of vulnerable BBB firms, these results suggest that these firms have used their cheap funding to expand their sales volume by charging lower markups. Lastly, we show that while vulnerable firms are on average less likely to engage in M&A activity, vulnerable BBB firms are more likely. This is found both by using the deal volumes relative to a firm's lagged assets, as well as by using a dummy variable which takes the value of one if a firm announces at least one M&A transaction in a given year.

5.2 Spillover Effects on Non-Vulnerable Firms

Having shown the effect of the funding advantage on employment, investment, and market share, we now focus on spillover effects from BBB vulnerable firms to non-vulnerable firms. In particular, we follow the literature on the spillover effects of zombie lending (most notably

Caballero et al. (2008)) and estimate the following regression at the firm-year level:

$$
\begin{aligned}
Y_{iht} &= \beta_1 \times Non-Vulnerable_{iht} \\
&+ \beta_2 \times Non-Vulnerable_{iht} \times Share\ VulnerableBBB_{ht-1} + \eta_{ht} + \epsilon_{iht}, \qquad (7)
\end{aligned}
$$

where i is a firm, h an industry, and t is a year. As in specification (6), our 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-vulnerable firms that operate in industries with a high share of vulnerable BBB firms perform differently than non-vulnerable firms in industries with a lower share of vulnerable BBB firms.

Panel A shows that in the sample of rated firms non-vulnerable investment-grade firms are negatively affected by the presence of vulnerable BBB firms. More precisely, Columns (1) and (2) show that while non-vulnerable firms have on average higher employment growth rates and invest more, both employment and investment are significantly impaired by the presence of vulnerable BBB firms. Moreover, these firms face lower sales growth and lower markups, compared with firms that do not compete with a large share of vulnerable BBB firms in their industry.

Importantly, Panel B shows that these spillover effects are not present when we replace that share of vulnerable BBB firms with the overall share of vulnerable rated firms. This suggests that it is indeed the specialness of the vulnerable BBB firms that drives the 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 10: Real Effects - Spillover Effects This table presents estimation results from Specification (7). The dependent variables are employment growth, CAPX/PPE, sales growth, and markup (defined as sales/cost of goods sold). Vulnerable/non-vulnerable is defined in Section 2.2. Panel A focuses on non-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-vulnerable firms. In Panel C we focus on non-vulnerable firms, using the entire sample of firms. $Share\,Vulnerable\,BBB$ measures the asset-weighted share of vulnerable BBB firms in a two-digit SIC industry. Firm level control variables include log of total assets, leverage, net worth, and 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.

6 Conclusion

In this paper we document the exorbitant privilege of prospective "fallen angels", i.e. firms on the cusp of the investment-grade cutoff, and the costs that such firms impose on the economy. We find that these firms have benefited from investors subsidizing their bond financing costs since the Global Financial Crisis. The subsidy appears to be driven by credit rating inflation and demand from yield-seeking investors.

Our results suggest that although the growth of risky investment-grade bond segment may have been a desired consequence of large scale central bank asset purchases, which push investors into riskier assets, the growing concentration of issuance in the riskiest investment-grade bucket also comes at a cost that may run counter to central bank objectives. First, the subsidised firms grow disproportionately large and increase their market share by reducing the markup on their products. Second, the resulting spillover effects force their competitors to reduce employment, investment, markups, and sales growth. An additional cost is the associated buildup of vulnerabilities in the corporate sector that arise from these subsidies. Such vulnerabilities could well become important after a shock.

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Appendix A. Data Set Construction

We start with the capital information provided by WRDS Capital IQ, which covers over 60,000 public and private companies globally. We drop the observations for which the debt categories[4] 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[5].

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 B.1 in the Appendix. Combing all the data sources, we investigate a total of 5,864 firms.

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 3,140 bond issues and 910 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 7,700 outstanding bonds by 1,130 issuers, with bond b, firm j, year t as unit of observation.

Holdings Data Lastly, we examine bond investor holding level data using eMAXX Bond Holders data from Thomson Reuters Eikon, a detailed data set that documents security-level holdings by individual investors at a quarterly frequency. We collapse holdings within an investor at the issuer level so that our unit of observation is holdings at quarter t by investor k of bonds issued by issuer j. Our data set includes 2,127,296 observations spanning 37 quarters from 2009Q4 to 2018Q4. There are 892 unique issuers and 569 unique investors, mostly investment managers (268) and insurance companies (210).

[4] 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.

[5] 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.

Appendix B. Additional Figures

B.1 Aggregate Evidence

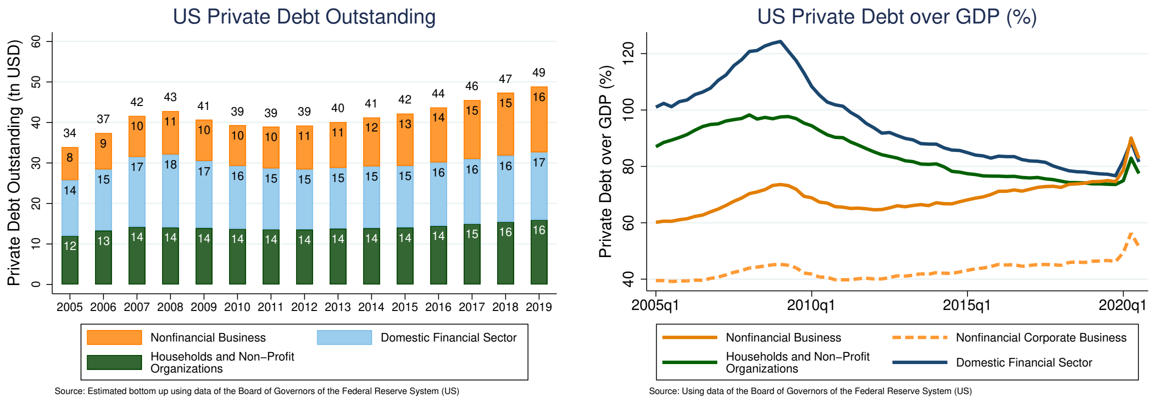

Figure B.1: US Private Debt. This figure shows the aggregate figures for the private debt outstanding in the U.S. using data of the FRED. In Panel A, we show the breakdown in absolute numbers. In Panel B, we relate the different debt components to GDP.

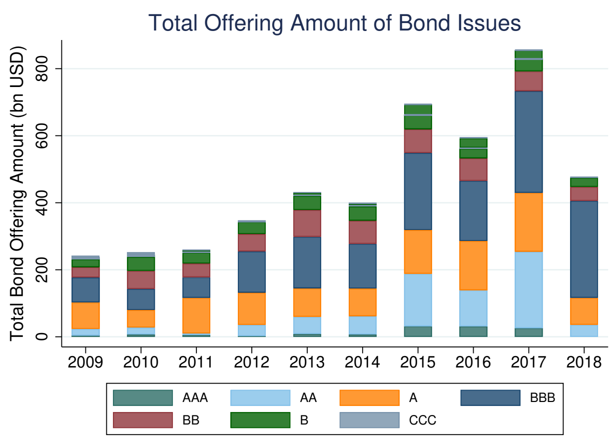

Figure B.2: US Bond Issues by Rating. This figure shows the offering amounts over time by firm rating bucket.

B.2 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 B.1. This way we can estimate the median rating for each rated firm in our data set.

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 B.1: Rating Classification. Based on the approach of Becker and Milbourn (2011).

B.3 Validation of the Vulnerability Measure

B.3.1 Rating Dynamics Aggregate

Figure B.3 shows that the downgrade propensity rises in the year after a firm becomes vulnerable for the first time, and peaks in the subsequent year.

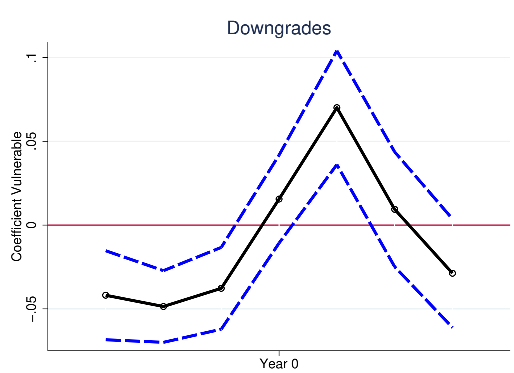

Figure B.3: Local Projection Figure - Downgrades This figure depicts the evolution of our coefficient of interest β_q of Specification (1), three years before and after a firm becomes vulnerable, with year zero corresponding to the first sample year when a firm is classified as vulnerable. The error bars represent 95 per cent confidence intervals, with standard errors clustered at the firm-level.

B.3.2 Rating Dynamics per Rating Category

To assess whether vulnerable firms are more likely to have a negative credit event or face a downgrade in each rating category, we run the following regression for firm i in industry h and year t separately for each rating category:

$$Y_{iht+1} = \quad \beta_1 Vulnerable_{iht} + \mathbf{\Gamma} X_{iht} + \mu_{ht} + \epsilon_{iht}$$

Y_{iht+1} refers to either a downgrade or negative credit event (watchlist/outlook). The results of these estimations are shown in Figure B.4.

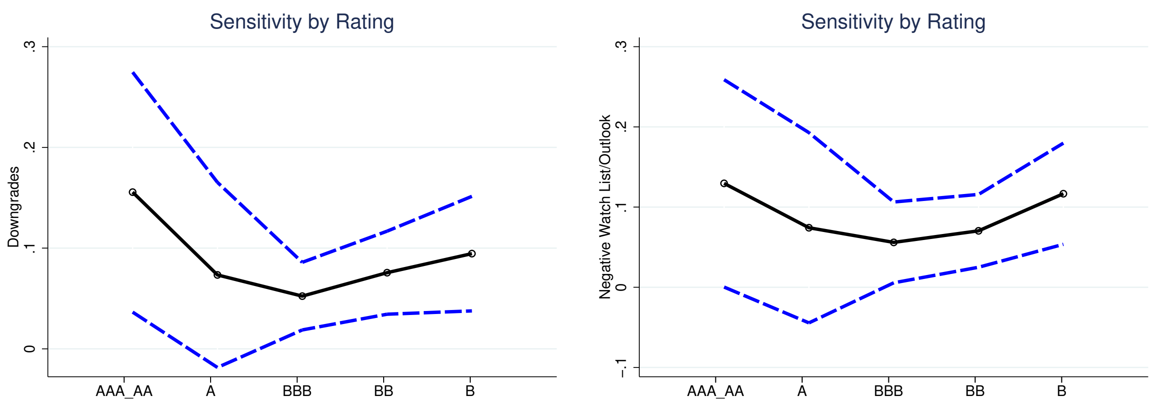

Figure B.4: Rating Actions by Rating Category This figure depicts the coefficient of interest β_1 of Specification (B1) for each rating category. The error bars represent 95 per cent confidence intervals, with standard errors clustered at the firm-level.

Panel A shows that relative to other rating categories, the vulnerable firms in the BBB-rated segment have a lower chance of being downgraded. Similarly, vulnerable firms are less likely to experience a negative credit event, compared to other rating categories. These results suggest that there is friction in the rating dynamics at the investment-grade cutoff.

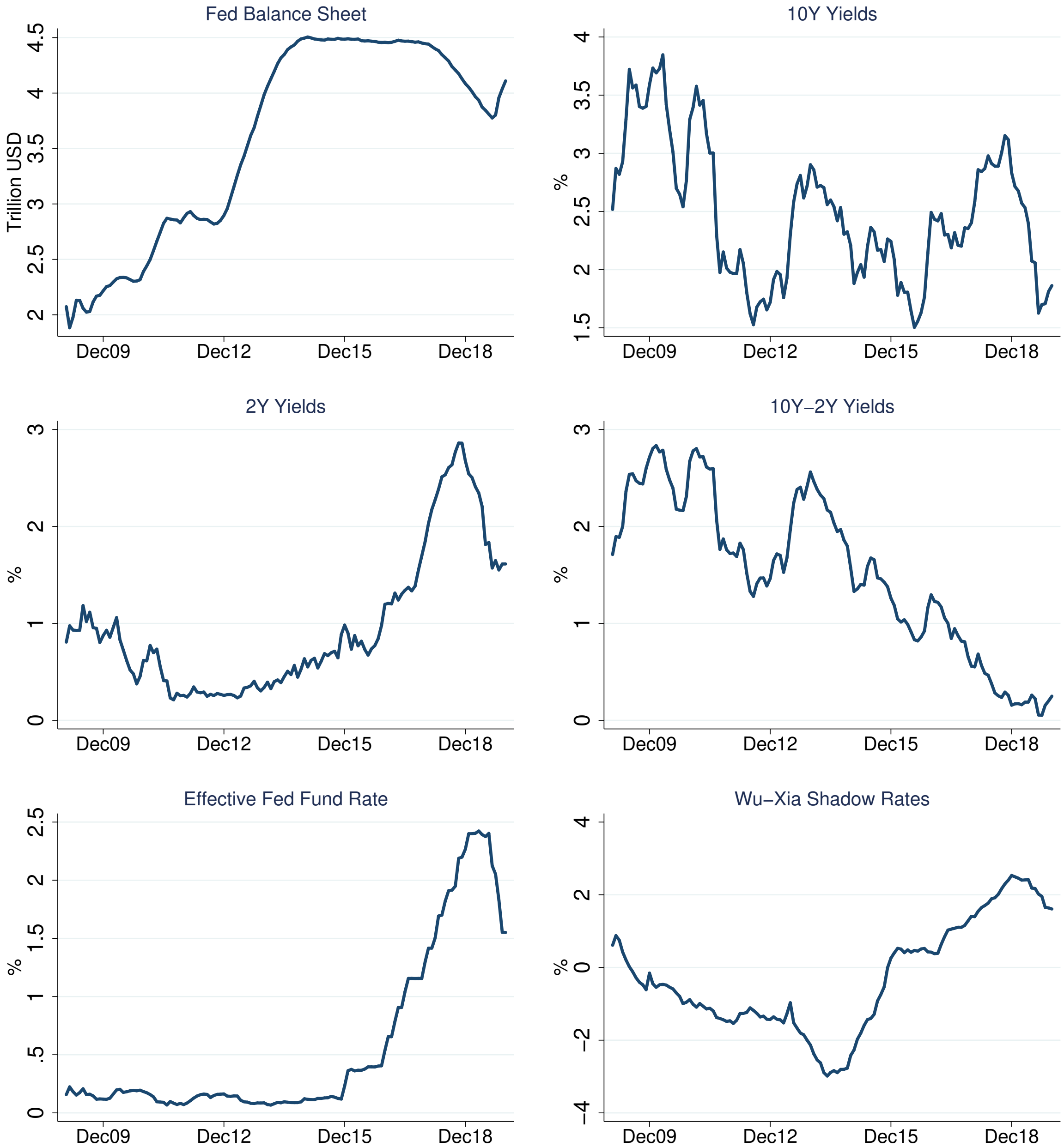

Figure B.5: Monetary Policy Stance. This figure shows the monetary policy stance in the U.S. during our sample period. The six panels show the size of the Fed balance sheet (trillion dollars), the 10-year Treasury yields (%), the 2-year Treasury yields (%), the difference between the 10-year and the 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.