Who Prices Credit Rating Inflation?

Christoph Herpfer and Gonzalo Maturana*

Abstract

Credit rating agencies (CRAs) are less likely and slower to downgrade firms with performance-sensitive debt (PSD) if these downgrades increase borrowing costs. This effect is stronger when CRAs rate their most profitable clients and is not driven by selection into PSD contracts, by borrowers adjusting their leverage, or by borrowers hiding information. Originating banks price the CRAs' conflicts of interest, and sell loans with more embedded conflicts more frequently. In contrast, secondary market participants do not price conflicts of interest to the same extent. The recent settlements between the major CRAs and the U.S. government do not prevent rating inflation.

*Herpfer, herpferc@darden.virginia.edu, University of Virginia Darden School of Business; Maturana, gonzalo.maturana@emory.edu, Emory University Goizueta Business School. We are grateful to George Pennacchi (the editor), an anonymous referee, Michela Altieri, Jess Cornaggia, Kimberly Cornaggia, John Griffin, William Mann, Aksel Mjøs, Jordan Nickerson, Andrea Passalacqua, Roberto Steri, Daniel Streitz, Xunhua Su, and David Yermack, as well as seminar and conference participants at Emory University, University of Luxembourg, University of South Carolina, the 7th IWH-FIN-FIRE Workshop, the 2021 Eastern Finance Association Meeting, and the 2022 Midwest Finance Association Meeting for their helpful comments. We also thank Cangyuan Li and Andrew Teodorescu for their excellent research assistance, and the Goizueta Business School Dean's Ad-Hoc Research Grant for research support. This paper was previously circulated under the title "Credit Rating Inflation: Is It Still Relevant and Who Prices It?" Supplementary results can be found in an Internet Appendix at the authors' websites.

I. Introduction

Credit rating agencies (CRAs) play a key role in financial markets by assessing the credit risk of debt issuers and financial securities. However, many observers have questioned CRAs' ability to provide reliable credit risk assessments. They argue that the *issuer–pays* business model, in which clients pay for their own ratings, distorts the incentives of CRAs to the extent that the fear of a loss of reputation or the fear of regulatory penalties are ineffective deterrents. Consistent with this concern, the two major CRAs, Standard and Poor's (S&P) and Moody's, recently settled with the U.S. government for contributing to the Financial Crisis by inflating the credit ratings of residential mortgage-backed securities (RMBSs) and collateralized debt obligations (CDOs). As part of these settlements, CRAs renewed their commitment to credit rating quality.

CRAs have argued that inaccurate credit ratings were confined to securitized products and explained by their high level of complexity (Credit Rating Agencies and the Financial Crisis (2008)), and therefore these inaccuracies do not affect other product markets. In this paper, we study whether the conflicts of interest of CRAs prevail in the performance-sensitive debt (PSD) market, a much more mature and less complex market than that of securitized products. Importantly, this market allows us to go beyond the literature on the existence of credit rating inflation. The availability of pricing data, both at origination and in secondary markets, allows us to study whether market participants price the conflicts of interest of CRAs and therefore to identify if any market participant is harmed by credit rating inflation. Prior research has not yet established whether secondary market participants (such as mutual funds and pension funds, which are often less informed) are harmed by credit rating inflation. Finally, unlike the market for RMBSs and CDOs, the PSD market did not disappear after 2007. This allows us to study whether CRAs effectively changed their behavior after the settlements.

In performance-sensitive debt contracts, interest payments depend directly on a measure of the borrower's financial health, such as credit ratings or financial ratios. Normally, if the borrower's financial health deteriorates, the interest rate associated with the PSD loan increases.[1] In this paper, we focus on the $900 billion subset of the PSD market which has interest payments that depend exclusively on credit ratings. In the context of these loans, a CRA experiences a conflict of interest when a credit rating downgrade causes an increase in the interest rate paid by the borrower (i.e., the client that pays the CRA for the credit rating). Thus, we consider the interest rate increase that would result from a credit rating downgrade as a measure of the conflicts of interest for CRAs for each loan. We then study whether this measure affects a CRA's rating behavior, such as the probability of issuing a credit rating downgrade.

However, identifying conflicts of interest in PSD is empirically challenging. First, the decision to take a PSD loan, and simultaneously the choice of interest payment schedules, is not random. Firms can self-select into PSD either because they have positive inside information about their future prospects (Manso, Strulovici, and Tchistyi (2010); Begley (2012)) or because they are overly optimistic (Adam, Burg, Scheinert, and Streitz (2020)). Moreover, even within PSD contracts, it is likely that there is a bias in a naïve comparison of the probability of a downgrade between firms that chose credit rating–based PSD loans and those that did not, with the former set of firms being downgraded less frequently. Second, there is another form of selection often referred to as *rating shopping* (Skreta and Veldkamp (2009); Faure-Grimaud, Peyrache, and Quesada (2009); Sangiorgi and Spatt (2017)). A firm may approach multiple CRAs and then ultimately do business with the CRA that offers the most favorable credit rating. As a result, credit ratings are inflated not due to CRAs yielding to conflicts of interest, but rather due to unintentional errors inherent in the credit rating process.

Our empirical setting allows us to mitigate these concerns. First, the ability to

[1]For example, a debt contract may stipulate an interest rate of LIBOR + 15 basis points if the borrower is rated A+. This interest rate may increase to LIBOR + 25 basis points if the borrower is rated A (i.e., if the borrower's credit rating worsens).

observe credit ratings through time allows us to exploit time-series variation within borrowers, effectively controlling for time-invariant characteristics of firms that may affect the choice of PSD contract and subsequent credit rating downgrades. Moreover, our data also allow us to include *loan* fixed effects in many of our tests. Since interest rate schedules are determined at loan origination, exploiting variation in the cost of downgrades across time and within loan contracts mitigates selection concerns. Second, the richness of the data allows us to account for time-varying firm-level factors such as borrower quality and managerial optimism, as well as various dimensions of loan contracts that are determined at origination.[2]

We start by investigating the relationship between the probability that a borrower is downgraded by a CRA and the increase in borrowing costs that would result from a downgrade. If CRAs internalize the additional cost to their client, a higher cost of a downgrade should be associated with a lower probability of a downgrade. Consistent with this proposition, we find that a one standard deviation increase in the cost of a downgrade is associated with a decreased downgrade likelihood of about 0.67 percentage points (pp) per quarter, which is a 26% reduction relative to the unconditional mean. This result is robust to a wide range of regression specifications (including the inclusion of loan fixed effects), to multiple measures of the cost of a downgrade, and to analyzing the downgrades by S&P and Moody's separately. We also show that, conditional on downgrading, CRAs are slower to downgrade their clients when the downgrade is more costly. Importantly, our analysis draws inferences from within-borrower–CRA relationships over time (i.e., from downgrades that occur after origination). This is inconsistent with borrowers rating shopping or self-selecting into PSD loans.

Next, we further refine our empirical strategy by exploiting variation in the relevance of each CRA's rating. When a CRA's rating is decisive for setting borrowing

[2]Notably, one of the major sources of variation that we exploit is the granularity of pricing grids. Many grids do not adjust interest rate spreads after every notch of credit ratings, but instead consider steps of two notches or more.

costs–either because it is the only rating or because it is the better rating–the CRA is significantly less likely to issue a downgrade. This reluctance is particularly pronounced for clients that are potentially more profitable. Moreover, we show that loans approaching maturity are also less likely to be downgraded. Overall, our findings are consistent with the proposition that CRAs yield to conflicts of interest that result from the issuer–pays business model of credit ratings.

One potential challenge to our interpretation of our results is that they could be driven by firms hiding negative financial information from CRAs rather than by CRAs catering to their clients. CRAs issue credit ratings based on the information reported by firms without conducting independent audits, and firms whose borrowing costs would experience a larger increase in the eventuality of a downgrade might be more likely to hide negative information. We exploit a dramatic drop in commodity prices as a highly visible negative shock to the creditworthiness of a subset of firms in our sample. We show that CRAs yield to conflicts of interest even in this setting, where affected firms arguably had little room to hide the negative information.[3]

Another potential challenge to our interpretation of our results is that our results may be driven by loans associated with firms that are close to losing their *investment grade* classification. CRAs could have implicit approval from investors to inflate credit ratings for those firms because the loss of an investment grade classification could translate not only to increased borrowing costs and a lower future availability of funding for firms, but also to reduced investment opportunities for investors due to regulatory restrictions (Bruno, Cornaggia, and Cornaggia (2016)). Inconsistent with this concern, we show that our results hold for borrowers irrespective of their initial rating. We note that this result is also inconsistent with our results being explained by CRAs internalizing the potential negative effects of downgrades on firms' subsequent access to credit, since these effects should be most prevalent for firms that are close to losing their investment grade classification. We

[3]Consistent with this result, we also show that our main results are not driven by a firm's "opaqueness," as proxied by intangibles divided by total assets and research and development (R&D) expenses.

further mitigate the concern that our results are driven by CRAs internalizing negative externalities to the firms they downgrade with empirical tests based on credit rating reversals and by showing that CRAs internalize the positive externalities of credit rating *upgrades*, and by analyzing downgrades and upgrades jointly using an ordered logit framework.

Next, we consider the possibility that our results are explained by firms with higher cost of downgrade being more aggressive in decreasing leverage when they perceive that their likelihood of experiencing a credit rating downgrade is high. Inconsistent with this concern, we show that there is no relationship between a firm's cost of downgrade and its debt issuance activities.

Lastly, we consider the possibility that our results are explained by managers with positive inside information about future firm performance selecting into contracts with higher cost of downgrade. We mitigate this concern in multiple ways. First, we show that our results hold even when excluding the first two years of the loans' lives. Since the value of inside information decays rapidly as information is revealed, this result is inconsistent with managers' optimism driving our results. Second, we proxy for CEO optimism using measures based on option holdings and find no indication that positive insider information is responsible for our findings. Furthermore, our results hold in regressions that exploit variation within loans (i.e., after all loan contract parameters have been set). Finally, we show that firms with higher cost of downgrade do not subsequently outperform their counterparts.[4]

All of our tests are consistent with the proposition that CRAs cater to the firms that pay them. While we recognize that it is possible to propose an alternative explanation for each one of our tests in isolation, it seems improbable that there is an alternative explanation consistent with the multiple tests.

[4]The previous results imply that credit rating inflation should cause ratings to become less accurate over time. Consistent with the idea that conflicts of interest distort the incentives of CRAs to accurately rate firms, within each credit rating notch, firms with a higher cost of downgrade have a lower Merton's distance to default.

We then investigate whether market participants price the conflicts of interest of CRAs or whether they are harmed by these conflicts. We first focus on well-informed market participants (e.g., the initial lenders). We find that a one standard deviation increase in the average cost of downgrade is associated with a 6% increase in interest spreads relative to the unconditional mean. This is consistent with lenders being (to some extent) aware of the conflicts of interest of CRAs and pricing them in the PSD market.

Next, we focus on the secondary market. Investors such as mutual funds and loan funds tend to be less informed than banks. Thus, it is possible that these investors do not internalize the conflicts of interest of CRAs. Consistent with this proposition, we find a significant decrease in the yield premiums associated with high cost of downgrade loans one year after loan origination. Moreover, this decrease in premiums persists through the remainder of the loan's life. In addition, we document that originating banks are more likely to sell loans with high costs of downgrade, and that among the loans they sell, loans with high cost of downgrade are sold faster.

Recently, CRAs have been accused of similar catering behavior in the market for RMBSs and CDOs. This behavior contributed to the Financial Crisis (Griffin (2019)) and resulted in large settlements between the two major CRAs and the Department of Justice (DOJ). Importantly, the lawsuits and the subsequent settlements were intended not only to punish past misbehavior but also to improve future CRA conduct. In fact, as part of their respective settlements, both CRAs renewed their commitment to credit rating quality and affirmed the importance of credit ratings being impartial and not driven by business concerns. We test whether the relationship between the probability of a downgrade and the cost of a downgrade weakens after the settlements and find no evidence of a weakened relationship. Moreover, CRAs might have adjusted their behavior shortly after the 2008 financial crisis (i.e., before the settlements) due to potential litigation threats. However, inconsistent with this explanation, we find that their catering behavior remained largely stable from 2001 to 2016. Overall, these results suggest that the settlements did not have the intended effect of improving credit rating quality and curbing CRA behavior, at least in the PSD market.

This paper relates to a recent literature on CRA behavior in the market for securitized products and its role in the Financial Crisis. Griffin and Tang (2012) show that CRAs adjusted the ratings of securitized products to benefit clients at the expense of investors. Griffin, Nickerson, and Tang (2013) show that CRAs inflated credit ratings beyond their models when facing competition. He, Qian, and Strahan (2011, 2012) and Efing and Hau (2015) show that CRAs issued increasingly optimistic credit ratings for asset-backed securities (ABSs) structured by large clients that provided them with more business. These positive credit ratings benefitted CRAs' clients through higher prices for their securities (Ashcraft, Goldsmith-Pinkham, Hull, and Vickery (2011)). Our paper shows that, despite claims by CRAs to the contrary, credit rating inflation is not limited to structured products but is also a feature of loan markets, and that credit rating inflation continued after CRAs settled with the government post-Crisis.

This paper also relates to the literature that studies the conflicts of interest of CRAs more generally. Opp, Opp, and Harris (2013) show that credit rating inflation can be induced by regulatory reliance on the credit ratings themselves. Mathis, McAndrews, and Rochet (2009) and Bolton, Freixas, and Shapiro (2012) develop models in which reputation is not always a sufficient deterrent to prevent CRAs from catering to clients.[5] In the case of corporate bonds, Becker and Milbourn (2011) show that increased competition from Fitch lowered the credit rating quality of S&P and Moody's.[6] In contemporaneous work, Cornaggia, Cornaggia, and Israelsen (2022) show credit rating inflation in the municipal bond market.

In our setting of PSD loans, prior work compares firms with credit rating–based

[5]Goldstein and Huang (2020) show that credit rating inflation leads to inefficient outcomes even with rational, well-informed investors.

[6]Cornaggia and Cornaggia (2013) show that issuer–pays ratings for specific debt issues diverge from the credit ratings paid by investors, while Xia (2014) shows that the latter can have a disciplining effect on issuer–pays ratings.

loans to firms with accounting ratio–based loans. These papers show that firms with credit rating–based loans experience fewer credit rating downgrades (Kraft (2015)) and more credit rating upgrades (Bannier and Wiemann (2011)), but are largely silent on causality. Our paper complements this work in multiple ways. First, we show evidence of CRA catering in the PSD market after accounting for selection concerns.[7] Second, we show that this catering behavior remains prevalent post-Crisis, which suggests that government settlements are insufficient deterrents. Third, we show that lenders are aware of and price the conflicts of interest of CRAs. In contrast, secondary market participants seem to be less aware of these conflicts, which suggests that the least informed investors are the most harmed by credit rating inflation.

Finally, this paper contributes to the literature that focuses on understanding the use and the implications of PSD loans. Asquith, Beatty, and Weber (2005) show that PSD loans can prevent agency conflicts and costly re-negotiations. Tchistyi, Yermack, and Yun (2011) show that PSD loans allow managers to gain private benefits at the expense of firm risk.[8]

II. Background

A. Performance-sensitive debt

Performance-sensitive debt (PSD) is a type of debt in which interest payments depend on a measure of a borrower's financial health (e.g., credit ratings, debt-to-cash flow ratio). The idea behind this type of debt obligation is to delay the costly renegotiation that results from borrowers violating covenants. In general, if a borrower's financial health deteriorates, the interest rate associated with the PSD obligation increases, thus

[7] Specifically, we exploit variation in the conflicts of interest of CRAs within the same firm over time, as opposed to comparing firms that self-select into accounting ratio–based PSD loans with firms that self-select into credit rating–based PSD loans.

[8] Adam and Streitz (2016) show that PSD loans can be used to reduce hold-up problems, and Beatty and Weber (2003) show that PSD loan contracts affect firms' accounting choices. Mjøs, Myklebust, and Persson (2013) show that PSD loans are priced to reflect the risk of shocks to the credit performance measure.

compensating the debt holder for the additional risk.

PSD contracts became common in the early 1990s. Now, the total size of the PSD market is over $2 trillion. In this paper, we focus on the $900 billion market in which interest payments depend exclusively on credit ratings.

In PSD contracts, interest rates are contractually linked to measures of a borrower's financial health through a *pricing grid*. Figure **1** shows the pricing grid from The Walt Disney Co.'s syndicated 5.25-year revolving credit facility issued on February 23, 2005. The loan amount was $2.25 billion. The facility's pricing grid indicates that The Walt Disney Co. can be subject to pay five different interest rates, depending on its long-term senior debt rating. For example, if the firm's credit rating by S&P is AA- or better, then The Walt Disney Co. is subject to an interest rate of 11.5 bp over the London Interbank Offered Rate (LIBOR). If their credit rating is between A and A+, the interest rate increases to 13 bp over LIBOR. The highest interest rate that The Walt Disney Co. may be required to pay under this facility is 30.0 bp over LIBOR, which is an increase triggered by a credit rating deterioration to BBB- or worse.

[Insert Figure **1** Here]

B. Credit rating agencies and conflicts of interest

The main role of CRAs is to perform a continual assessment of firms' creditworthiness. CRAs communicate these assessments to financial markets in the form of credit ratings. Credit ratings are important for the rated firm because they affect the firm's ability to access capital through the value placed on them by investors, either for informational or regulatory reasons. Importantly, it is not the investor who pays for the issuance of the credit rating but rather the rated firm itself. This issuer–pays business model of credit ratings has been subject to extensive criticism because it can generate a conflict of interest that can lead to CRAs catering to the firms that pay them.

In our setting of credit rating–based PSD loans, this conflict arises when a credit rating downgrade by a CRA causes a change in the pricing schedule that increases the interest rate paid by the borrower. For example, in the pricing grid from Figure **1**, there is no change in Disney's borrowing costs (i.e., the interest rate would remain 13 bp over LIBOR) if the firm is downgraded from a credit rating of A+ to a credit rating of A. However, if the firm is downgraded to A-, its borrowing costs would increase to 14 bp over LIBOR, implying additional annual interest expenses of up to approximately $225,000 if the entire credit facility were drawn. This number is about half the median annual cost of a downgrade in our sample (i.e., $520,000). We hypothesize that, all else being equal, a CRA will be more reluctant to downgrade a firm if the downgrade causes higher costs for the borrower. Moreover, the misalignment of incentives should be even more severe when a CRA's rating is the one that leads directly to an increase in borrowing costs.

Credit ratings are supposed to be an objective and high-quality assessment of borrower creditworthiness. CRAs claim to meet the highest standards of integrity, independence, objectivity, and transparency (U.S. Securities and Exchange Commission (2002)). CRAs are aware that credit ratings can negatively affect borrowers' funding costs (Moody's (2002)). However, CRAs' guidelines are explicit in that credit ratings are issued independently of the effect that they may have on the borrower (U.S. Securities and Exchange Commission (2002); S&P Global Ratings (2018)). Similarly, CRAs acknowledge the conflicts of interest that arise from the issuer–pays business model (Department of Justice (2015, 2017)). However, fear of diminished reputation and regulatory penalties are often thought to mitigate these conflicts. Internet Appendix C includes excerpts from CRA documents, regulator documents, congressional hearings, DOJ press releases, and settlement statements of facts discussing these issues.

CRAs catered to underwriting banks by inflating the credit ratings associated with RMBSs and CDOs, making them important contributors to the Financial Crisis (Griffin et al. (2013)). Recently, both S&P and Moody's agreed to settlements with the DOJ in which they (a) explicitly acknowledged failing to adhere to their own standards when rating securitized products and (b) renewed their commitment to credit rating quality (see Internet Appendix C).

The catering behavior of CRAs during the run-up to the Financial Crisis has partly been attributed to the complexity of securitized products (Griffin (2019)). In this paper, we study whether the conflicts of interest affecting CRAs prevail in other less complex markets, such as the PSD market. Importantly, pricing data are more reliable and available for PSD loans than for RMBSs and CDOs, which makes the PSD setting is ideal for studying whether market participants recognize and internalize the conflicts of interest, both at origination and in the secondary market. Finally, we also study whether the DOJ settlements were effective in holding CRAs to their renewed commitment to credit rating quality, a question that cannot be answered by studying the RMBS and CDO markets because those markets disappeared before the settlements.

III. Data, sample selection, and empirical framework

A. Primary data

We obtain loan-level data on performance pricing (i.e., pricing grids) from LPC DealScan. Recall that we focus on loans with performance provisions that depend exclusively on senior credit ratings. To identify where borrowers stand in the pricing grid, we assign to each loan the corresponding borrower's long-term senior unsecured credit rating from Bloomberg.[9] We consider the credit ratings issued by S&P and Moody's. Following Tchistyi et al. (2011), for cases in which borrowers have received credit ratings from both CRAs, we consider the better of the two ratings as relevant for pricing purposes.

We then use the pricing grids to assign each loan in each quarter the current interest spread, and the interest spread that would prevail after a credit rating downgrade. Some

[9]DealScan does not indicate whether the relevant senior credit rating refers to secured or unsecured debt. However, in the subset of loan comments that mention the word *rating*, approximately 75% refer specifically to *unsecured* credit ratings. While some loans do have a security-specific credit rating, pricing grids are generally based on issuer-level ratings. Accordingly, all references to credit rating fixed effects in the paper pertain to issuer credit ratings.

contracts give borrowers a choice between different types of reference rates for determining interest spreads (e.g., LIBOR, the bank's prime rate). Since interest spreads over LIBOR are by far the most common, we use this market rate as our baseline measure for interest spreads.[10] We use *cost of downgrade* to refer to the difference between the spread at the prevailing credit rating and the spread at the credit rating one notch below it.

B. Secondary data and final sample

Initially, we obtain pricing grid data for 31,005 facilities originated between 2000 and 2016. We link these facilities to Compustat using the latest DealScan-Compustat linking table (Chava and Roberts (2008)), which leaves 27,141 loans. We then require all relevant loan and firm information to be nonmissing, which leaves 3,700 loans. Of these loans, 2,075 have pricing grids that depend exclusively on credit ratings. Finally, we require borrowers to have credit ratings issued by S&P or Moody's.[11] The final sample consists of 1,988 loans spanning 22,760 loan-quarter observations.[12] The sample consists of 510 distinct borrowers, of which 415 obtain at least two loans, with an average of 4.1 loans per borrower. Among these, 387 firms have overlapping loans, meaning they hold more than one loan outstanding at the same time during the sample period.

Panels A and B of Table **1** describe the final sample. The mean increase in borrowing costs following a one-notch downgrade is 13.7 bp, with an inter-decile range of 25 bp. Moreover, the cost of downgrade is non-zero 80% of the time. Downgrades are a rare event: The likelihood of a borrower being downgraded in a given quarter is, on average, only 2.6%. The median credit rating throughout the sample is *BBB*. The average loan size is $914.0 million, 80% of loans are revolvers, and conditional on being

[10] The same approach is taken by, for example, Tchistyi et al. (2011).

[11] Compustat does not provide credit ratings issued by Moody's, so we consider the credit ratings from both CRAs (provided by Bloomberg) for consistency. In our final sample, 74.2% of loans are rated exclusively by S&P, 5.4% exclusively by Moody's, and the remaining 20.4% have ratings from both CRAs. In particular, as shown in Table IA.1, Moody's generally focuses on rating smaller, riskier firms.

[12] For a subset of our analysis, we merge the final sample with secondary market loan pricing data from Refinitiv's Loan Pricing Corporation. Details on the data and merging process are provided in Section V.B and Internet Appendix A.

downgraded, the average borrower is downgraded within 4.8 quarters of issuing a loan. Appendix A describes these and the remaining variables used in the paper, and specifies the numerical equivalence assigned to each credit rating (e.g., AAA/Aaa = 1, AA+/Aa1 = 2, AA/Aa = 3, etc.).

[Insert Table **1** Here]

Finally, Figure **2** shows the distribution of credit ratings at origination. The most common rating is BBB, followed by AA. Overall, 93% of observations are rated at or above investment grade.

[Insert Figure **2** Here]

C. Empirical framework

Pricing grids vary within loan contracts (and therefore the change in borrowing costs associated with a credit rating downgrade also varies). Thus, to study whether the conflicts of interests of CRAs affect the credit ratings they issue, we estimate specifications of the form

$$1(downgrade)_{i,t} = \beta_1 cost\ of\ downgrade_{i,l,t} + X'_{i,l,t}\Gamma + \epsilon_{i,l,t}, \tag{1}$$

where $1(downgrade)_{i,t}$ is an indicator that takes the value of 1 if borrower i is downgraded in quarter t, and 0 otherwise. The independent variable of interest is $cost\ of\ downgrade_{i,l,t}$, a measure of the increase in the loan spread that would result from a one-increment credit rating downgrade for loan l in quarter t. Thus, this variable captures the time-varying degree of the CRAs' *conflicts of interest* for each loan. The higher the increase in a firm's borrowing costs following a one-notch downgrade, the stronger the incentive for the CRA to avoid the downgrade. The variable $X_{i,l,t}$ is a vector of time-varying loan- and firm-level characteristics and fixed effects. In secondary tests, we also estimate specifications in which the dependent variable is the time interval in which the firm is downgraded after loan origination.

Identifying conflicts of interest in PSD is challenging for multiple reasons. First, firms could self-select into PSD either because they have inside information (Manso et al. (2010); Begley (2012)) or because they are overly optimistic (Adam et al. (2020)). Even within PSD contracts, a naïve comparison of the probability of a downgrade between firms that self-selected into ratings-based PSD and those that did not is likely to be biased, with the former set of firms being downgraded less frequently. Consistent with this concern, Table **2**, shows that firms with credit rating–based PSD loans differ significantly from those with accounting ratio–based PSD loans across a range of observable characteristics. Firms with credit rating–based PSD loans tend to be larger, less leveraged, and more likely to rely on larger, unsecured loans compared to firms whose PSD terms are based on accounting ratios.

[Insert Table **2** Here]

Second, there is another type of selection often referred to as *rating shopping*. A firm may approach a number of CRAs and then choose to do business with the agency that offers the most positive credit rating.[13] As a result, credit ratings are overly optimistic due to the unintentional errors inherent in the credit rating process rather than CRAs yielding to conflicts of interest.

Our empirical setting allows us to mitigate both of these selection concerns. Since both selection concerns are borrower-specific, we include borrower (i.e., firm) fixed effects in all specifications, effectively exploiting within-borrower variation in the impact of a credit rating downgrade on loan spreads. However, other variables likely correlated with downgrade likelihood (e.g., borrower quality, managerial optimism) are time-varying, so

[13] Skreta and Veldkamp (2009), Faure-Grimaud, Peyrache, and Quesada (2009), and Sangiorgi and Spatt (2017) provide theories of rating shopping. Kronlund (2019) shows empirical evidence of rating shopping in corporate bonds. Benmelech and Dlugosz (2010) show evidence consistent with rating shopping in ABS CDOs.

they are not accounted for by the borrower fixed effects. Thus, we include time-varying variables of financial health in $X_{i,l,t}$, such as the firm's current credit rating, size (measured by the log of total assets), profitability, asset tangibility, and leverage.

In addition, because the probability of a credit rating downgrade varies with the business cycle (Bar-Isaac and Shapiro (2013)), we include year–quarter fixed effects in $X_{i,l,t}$.[14] We also control for loan-level characteristics that are jointly determined at origination, including loan amount, number of financial covenants, whether the loan is secured, loan type (e.g., revolver or term loan), and deal purpose. Finally, in Section IV.C, we estimate a more stringent specification that includes loan fixed effects.[15]

D. Sources of variation

The most stringent specification in our initial analysis includes fixed effects for the current credit rating, borrower, and year–quarter. Thus, we exploit variation in credit rating downgrade probabilities and in borrowing costs from three separate sources. That is, we exploit variation in these variables (a) across loans and across time within credit ratings, (b) across loans and across time within borrower, and (c) across loans within time. In this section, we show that, even with these tight sets of fixed effects, there is enough variation in the data to identify the effects of CRAs' conflicts of interest in PSD.

Panel C of Table **1** shows within-group standard deviations of the dependent and independent variables that are most relevant to our regressions. The within-credit rating standard deviation of $1(downgrade)$ is 15.6 pp, which is very similar to its overall standard deviation of 15.8 pp. Similarly, the within-credit rating standard deviation of $cost\ of\ downgrade$ is 10.9 bp (compared to 12.1 bp overall). Figure **3** shows the distribution of the cost of a one-notch downgrade by credit rating category at origination. Borrowers rated above A+ or below BBB- exhibit a high incidence of zero downgrade

[14]This set of fixed effects corresponds to 68 indicators (17 years × 4 quarters) included in the specifications.
[15]This further helps address endogeneity concerns related to nonrandom pricing grid structures. Omitted variable bias would require an unobservable to be correlated with both the downgrade and its cost within the same loan and borrower, conditional on our controls.

costs. In contrast, firms rated between A+ and BBB- face downgrade costs more frequently and show greater variation in these costs.

[Insert Figure **3** Here]

Panel C of Table **1** also shows that the time required for the firm to be downgraded follows the same pattern as downgrades and the cost of a downgrade, and that there is significant variation in the previous three variables within firm and within year. Overall, there is more than sufficient variation in the data to expect that our specifications will have power.

IV. Credit rating agency behavior and the cost of downgrades

We start by investigating whether CRAs are less likely to downgrade their clients when the downgrade is potentially more costly. Next, we present several refinements to our identification strategy. We then explore additional possible explanations for our results.

A. Probability of downgrades

Table **3** presents the results from estimating different variants of equation (1). Recall that the dependent variable is $1(downgrade)$, which indicates whether a borrower is downgraded by a CRA in a given quarter. The independent variable of interest is $cost\ of\ downgrade$, a variable that measures a firm's increase in borrowing costs following a one-notch downgrade. For ease of exposition, $1(downgrade)$ is multiplied by 100, and $cost\ of\ downgrade$ is standardized so that the coefficients represent the effect (in percentage points) on the probability of a downgrade associated with changing the cost variable by one standard deviation. Standard errors are clustered at the borrower (i.e., the firm) level.

[Insert Table **3** here]

Column 1 of Table **3** presents the results from our most basic specification, which includes only firm and year–quarter fixed effects. The point estimate on $cost\ of\ downgrade$ is -0.76, indicating that a one standard deviation increase in borrowing costs in the eventuality of a one-notch downgrade decreases the quarterly downgrade likelihood by almost 0.8 pp. This effect is statistically significant at the 1% level and is economically important: It represents a 30% decrease relative to the sample mean quarterly downgrade likelihood of 2.57%.

The previous specification presents initial evidence that CRAs are more reluctant to downgrade the credit ratings of borrowers who are the most likely to be negatively affected. However, one remaining concern is that the various features of loan contracts are determined at origination, and these features could correlate with the likelihood of future downgrades. To address this concern, Column 2 adds controls for loan-level characteristics such as loan amount, loan type (revolver or term loan), the number of financial covenants, and deal purpose.[16] Moreover, the specification also includes issuer credit rating fixed effects that capture the average probability of a downgrade at each credit rating level. The coefficient of $cost\ of\ downgrade$ changes slightly to -0.70 pp.

Another remaining concern is that borrower quality is time variant and therefore not accounted for by the firm fixed effects. Thus, to mitigate this concern, Columns 3 and 4 include firm-level control variables that capture a borrower's time-varying ability to repay. Specifically, the specifications include firm size (i.e., log of assets), leverage, profitability (i.e., return on assets), and asset tangibility (i.e., intangibles divided by assets). In Column 3, we replace the loan-level controls with the firm-level controls. The point estimate on $cost\ of\ downgrade$ is -0.62 pp. Finally, Column 4 presents our most complete specification, which includes the full set of fixed effects and control variables. The coefficient of $cost\ of\ downgrade$ is -0.67 pp, statistically significant at the 1% level.

[16]The loan type dummies also include a small residual "other" category, which accounts for about 2% of loans in the sample. This category primarily includes facilities such as acquisition facilities, bridge loans, and standby letters of credit.

Overall, the results in Table **3** show that CRAs are significantly less likely to downgrade their clients when the downgrade is more costly to the client.

In the Internet Appendix, we present a series of robustness checks for the previous results. Table IA.2 shows that results hold in a subsample of loans that excludes loans rated above A+ and below BBB−, that is, those ratings where zero downgrade costs are more prevalent. Table IA.3 shows that the results hold for the subsample of revolver loans, with slightly weaker significance (p-value of 5.1%) in the sample of term loans.[17] Tables IA.4 and IA.5 show that the main results are robust to alternative constructs of the variable for the costs of a downgrade. Specifically, these alternate constructs are (a) constructing the variable based on two-notch downgrades (instead of one notch) and (b) constructing the variable as a dollar cost divided by assets. In Table IA.6, we analyze the firms rated exclusively by S&P and Moody's separately, and we find similar regression coefficients as Table **3** in both samples. In Table IA.7, we conduct a placebo test using a sample of accounting ratio–based PSD loans and find that the steepness of the pricing grid is not associated with a higher probability of a credit rating downgrade for these loans, where conflicts of interest for CRAs are absent.

Finally, in Table IA.8, we examine the effect of cost of downgrade on a related outcome variable, namely the number of quarters between origination and the eventual downgrade. Consistent with the previous results, the table's most stringent specification (in Column 4) shows that a one standard deviation increase in the borrowing costs following a one-notch downgrade is associated with 155 additional days (1.72×90) before the borrower is downgraded by a CRA.

[17]This difference in regression coefficients is consistent with the idea that downgrade costs may have a larger economic impact for term loans, since these are fully drawn at origination, whereas revolvers may be only partially utilized.

B. Profitability of borrowers and decisive credit ratings

Next, we investigate whether CRAs are more likely to yield to conflicts of interest when rating clients that are potentially more profitable for the agency. We consider two measures of client profitability: (a) the natural logarithm of the total volume of loans issued by the firm in the past four years and (b) an indicator variable for whether the firm is a *high yield* issuer (i.e., an issuer rated BB+ or lower).[18] We supplement our main specification with these measures as well as with the interaction of these variables and *cost of downgrade*.

Table **4** presents the estimation results. Specifically, the negative (statistically significant) coefficients on the interaction terms in Columns 1 and 2 indicate that CRAs are more likely to yield to conflicts of interest when dealing with more profitable clients. This result is confirmed by the negative coefficient on the triple interaction in column 3 of Table **4**.

[Insert Table **4** here]

Finally, we exploit variation in the CRAs issuing the decisive credit rating, which occurs when (a) a borrower is rated by only one CRA or (b) two CRAs issue different ratings, with the higher rating being decisive (following Tchistyi et al. (2011)). If conflicts of interest affect downgrade decisions, the decrease in downgrade likelihood should concentrate when the CRA's rating determines borrowing costs.

To test this, we introduce an indicator variable 1(*decisive rating*), which is 1 when the CRA is decisive. We then interact this variable with *cost of downgrade*. The results, shown in Table IA.9, indicate that CRAs are more hesitant to downgrade when their rating is decisive. For example, when S&P is decisive, the interaction term is statistically significant at −1.2 pp, suggesting S&P is particularly hesitant to downgrade in these cases. A similar pattern is observed for Moody's.

[18] For example, high yield ratings represented 36% of the revenue that Moody's generated from rating corporate issues in 2020, but only 19% of credit ratings (Moody's (2021)).

In sum, these results suggest that CRAs are more reluctant to downgrade when their rating directly affects borrowing costs.

C. Loan fixed effects regressions

Our previous analysis relies on within-borrower (i.e., firm) variation as a primary source of variation for identification purposes. This reliance on borrower fixed effects is intuitive from an economic perspective and consistent with the pricing analysis that we conduct below, which does not allow accommodating a tighter set of fixed effects. However, in the context of our probability of downgrade regressions, the possibility remains that borrowers self-select into particular types of PSD contracts at different points in time. To address this concern, we estimate a more stringent regression specification that includes loan fixed effects (instead of firm fixed effects). This allows accounting for unobserved dimensions of loan contracts and selection into contracts at origination (i.e., inference stems from borrowers who experience a change in cost of downgrade after loan parameters are set).

The estimation results are presented in Table **5**. Specifically, Column 1 shows a statistically significant coefficient on *cost of downgrade* of an even greater magnitude than that in Column 4 of Table **3**. The coefficient of -1.43 indicates that a one standard deviation increase in borrowing costs in the eventuality of a one-notch downgrade decreases the quarterly downgrade likelihood by slightly over 1.4 pp. Once again, results strongly support the idea that CRAs yield to the conflicts of interest that result from the issuer–pays business model of credit ratings.

[Insert Table **5** here]

Columns 2 to 4 of Table **5** report regressions analogous to those in Table **4**. All coefficients of interest except that when profitability of borrowers is measured using loan volume (Column 2) remain strong and statistically significant.[19] Overall, the inferences from previous sections remain unchanged with the inclusion of loan fixed effects in our regressions.[20]

D. Potential alternative explanations

Our evidence indicates that CRAs are significantly less likely to downgrade credit ratings when the downgrade is more costly to the client. This result is consistent with the proposition that CRAs yield to the conflicts of interest that result from the issuer–pays business model of credit ratings. This interpretation is further supported by the fact that the previous result (a) is driven by those instances in which the CRA is the decisive one for the determination of the borrowing costs, (b) is stronger when CRAs rate clients that are potentially more profitable for the agency, and (c) holds when exploiting variation in the cost of downgrade within loan contracts. In this section, we address a number of potential challenges to our interpretation of the results.

1. Selection into steeper pricing grids

A first potential challenge to our interpretation of the results is that managers with positive inside information about future firm fundamentals may not just self-select into PSD contracts, but also into steeper pricing grids (Begley (2012)). While the loan fixed effects regressions account for the average steepness of the loan's pricing grid, we further explore this concern. To do this, we construct a measure of firm creditworthiness based on firm fundamentals. First, we regress observed credit ratings on firm variables, including leverage, size, profitability, cash flow, and asset tangibility, as well as industry and

[19] In both of these cases, however, the magnitude of the coefficient of interest is very similar to that of the corresponding firm fixed effects regression.

[20] In Table IA.10 of the Internet Appendix, we show that our main results remain unchanged when (a) excluding loans that have been previously downgraded and (b) adding an indicator variable for whether a firm has been downgraded in the previous four years (i.e., roughly the average maturity of the loans in our sample). These results mitigate concerns of our main results being driven by a negative autocorrelation in the likelihood of being downgraded, combined with the fact that the cost of downgrade increases with each additional downgrade notch.

year–quarter fixed effects. Then, we use this model to generate a predicted value, that is, our measure of firm creditworthiness. If managers have inside information about an imminent improvement in firm fundamentals after loan issuance, firm creditworthiness should improve after issuance. Thus, if selection into steeper pricing grids is affecting our previous results, the measure of creditworthiness should decrease more for firms with loans with high cost of downgrade.[21]

Figure **4** plots the progression of the measure of creditworthiness over the four-year period following loan issuance for firms with high (above median) and low (below median) cost of downgrade.[22] The figure shows overall a slight deterioration of creditworthiness during the lifetime of the loan that affects both groups of firms. In addition, there are no distinguishable differences in the progression of the measure between high and low-cost downgrade firms. In fact, the average difference in the measure of creditworthiness across both groups of firms is only 0.18 notches.

[Insert Figure **4** here]

Next, we provide two additional tests to further mitigate selection concerns. First, we exploit the fact that managers are more likely to possess insider information that is relevant for the short run that for the long run (e.g., Larcker, Levy, Quinn, Tayan, and Taylor (2021)).[23] Specifically, in Table **6**, we repeat our main analysis while dropping observations 1, 2, 4, and 8 quarters after loan origination. If managers select into steeper pricing grids because of positive insider information, the relationship between cost of downgrade and probability of downgrade should concentrate in the quarters shortly after loan origination and therefore excluding the early quarters from the sample should weaken

[21]Note that our regression uses a numeric credit rating, where lower values represent better ratings. Thus, an improvement in creditworthiness corresponds to a decrease of our measure.

[22]We split the cost of downgrade into above- and below-median groups because the sample is small and outliers have a large influence on linear regressions, making comparisons with the continuous measure less reliable.

[23]This can be explained because (a) managers have to disclose material information no later than at the next quarterly report and (b) uncertainty increases with time, and most material insider information such as upcoming contracts, strong growth, or technological breakthroughs are not known far in advance.

the effects shown in Table **3**. Inconsistent with this concern, Table **6**, shows that the relationship between cost of downgrade and probability of downgrade remains essentially the same irrespective of the time window that we investigate.

[Insert Table **6** here]

Second, we follow the corporate governance literature and exploit measures of CEO optimism based on options holdings. Specifically, we proxy for CEO optimism using (a) the fraction of CEOs that hold 67% deep-in-the-money options (Campbell, Gallmeyer, Johnson, Rutherford, and Stanley (2011)) and (b) the fraction of CEOs that hold in-the-money options with less than one year to expiration (Malmendier and Tate (2008)). We add interactions between these measures of CEO optimism and cost of downgrade to our main specification and report the estimation results in Internet Appendix Table IA.11. If CEOs with positive information regarding their firm prospects select into steeper pricing grids, one would expect that the majority of the effect of cost of downgrade is driven by optimistic CEOs (i.e., the coefficients on the interaction terms should be negative and the coefficients on the standalone cost of downgrade should lose its predictive power). However, this is not what Table IA.11 shows. Overall, the results in this section are inconsistent with the proposition that our previous results are driven by self-selection of executives with positive inside information into steeper pricing grids.

Finally, one implication of the previous results is that credit rating inflation should cause ratings to become less accurate over time. That is, a wedge should eventually occur between objective credit quality and nominal credit ratings, similar to the effect caused by credit rating inflation in the RMBS market Griffin, Nickerson, and Tang (2013). We examine this possibility in Internet Appendix Table IA.12. For each firm in our sample, we proxy for credit quality using Merton's distance-to-default and then estimate regressions of distance to default on the cost of downgrade. A higher cost of downgrade is associated with a lower distance to default, though this relationship is statistically significant only in the specification with industry-year fixed effects and not in the baseline regression. This approach is appropriate, as default risk is typically highly correlated within industries at any given time, owing to common economic shocks and similar cost and revenue structures among peers. Within each credit rating notch, the pattern in the more stringent specification is generally consistent with the idea that conflicts of interest distort the incentives of CRAs to accurately rate firms.

2. Undisclosed firm information

A second potential challenge to our interpretation of the results is that the results could be driven by firms hiding negative financial information from the CRAs rather than by CRAs catering to their clients. CRAs issue credit ratings based on information provided by a borrower, and they do not verify this information (see Internet Appendix C). Firms whose borrowing costs would experience the highest interest rate increase in the eventuality of a credit rating downgrade have the strongest incentive to hide detrimental information, which could explain why CRAs are less likely to downgrade firms when the downgrade is potentially more costly.

To address this concern, we exploit an observable negative shock to the creditworthiness of a subset of the firms in our sample. Specifically, between the third quarter of 2014 and the end of 2015, commodities experienced a dramatic loss in value, with the Dow Jones Commodity Index plummeting by 50%. Arguably, this loss negatively affected firms that depended on commodity values to generate profits, such as firms from the oil, gas, and mining sectors. Consistent with this proposition, there was significant public concern about the prospects of these affected firms during this time.[24] The idea of this test is to compare the CRAs' behavior when they rate firms that were affected by the commodity shock (which the public saw as deteriorated) with the CRAs' behavior when rating the remaining, unaffected firms. Since the shock was visible and highly public, the ability of borrowers in the affected sectors to hide adverse information was particularly low.

[24] See, for example, Egan (2015), "Copper, aluminum and steel collapse to crisis levels," *CNN*, December 9.

If our results are driven by unobserved (i.e., hidden) firm information, we should see a weaker link between the cost of a downgrade and the likelihood of a downgrade among borrowers in the affected sectors during this downturn.[25]

In Table **7**, we supplement our main specification with an indicator variable for firms in industry sectors that depend on commodity values (1(*commodities*)), an indicator variable that captures the time when commodity values fell (1(*commodities shock*)), and the interaction of these indicators with *cost of downgrade*.[26] The coefficient on the standalone *cost of downgrade* remains statistically significant and similar in magnitude to the estimates in Table **3** in all specifications. Consistent with falling commodity values adversely affecting borrowers, the coefficient on 1(*commodities*) $\times$ 1(*commodities shock*) is positive, ranging from 0.7 to 6.2 pp. However, the coefficient on the triple interaction ranges from -5.7 to -3.9 pp (always statistically significant at the 1% level), indicating that downgrades were concentrated among borrowers for whom the cost of a downgrade is lower. Since arguably all market participants were well aware of these commodities setbacks, these results are inconsistent with the idea that our main results are driven by firms hiding negative financial information. In contrast, these results are consistent with conflicts of interest.

[Insert Table **7** here]

We further examine the possibility that the hiding of negative financial information drives our results in the Internet Appendix. First, we conduct a test based on earnings

[25]In contrast, if our results are driven by rating catering, results should be particularly strong within the affected sectors, since there was an unusually strong pressure to downgrade. In fact, our sample shows 16 downgrades of firms in the affected sectors during the time of the shock, but it shows no downgrades from 2002 to early 2014.

[26]Specifically, we assign a value of 1 to 1(*commodities*) for firms in the following sectors: (1) oil and gas extraction, (2) coal mining, (3) metal ore mining, and (4) support activities for mining (i.e., NAICS codes 2111, 2121, 2122, and 2131). We assign a value of 1 to 1(*commodities shock*) for the quarters 2014Q3 to 2016Q4. We include 2016 to allow for the possibility that CRAs do not process information and adjust ratings instantaneously. Internet Appendix, Table IA.13, shows that inferences remain unchanged when restricting the dummy variable to take the value of 1 for the quarters 2014Q3 to 2015Q4. Finally, Column 1 of Table IA.14 shows that results remain qualitatively unchanged when loan fixed effects are included in the regression, although statistical significance weakens slightly, with a p–value of approximately 6%.

surprises. Following a similar idea to that of our previous test, we use negative earnings surprises as an unanticipated shock to firm information and quality. Results are presented in Table IA.15. Similar to the results in Table **7**, Table IA.15 shows that in times of negative earnings surprises, the negative relationship between cost of downgrade and probability of downgrade is strongly amplified.

Second, we exploit cross-sectional differences in the ease with which firms can hide or manipulate financial information. Specifically, the idea of this test is to compare (a) the CRAs' behavior when rating firms that are relatively more opaque in nature (i.e., firms that have more room to manipulate their financials) to (b) the CRAs' behavior when rating the remaining, less opaque firms.

We use a firm's intangibles divided by total assets and a firm's R&D expenses as proxies for a firm's "opaqueness" (Wyatt (2005); Cañibano, Garcia-Ayuso, and Sanchez (2000)). In Columns 1 and 2 of Table IA.16, we supplement our main specification with indicator variables for above-median values of these proxy variables, as well as with the interaction between these indicators and *cost of downgrade*. The coefficients on both interaction terms are statistically insignificant, inconsistent with the proposition that our main results are driven by firms hiding negative financial information from the CRAs.

3. Avoidance of non-investment grade classification

A third potential challenge to our interpretation of the results is that they could be driven by CRAs being less likely to downgrade a client if the credit rating downgrade would change their client's classification from investment grade to non-investment grade. Losing the investment-grade classification could result not only in increased borrowing costs and a lower future availability of funding for borrowers but also reduced investment opportunities for investors. CRAs' guidelines are clear: Credit ratings should be issued independently of the effect that they may have on the borrower (see Internet Appendix C). However, when a firm is on the border of a non-investment grade classification, CRAs may have the implicit consent of investors to avoid downgrading (Bruno et al. (2016)).

To investigate this possibility, we introduce the indicator variable 1(*border junk*), which takes the value 1 when the borrower has a credit rating of BBB- (i.e., just above non-investment grade), and 0 otherwise. As before, we supplement our main specification with this variable as well as with the interaction between this variable and *cost of downgrade*. We report the results in Column 3 of Table IA.16. While the point estimate on *cost of downgrade* is -0.56 pp (similar to Table **3**), the point estimate on the interaction term is statistically insignificant. Overall, this result indicates that CRAs are hesitant to downgrade their clients when the costs of doing so are higher across the whole spectrum of ratings, not just close to the non-investment grade classification.[27]

4. Prevention of credit rating downgrades by adjusting firm policies

A fourth potential challenge to our interpretation of the results is that they could be driven by firms adjusting their leverage to avoid a credit rating downgrade (e.g., Kisgen (2006)). However, inconsistent with this concern, results in the Internet Appendix show that a firm's cost of downgrade is unrelated to its (a) loan and bond issuance activity (Table IA.17) and (b) investment activity (Table IA.18). We note that these tests do not imply that firms never manage their credit ratings by adjusting their leverage. Rather, these tests imply that, conditional on having the *same* initial credit rating, differences in costs of downgrade and probability of downgrade are unrelated to firm leverage policies.

5. Internalization of externalities

The final challenge to our interpretation of the results is that they could be driven by CRAs internalizing negative externalities to the firms they downgrade. Specifically, a

[27]Note that the previous result is consistent with our PSD loan setting differing from the bond setting in Bruno et al. (2016) in one important aspect; in PSD loans, investors benefit directly from downgrades through higher spreads, potentially offsetting other benefits of delaying downgrades. For bonds, however, the incentives of borrowers and investors are aligned because bonds do not adjust their payments based on downgrades.

credit rating downgrade can reduce a firm's access to credit, which subsequently may undermine the firm's financial health, thereby leading to a self-fulfilling prophecy of creditworthiness deterioration and downgrades (Manso et al. (2010)). While CRA guidelines explicitly forbid considering the effects of rating actions when issuing or changing ratings (see Section 4 of Internet Appendix C for excerpts from CRA guidelines), the possibility remains that CRAs differentially deviate more from their guidelines when rating firms with a higher cost of downgrade. While the negative externalities of downgrades should be most prevalent for firms that are close to losing their investment grade classification and thus the fact that our results hold for borrowers irrespective of their initial credit rating mitigates the aforementioned concern (see Column 3 of Table IA.16), we implement two additional empirical tests.

First, we exploit the fact feedback effects that the internalization of externalities concern should be absent for credit rating *upgrades*, since these only have positive externalities for borrowers. To test this idea, we first construct a sample of loans with upgrade grids, that is, loans where borrower credit rating at origination is towards the lower end of the grid.[28] We define two variables: (a) $1(upgrade)$, which takes the value 1 if the borrower experiences a credit rating upgrade by a CRA in a given quarter, and (b) *benefit of upgrade*, which measures the lowering in interest rate spreads following a one-notch increase in a credit rating. We then regress $1(upgrade)$ on the benefit of an upgrade and report the estimation results in Table **8**. Column 1 uses the full sample, while Column 2 restricts the sample to loans with upgrade grids.

[Insert Table **8** here]

We find that loans with upgrade grids are more likely to receive upgrades, though the effect is statistically insignificant in the full sample and significant at the 10% level in

[28]This condition is necessary since most grids are downgrade-based, that is, firms start at the top of the grid and suffer costs from downgrades, but experience limited or no upside from upgrades.

the subsample. When we include loan fixed effects (Table IA.19 in the Internet Appendix), the effect in the full sample becomes significant at the 5% level.[29]

Next, building on the previous test, we estimate an ordered logit regression, which allows us to incorporate both the cost of downgrades and the benefit of upgrades using a continuous variable. The dependent variable is the change in credit rating, defined such that positive values indicate downgrades and negative values indicate upgrades. Table **9** presents the results. Column 1 reports OLS estimates for completeness and as a benchmark, while Column 2 reports the ordered logit results.[30] Consistent with our earlier findings, the coefficients on the cost of downgrade are negative in both specifications.

[Insert Table **9** here]

Overall, these results are not only inconsistent with the idea that CRAs systematically internalize negative borrower externalities, but also suggest that any conflicts of interest may be, to some extent, symmetric.

Second, if CRAs were to internalize the externalities of their downgrade decisions, CRAs should be especially hesitant to issue downgrades when uncertainty is high in fear of causing unnecessary spillover damages to firms. Thus, if our results are driven by CRAs being more conservative when rating firms with a higher cost of downgrade, then these firms should experience fewer credit rating reversals after a downgrade. To test this conjecture, we introduce the indicator $1(reversal)$, which takes the value 1 if a firm receives a credit rating that offsets a previous credit rating change during the lifetime of the same loan (i.e., there was a previous credit rating downgrade followed by a credit rating upgrade or vice versa), and 0 otherwise. We then estimate regressions of $1(reversal)$ on $cost\ of\ downgrade$ and report the estimation results in Internet Appendix Table IA.21. We find no relationship between cost of downgrade and the reversal of credit rating decisions.

[29]Similar to the results in Section IV.B for the cost of downgrade, Table IA.20 shows that the effects are generally stronger for more profitable clients.

[30]Firm fixed effects are excluded from the ordered logit specification due to the incidental parameters problem that arises with many fixed effects in nonlinear models.

E. Additional proxy for conflicts of interest

In this section, we consider that, since loans are often rolled over at maturity, a credit rating downgrade shortly before the maturity date can be particularly costly for the borrower, as it negatively affects the terms of a new loan. Accordingly, one would expect loans closer to maturity to be less likely to be downgraded. This relationship also provides a useful benchmark for interpreting the cost-of-downgrade results.

In Table **10**, we regress the downgrade indicator on a continuous time-to-maturity variable (Column 1) and its interaction with the cost of downgrade (Column 2). The results show that loans closer to maturity are less likely to be downgraded, consistent with the idea discussed above, and this effect remains robust after controlling for the cost of downgrade. In economic terms, each additional quarter of remaining maturity is associated with an increase in the probability of downgrade of 9.8 to 10.9 basis points.

[Insert Table **10** here]

The previous results provide an alternative perspective on the effect of the cost of downgrade: as shown in Section IV.A, a one standard deviation increase in borrowing costs in the event of a one-notch downgrade reduces the quarterly probability of downgrade by nearly 0.8 pp, equivalent to shortening loan maturity by approximately 7.4 quarters. Overall, these findings support the conclusion that CRAs face significant conflicts of interest, which meaningfully affect their rating behavior.

V. Loan pricing and the cost of downgrades

If CRAs are less likely (or slower) to downgrade a borrower when the costs of doing so are higher for the borrower, loan pricing grids are less effective at compensating the lenders (i.e., investors) for a deterioration in the borrower's financial health. This may affect loan pricing at the time of loan origination if primary market participants are aware of this problem. Loan contracts that are more affected by the conflicts of interest of CRAs by way of steeper pricing grids should be priced at a discount compared to similar loans with fewer potential agency issues. On the other hand, secondary market participants such as collateralized loan obligation investors or pension funds are arguably less informed than banks in regard to these loan contracts. In this section, we test if agency conflicts stemming from performance sensitive debt are priced in the primary and secondary markets.

A. Loan pricing and the cost of downgrades in the primary market

We investigate the relationship between loan spreads and pricing grid design at origination. We introduce the variable *average cost of downgrade*, computed as the average cost of downgrade across all rating levels in the initial grid. Thus, this variable is a measure of the *ex ante* (i.e., expected) conflicts of interests of CRAs captured by the average steepness of the pricing grid, as opposed to a measure of the *ex post* (i.e., realized) conflicts of interest of CRAs over the life of the loan.[31] Table **11** shows the results of regressions in which the dependent variable is the loan's interest rate spread at origination and the independent variable of interest is *average cost of downgrade*. As in previous analyses, the variable is standardized, and standard errors are clustered by firm. We retain only one observation per loan (i.e., at origination). Importantly, while the four specifications in Table **11** vary in terms of control variables and fixed effects, they all include firm fixed effects. Thus, the estimations effectively compare loan contracts with different pricing grids by the same borrower.

[Insert Table **11** here]

The point estimates on *average cost of downgrade* are positive and statistically significant at the 1% level in the four specifications, ranging from 3.7 to 4.7 bp. Thus, the regression results are consistent with borrowers and lenders being aware of and pricing the conflicts of interest of CRAs.

[31] In Table IA.22 of the Internet Appendix, we show that the analysis remains robust–yielding even larger economic magnitudes–when using the alternative measure of conflicts of interest. In Table IA.23, we further show that the results hold in both the subsamples of revolvers and term loans.

The previous result can seem somewhat surprising at first, since it indicates that, all else being equal, a steeper pricing grid is detrimental to the borrower (i.e., borrowing costs are higher at origination). Since interest rates increase when the borrower is downgraded, PSD loans effectively embed an insurance mechanism for the lender against the deterioration of the borrower's financial health. If the pricing grid is steeper, the insurance payment is higher. Intuitively, a loan with a larger premium should be *cheaper* for the borrower, not more expensive. However, the previous result can be understood in the context of our analysis. Our analysis compares *only* loans that have a pricing grid to begin with. Specifically, our regressions compare loan spreads across loans that have pricing grids of varying steepness, and the coefficient estimates reflect the decreasing *relative* efficiency of pricing grids. Compared to a very small increase in interest rates for downgrades, a large increase in interest rates after downgrades is less efficient, since, as the results in Section IV indicate, CRAs are more reluctant to downgrade their clients when the costs of a downgrade are higher.

B. Loan pricing and the cost of downgrades in the secondary market

The trading of loans in the secondary market has increased substantially in recent years (Beyhaghi and Ehsani (2017)).[32] One concern with these trades is that originating banks may have an advantage over investors in the secondary market because they have superior information regarding loan quality (Dahiya, Puri, and Saunders (2003)). While some investors are well-informed and even have access to insider information (Addoum and Murfin (2020)), many, such as mutual funds and loan funds, are non-bank investors (who tend to be less informed). Previously, we showed that the potential for credit inflation is, to some extent, priced at origination. We now investigate whether this pricing of the potential for credit inflation persists once loans are traded in the secondary market.

[32]Among the possible reasons for this increase are the "originate to distribute" model (Ivashina and Scharfstein (2010)) and increased regulatory pressure on banks to increase capital ratios and reduce risk (Pierret and Steri (2019)).

We obtain secondary market loan pricing data from Refinitiv's Loan Pricing Corporation (LPC). The secondary market data consists of self-reported information from brokers that quote daily prices on loans. While a quote does not guarantee a trade, brokers tend to make markets for more liquid loans, and any loan in the LPC database is almost surely traded at some point.[33] We match these data to our sample of PSD loans using a proprietary linking table provided by Refinitiv. The Refinitiv linking table matches 4.1% of the loans in our sample (i.e. 75 loans) to the secondary market data. While this matching rate may seem low, it is similar to the 4.9% matching rate that we find for all loans in DealScan and to the matching rate reported by other research using similar data.[34] Internet Appendix A details the matching procedure. Although the sample is small, it supports useful–albeit mostly descriptive–analyses, which are still valuable given the limited evidence on whether secondary market participants price conflicts of interest.

We construct a quarterly panel with quoted prices for the traded loans in our sample and compare the prices of PSD loans with high (i.e., above-median) downgrade cost at origination to the prices of PSD loans with low (i.e., below-median) downgrade cost at origination. Specifically, we estimate a regression where the dependent variable is *loan price* (measured as the average of the mid-prices quoted each quarter) and the independent variables of interest are the interactions of an indicator for above-median cost of downgrade and indicators for each quarter since loan issuance. The regression includes the same set of control variables and fixed effects as in Column 4 of Table **3** (i.e., our most stringent specification) plus loan fixed effects, and we consider the first four years of each loan's lifetime.[35]

[33] In fact, the main purpose of LPC is to "facilitate trading and investment decisions" (`https://www.lsta.org/members/lpc-from-refinitiv/`).

[34] Wittenberg-Moerman (2008) matches about 7% of U.S. syndicated loans and Pierret and Steri (2019) matches about 6% of loans in DealScan. Altman, Gande, and Saunders (2010) find 80 firms with bonds and loans with secondary market pricing data. Billett, Elkamhi, Mauer, and Pungaliya (2015) match loans from 156 firms among firms from COMPUSTAT that do share repurchases. Gande and Saunders (2012) find 314 borrowers with a first-time traded loan.

[35] We require at least 10 traded loan facilities each quarter. After four years from origination, there are only nine loans left with available secondary market prices, which limits statistical power.

Figure **5** shows the coefficients for each quarterly interaction along with their corresponding 95% confidence interval based on standard errors clustered by loan. We use the first quarter's estimate as our coefficient of reference. The price difference in this quarter is 1.3 pp, meaning the zero line in this graph represents low cost of downgrade loans priced 1.3% higher than high cost of downgrade bonds. Thus, since each interaction coefficient captures the average difference in price between PSD loans with high cost of downgrade and PSD loans with low cost of downgrade, a positive coefficient in a given quarter means that the differences in prices between the two groups of loans increased in that quarter relative to the difference that prevailed in the first quarter. Note that an increase in price is equivalent to a decrease in yield. Thus, a positive coefficient implies a decrease in the initial yield premium associated with loans that have a high cost of downgrade.

[Insert Figure **5** here]

The figure shows that there is no change in price differences between high and low cost of downgrade loans in the first three quarters after loan origination. Coincidently, the average time from origination to first recorded sale for loans with above-median cost of downgrade is 100 days (denoted by the dashed vertical line in the figure). From the fourth quarter onwards, coefficient estimates turn positive, consistent with a decrease in the premium associated with high cost of downgrade loans as they are sold to secondary market participants. On average, these loans become about 2% more expensive than low cost of downgrade loans three years after the first quarter of trading. Overall, the point estimates in Figure **5** are consistent with secondary market participants overpaying for above-median cost of downgrade loans (and therefore pricing less of the conflicts of interest of CRAs) relative to originating banks.

C. Probability of trade and time to first trade

To complement the previous analysis, we also study whether there is a relationship between a loan's cost of downgrade, its probability of being traded, and the speed at which it is first traded. We continue to focus on the 75 loans in our sample for which we have secondary market pricing data. Since this sample is relatively small and the nature of this analysis is cross-sectional, we lack the additional observations provided by the quarterly-panel structure from the previous section. Consequently, we display the results graphically.

We begin by investigating whether banks are more likely to sell loans with higher CRA conflicts. To facilitate the comparison between loans that are traded and loans that are not traded, we match the 75 loans with similar non-traded loans using a nearest neighbor matching technique based on all continuous control variables.[36] We then split these 150 observations into three groups based on their cost of downgrade, and plot the probability of a loan being sold by the originating bank for each group in Figure **6**.

[Insert Figure **6** here]

The figure shows a nonlinear relationship between our measure of CRA conflicts and the likelihood of a loan being traded. Loans in the highest group of *cost of downgrade* have a 58% probability of being traded in the secondary market, almost 10% higher than that of the other two groups with lower downgrade costs.

Next, we investigate whether banks, conditionally on selling a loan, are selling loans with higher CRA conflicts faster. The underlying assumption for this analysis is that originating banks sell parts of the loan on the same day a dealer quotes a price for the loan for the first time. Thus, we compare the time elapsed between loan origination and when

[36]These variables include firm characteristics (current credit rating, size, profitability, asset tangibility, and leverage) and loan characteristics (amount, number of financial covenants, loan type, and whether the loan is secured or not). Table IA.24 shows that the matching identifies observationally equivalent non-traded loans to traded loans, except that traded loans are slightly larger and riskier.

the loan gets quoted for the first time across groups of loans based on costs of downgrade. As before, we split the sample into three groups based on cost of downgrade and plot the average time-to-first-trade for each group in Figure **7**.

[Insert Figure **7** here]

Once again, the figure shows a nonlinear relationship between our measure of CRA conflicts and the outcome variable. Loans in the lowest group of *cost of downgrade* stay on banks' balance sheets for about 470 days before getting quoted, whereas loans in the other two groups experience their first quote after about 200 days, on average. This is a 270-day difference, equivalent to a 57% relative change. Overall, the results in this section are consistent with banks being more likely to sell loans with a higher potential for credit rating inflation. The results are also consistent with these loans being traded faster. Note that we only observe quotes for the most liquid loans that have brokers providing daily prices. Since 40% (i.e., about eight times as many loans as in our sample) are traded (Beyhaghi and Ehsani (2017)), the actual number of loans and investors affected by CRA conflicts is arguably quite large.

VI. Credit rating agency behavior and settlements with the DOJ

Recently, both S&P and Moody's agreed to settlements with the DOJ for failing to adhere to their standards when rating securitized products during the run-up to the Financial Crisis.[37] The statements of facts indicate that both CRAs deviated from their methodologies without disclosing those changes to investors or the public. Moreover, both CRAs avoided the downgrading of underperforming assets because doing so could negatively affect their business (see Internet Appendix C for excerpts from these statements of facts). The results in Section IV show that the conflicts of interest of CRAs were pervasive and were not restricted to structured products. S&P and Moody's also

[37] S&P settled with the DOJ for $1.375 billion in February 2015, and Moody's settled for $864 million in January 2017.

avoided downgrading their clients when the downgrade would translate into an increase in the borrowing costs associated with their PSD obligations. Consistent with CRAs catering to their clients, this reluctance to downgrade is driven precisely by those instances in which the CRA's credit rating is the decisive one in determining borrowing costs.

As a result of these settlements, CRAs committed to improving their credit models, becoming more transparent, and addressing conflicts of interest more generally. In this section, we investigate whether CRAs have delivered on these commitments.

The question of whether CRAs improved their approach to credit ratings post-settlements cannot be answered by studying the securitized products market, where the infractions linked to the settlements occurred. The main limitation is that the nonagency RMBS and CDO markets virtually disappeared after the Financial Crisis. In contrast, in our setting of PSD loans, issuances have remained relatively stable during the last 15 years (Figure IA.1).

We study whether the relationship between the probability of a downgrade and the increase in borrowing costs after a downgrade varies with the settlements. We introduce the indicator variable 1(*post settlement*), which takes the value 1 from the second quarter of 2015 (i.e., the quarter after S&P settled with the DOJ), and 0 before the second quarter of 2015. We focus on the date of S&P's settlement because (1) our data coverage ends in December 2016 (i.e., before the Moody's settlement) and (2) the first (and largest) settlement in the history of CRAs is likely to affect the rest of the market. Once again, we supplement our main specification with this variable, as well as with the interaction between this variable and the cost of a downgrade.

The estimation results are presented in Table **12**. All specifications include the complete set of controls and fixed effects. If CRAs changed their approach to credit ratings to deal with conflicts of interest post-settlement, the coefficient on the interaction term should be positive. However, Column 1 of Table **12** shows a statistically insignificant and negative coefficient on $cost\ of\ downgrade \times 1(post\ settlement)$.[38] In contrast, consistent with the results in Section IV, the coefficient on the standalone variable that represents the cost of a downgrade continues to be statistically significant and negative. Column 2 of Table **12** also yields a statistically insignificant coefficient on $cost\ of\ downgrade \times 1(post\ settlement)$ when considering the time required for the firm to be downgraded after loan origination as the dependent variable in the regression.

[Insert Table **12** Here]

In the Internet Appendix, we consider the possibility that immediately after the financial crisis, CRAs may have changed their credit rating behavior due to the potential threat of litigation. In Table IA.25, we estimate regressions similar to those in Table **12**, replacing the post-settlement indicator with a post-crisis indicator, which takes a value of one from 2008 to 2015. The interaction coefficient between the cost of downgrade and the post-crisis indicator is statistically indistinguishable from zero in both the downgrade (Column 1) and time-to-downgrade (Column 2) regressions, indicating no evidence of a change in behavior. As a refinement, Figure IA.2 shows the effect of the cost-of-downgrade variable on the probability of a downgrade year by year throughout the sample period, confirming that the results are consistent across all years.

Overall, the previous results suggest that the DOJ settlements did not have the intended effect of improving credit rating quality, and CRAs did not change their credit rating behavior, at least almost two years after the settlement and when rating firms associated with PSD. Notably, these results are also consistent with recent allegations by the Securities and Exchange Commission that credit rating catering has resurfaced after the recovery of the RMBS market.[39]

[38]Column 2 of Table IA.14 shows that this result remains unchanged when including loan fixed effects in the regression.

[39]See `https://www.sec.gov/news/press-release/2022-205`.

VII. Conclusion

We show evidence that conflicts of interest affect the behavior of CRAs, specifically in the context of credit rating–dependent PSD. CRAs are significantly less likely to downgrade borrowers if these downgrades would translate into larger increases in borrowing costs for their clients. This behavior is driven by instances in which the CRA's credit rating is the decisive one in determining loan spreads and by instances in which the CRA rates clients that are potentially more profitable for the agency. This indicates that CRAs cater to their clients outside the market for complex structured products. Even conditionally on eventually downgrading, CRAs delay their decision when the costs of downgrading are higher.

The potential for credit inflation is, to some extent, priced at origination. This suggests that borrowers and lenders are aware of these problems. In contrast, secondary market participants do not seem to internalize the conflicts of interests of CRAs: yield premiums decrease when these loans are sold. In addition, also consistent with originating banks internalizing the additional risk, originating banks are more likely to sell loans with high costs of downgrade, and among the loans that they sell, loans with high cost of downgrade are also sold faster. A concerning implication of these findings is that originating banks, arguably the most informed market participants and the ones in an ideal position to monitor CRAs, have little incentive to do so.

Overall, our results suggest that the catering behavior of CRAs is not confined to complex markets such as the securitized products market. The major CRAs settled with the DOJ for inflating the credit ratings of nonagency RMBSs and CDOs during the run-up to the Financial Crisis, and they renewed their commitment to credit rating quality. However, we find no evidence of reduced catering in the market for PSD post-settlements. This result calls into question the effectiveness of the settlements in influencing CRA behavior, and it highlights the pervasiveness of these conflicts of interest that stem from the issuer–pays business model of CRAs.

Appendix

A. Variable description

Variable name	Description
Borrower-quarter characteristics	
Assets	Total assets (in billions USD)
Credit rating	Long-term issuer credit rating. Either from S&P or Moody's, depending on which CRA is decisive. Ratings are converted into a numerical scale ranging from 1 (AAA/Aaa) to 22 (D), following the standard ordering of S&P and Moody's long-term rating categories (e.g., 1 = AAA/Aaa, 2 = AA+/Aa1, 3 = AA/Aa2, ..., 10 = BBB–/Baa3, ..., 22 = D).
Leverage	Total liabilities÷$Assets$
Loan volume	Cumulative volume of loans issued in the rolling 4 year windows prior to each loan, excluding the actual loan.
Profitability	EBITDA÷$Assets$
1(border junk)	Indicator variable that takes the value of 1 if the borrower has a credit rating of BBB-, and 0 otherwise.
1(commodities)	Indicator variable that takes the value of 1 if the firm is in the oil and gas extraction, coal mining, metal ore mining, or the support activities for mining sectors (i.e., NAICS codes 2111, 2121, 2122, and 2131), and 0 otherwise.
Intangibles over assets	Intangibles÷$Assets$
1(high intangibles)	Indicator variable that takes the value of 1 if intangibles divided by assets is above the sample median, and 0 otherwise.
R&D	Research and development expenses (in millions USD)
1(high R&D)	Indicator variable that takes the value of 1 if *R&D* is above the sample median, and 0 otherwise.
1(high yield issuer)	Indicator variable that takes the value of 1 if the borrower has a credit rating at of BB+ or lower, and 0 otherwise.
Loan characteristics at origination	
All in spread drawn	All in spread drawn above LIBOR
Loan size	Total loan size (in millions USD)
Loan type	Set of indicator variables for the following loan types: 1) revolver, 2) term loan, and 3) other. The "other" category primarily includes facilities such as acquisition facilities, bridge loans, and standby letters of credit.
Loan-quarter characteristics	
Cost of downgrade	The increase in a loan's interest spread that results from a credit downgrade of one notch (in basis points).
Cost of 2-notch downgrade	The increase in a loan's interest spread that results from a downgrade of two notches (in basis points).
Cost of downgrade (% of assets)	The increase in the costs that results from a downgrade of one notch measured as $Cost\ of\ downgrade \times Loan\ size \div Assets$.
1(decisive rating)	Indicator variable that takes the value of 1 if the CRA holds the decisive rating, and 0 otherwise.
1(commodities shock)	Indicator variable that takes the value of 1 from 2014Q3 to 2015Q4, and 0 otherwise.
1(post settlement)	Indicator variable that takes the value of 1 from 2015Q2 to 2016Q4, and 0 otherwise.

References

Adam, T. R., V. Burg, T. Scheinert, and D. Streitz. 2020, Managerial biases and debt contract design: The case of syndicated loans, *Management Science*, 66:352–75.

Adam, T. R., and D. Streitz. 2016, Hold-up and the use of performance-sensitive debt, *Journal of Financial Intermediation*, 26:47–67.

Addoum, J. M., and J. R. Murfin. 2020, Equity price discovery with informed private debt, *The Review of Financial Studies*, 33:3766–803.

Altman, E. I., A. Gande, and A. Saunders. 2010, Bank debt versus bond debt: Evidence from secondary market prices, *Journal of Money, Credit and Banking*, 42:755–67.

Ashcraft, A., P. Goldsmith-Pinkham, P. Hull, and J. Vickery. 2011, Credit ratings and security prices in the subprime mbs market, *American Economic Review*, 101:115–9.

Asquith, P., A. Beatty, and J. Weber. 2005, Performance pricing in bank debt contracts, *Journal of Accounting and Economics*, 40:101–28.

Bannier, C. E., and M. Wiemann. 2011, Accounting-based versus rating-based performance pricing in bank loan contracts–immediate punishment but gradual reward?
Working Paper.

Bar-Isaac, H., and J. Shapiro. 2013, Ratings quality over the business cycle, *Journal of Financial Economics*, 108:62–78.

Beatty, A., and J. Weber. 2003, The effects of debt contracting on voluntary accounting method changes, *The Accounting Review*, 78:119–42.

Becker, B., and T. Milbourn. 2011, How did increased competition affect credit ratings?, *Journal of Financial Economics*, 101:493–514.

Begley, T. A. 2012, Signaling, financial constraints, and performance sensitive debt, *Working Paper, Washington Univeristy St Louis*.

Benmelech, E., and J. Dlugosz. 2010, The credit rating crisis, *NBER Macroeconomics Annual*, 24:161–208.

Beyhaghi, M., and S. Ehsani. 2017, The cross-section of expected returns in the secondary corporate loan market, *The Review of Asset Pricing Studies*, 7:243–77.

Billett, M., R. Elkamhi, D. Mauer, and R. Pungaliya. 2015, Bank loan price reactions to corporate events: Evidence from traded syndicated loans, *Kelley School of Business Research Paper*.

Bolton, P., X. Freixas, and J. Shapiro. 2012, The credit ratings game, *Journal of Finance*, 67:85–111.

Bruno, V., J. Cornaggia, and K. J. Cornaggia. 2016, Does regulatory certification affect the information content of credit ratings?, *Management Science*, 62:1578–97.

Campbell, T. C., M. Gallmeyer, S. A. Johnson, J. Rutherford, and B. W. Stanley. 2011, Ceo optimism and forced turnover, *Journal of Financial Economics*, 101:695–712.

Cañibano, L., M. Garcia-Ayuso, and P. Sanchez. 2000, Accounting for intangibles: A literature review, *Journal of Accounting Literature*, 19:102–30.

Chava, S., and M. R. Roberts. 2008, How does financing impact investment? The role of debt covenants, *Journal of Finance*, 63:2085–121.

Cornaggia, J., K. Cornaggia, and R. D. Israelsen. 2022, Rating agency fees: Pay to play or pay for work?, *forthcoming, Review of Financial Studies*.

Cornaggia, J., and K. J. Cornaggia. 2013, Estimating the costs of issuer-paid credit ratings, *Review of Financial Studies*, 26:2229–69.

Credit Rating Agencies and the Financial Crisis. 2008, Hearing Before the Committee on Oversight and Government Reform, Serial No. 110–155.

Dahiya, S., M. Puri, and A. Saunders. 2003, Bank borrowers and loan sales: New evidence on the uniqueness of bank loans, *The Journal of business*, 76:563–82.

Department of Justice. 2015, Settlement agreement with Standard & Poor's Financial Services LLC, Statement of Facts.

Department of Justice. 2017, Settlement agreement with Moody's Corporation, Statement of Facts.

Efing, M., and H. Hau. 2015, Structured debt ratings: Evidence on conflicts of interest, *Journal of Financial Economics*, 116:46–60.

Egan, M. 2015, Copper, aluminum and steel collapse to crisis levels.
CNN, December 9.

Faure-Grimaud, A., E. Peyrache, and L. Quesada. 2009, The ownership of ratings, *RAND Journal of Economics*, 40:234–57.

Gande, A., and A. Saunders. 2012, Are banks still special when there is a secondary market for loans?, *The Journal of Finance*, 67:1649–84.

Goldstein, I., and C. Huang. 2020, Credit rating inflation and firms' investments, *Journal of Finance*, 75:2929–72.

Griffin, J. M. 2019, Ten years of evidence: Was fraud a force in the financial crisis?, *Working Paper, University of Texas at Austin*.

Griffin, J. M., J. Nickerson, and D. Y. Tang. 2013, Rating shopping or catering? An examination of the response to competitive pressure for CDO credit ratings, *Review of Financial Studies*, 26:2270–310.

Griffin, J. M., and D. Y. Tang. 2012, Did subjectivity play a role in cdo credit ratings?, *Journal of Finance*, 67:1293–328.

He, J., J. Qian, and P. E. Strahan. 2011, Credit ratings and the evolution of the mortgage-backed securities market, *American Economic Review*, 101:131–35.

——. 2012, Are all ratings created equal? the impact of issuer size on the pricing of mortgage-backed securities, *Journal of Finance*, 67:2097–137.

Ivashina, V., and D. Scharfstein. 2010, Loan syndication and credit cycles, *American Economic Review*, 100:57–61.

Kisgen, D. J. 2006, Credit ratings and capital structure, *The Journal of Finance*, 61:1035–72.

Kraft, P. 2015, Do rating agencies cater? Evidence from rating-based contracts, *Journal of Accounting and Economics*, 59:264–83.

Kronlund, M. 2019, Do bond issuers shop for favorable credit ratings?, *Management Science, Forthcoming.*

Larcker, D. F., B. Levy, P. J. Quinn, B. Tayan, and D. J. Taylor. 2021, Gaming the system: Three'red flags' of potential 10b5-1 abuse, *Rock Center for Corporate Governance at Stanford University Working Paper Forthcoming.*

Malmendier, U., and G. Tate. 2008, Who makes acquisitions? ceo overconfidence and the market's reaction, *Journal of financial Economics*, 89:20–43.

Manso, G., B. Strulovici, and A. Tchistyi. 2010, Performance-sensitive debt, *Review of Financial Studies*, 23:1819–54.

Mathis, J., J. McAndrews, and J.-C. Rochet. 2009, Rating the raters: Are reputation concerns powerful enough to discipline rating agencies?, *Journal of Monetary Economics*, 56:657–74.

Mjøs, A., T. A. Myklebust, and S.-A. Persson. 2013, On the pricing of performance sensitive debt. Working Paper.

Moody's. 2002, Moody's Investor Services Special Comment: Understanding Moody's Corporate Bond Ratings and Rating Process.

Moody's. 2021, Moody's Investors Services: 2020 10-K Form.

Opp, C. C., M. M. Opp, and M. Harris. 2013, Rating agencies in the face of regulation, *Journal of Financial Economics*, 108:46–61.

Pierret, D., and R. Steri. 2019, Stressed banks, *Swiss Finance Institute Research Paper.*

Sangiorgi, F., and C. Spatt. 2017, Opacity, credit rating shopping, and bias, *Management Science*, 63:4016–36.

Skreta, V., and L. Veldkamp. 2009, Ratings shopping and asset complexity: A theory of ratings inflation, *Journal of Monetary Economics*, 56:678–95.

S&P Global Ratings. 2018, S&P Global Ratings Code of Conduct.

Tchistyi, A., D. Yermack, and H. Yun. 2011, Negative hedging: Performance-sensitive debt and CEOs' equity incentives, *Journal of Financial and Quantitative Analysis*, 46:657–86.

U.S. Securities and Exchange Commission. 2002, Role and Function of Credit Rating Agencies in the U.S. Securities Markets, Public Hearing (November 15).

Wittenberg-Moerman, R. 2008, The role of information asymmetry and financial reporting quality in debt trading: Evidence from the secondary loan market, *Journal of Accounting and Economics*, 46:240–60.

Wyatt, A. 2005, Accounting recognition of intangible assets: theory and evidence on economic determinants, *The Accounting Review*, 80:967–1003.

Xia, H. 2014, Can investor-paid credit rating agencies improve the information quality of issuer-paid rating agencies?, *Journal of Financial Economics*, 111:450–68.

FIGURE 1
Example pricing grid

This figure shows the pricing grid from The Walt Disney Co.'s syndicated 5.25-year revolving credit facility issued on February 23, 2005. Panel A shows that there is no change in the loan's interest rate if the firm's credit rating changes from A+ to A. Panel B shows that the loan's interest rate changes from LIBOR + 13 bps to LIBOR + 14 bps if the firm's credit rating changes from A to A-. The 1 bps increase translates into additional borrowing costs of as high of $225,000 per year.

Panel A: One-notch credit rating downgrade from A+

Firm's name	Quarter	Current rating	Minimum rating	Maximum rating	Spread over LIBOR (bps)
Disney	2006 Q1	A+	AA-		11.5
Disney	2006 Q1	A+	A	A+	13
Disney	2006 Q1	A+	A-	A-	14
Disney	2006 Q1	A+	BBB-	BBB+	17.5
Disney	2006 Q1	A+		BBB-	30

Downgrade does not change the loan's interest rate

Panel B: One-notch credit rating downgrade from A

Firm's name	Quarter	Current rating	Minimum rating	Maximum rating	Spread over LIBOR (bps)
Disney	2006 Q1	A	AA-		11.5
Disney	2006 Q1	A	A	A+	13
Disney	2006 Q1	A	A-	A-	14
Disney	2006 Q1	A	BBB-	BBB+	17.5
Disney	2006 Q1	A		BBB-	30

Downgrade does change the loan's interest rate

Loan amount = $2.25 billion, 1 bps = up to $225,000 in annual savings

FIGURE 2
Distribution of credit ratings at origination

The figure shows the distribution of credit ratings at the time of loan origination for our sample of credit rating–based PSD loans. The credit rating scale is simplified by combining the credit ratings within each letter credit rating category. For example, we combine the initial credit ratings of A+, A, and A- into one group, A.

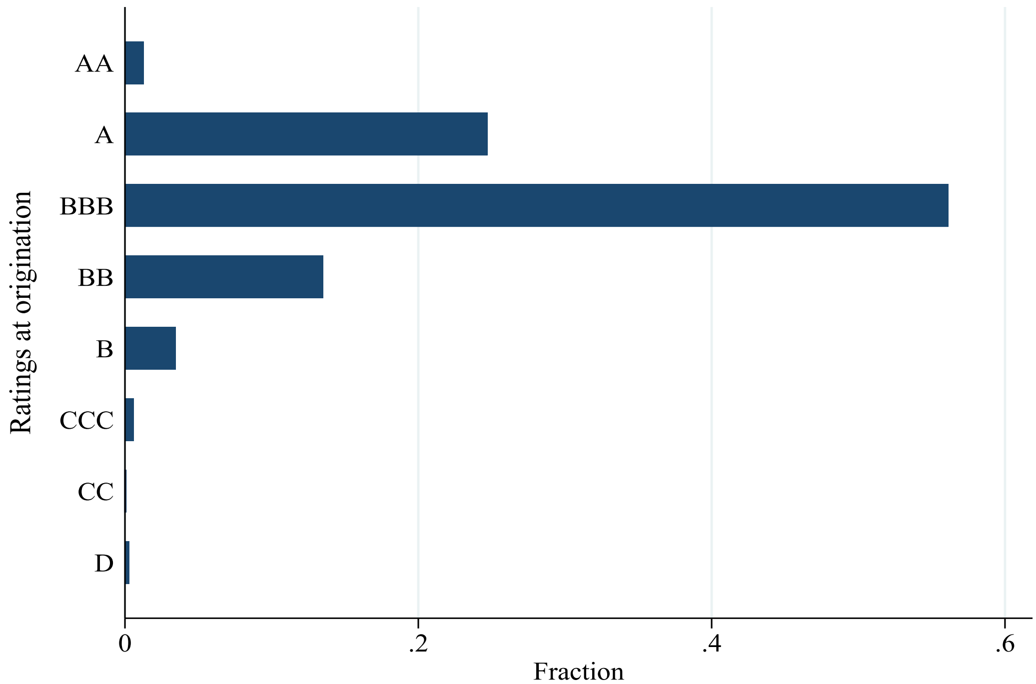

FIGURE 3
Distribution of cost of downgrade by rating

This figure shows the distribution of the cost of a one-notch credit rating downgrade across the different credit rating groups (at origination). The bottom row tabulates the fraction of observations within each credit rating group that have a cost of downgrade of zero.

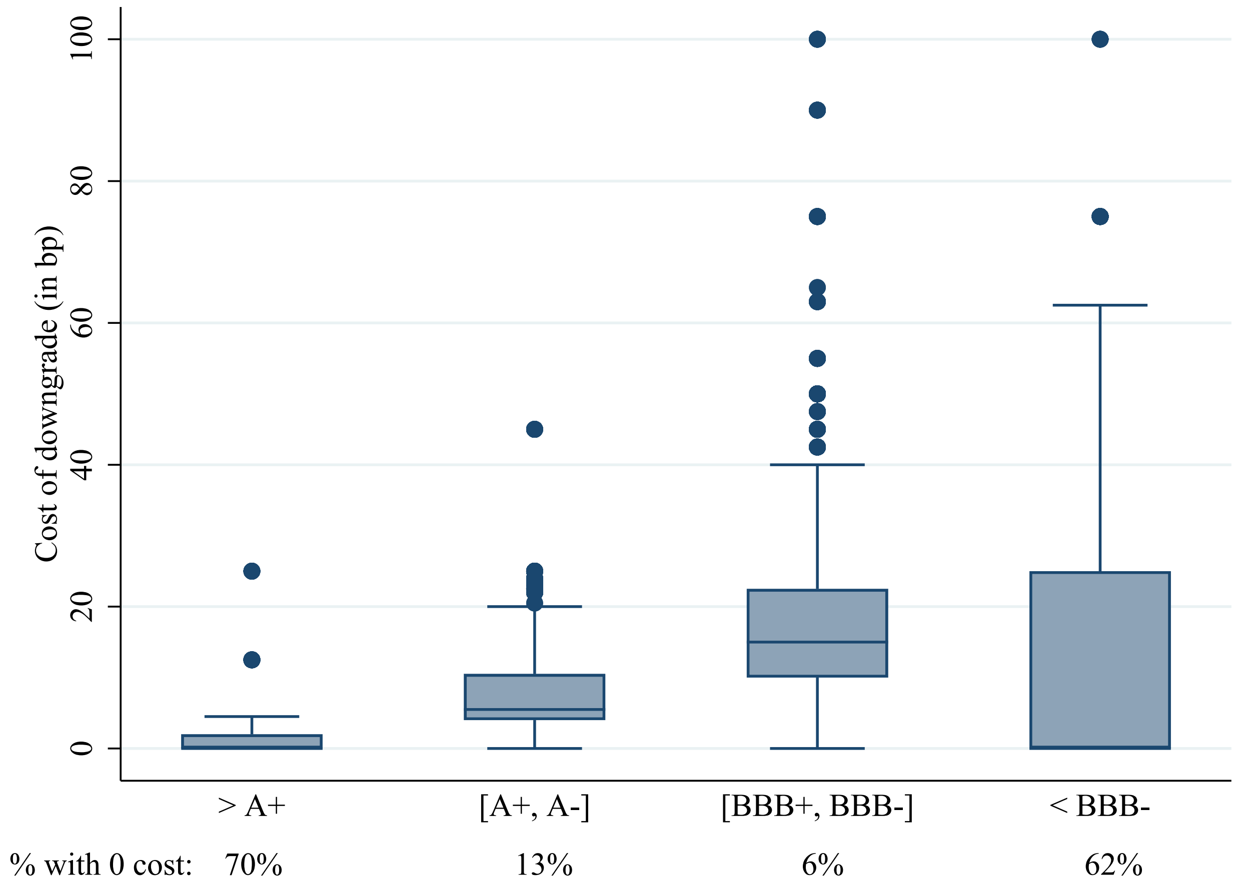

FIGURE 4

Borrower creditworthiness over time

This figure shows the measure of creditworthiness for firms with loans with high (i.e., above median) and low (i.e., below median) costs of downgrade at origination. To construct the measure of creditworthiness, observed (numeric) credit ratings are regressed on firm variables, including leverage, size, profitability, cash flow, and asset tangibility, as well as industry and year fixed effects. Numeric credit ratings reflect the number of notches away from AAA (rating = 1), with a rating of 9 corresponding to BBB, and a rating of 8 corresponding to BBB+. The measure of creditworthiness comes from obtaining the fitted values from the regression model. The average cost of a downgrade for the high-cost group (circles) is 22.3 bp whereas the average cost of a downgrade for the low-cost group (triangles) is 6.7 bp. The analysis is restricted to the first four years of each loan's life. The shaded areas denote the 95% confidence interval for each estimation.

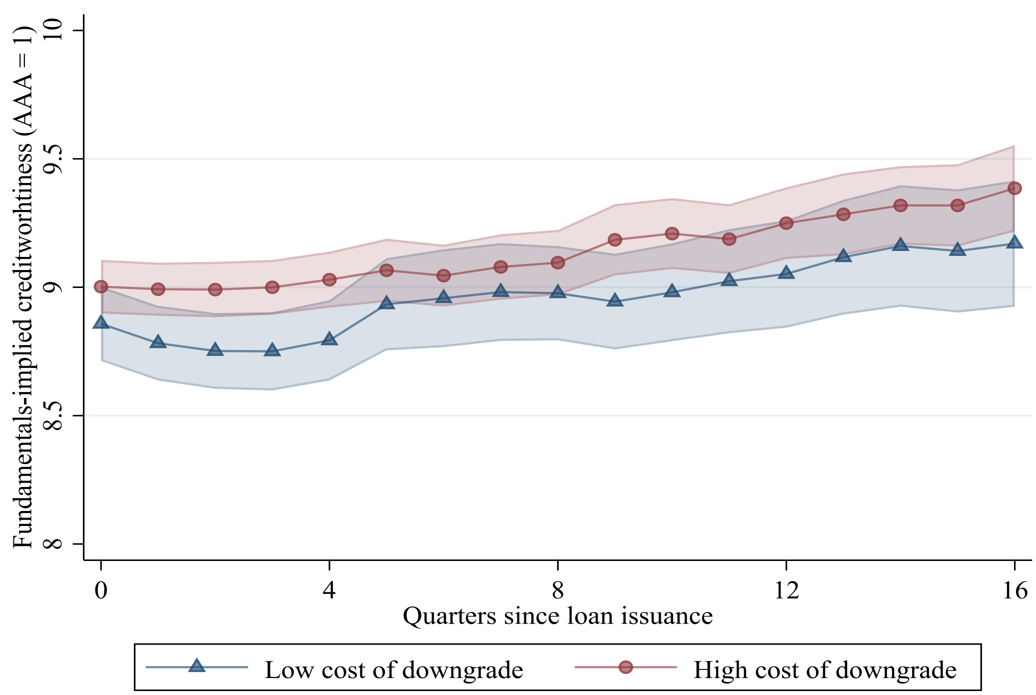

FIGURE 5
Dynamics of secondary market prices

This figure shows the dynamics of the pricing of loans with high cost of downgrade in the secondary market. *Loan price* (measured as the average of the mid-prices quoted each quarter) is regressed on the interactions of an indicator for above-median cost of downgrade and indicators for each quarter since loan issuance. The regression includes the same set of control variables and fixed effects as in Column 4 of Table **3** plus loan fixed effects, and the first four years of each loan's lifetime are considered. The coefficients associated with the interactions are denoted by solid circles, and the vertical bars denote the corresponding 95% confidence interval (based on standard errors clustered by loan). The dashed vertical line denotes the average time from origination to first sale for loans with above-median cost of downgrade.

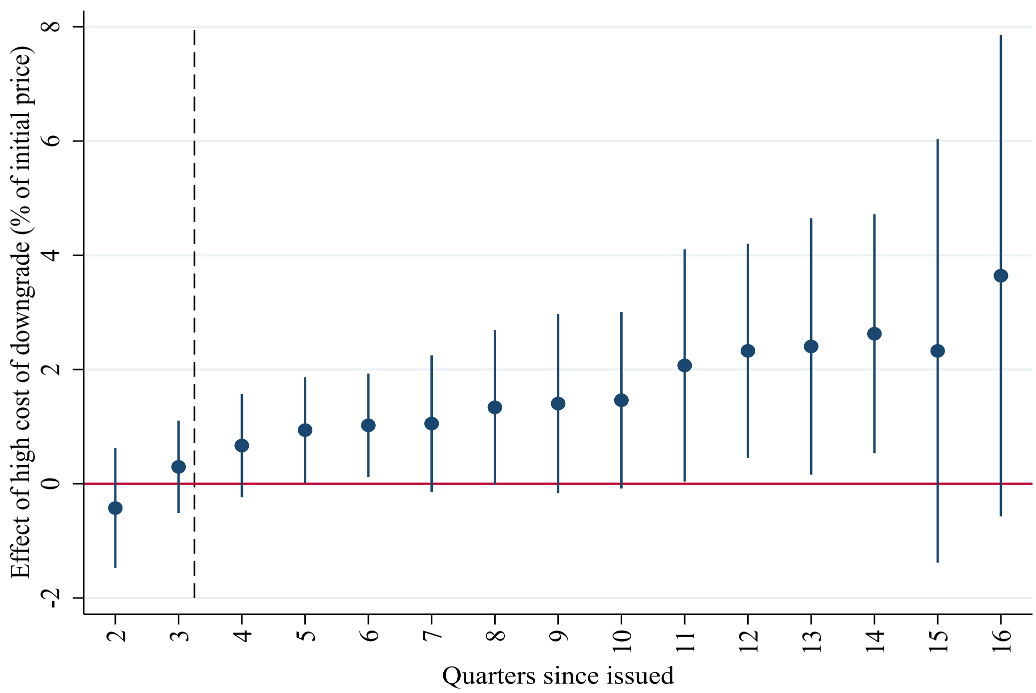

FIGURE 6
Probability of loan sale

This figure shows the probability of loan trade in the secondary market by terciles of average cost of downgrade. The sample consists of 75 traded loans and 75 non-traded loans. The non-traded loans are selected so that they resemble the traded loans using a nearest neighbor matching framework based on firm characteristics (current credit rating, size, profitability, asset tangibility, and leverage) and loan characteristics (amount, number of financial covenants, loan type, and whether the loan is secured or not).

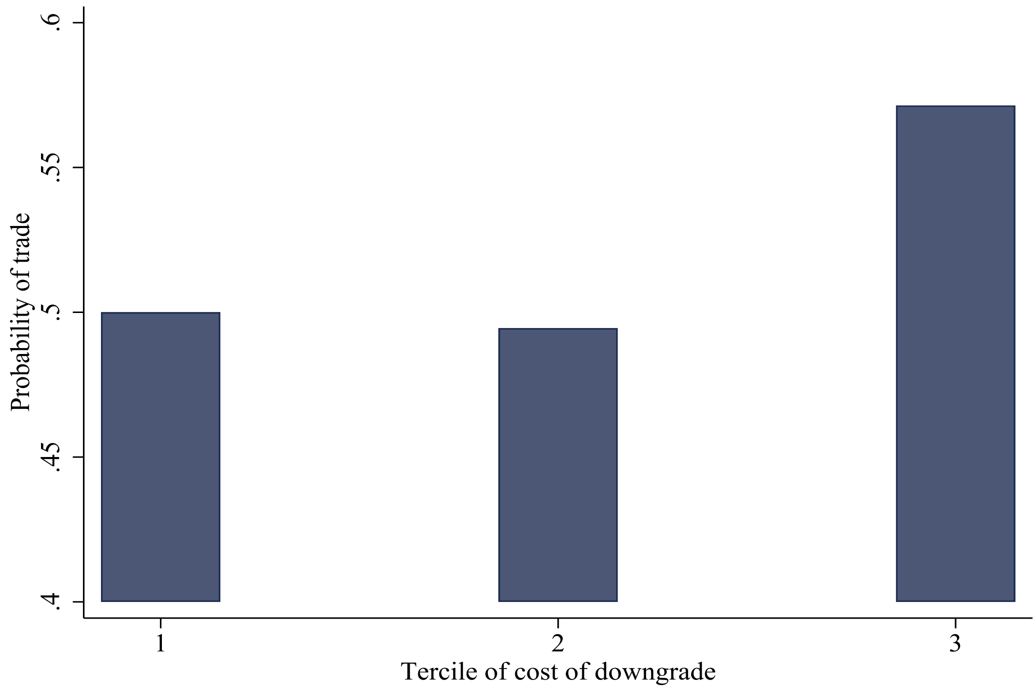

FIGURE 7

Time to first sale

This figure shows the average time-to-first-trade (days) in the secondary market by terciles of average cost of downgrade. The sample consists of 75 traded loans.

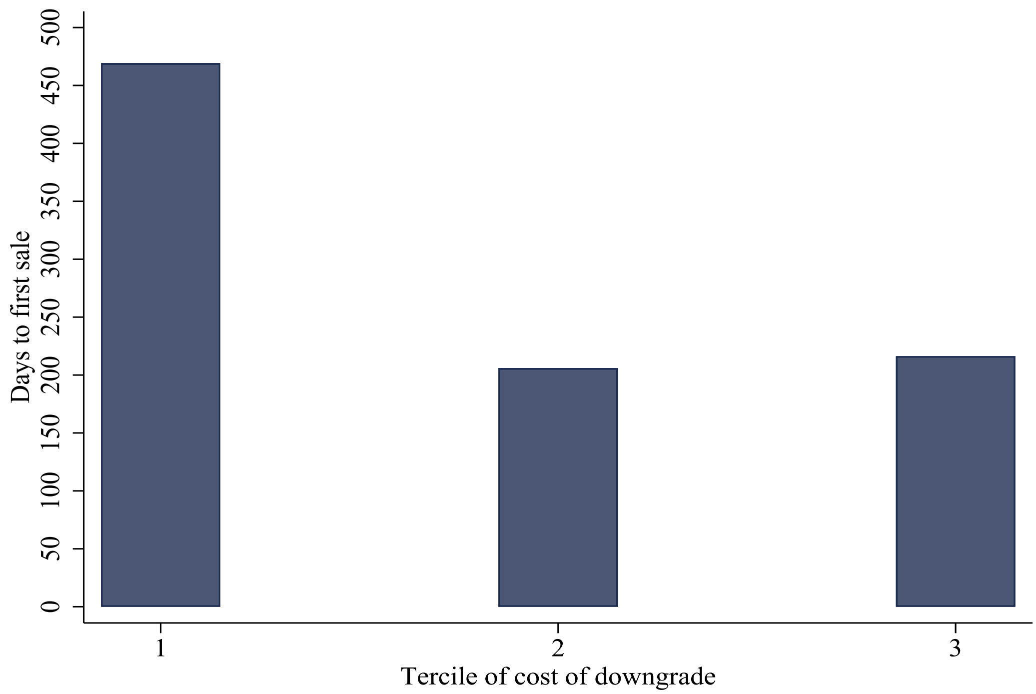

TABLE 1
Data summary

This table describes the final sample. Panel A shows summary statistics at the borrower–quarter level. Panel B shows summary statistics for the PSD loan contracts contained in the final sample. Panel C shows overall and within-group standard deviations for the main variables in equation (1). A detailed description of all variables is available in Appendix A. 1(·) denotes indicator variables.

Panel A: Borrower–quarter characteristics

	N	Mean	SD	p10	p50	p90
Cost of downgrade (bps)	22,760	13.74	12.07	0.00	12.50	25.00
Leverage	22,760	0.31	0.17	0.12	0.30	0.51
Total assets ($ billion)	22,760	23.42	56.15	2.08	8.81	47.02
Intangibles over assets	22,760	0.21	0.20	0.00	0.14	0.55
Profitability (ROA)	22,760	0.01	0.02	-0.00	0.01	0.03
1(downgrade) (percent)	22,760	2.57	15.81	0.00	0.00	0.00
Issuer credit rating (numeric)	22,760	9.16	2.63	6.00	9.00	12.00
R&D ($ million)	10,401	283.81	620.20	0.00	65.92	718.10

Panel B: Loan characteristics

	N	Mean	SD	p10	p50	p90
Number of financial covenants	1,988	1.46	0.83	0.00	1.00	2.00
Loan amount ($ million)	1,988	914.04	910.40	150.00	550.00	2200.00
1(secured)	1,988	0.16	0.37	0.00	0.00	1.00
Average cost of downgrade	1,988	14.82	8.50	6.83	12.50	25.00
1(revolver)	1,988	0.80	0.40	0	1	1
Time to downgrade (quarters)	455	4.77	5.14	0.00	3.00	12.00

Panel C: Variation within groups

	N	Overall SD	SD within credit rating	SD within firm	SD within year
1(downgrade) (percent)	22,760	15.81	15.59	15.03	15.76
Cost of downgrade (bps)	22,760	12.07	10.94	8.84	11.90
Time to downgrade (quarters)	22,760	4.39	4.30	3.56	4.17

TABLE 2
Accounting ratio–based PSD loans versus credit rating–based PSD loans

This table compares a sample of accounting ratio–based PSD loans with our sample of credit rating–based PSD loans across observable characteristics. Observations are at the loan–year level. $1(\cdot)$ denotes indicator variables. Statistical significance computations are based on heteroscedasticity-robust standard errors clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	Mean		
	Accounting ratio–based	Credit rating–based	Difference
Leverage	0.41	0.31	0.10***
Total assets ($ billions)	4.92	23.42	-18.50***
Intangibles over assets	0.29	0.21	0.09***
Profitability (ROA)	0.005	0.009	-0.004**
R&D ($ millions)	61.53	283.80	-220.96***
Number of financial covenants	2.12	1.52	1.24***
Loan amount ($ millions)	350.9	894.5	-543.64***
1(secured)	0.88	0.18	0.70***
Cost of one grid (rating or ratio, bp)	18.36	13.74	4.63***
N	21,789	22,760	44,549

TABLE 3
Probability of downgrade and cost of downgrade

This table shows OLS regressions for different variants of equation (1). The dependent variable is an indicator that takes the value of 1 if the borrower is downgraded, and 0 otherwise. The indicator is multiplied by 100 so that regression coefficients are in percentage points. The independent variable of interest is *cost of downgrade*, a measure of the increase in loan spread that would result from a credit rating downgrade of one notch. The variable is standardized so that regression coefficients reflect the impact of changing the variable by one standard deviation. Loan- and firm-level controls, as well as current credit rating, year–quarter, and firm fixed effects are included as reported. Loan-level controls include loan type, amount, number of financial covenants, whether the loan is secured, and deal purpose. Firm-level controls include size, profitability, asset tangibility, and leverage. A detailed description of all variables is available in Appendix A. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

	1(downgrade)			
	(1)	(2)	(3)	(4)
Cost of downgrade	-0.755***	-0.701***	-0.617***	-0.674***
	(0.237)	(0.213)	(0.210)	(0.209)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Rating FE	No	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes
N	22,760	22,760	22,760	22,760
$Adj.R^2$	0.09	0.11	0.12	0.12
Mean of dependent variable	2.57	2.57	2.57	2.57

TABLE 4

Probability of downgrade and cost of downgrade: Profitability of clients

This table shows OLS regressions where the dependent variable is an indicator that takes the value of 1 if the borrower is downgraded, and 0 otherwise. The indicator is multiplied by 100 so that regression coefficients are in percentage points. The independent variables of interest are *cost of downgrade*, *loan volume*, 1(*high yield issuer*), and the interaction between the three variables. *Cost of downgrade* is a measure of the increase in loan spread that would result from a credit rating downgrade of one notch. The variable is standardized so that regression coefficients reflect the impact of changing the variable by one standard deviation. *Loan volume* is the natural logarithm of the total volume of loans issued by the borrower in the past four years. 1(*high yield issuer*) is an indicator that takes the value of 1 if the borrower is a high-yield issuer (i.e., an issuer rated BB+ or lower). Standalone variables that are not included in the table are absorbed by fixed effects. All regressions include loan- and firm-level controls, as well as current credit rating, year–quarter, and firm fixed effects. Loan-level controls include loan type, amount, number of financial covenants, whether the loan is secured, and deal purpose. Firm-level controls include size, profitability, asset tangibility, and leverage. A detailed description of all variables is available in Appendix A. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***$p<0.01$, **$p<0.05$, *$p<0.10$.

	1(downgrade)		
	(1)	(2)	(3)
Cost of downgrade	-0.256	-0.509**	-0.183
	(0.243)	(0.210)	(0.247)
Cost of downgrade × Loan volume	-0.029**		-0.021*
	(0.012)		(0.012)
Cost of downgrade × 1(High yield issuer)		-2.459***	0.159
		(0.874)	(1.225)
Cost of downgrade × Loan volume × 1(High yield issuer)			-0.423***
			(0.090)
Loan volume	-0.012		-0.017
	(0.019)		(0.018)
Firm FE	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
N	22,760	22,760	22,760
$Adj.R^2$	0.13	0.13	0.13
Mean of dependent variable	2.57	2.57	2.57

TABLE 5
Loan fixed effects regressions

This table shows OLS regressions identical to the most complete specifications in Tables **3** to **4**, except that the regressions include loan fixed effects. Standalone variables that are not included in the table are absorbed by fixed effects. All regressions include firm-level controls, as well as current credit rating, year–quarter, and loan fixed effects. Firm-level controls include size, profitability, asset tangibility, and leverage. A detailed description of all variables is available in Appendix A. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	1(downgrade)			
	Table **3**	Table **4**		
	(1)	(2)	(3)	(4)
Cost of downgrade	-1.426**	-0.921	-0.915	-0.508
	(0.642)	(0.702)	(0.652)	(0.717)
Cost of downgrade × Loan volume		-0.031		-0.012
		(0.022)		(0.023)
Cost of downgrade × 1(high yield issuer)			-5.244***	-2.444
			(1.709)	(1.705)
Cost of downgrade × Loan volume × 1(high yield issuer)				-0.462***
				(0.105)
Loan volume		-0.033		-0.039
		(0.025)		(0.025)
Loan FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
N	22,650	22,650	22,650	22,650
$Adj.R^2$	0.11	0.11	0.11	0.12
Mean of dependent variable	2.57	2.57	2.57	2.57

TABLE 6

Probability of downgrade and cost of downgrade: Different time windows

This Table shows OLS regressions that are identical to Table **3** except that the regressions are estimated on samples from different time windows. Specifically, each column excludes a certain period of time after the origination of the loan. Column 1 excludes the first quarter after loan origination. Column 2 excludes the first two quarters after loan origination. Column 3 excludes the first year after loan origination. Column 4 excludes the first two years after loan origination. The dependent variable is an indicator that takes the value of 1 if the borrower is downgraded, and 0 otherwise. The indicator is multiplied by 100 so that regression coefficients are in percentage points. The independent variable of interest is *cost of downgrade*, a measure of the increase in loan spread that would result from a credit rating downgrade of one notch. The variable is standardized so that regression coefficients reflect the impact of changing the variable by one standard deviation. All regressions include loan- and firm-level controls, as well as current credit rating, year–quarter, and firm fixed effects. Loan-level controls include loan type, amount, number of financial covenants, whether the loan is secured, and deal purpose. Firm-level controls include size, profitability, asset tangibility, and leverage. A detailed description of all variables is available in Appendix A. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***$p<0.01$, **$p<0.05$, *$p<0.10$.

	1(downgrade), excluding:			
	1st quarter	1st halfyear	1st year	2 years
	(1)	(2)	(3)	(4)
Cost of downgrade	-0.635***	-0.586***	-0.726***	-0.590**
	(0.204)	(0.222)	(0.251)	(0.283)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
N	20,657	18,759	15,275	9,856
$Adj.R^2$	0.13	0.12	0.12	0.11
Mean of dependent variable	2.24	2.04	2.00	1.79

TABLE 7

Probability of downgrade and cost of downgrade: Observable shock to borrower quality

This table shows OLS regressions where the dependent variable is an indicator that takes the value of 1 if the borrower is downgraded, and 0 otherwise. The indicator is multiplied by 100 so that regression coefficients are in percentage points. The independent variables of interest are *cost of downgrade*, 1(*commodities*), 1(*commodities shock*), and the interaction between the three variables. *Cost of downgrade* is a measure of the increase in loan spread that would result from a credit rating downgrade of one notch. The variable is standardized so that regression coefficients reflect the impact of changing the variable by one standard deviation. 1(*commodities*) is an indicator that takes the value of 1 for firms in the following sectors: (1) oil and gas extraction (NAICS codes 2111), (2) coal mining (2121), (3) metal ore mining (2122), and (4) support activities for mining (2131). 1(*commodities shock*) is an indicator that takes the value of 1 from the third quarter of 2014 to the end of 2016. Standalone variables that are not included in the table are absorbed by fixed effects. Loan- and firm-level controls, as well as current credit rating, year–quarter, and firm fixed effects are included as reported. Loan-level controls include loan type, amount, number of financial covenants, whether the loan is secured, and deal purpose. Firm-level controls include size, profitability, asset tangibility, and leverage. A detailed description of all variables is available in Appendix A. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	1(downgrade)			
	(1)	(2)	(3)	(4)
Cost of downgrade	-0.629***	-0.640***	-0.540**	-0.626***
	(0.238)	(0.217)	(0.211)	(0.215)
1(commodities) × 1(commodities shock)	6.279***	3.994***	1.121	0.841
	(1.186)	(1.023)	(1.318)	(1.293)
Cost of downgrade × 1(commodities) × 1(commodities shock)	-5.774***	-4.476***	-4.048***	-4.024***
	(1.442)	(1.375)	(1.492)	(1.498)
Cost of downgrade × 1(commodities shock)	-0.453	-0.111	-0.044	0.018
	(0.620)	(0.576)	(0.552)	(0.553)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Rating FE	No	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes
Other interactions	Yes	Yes	Yes	Yes
N	22,760	22,760	22,760	22,760
$Adj.R^2$	0.09	0.11	0.12	0.13
Mean of dependent variable	2.57	2.57	2.57	2.57

TABLE 8
Probability of upgrade and benefit from upgrade

This table shows OLS regressions where the dependent variable is an indicator that takes the value of 1 if the borrower is upgraded, and 0 otherwise. The indicator is multiplied by 100 so that regression coefficients are in percentage points. *Benefit of upgrade* is the reduction in interest rate based on the pricing grid following a one notch upgrade for the borrower. *1(Upgrade grid)* is an indicator for grids that have potential benefits from upgrades, as opposed to loans that only provide increases in interest rates as a function of downgrades without benefits from upgrades. Observations are at the loan level. All regressions include loan- and firm-level controls, as well as current credit rating, year–quarter, and firm fixed effects. Loan-level controls include loan type, amount, number of financial covenants, whether the loan is secured, and deal purpose. Firm-level controls include size, profitability, asset tangibility, and leverage. A detailed description of all variables is available in Appendix A. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	1(Upgrade)	
	(1)	(2)
Benefit of upgrade × 1(Upgrade grid)	0.763	
	(0.996)	
Benefit of upgrade	-0.484***	2.107*
	(0.165)	(1.234)
1(Upgrade grid)	2.651***	
	(0.988)	
Firm FE	Yes	Yes
Year-quarter-FE	Yes	Yes
Rating FE	Yes	Yes
Loan controls	Yes	Yes
Firm controls	Yes	Yes
N	22702	1889
$Adj.R^2$	0.05	0.15
Mean of dependent variable	1.70	3.71

TABLE 9
Ordered logit regression

This table reports OLS and ordered logit regressions in which the dependent variable is a continuous measure of credit rating changes, with positive values indicating a deterioration in the rating. Column 1 presents results from an OLS regression, and Column 2 presents results from an ordered logit regression. The independent variable of interest is *cost of downgrade*, a measure of the increase in loan spread that would result from a credit rating downgrade of one notch. The variable is standardized so that regression coefficients reflect the impact of changing the variable by one standard deviation. Loan- and firm-level controls, as well as current credit rating, year–quarter, industry, and firm fixed effects are included as reported. Loan-level controls include loan type, amount, number of financial covenants, whether the loan is secured, and deal purpose. Firm-level controls include size, profitability, asset tangibility, and leverage. A detailed description of all variables is available in Appendix A. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	Worsening in rating	
	(1) OLS	(2) Ordered logit
Cost of downgrade	-0.013**	-0.141**
	(0.006)	(0.066)
Firm FE	Yes	No
Industry FE	No	Yes
Year-quarter FE	Yes	Yes
Rating FE	Yes	Yes
Loan controls	Yes	Yes
Firm controls	Yes	Yes
N	22,760	22,760
$Adj.R^2$	0.11	-
Mean of dependent variable	0.02	0.02

TABLE 10
Probability of downgrade and time-to-maturity

This table shows OLS regressions where the dependent variable is an indicator that takes the value of 1 if the borrower is downgraded, and 0 otherwise. The indicator is multiplied by 100 so that regression coefficients are in percentage points. The independent variable of interest is *Time to maturity*, measured as the number of quarters remaining until the loan matures. All regressions include loan- and firm-level controls, as well as current credit rating, year–quarter, and firm fixed effects. Loan-level controls include loan type, amount, number of financial covenants, whether the loan is secured, and deal purpose. Firm-level controls include size, profitability, asset tangibility, and leverage. A detailed description of all variables is available in Appendix A. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	1(downgrade)	
	(1)	(2)
Time to maturity (quarters)	0.098***	0.109***
	(0.024)	(0.024)
Cost of downgrade × time to maturity		-0.061**
		(0.027)
Cost of downgrade		-0.418*
		(0.244)
Firm FE	Yes	Yes
Year-quarter FE	Yes	Yes
Rating FE	Yes	Yes
Loan controls	Yes	Yes
Firm controls	Yes	Yes
N	22,756	22,756
$Adj.R^2$	0.12	0.13
Mean of dependent variable	2.57	2.57

TABLE 11

Loan pricing at initiation and conflicts of interest

This table shows OLS regressions where the dependent variable is the loan spread at origination. The independent variable of interest is *cost of downgrade*, the average increase in interest rates after a downgrade by one notch across all levels of the initial loan contract. The variable is standardized so that regression coefficients reflect the impact of changing the variable by one standard deviation. Loan- and firm-level controls, as well as credit rating at origination, year–quarter, and firm fixed effects are included as reported. Loan-level controls include loan type, amount, number of financial covenants, whether the loan is secured, and deal purpose. Firm-level controls include size, profitability, asset tangibility, and leverage. A detailed description of all variables is available in Appendix A. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	Loan spread			
	(1)	(2)	(3)	(4)
Avg. cost of downgrade	4.683***	3.823***	4.106***	3.685***
	(0.576)	(0.438)	(0.512)	(0.425)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Rating at origination FE	No	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes
N	1,702	1,697	1,701	1,697
$Adj.R^2$	0.77	0.82	0.81	0.83
Mean of dependent variable	115.94	116.00	116.00	116.00

TABLE 12

Probability of downgrade and cost of downgrade: The effect of DOJ settlements

This table shows OLS regressions where the dependent variable is an indicator that takes the value of 1 if the borrower is downgraded (Column 1) or the number of quarters between loan origination and the first time the firm was downgraded (Column 2). The independent variables of interest are *cost of downgrade* and the interaction between *cost of downgrade* and 1(*post settlement*). *Cost of downgrade* is a measure of the increase in loan spread that would result from a credit rating downgrade of one notch. The variable is standardized so that regression coefficients reflect the impact of changing the variable by one standard deviation. 1(*post settlement*) is an indicator that takes the value of 1 for the quarters after the settlement between S&P and the DOJ in February 2015. Standalone variables that are not included in the table are absorbed by fixed effects. All regressions include loan- and firm-level controls, as well as current credit rating, and firm fixed effects. Year or year-quater fixed effects are included as reported. A detailed description of all variables is available in Appendix A. Loan-level controls include loan type, amount, number of financial covenants, whether the loan is secured, and deal purpose. Firm-level controls include size, profitability, asset tangibility, and leverage. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	1(downgrade)	Time to downgrade
	(1)	(2)
Cost of downgrade	-0.513***	1.396**
	(0.176)	(0.560)
Cost of downgrade × 1(post settlement)	-0.587	1.223
	(0.476)	(2.523)
Firm FE	Yes	Yes
Year FE	No	Yes
Year-quarter FE	Yes	No
Rating FE	Yes	Yes
Loan controls	Yes	Yes
Firm controls	Yes	Yes
N	22760.00	247.00
$Adj.R^2$	0.11	0.74
Mean of dependent variable	1.57	6.10

Internet Appendix
Who Prices Credit Rating Inflation?

This internet appendix is divided into two sections. The first section describes the secondary market data and its matching with DealScan. The second section provides supplementary figures and tables.

A. Secondary market data

LPC collects self-reported data starting from 1998 from brokers that quote prices on secondary market loans. There are 27,129 unique loans in the database which are identified by a proprietary loan identification number (*lin*). Refinitiv provides a proprietary "translation matrix" linking *lin* to the FacilityID identifiers from DealScan. This link is available for 22,671 loans.

Not all loans with quotes in LPC are featured in DealScan. In fact, a direct merge between the two complete databases using the translation matrix matches 4.9% of the 379 thousand unique FacilityIDs in DealScan. This low matching rate is partly explained by the fact that loans traded less frequently in the past–the fraction of traded loans increased from 10% in the early 2000s to 40% in 2013 (Beyhaghi and Ehsani (2017)). It is likely that LPC has low coverage for loans that are sold infrequently, and loans that are sold directly without the involvement of a broker.

We are able to match 75 of the 1,814 facilities in our loan sample, which translates into a 4.1% matching rate. One reason why our matching rate is slightly lower than the overall matching rate of 4.9% is that 80% of our sample are revolving loan facilities, whereas revolving loans represent only about 40% of loans in DealScan. Revolving loans are traded less frequently, with only about 14% of loans with secondary market data being revolving loans.

Since our matched sample is small, we formally test whether these loans are different from the universe of traded loans or from the PSD loans in our sample that are not in the secondary market data. In Table IA.26, we compare the 75 matched loans to the remaining loans traded in the secondary market. We find that while matched loans tend to be offered at lower discounts upon their first quote and exhibit lower standard deviations of their price over time, these differences are not statistically significant. The only statistically significant difference is that matched loans have an average of 1.5 brokers quoting a price on them, compared to an average of 2.2 brokers for non-matched loans. Overall, the matched loans seem to be representative of the universe of traded loans.

In Table IA.27, we compare the firms that issued our 75 matched loans to the firms that issued the remaining PSD loans in our sample. These two types of borrowers are similar across most dimensions. However, the matched firms tend to have credit ratings about 1.5 notches below and larger loans than their counterparts. To avoid any observable difference from impacting our comparison between traded and non-traded loans, we use a nearest neighbor matching framework in our analysis of whether loans are more likely to be traded if they feature higher costs of downgrades. We test for differences between the two types of loans in Table IA.24. We find that there are no economically or statistically significant differences between the firms in the two samples, except that traded loans are slightly larger and riskier.

References

Beyhaghi, M., and S. Ehsani. 2017, The cross-section of expected returns in the secondary corporate loan market, *Review of Asset Pricing Studies*, 7:243–77.

B. Supplementary figures and tables

FIGURE IA.1
Annual volume of newly issued credit rating rating-based PSD
This figure shows the volume of newly issued credit rating–based performance-sensitive debt, by year.

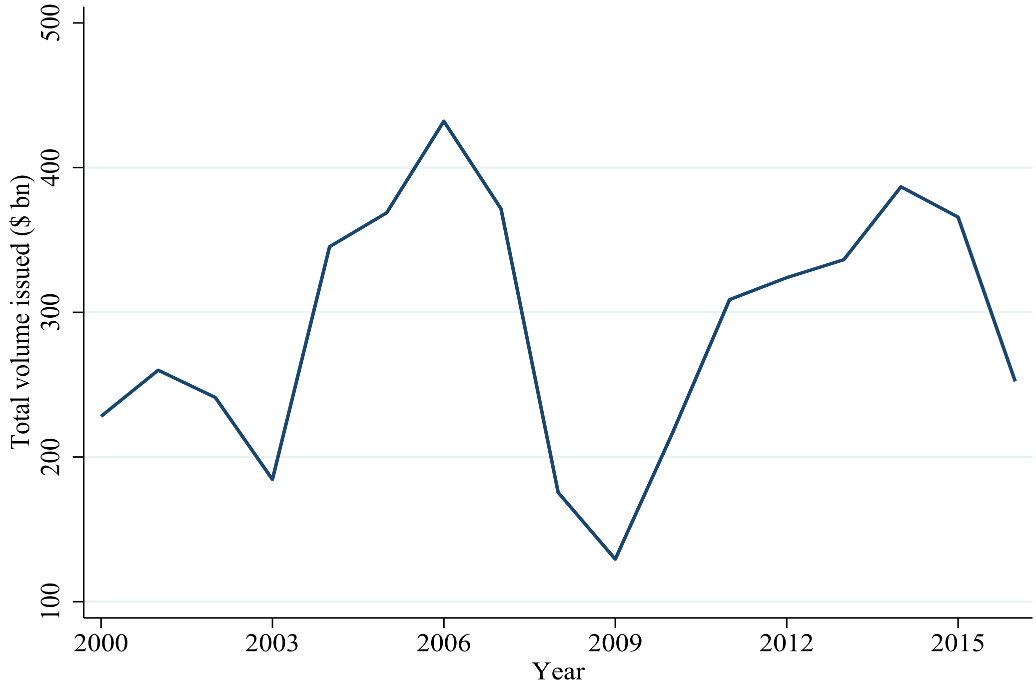

FIGURE IA.2

Coefficient estimate on cost of downgrade by year

This figure shows the effect of a one standard deviation increase in *cost of downgrade* on the probability that the borrower is downgraded, by year. We regress an indicator that takes the value of 1 if the borrower is downgraded on the interaction between *cost of downgrade* (a measure of the increase in the loan spread that would result from a credit rating downgrade of one notch) and indicator variables for each year. *cost of downgrade* is standardized so that regression coefficients reflect the impact of changing the variable by one standard deviation. Loan- and firm-level controls, as well as current credit rating, year, and firm fixed effects are included in the regression. The coefficients (in percentage points) associated with the interactions are denoted by solid circles, and the vertical bars denote the corresponding 95% confidence interval (based on standard errors clustered by firm).

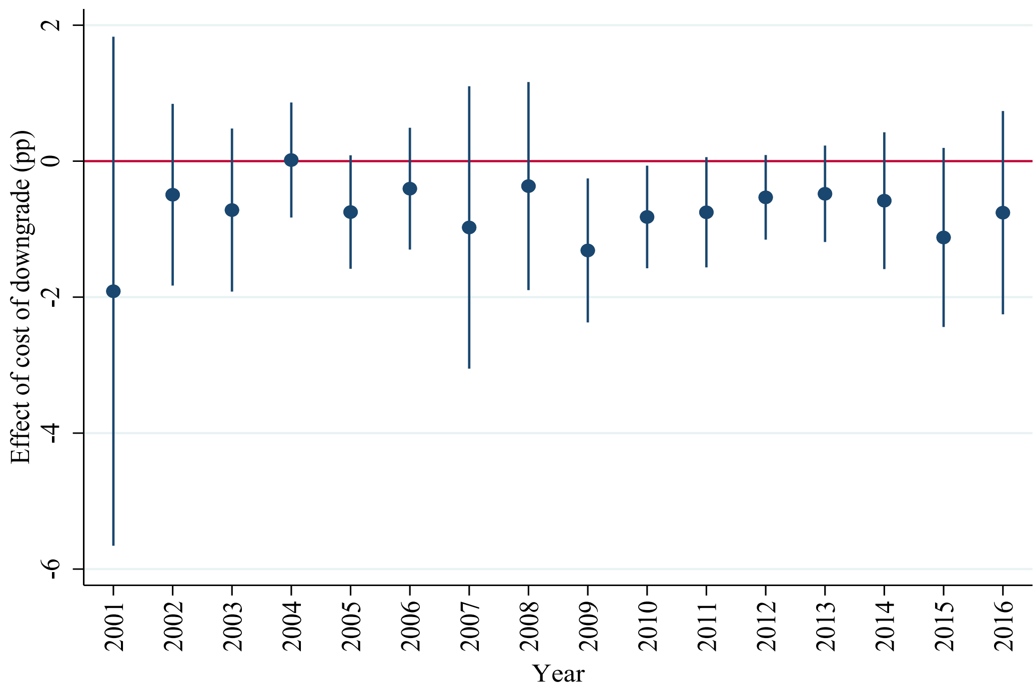

TABLE IA.1
Loans rated by Moody's versus other loans

This table compares the subsample of loans rated by Moody's in the sample with the remaining loans across observable characteristics. Observations are at the loan–year level. $1(\cdot)$ denotes indicator variables. Statistical significance computations are based on heteroscedasticity-robust standard errors clustered by loan. ***p <0.01, **p <0.05, *p <0.10.

	Mean		
	Other loans	Moody's rating	Difference
Leverage	0.3008	0.3269	-.026***
Total assets (log)	9.1819	9.0246	0.157***
Intangibles/assets	0.2207	0.1878	.032***
Profitability (ROA)	0.00979	0.00745	0.002***
1(secured)	1.1262	1.2527	-0.126***
Facility amount	952.878	809.101	143.7***
N	13,522	9,238	22,760

TABLE IA.2

Robustness for Table 3: Sample excluding loans rated above A+ and below BBB-

Regressions reported in this table are identical to Table 3, except that the sample excludes loans rated above A+ (column 1) below BBB- (column 2) and either of the two (column 3). Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	1(downgrade)		
	< A+	> BBB-	BBB- − A+
	(1)	(2)	(3)
Cost of downgrade	-0.665***	-0.482***	-0.465**
	(0.210)	(0.182)	(0.185)
Firm FE	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
N	22,399	18,241	17,880
$Adj.R^2$	0.13	0.13	0.13
Mean of dependent variable	2.54	1.67	1.63

TABLE IA.3

Robustness for Table 3: Revolver and term loan subsamples

Regressions reported in this table are identical to Table 3, except that the regressions are estimated separately for revolvers (Column 1) and term loans (Column 2). Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	1(downgrade)	
	Revolver	Term loan
	(1)	(2)
Cost of downgrade	-0.703***	-1.125*
	(0.205)	(0.574)
Firm FE	Yes	Yes
Year-quarter FE	Yes	Yes
Rating FE	Yes	Yes
Loan controls	Yes	Yes
Firm controls	Yes	Yes
N	18,568	4,179
$Adj.R^2$	0.12	0.16
Mean of dependent variable	2.38	3.37

TABLE IA.4

Robustness for Table 3: Cost of downgrade based on two-notch downgrades

Regressions reported in this table are identical to Table 3, except that the variable for the cost of downgrade is based on two-notch downgrades instead of one-notch downgrades. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	1(downgrade)			
	(1)	(2)	(3)	(4)
Cost of downgrade (2 notches)	-1.469***	-1.156***	-0.944***	-1.026***
	(0.331)	(0.261)	(0.235)	(0.245)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Rating FE	No	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes
N	22,021	22,021	22,021	22,021
$Adj.R^2$	0.09	0.11	0.13	0.13
Mean of dependent variable	2.60	2.60	2.60	2.60

TABLE IA.5

Robustness for Table 3: Cost of downgrade as fraction of total assets

Regressions reported in this table are identical to Table 3, except that the variable for the cost of downgrade is constructed as a dollar cost divided by total assets. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	1(downgrade)			
	(1)	(2)	(3)	(4)
Cost of downgrade (% of assets)	-0.692***	-0.801***	-0.310*	-0.455**
	(0.187)	(0.192)	(0.183)	(0.204)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Rating FE	No	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes
N	22,760	22,760	22,760	22,760
$Adj.R^2$	0.09	0.11	0.12	0.12
Mean of dependent variable	2.57	2.57	2.57	2.57

TABLE IA.6
Robustness for Table 3: When S&P and Moody's are the only CRA

Regressions reported in this table are identical to Table 3, except that the regressions are estimated separately for borrowers rated by S&P (Column 1) and Moody's (Column 2). Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	1(downgrade)	
	S&P	Moody's
	(1)	(2)
Cost of downgrade	-0.967***	-1.392*
	(0.233)	(0.726)
Firm FE	Yes	Yes
Year-quarter FE	Yes	Yes
Rating FE	Yes	Yes
Loan controls	Yes	Yes
Firm controls	Yes	Yes
N	16,895	1,234
$Adj.R^2$	0.12	0.26
Mean of dependent variable	1.79	4.94

TABLE IA.7

Placebo test for Table 3: Sample of accounting ratio-based PSD loans

Regressions reported in this table are identical to Table 3, except the regressions are estimated using a sample of accounting ratio–based PSD loans (instead of credit rating–based PSD loans) and the independent variable of interest is *cost of moving to lower ratio bracket*, which represents the interest rate increase that would result from declining by one bracket in the pricing grid. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	1(downgrade)			
	(1)	(2)	(3)	(4)
Cost of moving to lower ratio-bracket	1.476***	1.042***	0.788***	0.815***
	(0.276)	(0.274)	(0.279)	(0.287)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Rating FE	No	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes
N	23,586	23,586	23,586	23,586
$Adj.R^2$	0.11	0.14	0.15	0.15
Mean of dependent variable	2.37	2.37	2.37	2.37

TABLE IA.8
Time-to-downgrade and cost of downgrade

This table shows OLS regressions where the dependent variable is the number of quarters between loan origination and the first time the firm was downgraded. The independent variable of interest is *cost of downgrade*, a measure of the increase in loan spread that would result from a credit rating downgrade of one notch. The variable is standardized so that regression coefficients reflect the impact of changing the variable by one standard deviation. Loan- and firm-level controls, as well as current credit rating, year-quarter, and firm fixed effects are included as reported. Loan-level controls include loan type, amount, number of financial covenants, whether the loan is secured, and deal purpose. Firm-level controls include size, profitability, asset tangibility, and leverage. A detailed description of all variables is available in Appendix A. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	Time to downgrade			
	(1)	(2)	(3)	(4)
Cost of downgrade	1.591***	1.627***	1.428**	1.718***
	(0.586)	(0.557)	(0.588)	(0.560)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Rating FE	No	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes
N	247	247	247	247
$Adj.R^2$	0.74	0.75	0.74	0.74
Mean of dependent variable	6.10	6.10	6.10	6.10

TABLE IA.9
Probability of downgrade and cost of downgrade when rating is decisive

This table shows OLS regressions where the dependent variable is an indicator that takes the value of 1 if the borrower is downgraded, and 0 otherwise. The indicator is multiplied by 100 so that regression coefficients are in percentage points. The independent variables of interest are *cost of downgrade*, 1(*decisive rating*), and the interaction between the two variables. *Cost of downgrade* is a measure of the increase in loan spread that would result from a credit rating downgrade of one notch. The variable is standardized so that regression coefficients reflect the impact of changing the variable by one standard deviation. 1(*decisive rating*) is an indicator that takes the value of 1 if the a potential downgrade by a credit rating agency would be the marginal downgrade to determine the loan's interest rate. Columns 1 and 2 shows the regression results when S&P is the decisive credit rating agency, and Columns 3 and 4 show the regression results when Moody's is the decisive credit rating agency. Loan- and firm-level controls, as well as current credit rating, year–quarter, and firm fixed effects are included as reported. Loan-level controls include loan type, amount, number of financial covenants, whether the loan is secured, and deal purpose. Firm-level controls include size, profitability, asset tangibility, and leverage. A detailed description of all variables is available in Appendix A. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***$p<0.01$, **$p<0.05$, *$p<0.10$.

	1(downgrade)			
	S&P		Moody's	
	(1)	(2)	(3)	(4)
Cost of downgrade	0.443	0.383	0.110	0.083
	(0.328)	(0.338)	(0.099)	(0.093)
1(decisive rating)	-0.452	-0.298	-1.059	-1.172
	(0.817)	(0.818)	(2.304)	(2.346)
Cost of downgrade × 1(decisive rating)	-1.237***	-1.200***	-0.932*	-0.961*
	(0.363)	(0.375)	(0.538)	(0.538)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	Yes	Yes	Yes	Yes
N	22,760	22,760	22,760	22,760
$Adj.R^2$	0.11	0.11	0.14	0.14
Mean of dependent variable	1.57	1.57	1.10	1.10

TABLE IA.10
Robustness for Table 3: Previous downgrades

Regressions reported in this table are identical to Table 3, except that the regressions are estimated separately for loans that have not been downgraded in the last 4 years (Column 1) the full sample while directly controlling for recent downgrades (Column 2). Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***$p<0.01$, **$p<0.05$, *$p<0.10$.

	1(downgrade)	
	No downgrade	Full sample
	(1)	(2)
Cost of downgrade	-6.462***	-2.588***
	(2.059)	(0.944)
Downgraded previous 4 years		-0.216***
		(0.020)
Loan FE	Yes	Yes
Year-quarter FE	Yes	Yes
Rating FE	No	Yes
Loan controls	No	Yes
Firm controls	No	No
N	17,140	21,720
$Adj.R^2$	0.37	0.20
Mean of dependent variable	1.45	2.31

TABLE IA.11

Probability of downgrade and cost of downgrade: Managerial optimism

This table shows OLS regressions where the dependent variable is an indicator that takes the value of 1 if the borrower is downgraded, and 0 otherwise. The indicator is multiplied by 100 so that regression coefficients are in percentage points. The independent variables of interest are *cost of downgrade* and the interaction between *cost of downgrade* and measures of CEO optimism about the future prospects of their firms. Specifically, *Confidence (moneyness)* is the fraction of top executives that hold options that are at least 67% in-the-money (Campbell et al, 2011). The variable *Confidence (holding time)* measures the fraction of top executives that hold an option that is at least 40% in-the-money 12 months prior to expiration. Standalone confidence variables not included in the table are absorbed by fixed effects. All regressions include firm-level controls, as well as current credit rating, year–quarter, and loan fixed effects. Firm-level controls include size, profitability, asset tangibility, and leverage. A detailed description of all variables is available in Appendix A. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

	1(downgrade)			
	(1)	(2)	(3)	(4)
Cost of downgrade	-0.821***	-1.229*	-0.740**	-1.289**
	(0.296)	(0.715)	(0.311)	(0.613)
Cost of downgrade × Confidence (moneyness)	0.541			
	(0.549)			
Cost of downgrade × 1(Confidence (moneyness) above median)		0.389		
		(0.433)		
Cost of downgrade × Confidence (holding time)			0.389	
			(0.638)	
Cost of downgrade × 1(Confidence (holding time) above median)				0.508
				(0.408)
Confidence (moneyness)	0.142			
	(0.922)			
1(Confidence (moneyness) above median)		-0.299		
		(0.651)		
Confidence (holding time)			-0.749	
			(1.542)	
1(Confidence options holding time above median)				-0.090
				(0.674)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
N	19,709	19,709	18,249	18,249
$Adj.R^2$	0.11	0.11	0.11	0.11
Mean of dependent variable	2.46	2.46	2.33	2.33

TABLE IA.12
Nominal credit ratings versus Merton's distance-to-default

This table shows OLS regressions where the dependent variable is Merton's distance-to-default (in a given quarter). The independent variables of interest is *cost of downgrade*, a measure of the increase in loan spread that would result from a credit rating downgrade of one notch. Specifically, *distance-to-default* is the 5-year-future likelihood of default of the borrower based on Merton's model, standardized to have a mean of 0 and standard deviation of 1. Observations are at the loan level. Loan- and firm-level controls, as well as current credit rating, year–quarter, firm, and industry-year fixed effects are included as reported. Loan-level controls include loan type, amount, number of financial covenants, whether the loan is secured, and deal purpose. Firm-level controls include size, profitability, asset tangibility, and leverage. A detailed description of all variables is available in Appendix A. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***$p<0.01$, **$p<0.05$, *$p<0.10$.

	Distance to default	
	(1)	(2)
Cost of downgrade	-0.003	-0.014**
	(0.013)	(0.007)
Year-quarter FE	Yes	Yes
Firm FE	Yes	Yes
Rating FE	Yes	Yes
Industry-year FE	No	Yes
Loan controls	Yes	Yes
Firm controls	Yes	Yes
N	20,814	20,814
$Adj.R^2$	0.82	0.90
Mean of dependent variable	0.00	0.00

TABLE IA.13

Robustness for Table 7: Alternative definition of the commodities shock variable

Regressions reported in this table are identical to Table 7, except that the variable 1(*commodities shock*) is defined to take the value of 1 between 2014Q3 and 2015Q4. Standalone variables that are not included in the table are absorbed by fixed effects. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	1(downgrade)			
	(1)	(2)	(3)	(4)
Cost of downgrade	-0.664***	-0.651***	-0.540**	-0.618***
	(0.244)	(0.222)	(0.215)	(0.219)
1(commodities) × 1(commodities shock)	6.305**	5.278**	2.408	2.124
	(2.601)	(2.335)	(2.245)	(2.252)
Cost of downgrade × 1(commodities) × 1(commodities shock)	-5.274**	-5.067**	-4.493**	-4.502**
	(2.622)	(2.402)	(2.194)	(2.186)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Rating FE	No	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes
Other interactions	Yes	Yes	Yes	Yes
N	22,760	22,760	22,760	22,760
$Adj.R^2$	0.09	0.11	0.12	0.13
Mean of dependent variable	2.57	2.57	2.57	2.57

TABLE IA.14
Robustness: Additional loan fixed effect regressions

This Table shows OLS regressions identical to the most complete specifications in Tables 7 and 12, except that the regressions include loan fixed effects. Standalone variables that are not included in the table are absorbed by fixed effects. All regressions include firm-level controls, as well as current credit rating, year–quarter, and loan fixed effects. Firm-level controls include size, profitability, asset tangibility, and leverage. A detailed description of all variables is available in Appendix A. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

	1(downgrade)	
	Table 7	Table 12
	(1)	(2)
Cost of downgrade	-1.159*	-1.383**
	(0.643)	(0.559)
Cost of downgrade × 1(commodities) × 1(commodities shock)	-3.518*	
	(1.799)	
Cost of downgrade × 1(post settlement)		-0.609
		(0.689)
Loan FE	Yes	Yes
Year-quarter FE	Yes	Yes
Rating FE	Yes	Yes
Firm controls	Yes	Yes
N	22,650	22,650
$Adj.R^2$	0.11	0.10
Mean of dependent variable	2.57	1.58

TABLE IA.15

Probability of downgrade and cost of downgrade during earnings surprises

This table shows OLS regressions where the dependent variable is an indicator that takes the value of 1 if the borrower is downgraded, and 0 otherwise. The indicator is multiplied by 100 so that regression coefficients are in percentage points. The independent variables of interest are *cost of downgrade* and the interaction between *cost of downgrade* and indicators for earnings surprises. *Cost of downgrade* is a measure of the increase in loan spread that would result from a credit rating downgrade of one notch. The variable is standardized so that regression coefficients reflect the impact of changing the variable by one standard deviation. The variable *1(Negative earnings surprise)* is an indicator for firm-quarters with significant negative earnings updates, defined as those in the bottom 10% of earnings updates. *Earnings expectation change* is a continuous measure of earnings updates. Observations are at the loan level. All regressions include loan- and firm-level controls, as well as credit rating at origination, year–quarter, and firm fixed effects. Loan-level controls include loan type, amount, number of financial covenants, whether the loan is secured, and deal purpose. Firm-level controls include size, profitability, asset tangibility, and leverage. A detailed description of all variables is available in Appendix A. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***$p<0.01$, **$p<0.05$, *$p<0.10$.

	1(downgrade)	
	(1)	(2)
Cost of downgrade × 1(Negative earnings surprise)	-1.305*	
	(0.737)	
Cost of downgrade × Earnings expectation change		0.002
		(0.025)
Cost of downgrade	-0.507**	-0.639***
	(0.231)	(0.231)
1(Negative earnings surprise)	1.494	
	(1.069)	
Earnings expectation change		0.023
		(0.025)
Firm FE	Yes	Yes
Year-quarter FE	Yes	Yes
Rating FE	Yes	Yes
Loan controls	Yes	Yes
Firm controls	Yes	Yes
N	19,437	19,437
$Adj.R^2$	0.13	0.13
Mean of dependent variable	2.29	2.29

TABLE IA.16

Probability of downgrade and cost of downgrade: Firm opaqueness and non-investment grade

This table shows OLS regressions where the dependent variable is an indicator that takes the value of 1 if the borrower is downgraded, and 0 otherwise. The indicator is multiplied by 100 so that regression coefficients are in percentage points. The independent variables of interest are *cost of downgrade* and the interaction between *cost of downgrade* and indicators for above-median values of proxies for firm opaqueness and an indicator of having a credit rating just above non-investment grade. *Cost of downgrade* is a measure of the increase in loan spread that would result from a credit rating downgrade of one notch. The variable is standardized so that regression coefficients reflect the impact of changing the variable by one standard deviation. 1(*high intangibles*) is an indicator variable that takes the value of 1 if the firm's intangibles divided by total assets is above the sample median. 1(*high R&D*) is an indicator variable that takes the value of 1 if the firm's R&D expenses are above the sample median. 1(*high coverage*) is an indicator variable that takes the value of 1 if the firm is covered by more stock market analysts than the sample median. 1(*border junk*) is an indicator that takes the value of 1 if the firm is rated BBB- (i.e., one credit rating notch above the non-investment grade classification). Standalone variables that are not included in the table are absorbed by fixed effects. All regressions include loan- and firm-level controls, as well as current credit rating, year–quarter, and firm fixed effects. Loan-level controls include loan type, amount, number of financial covenants, whether the loan is secured, and deal purpose. Firm-level controls include size, profitability, asset tangibility, and leverage. A detailed description of all variables is available in Appendix A. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	1(downgrade)		
	(1)	(2)	(3)
Cost of downgrade × 1(high intangibles)	0.429		
	(0.435)		
Cost of downgrade × 1(high R&D)		-0.154	
		(0.439)	
Cost of downgrade × 1(border junk)			-0.400
			(0.529)
Cost of downgrade	-0.886***	-0.649***	-0.545**
	(0.262)	(0.229)	(0.218)
1(high intangibles)	0.212		
	(0.862)		
1(high R&D)		-2.587*	
		(1.415)	
Firm FE	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
N	22,760	22,760	22,760
$Adj.R^2$	0.12	0.12	0.12
Mean of dependent variable	2.57	2.57	2.57

TABLE IA.17
Debt issuance and cost of downgrade

This table shows OLS regressions of quarterly issuing of loans and bonds on *cost of downgrade*. The variable is standardized so that regression coefficients reflect the impact of changing the variable by one standard deviation. The dependent variable in Column 1 is the number of newly issued loans, the dependent variable in Column 2 is the logarithm of the dollar amount of newly issued loans, the dependent variable in Column 3 is the number of newly issued bonds, and the dependent variable in Column 4 is the combined number of newly issued loans and bonds. All regressions include firm-level controls, as well as current credit rating, year–quarter, and loan fixed effects. Loan-level controls include loan type, amount, number of financial covenants, whether the loan is secured, and deal purpose. Firm-level controls include size, profitability, asset tangibility, and leverage. A detailed description of all variables is available in Appendix A. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

	Number loans	Volume loans (log)	Number bonds	Number loans + bonds
	(1)	(2)	(3)	(4)
Cost of downgrade	-0.000	0.220*	-0.019	-0.019
	(0.000)	(0.131)	(0.033)	(0.033)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
N	22,760	22,760	22,760	22,760
$Adj.R^2$	1.00	0.48	0.46	0.71
Mean of dependent variable	2.46	18.77	0.85	3.31

TABLE IA.18
Investment and cost of downgrade

This table shows OLS regressions of quarterly investment in property plant and equipment on *cost of downgrade*. Data is on the firm-quarter level. For firms with more than one performance pricing loan outstanding *cost of downgrade* is the average cost of downgrade across all outstanding loans. Loan- and firm-level controls, as well as current credit rating, year–quarter, and firm fixed effects are included as reported. Loan-level controls include loan type, amount, number of financial covenants, whether the loan is secured, and deal purpose. Firm-level controls include size, profitability, asset tangibility, and leverage. A detailed description of all variables is available in Appendix A. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	PPE Investment/Assets (%)			
	(1)	(2)	(3)	(4)
Cost of downgrade	0.118	0.147	0.091	0.067
	(0.125)	(0.130)	(0.127)	(0.125)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Rating FE	No	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes
N	8,354	8,354	8,354	8,354
$Adj.R^2$	0.00	0.00	0.01	0.01
Mean of dependent variable	1.11	1.11	1.11	1.11

TABLE IA.19

Robustness for Table 8: Probability of upgrade and benefit from upgrade (loan fixed effects regressions)

Regressions reported in this table are identical to Table 8, except that all regressions include loan fixed effects instead of firm fixed effects. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	1(Upgrade)	
	(1)	(2)
Benefit of upgrade × 1(Upgrade grid)	3.771**	
	(1.496)	
Benefit of upgrade	-2.695***	1.898
	(0.465)	(1.351)
Loan FE	Yes	Yes
Year-quarter-FE	Yes	Yes
Rating FE	Yes	Yes
Loan controls	No	No
Firm controls	Yes	Yes
N	22,595	1,877
$Adj.R^2$	0.03	0.13
Mean of dependent variable	1.69	3.73

TABLE IA.20

Probability of upgrade and benefit from upgrade: Profitability of clients

Regressions reported in this table are similar to Table 8, except that 1(*high yield issuer*) is added as an independent variable of interest. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	1(upgrade)
	(1)
Benefit of upgrade	-0.379**
	(0.180)
Benefit of upgrade × 1(Upgrade grid) × 1(high yield issuer)	5.234***
	(1.688)
Benefit of upgrade × 1(Upgrade grid)	-1.443
	(1.045)
1(Upgrade grid)	4.204***
	(1.188)
Firm FE	Yes
Year-quarter FE	Yes
Rating FE	Yes
Firm controls	Yes
N	22,702
$Adj.R^2$	0.05

TABLE IA.21
Credit rating reversals and cost of downgrade

This table shows OLS regressions where the dependent variable is an indicator that takes the value of 1 if a firm experiences a credit rating change that fully offsets the last change (i.e., either an upgrade followed by a downgrade or vice versa) during the lifetime of the loan, and 0 otherwise. The indicator is multiplied by 100 so that regression coefficients are in percentage points. The independent variable of interest is $cost\ of\ downgrade$, a measure of the increase in loan spread that would result from a credit rating downgrade of one notch. The variable is standardized so that regression coefficients reflect the impact of changing the variable by one standard deviation. Loan- and firm-level controls, as well as current credit rating, year–quarter, and firm fixed effects are included as reported. Loan-level controls include loan type, amount, number of financial covenants, whether the loan is secured, and deal purpose. Firm-level controls include size, profitability, asset tangibility, and leverage. A detailed description of all variables is available in Appendix A. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	1(reversal)			
	(1)	(2)	(3)	(4)
Cost of downgrade	-0.000	0.006	0.004	0.005
	(0.003)	(0.005)	(0.005)	(0.005)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Rating FE	No	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes
N	22,760	22,760	22,760	22,760
$Adj.R^2$	0.01	0.02	0.02	0.02
Mean of dependent variable	0.01	0.01	0.01	0.01

TABLE IA.22

Robustness for Table 11: Loan pricing at initiation and average realized cost of downgrade

Regressions reported in this table are identical to Table 11, except the variable for the average cost of a downgrade is computed as the average increase in interest rates after a downgrade by one notch over the lifetime of a loan (as opposed to the average across all levels of the initial loan contract). Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	Loan spread			
	(1)	(2)	(3)	(4)
Average cost of downgrade	12.157***	7.331***	9.822***	7.294***
	(2.063)	(2.131)	(1.917)	(2.030)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Rating at origination FE	No	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes
N	1,988	1,988	1,988	1,988
$Adj.R^2$	0.67	0.77	0.73	0.77
Mean of dependent variable	113.60	113.60	113.60	113.60

TABLE IA.23

Robustness for Table 11: Revolver and term loan subsamples

Regressions reported in this table are identical to Table 11, except that the regressions are estimated separately for revolvers (Column 1) and term loans (Column 2). Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	Loan spread	
	Revolver	Term loan
	(1)	(2)
Avg. cost of downgrade	3.397***	4.005***
	(0.491)	(0.960)
Firm FE	Yes	Yes
Year-quarter FE	Yes	Yes
Rating at origination FE	Yes	Yes
Loan controls	Yes	Yes
Firm controls	Yes	Yes
N	1,299	249
$Adj.R^2$	0.79	0.94
Mean of dependent variable	104.02	157.29

TABLE IA.24
Traded versus non-traded loans

This table compares the sub-sample of traded loans in the sample with the matched non-traded loans across observable characteristics. The non-traded loans are selected so that they resemble the traded loans using a nearest neighbor matching framework based on firm characteristics (current credit rating, size, profitability, asset tangibility, and leverage) and loan characteristics (amount, number of financial covenants, and whether the loan is secured or not). Observations are at the loan level. $1(\cdot)$ denotes indicator variables. Statistical significance computations are based on heteroscedasticity-robust standard errors clustered by firm. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.10$.

	Mean		
	Traded	Not traded	Difference
Leverage	0.35	0.35	0
Total assets (log)	9.37	9.37	0.01
Intangibles over assets	0.28	0.27	0.01
Profitability (ROA)	0.03	0.03	0
Issuer credit rating (numeric)	10.05	9.94	0.1
Number of financial covenants	1.57	1.55	0.03
Loan amount ($ millions)	1339	1338	0.1
1(secured)	1.17	1.17	0
1(Revolver)	0.17	0.19	0.1
N	75	75	

TABLE IA.25

Probability of downgrade and cost of downgrade: The effect of the financial crisis

This table shows OLS regressions where the dependent variable is an indicator that takes the value of 1 if the borrower is downgraded (Column 1) or the number of quarters between loan origination and the first time the firm was downgraded (Column 2). The independent variables of interest are *cost of downgrade* and the interaction between *cost of downgrade* and 1(*post crisis*). *Cost of downgrade* is a measure of the increase in loan spread that would result from a credit rating downgrade of one notch. The variable is standardized so that regression coefficients reflect the impact of changing the variable by one standard deviation. 1(*post crisis*) is an indicator that takes the value of 1 for the quarters from January 2008 onwards. Standalone variables that are not included in the table are absorbed by fixed effects. All regressions include loan- and firm-level controls, as well as current credit rating, and firm fixed effects. Year or year-quater fixed effects are included as reported. A detailed description of all variables is available in Appendix A. Loan-level controls include loan type, amount, number of financial covenants, whether the loan is secured, and deal purpose. Firm-level controls include size, profitability, asset tangibility, and leverage. Reported standard errors in parentheses are heteroscedasticity-robust and clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	1(downgrade)	Time to downgrade
	(1)	(2)
Cost of downgrade	-0.533*	1.446*
	(0.296)	(0.771)
Cost of downgrade × 1(post crisis)	-0.138	0.105
	(0.372)	(1.366)
Firm FE	Yes	Yes
Year FE	No	Yes
Year-quarter FE	Yes	No
Rating FE	Yes	Yes
Loan controls	Yes	Yes
Firm controls	Yes	Yes
N	22,760	247
$Adj.R^2$	0.11	0.74
Mean of dependent variable	1.57	6.10

TABLE IA.26
Traded loans in sample versus traded loans not in sample

This table compares the subsample of traded loans in the sample with the remaining traded loans in LPC across observable characteristics. Observations are at the loan level. $1(\cdot)$ denotes indicator variables. Note, since LPC does not provide a firm identifier for all traded loans, standard errors are not clustered. ***p <0.01, **p <0.05, *p <0.10.

	Mean		
	In sample	Not in sample	Difference
Initial quote (mid spread)	98.3	94.9	3.38
Standard deviation of quotes	1.19	3.93	-2.73
Number of quotes	1.51	2.23	-0.71***
N	75	27,054	

TABLE IA.27
Traded loans versus remaining PSD loans

This table compares the subsample of traded loans in the sample with the remaining loans across observable characteristics. Observations are at the loan level. 1(·) denotes indicator variables. Statistical significance computations are based on heteroscedasticity-robust standard errors clustered by firm. ***p <0.01, **p <0.05, *p <0.10.

	Mean		
	Traded	Not traded	Difference
Leverage	0.35	0.32	0.03
Total assets (log)	9.37	9.09	0.29
Intangibles over assets	0.28	0.20	0.08
Profitability (ROA)	0.03	0.03	0.00
Issuer credit rating (numeric)	10.05	8.62	1.43**
Number of financial covenants	1.57	1.46	0.11
Loan amount ($ millions)	1339	875	464**
1(secured)	1.17	1.15	0.02
N	75	1,739	

Internet Appendix for "Who Prices Credit Rating Inflation?"

C. Excerpts from credit rating agency documents and government documents

All excerpts are *exact quotes* from credit rating agency internal and industry documents, Securities and Exchange Commission documents, Congressional hearings, and DOJ press releases and settlement statements of facts.

1. Statements describing the role of credit rating agencies

- Rating agencies generally view their role as assessing the creditworthiness of issuers on an ongoing basis, and the likelihood that debt will be repaid in a timely manner.[1]

- Credit ratings are used by these institutions [mutual funds and broker dealers] both for informational and regulatory purposes. These firms typically have their own internal credit research departments staffed with analysts who use ratings issued by credit rating agencies as one of several valuable "inputs" to their independent credit analysis.[2]

- Issuer representatives indicated that they seek credit ratings because of the value placed on the ratings by investors, and the effect credit ratings have on their ability to access capital.[3]

- A credit rating is Standard & Poor's opinion of the general creditworthiness of an obligor, or the creditworthiness of an obligor with respect to a particular debt security or other financial obligation, based on relevant risk factors.[4]

- Our role is to disseminate opinions about the relative creditworthiness of bonds and other debt instruments.[5]

2. Statements indicating that credit ratings are supposed to be an objective and high quality assessment of an issuer's creditworthiness

- Critical to a credit rating agency's ability to serve this key market role [help the market to effectively and efficiently evaluate and assess credit risk] is its meeting the highest standards of integrity, independence, objectivity, transparency, credibility and quality.[6]
- Moody's 2005 Code set forth its general policies to promote Moody's stated objectives of integrity, objectivity, and transparency of the credit rating process. Section III(2)(A) of

---

[1] U.S. Securities and Exchange Commission: Report on the Role and Function of Credit Rating Agencies in the Operation of the Securities Markets (January 2003), page 21.
[2] *Ibid.*
[3] *Ibid.*
[4] Standard & Poor's Corporate Ratings Criteria (2006), page 8.
[5] Credit Rating Agencies and the Financial Crisis: Hearing before the Committee on Oversight and Government Reform, page 117.
[6] Standard & Poor's Rating Services. U.S. Securities and Exchange Commission Public Hearing – November 15, 2002. Role and Function of Credit Rating Agencies in the U.S. Securities Markets.

Moody's 2005 Code, titled "Independence and Management of Conflicts of Interest," stated:

> 2.2 Moody's and its Analysts will use care and professional judgment to maintain both the substance and appearance of independence and objectivity.
> 2.3 The determination of a Credit Rating will be influenced only by factors relevant to the credit assessment.
> 2.4 The Credit Rating Moody's assigns to an Issuer, debt or debt-like obligation will not be affected by the existence of, or potential for, a business relationship between Moody's (or its affiliates) and the Issuer (or its affiliates) or any other party, or the non-existence of any such relationship.[7]

- Moody's 2005 Code also contained a section captioned the "Quality of the Rating Process," which stated:

> 1.6 Moody's and its Analysts will take steps to avoid issuing any credit analyses, ratings or reports that knowingly contain misrepresentations or are otherwise misleading as to the general creditworthiness of an Issuer or obligation.[8]

3. Statements indicating that credit rating agencies are aware that rating changes affect issuers

- *Judicious rating process*: because of the potential importance of the rating to the issuer and investor, Moody's carefully and deliberately considers all information relevant to the issuer's rating that the issuer and its advisors present to us. Moody's understands that its ratings can potentially become self-fulfilling forecasts. In the case of upgrades, that can mean greater capital market access and interest cost savings for issuers, and improved securities prices for investors. In the case of downgrades, it can mean higher capital costs for issuers, and portfolio turnover and losses for investors; most dramatically, however, it can terminate an issuer's access to capital, possibly even leading to default. Especially in the case of downgrades, the potentially self-fulfilling nature of ratings requires that Moody's particularly endeavor to avoid "false" negative predictions.[9]

- Standard & Poor's will consider additional ways to more explicitly incorporate contingent liquidity concerns in its credit ratings. In some cases, the analytical challenges are formidable, especially with respect to rating triggers. For one thing, there is a certain circularity to lowering a rating because of the risk you might lower that rating! Furthermore, in some cases, lowering the rating to reflect the added risk would not be commenting on the credit risk, but determining it. Consider an extreme case to illustrate the point: a company currently rated 'BBB-' introduces a rating trigger into debt of a substantial amount, allowing it to be put back to the company if the credit rating falls one

[7] DOJ's Settlement with Moody's – Statement of Facts, page 1.
[8] *Id.* at page 2.
[9] Moody's Investor Services Special Comment: Understanding Moody's Corporate Bond Ratings and Rating Process (May 2002), page 4.

notch, to non-investment grade. A downgrade would precipitate the very crisis that was the cause for concern.[10]

- Many companies go one step further and incorporate specific rating objectives as corporate goals. Indeed, possessing an 'A' rating, or at least an investment-grade rating, affords companies a measure of flexibility and may be worthwhile as part of an overall financial strategy.[11]

- As a general rule, the more creditworthy an issuer or an issue is, the lower the interest rate the issuer would typically have to pay to attract investors. The reverse is also true: an issuer with lower creditworthiness will typically pay a higher interest rate to offset the greater credit risk assumed by investors.[12]

- Credit rating adjustments may play a role in how the market perceives a particular issuer or individual debt issue. Sometimes, for example, a downgrade by a rating agency may change the market's perception of the credit risk of a debt security which, combined with other factors, may lead to a change in the price of that security.[13]

4. Statements indicating that credit rating agencies rate issuers independently of the effect on the issuer (includes rating triggers)

- *Effect of a rating action on an issuer:* Moody's will proceed with issuing or changing a rating, notwithstanding the effect of the rating action on the issuer, including the possible effect on the issuer's market access or conditional obligations. The level of rating that Moody's assigns to an issuer that might experience potential changes in market access or conditional obligations will reflect Moody's assessment of the issuer's creditworthiness, including such considerations.[14]

- S&P Global Ratings will take a Credit Rating Action regardless of the potential effect (economic, political, or otherwise) of that action on S&P Global Ratings, an affiliate, an Issuer, an investor, or any other market participant.[15]

- In the U.S., Standard & Poor's assigns and publishes its ratings irrespective of issuer request, if the financing is a public deal.[16]

- The rating committee evaluates the matter, arrives at a rating decision, and notifies the company—after which Standard & Poor's publishes the rating. The process is exactly the

---

[10] RatingsDirect: Identifying Rating Triggers and Other Contingent Calls on Liquidity, page 1.
[11] Standard & Poor's Corporate Ratings Criteria (2006), page 11.
[12] Standard & Poor's Rating Services: Guide to Credit Rating Essentials, page 6.
[13] *Id*. at page 15.
[14] Moody's Investor Services Special Comment: Understanding Moody's Corporate Bond Ratings and Rating Process (May 2002), page 4.
[15] S&P Global Ratings Code of Conduct (2018), page 6.
[16] Standard & Poor's Corporate Ratings Criteria (2006), page 10.

same as the rating of a new issue. Reflecting this surveillance, the timing of rating changes depends neither on the sale of new debt issues nor on our internal schedule for reviews.[17]

- *Rating triggers*: Rating triggers — especially if near an existing rating and requiring significant remedies, such as repayments or posting of collateral — can severely restrict a company's available outcomes and create additional volatility in a company's creditworthiness. The use of ratings in triggers can make the rating a causal element of a company's creditworthiness. In managing the rating system, Moody's will treat rating triggers as we would other elements of "conditionality" such as stock-price triggers or material adverse-change clauses. To the extent that these elements of conditionality are consequential to a company's future creditworthiness (or even viability), Moody's acts as judiciously as possible in reaching a rating conclusion. We do not, however, forbear, or allow a company's use of our ratings, to delay rating actions.[18]

- On the other hand, Standard & Poor's has not shied away from changing a rating where that was deserved—even knowing full well that the rating action would trip ratings triggers. Standard & Poor's behaves responsibly and takes pains to communicate to the company well ahead of time its ratings vulnerability—and the need to anticipate liquidity contingency. But Standard & Poor's would not maintain a rating that was inconsistent with its credit judgment merely because the rated company would suffer the consequences.[19]

- Standard & Poor's has never encouraged companies to utilize ratings-related triggers or covenants. In fact, we regularly have told companies that doing so was troubling to us—if for no other reason than its potential for embroiling Standard & Poor's in a company crisis. Now Standard & Poor's is considering a more active posture, one that encourages companies that have triggers to remove them or perhaps face a downgrade![20]

5. Statements indicating that credit rating agencies acknowledge conflicts of interest arising from the "issuer-pays" business model

- During the relevant time period it was generally understood that potential conflicts of interest existed in Moody's business model. Moody's acknowledged this in public statements, including for example, in a July 28, 2003 letter to the United States Securities and Exchange Commission, in which Moody's stated that "the rating agency model which has developed is an 'issuer fee-based' model. This model has two intrinsic conflicts of interest which must be effectively managed: a) issuers pay rating agencies for their credit opinions; and, b) issuers are one source of input in a rating agency's formation of its opinion. . . ."[21]

[17] Standard & Poor's Corporate Ratings Criteria (2006), page 18.
[18] Moody's Investor Services Special Comment: Understanding Moody's Corporate Bond Ratings and Rating Process (May 2002), page 4.
[19] RatingsDirect: Identifying Rating Triggers and Other Contingent Calls on Liquidity.
[20] *Ibid*.
[21] DOJ's Settlement with Moody's – Statement of Facts, page 2.

- In a February 2006 "Report On Implementation of Standard & Poor's Rating Services Code of Conduct," also published on S&P's website, S&P stated, among other things: (a) "[S&P] recognizes its role in the global capital markets and is committed to providing ratings that are objective, independent and credible"; and (b) "It is a central tenet of [S&P] that its ratings decisions not be influenced by the fact that [S&P] receives fees from issuers.[22]

- The practice of issuers paying for their own ratings creates the potential for a conflict of interest. Arguably, the dependence of rating agencies on revenues from the companies they rate could induce them to rate issuers more liberally, and temper their diligence in probing for negative information.[23]

6. Statements indicating that credit rating agencies did not appropriately address conflicts of interest arising from the "issuer-pays" business model and did not adhere to their own standards in the run-up to the financial crisis

- "On more than one occasion, the company's leadership ignored senior analysts who warned that the company had given top ratings to financial products that were failing to perform as advertised," said Attorney General Holder. "As S&P admits under this settlement, company executives complained that the company declined to downgrade underperforming assets because it was worried that doing so would hurt the company's business. While this strategy may have helped S&P avoid disappointing its clients, it did major harm to the larger economy, contributing to the worst financial crisis since the Great Depression."[24]

- "Our investigation revealed, and Moody's has now acknowledged, that Moody's used a more lenient standard than it had itself published," said Principal Deputy Assistant Attorney General Benjamin C. Mizer, head of the Justice Department's Civil Division. "Investors relied on Moody's credit ratings to be objective and independent, and they naturally expected Moody's to follow its own published methods."[25]

- "Moody's now admits that it deviated from its methodologies and failed to disclose those changes to the public…."[26]

- This tension [the conflict generated by the "issuer fee-based" model], in many cases, was passed on to the managing directors, who were given both market share and ratings quality targets and asked to manage any tension. One managing director, reflecting on his

[22] DOJ's Settlement with Standard & Poor's – Statement of Facts, page 1.
[23] U.S. Securities and Exchange Commission: Report on the Role and Function of Credit Rating Agencies in the Operation of the Securities Markets (January 2003), page 41.
[24] DOJ's press release. Justice Department and State Partners Secure $1.375 Billion Settlement with S&P for Defrauding Investors in the Lead Up to the Financial Crisis, February 3, 2015.
[25] DOJ's press release. Justice Department and State Partners Secure nearly $864 Million Settlement with Moody's arising from Conduct in the Lead up to the Financial Crisis, January 13, 2017.
[26] *Ibid*.

experience with rating corporate bonds, wrote in October 2007 that "on the one hand, we need to win business and maintain market share, or we cease to be relevant. On the other hand, our reputation depends on maintaining ratings quality. . . . For the most part, we hand the dilemma off to the team [managing directors] to solve."[27]

- The documents from Standard & Poor's paints a similar picture. In one document, an S&P employee in the structured finance division writes, ``it could be structured by cows, and we would rate it.''[28]

7. Statements indicating that credit rating agencies renewed their commitment to credit rating quality following the financial crisis

- "Moody's failed to adhere to its own credit rating standards and fell short on its pledge of transparency in the run-up to the Great Recession," said Principal Deputy Associate Attorney General Bill Baer. "Today's settlement contains not only a significant penalty and factual admissions of its conduct, but also a commitment by Moody's to new and continued compliance measures designed to ensure the integrity of credit ratings going forward."[29]

- In conclusion, we [Moody's] believe in this process, but continually strive to do better. For example, as described more fully in my written statement, we're refining our rating methodologies, increasing the transparency of our analysis and adopting new measures to reinforce and enhance existing processes and policies that address potential conflicts of interest.[30]

- Since 2008, we [Standard & Poor's] have undertaken a number of initiatives aimed at promoting four broad objectives: (i) ensuring the integrity and independence of the ratings process; (ii) enhancing analytical quality; (iii) providing greater transparency to the market by disseminating more information about ratings, as well as information to help investors form their own views of the soundness of rating analysis; and (iv) more effectively training our analysts and educating the marketplace about ratings.[31]

- Standard & Poor's is committed to taking action to help restore confidence in ratings. As one example, over the past year, we have launched a number of initiatives designed to foster greater transparency in our analytics and processes. These initiatives have included publishing "what-if" scenario analyses discussing factors that could cause ratings to change, more explicit discussions of the assumptions we used in forming our opinions, and

[27] DOJ's Settlement with Moody's – Statement of Facts, page 3.
[28] Credit Rating Agencies and the Financial Crisis: Hearing Before the Committee on Oversight and Government Reform, page 3.
[29] DOJ's press release. Justice Department and State Partners Secure nearly $864 Million Settlement with Moody's arising from Conduct in the Lead up to the Financial Crisis, January 13, 2017.
[30] Credit Rating Agencies and the Financial Crisis: Hearing Before the Committee on Oversight and Government Reform, page 117.
[31] Testimony of Deven Sharma, President, Standard & Poor's. Before the United States House of Representatives Committee on Financial Services Subcommittee on Oversight and Investigations – July 27, 2011, page 3.

changes we have made to our rating criteria for several asset classes resulting from macroeconomic developments and ongoing performance data.[32]

8. Statements indicating that credit rating agencies do not audit the information provided by issuers

- Standard & Poor's does not perform an audit of the rated company or otherwise undertake to verify information provided by the company; nor does Standard & Poor's audit or rate the work of the company's auditors or repeat the auditors' accounting review. Standard & Poor's relies on the integrity and quality of the company's publicly available financial reports and financial statements and expressly relies on the rated company to provide current and timely information - both at the time of the initial rating and on an ongoing basis for the proper conduct of surveillance of the company's creditworthiness.[33]

- Analysts should keep in mind, as we make clear in our rating publications, that MIS is not obligated to perform, and does not perform, audits or due diligence with respect to verifying the accuracy of information received or obtained in connection with the Credit Rating process; accountants, underwriters, Issuers and others serve these functions in the market.[34]

9. Statements discussing the barriers to entry and consequent oligopoly in the U.S. securities market

- The recent growth in the number of firms operating as credit rating agencies suggests a growing appetite among market participants for advice about credit quality, and that new entrants are able to develop a following for their credit judgments. At the same time, few would dispute that new entrants generally have been unable to evolve into a substantial presence in the ratings industry. Many believe this is due primarily to the longstanding dominance of the credit rating business by a few firms – essentially the NRSROs – as well as the fact that the marketplace may not demand ratings from more than two or three rating agencies.[35]

- As to the regulatory impact on rating agency competition, a wide range of observers has criticized the regulatory use of the NRSRO concept – particularly the "national recognition" requirement – as creating a substantial barrier to entry. In essence, these critics contend that important users of securities ratings have a regulatory incentive to obtain ratings issued by NRSROs, and that without NRSRO status new entrants encounter great difficulties achieving the "national recognition" necessary to acquire the NRSRO

---

[32] RatingsDirect: Understanding Standard & Poor's Rating Definitions – June 3, 2009, page 2.
[33] Standard & Poor's Rating Services. U.S. Securities and Exchange Commission Public Hearing – November 15, 2002. Role and Function of Credit Rating Agencies in the U.S. Securities Markets.
[34] Moody's Investor Service Best Practices Guidance for the Credit Rating Process – October 29, 2010, page 9.
[35] U.S. Securities and Exchange Commission: Report on the Role and Function of Credit Rating Agencies in the Operation of the Securities Markets (January 2003), page 37.

designation. In other words, new entrants are faced with something akin to a "chicken and egg" problem in achieving NRSRO status, which they view as necessary or, at a minimum, very important for becoming a substantial presence in the credit rating industry.[36]

[36] *Ibid.*