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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 not driven by selection into PSD contracts, borrowers hiding information from CRAs, or by firms about to lose their investment grade classification. Moreover, originating banks seem aware of 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 appear to prevent credit inflation.

JEL classification: G14, G24, G28

keywords: Credit ratings, performance-sensitive debt, rating catering

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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 not driven by selection into PSD contracts, borrowers hiding information from CRAs, or by firms about to lose their investment grade classification. Moreover, originating banks seem aware of 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 appear to prevent credit inflation.

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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 fee–based* 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). In these settlements, CRAs renewed their commitment to credit rating quality. In this paper, we study whether the conflicts of interest of CRAs prevail in the performance-sensitive debt (PSD) market, a much less complex market than that of securitized products. Importantly, the availability of pricing data, both at origination and in secondary markets, allows us to study whether market participants internalize these conflicts. Moreover, 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.[1]

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.[2] 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

[1]Graham and Harvey (2001) survey 392 CFOs, and they find that 57% of CFOs consider credit ratings as important, making credit ratings the second most important debt policy factor after financial flexibility. Cornaggia, Cornaggia, and Israelsen (2018) show that investors continue to rely on CRAs for assessing credit risk post-Crisis.

[2]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).

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 endogenous. Firms can self-select into PSD either because they have positive inside information (Begley, 2012) or because they are overly optimistic (Adam et al., 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 et al., 2009; Sangiorgi and Spatt, 2017). A firm may approach multiple CRAs, 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 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. Since loan interest rate payment schedules are determined at the time of origination of the loan, exploiting time-series variation in the cost of downgrades 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. Third, we include year fixed effects in all specifications to account for the fact that the probability of a credit rating downgrade varies with the business cycle. Importantly, although our more stringent specification includes fixed effects for firm, year, and current credit rating, we show that there is enough variation in the data to expect our analysis to have sufficient power.

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 0.8 percentage points (pp) per quarter, which is a 27% reduction relative to the unconditional mean. This result is robust to multiple regression specifications (including the inclusion of loan fixed effects), to multiple definitions for the variable that represents 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 relationships and 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. Our results are confirmed using a nonparametric survival analysis that specifically models the hazard rate of credit rating downgrades.

Next, we further sharpen our empirical strategy by exploiting variation in the relevancy of each CRA's rating. If two credit ratings by different CRAs disagree, most PSD contracts will use the better rating to determine interest rates (Tchistyi et al., 2011). We find that the tendency of CRAs to avoid downgrading their clients is concentrated precisely among those instances in which their rating is decisive for setting borrowing costs, either because they are the only CRA providing a credit rating or because they are the CRA that issued the better credit rating. Overall, our findings are consistent with the proposition that CRAs yield to conflicts of interest that result from the issuer fee–based 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. Firms whose borrowing costs would experience a larger increase in the eventuality of a downgrade might be more likely to hide negative information. Inconsistent with this concern, we show that CRA rating behavior does not vary with the ease with which firms can hide or manipulate financial information, as proxied by a firm's fraction of intangibles assets and by the firm's R&D expenditures. Moreover, we show that CRAs yield to conflicts of interest even within a group of firms that were negatively affected by a (very public) shock to commodity values, a setting in which information asymmetries should play a much less important role.

Another potential challenge to our interpretation 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 or investment restrictions (Bruno et al., 2016). Inconsistent with this concern, we show that results are not driven by the subset of loans described above.[3]

PSD provides an insurance mechanism for lenders that directly compensates them for the deterioration of a borrower's financial health. The agency conflicts embedded in the issuer fee–based business model effectively reduce the efficiency of this insurance mechanism. As a direct function of the increase in loan interest rates, CRAs are less likely to downgrade borrowers, and they are slower to downgrade borrowers. We test whether well-informed market participants (e.g., the initial lenders) internalize this conflict. We find that a one

[3]Bruno, Cornaggia, and Cornaggia (2016) show that Moody's avoids downgrading issuers of corporate bonds that are close to losing their investment grade certification. A likely explanation for our result is that in PSD loans, investors benefit directly from downgrades through higher spreads. In contrast, the incentives of borrowers and investors are aligned for bonds, because most bonds do not adjust their payment after a downgrade.

standard deviation increase in the average cost of downgrade is associated with a higher initial loan interest spread of about 6 basis points (bp), a 5% increase relative to the unconditional mean. This is consistent with lenders and borrowers being (to some extent) aware of these conflicts of interests among 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 many 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 had 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 important settlements between the two major CRAs and the Department of Justice (DOJ). Importantly, the lawsuits brought by the DOJ and the subsequent settlements 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 settlement. We find no evidence of a weakened relationship. Overall, this result suggests 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) issued by large clients that provided them with more business. These positive credit ratings benefitted CRAs' clients through higher prices for their securities (Ashcraft et al., 2011).[4] Our paper shows that credit rating inflation is also a feature of the PSD market, and 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. 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.[5] In our setting of PSD loans, prior work compares firms with credit rating–based 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). While this result is consistent with CRA catering, it is not obvious that CRAs are at fault, given the selection concerns described above. Our paper complements this work by showing evidence of CRA catering in the PSD market after accounting for these selection concerns. Furthermore, we show that this catering behavior remains prevalent post-Crisis, and that lenders and borrowers are aware of the conflicts of interest of CRAs. In contrast, secondary market participants seem to be less aware of these conflicts.

[4] Griffin (2019) provides a detailed overview of the literature on the behavior of the various participants in the securitized product market during the run-up to the Financial Crisis.

[5] Cornaggia and Cornaggia (2013) show that issuer fee–based 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 fee–based ratings.

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 renegotiations. Manso, Strulovici, and Tchistyi (2010) and Begley (2012) show that firms may use PSD loans to signal higher quality. Adam et al. (2020) shows that managerial overconfidence affects the use of PSD loans, and Tchistyi, Yermack, and Yun (2011) show that PSD loans allow managers to gain private benefits at the expense of firm risk.[6] Our paper shows that there are long-lasting consequences of the use of PSD loans through their impact on the reliability of credit ratings. Importantly, this impact extends beyond the initial decision of PSD loan issuance.

The rest of the paper is organized as follows. Section 1 describes the PSD market and the incentives that drive CRAs. Section 2 describes the data, sample selection process, and empirical framework. Section 3 shows that CRAs cater to their clients. Section 4 investigates whether the catering behavior of CRAs is priced in the primary and secondary markets. Section 5 investigates whether CRAs improved their approach to credit ratings post-settlements. Finally, Section 6 concludes.

1. Background

1.1. 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 triggering responses to covenant violations. In general, if a borrower's financial health deteriorates, the interest rate associated with the PSD obligation increases, thus compensating the debt holder for the additional risk.

PSD contracts became common in the early 1990s. Now, the total size of the PSD

[6] 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.

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. In this paper, we exploit heterogeneity in interest rate changes following a credit rating downgrade.

[Insert Figure 1 Here]

1.2. 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 fee–based 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., borrowing costs 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, or $225,000 a year. 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 faces competition and when its 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 (Credit Rating Agencies and the Financial Crisis, 2002). CRAs are aware that credit ratings can negatively affect borrowers' funding costs (Moody's, 2002). However, CRAs' guidelines are clear in that credit ratings are issued independently of the effect that they may have on the borrower (Credit Rating Agencies and the Financial Crisis, 2002; S&P Global Ratings, 2018). Similarly, CRAs acknowledge the conflicts of interest that arise from the issuer fee–based 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; Griffin, 2019). 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. While the lower complexity of these financial products could reduce the scope for CRAs to inflate ratings, the continuous nature of credit ratings and their small measurement increments could facilitate it. Importantly, pricing data are more reliable and available for PSD loans than for RMBSs and CDOs, which makes the PSD setting 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.

2. Data, sample selection, and empirical framework

2.1. Primary data

We obtain data on loan 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.[7] We consider the credit ratings issued by S&P and Moody's. Following Tchistyi, Yermack, and Yun (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 contracts give borrowers a choice between different types of reference rates for determining

[7]DealScan does not generally specify whether the relevant senior credit rating is that of unsecured or secured debt. However, DealScan sometimes provides separate comments regarding this issue. In about 75% of the roughly 8,700 comments that include the word *rating*, there is a reference to unsecured credit ratings.

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.[8] 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.

2.2. 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 loans to have credit ratings issued by S&P or Moody's.[9] The final sample consists of 1,829 loans spanning 20,725 loan–quarter observations.[10]

Panels A and B of Table **1** describe the final sample. The mean increase in borrowing costs following a one-notch downgrade is 13.3 bp, with an interdecile range of 25 bp. Downgrades are a rare event: The likelihood of a borrower being downgraded in a given quarter is, on average, only 2.9%. The median credit rating throughout the sample is *BBB*.[11] The average loan size is $886.7 million. Finally, conditional on being downgraded, the average borrower is downgraded within four quarters of issuing a loan.

[Insert Table **1** Here]

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

[9] Compustat does not provide credit ratings issued by Moody's, so we consider the credit ratings from both CRAs (provided by Bloomberg) for consistency.

[10] For a subset of our analysis, we merge the final sample with secondary market loan pricing data from Refinitiv's Loan Pricing Corporation. We describe these data and the merging process in Section 4.2 and Internet Appendix A.

[11] Internet Appendix Figure IA.**1** shows the distribution of credit ratings at origination.

2.3. 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.[12] 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 (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 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.[13] Second, there is another type of selection often referred to as

[12]While most downgrades occur in single increments, some downgrades are larger. For example, the average number of downgrade increments was 1.37, conditional on a downgrade from S&P in 2018 (S&P Global Ratings, 2019). In the Internet Appendix, we show that our regression results are robust to constructing the variable for the costs of a downgrade based on two-increment downgrades.

[13]Kraft (2015) and Bannier and Wiemann (2011) compare firms with credit rating–based loans to firms with accounting ratio–based loans, and they show that firms with credit rating–based loans experience fewer

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.[14] 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 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 robustness tests, we estimate an even more stringent specification that includes loan fixed effects.[15]

In addition, since the probability of a credit rating downgrade varies with the business cycle (Bar-Isaac and Shapiro, 2013), $X_{i,l,t}$ also includes year fixed effects. Finally, the various dimensions of loan contracts are jointly determined at origination. Thus, we include loan-level control variables for loan type, loan amount, the number of financial covenants, whether the loan is secured, and deal purpose.

2.4. Sources of variation

In our most stringent specification, we include fixed effects for the current credit rating, borrower, and year. Thus, we exploit variation in credit rating downgrade probabilities and

credit rating downgrades and more credit rating upgrades, respectively. Internet Appendix, Table IA.**1**, shows that firms with credit rating–based PSD loans and firms with accounting ratio–based PSD loans differ significantly in terms of observable characteristics.

[14] 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.

[15] There are 471 firms in our sample. Of these firms, 18 have one credit rating–based PSD loan. In these cases, the regression specifications exploit within-loan variation with the inclusion of borrower fixed effects.

in borrowing costs following a one-notch downgrade 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 16.6 percentage points (pp), which is very similar to its overall standard deviation of 16.9 pp. Similarly, the within–credit rating standard deviation of $cost\ of\ downgrade$ is 10.7 bp (compared to 11.9 bp overall). The time required for the firm to be downgraded follows the same pattern. The panel also shows a 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.

3. 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 refine our identification strategy by contrasting (a) instances in which credit rating downgrades would directly cause a change in a firm's borrowing costs with (b) instances in which credit rating downgrades are irrelevant. We then explore additional possible explanations for our main result. Finally, for loans from firms that experience a downgrade, we study the effect of the variable that represents the costs of a downgrade on a different outcome variable, namely the time interval from loan origination to the eventual downgrade.

3.1. Probability of downgrades

Table **2** 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 2 here]

Column (1) of Table 2 presents the results from our most basic specification, which includes only firm and year fixed effects. The point estimate on *cost of downgrade* is -0.79, 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 27% decrease relative to the sample mean quarterly downgrade likelihood of 2.93%.

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. In particular, borrower creditworthiness at origination certainly influences loan contract terms. To address this concern, Column (2) adds controls for loan-level characteristics such as loan amount, loan type, the number of financial covenants, and deal purpose. Moreover, the specification also includes 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 -0.86 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 -0.75 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 -0.83 pp, statistically significant at the 1% level. Overall, the results in Table **2** 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 the point estimates in Table **2** remain unchanged after the inclusion of year–quarter fixed effects. Similarly, Table IA.**3** shows that the point estimates on *cost of downgrade* range from -1.89 pp to -1.72 pp when estimating a much more stringent specification that includes loan fixed effects instead of firm fixed effects. 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 by S&P and Moody's separately, and we find similar regression coefficients as Table **2** in both samples.[16] Finally, in Table IA.**7**, we conduct a placebo test using a sample of accounting ratio–based PSD loans, and we find that the steepness of the pricing grid is not associated with a higher probability of a credit rating downgrade for these loans.

3.2. Decisive credit ratings

In this section, we further sharpen our identification strategy by exploiting variation in the CRAs that issue the decisive credit rating (i.e., the credit rating that causes the change in the firm's borrowing costs). This occurs in two instances: (a) when a borrower is rated

[16]While point estimates for the Moody's sample are significant at the 10% level, their size is essentially the same as in Table **2**. The decreased statistical significance is driven mostly by lower Moody's credit rating coverage, which translates into a decrease of 74% in sample size compared to the full sample.

solely by a single CRA and (b) when a borrower is rated by two CRAs that do not issue the same credit rating. In this latter case, we follow Tchistyi et al. (2011) and consider the higher of the two ratings as the decisive one.

If conflicts of interest affect the downgrade decisions of CRAs, then the decrease in downgrade likelihood that occurs when downgrades are more costly to clients should concentrate when the credit rating is the decisive one. To investigate this idea, we introduce the indicator variable $1(decisive\ rating)$, which takes the value 1 when the CRA is either the only CRA providing a rating or the CRA that issued the more positive rating, and 0 otherwise. We supplement our main specification with this variable as well as with the interaction of this variable and $cost\ of\ downgrade$.

The estimation results are presented in Table **3**. Specifically, Columns (1) and (2) show the results when S&P is the decisive CRA, and Columns (3) and (4) show the results when Moody's is the decisive CRA. The results are very similar across specifications. For example, the more stringent specification for when S&P is the decisive CRA (Column (2)) shows a statistically insignificant point estimate on the standalone variable for the cost of a downgrade of 0.12 pp. This indicates that when Moody's is the decisive CRA, S&P's propensity to downgrade their client is unaffected by the magnitude of the potential increase in borrowing costs. On the other hand, the coefficient estimate on the interaction term is -1.01 pp (statistically significant at the 5% level), which indicates that S&P is especially hesitant to downgrade their clients when their rating would be responsible for the increase in borrowing costs. Table **3** shows that the same is true for Moody's, with the coefficient on $cost\ of\ downgrade \times 1(decisive\ rating)$ being -0.85 pp (Column (4)).

[Insert Table **3** here]

Overall, the previous results indicate that CRAs are more hesitant to downgrade the credit ratings of their clients only when the CRA's rating is the decisive one in determining borrowing costs. The fixed effects employed in these regressions imply that they estimate the difference in the behavior of the CRA when the CRA rates the same borrower over time, at the same current rating, with the sole difference being whether the CRA's rating is decisive. An additional test shown in Internet Appendix Table IA.8 goes further and includes CRA×firm fixed effects, effectively absorbing the average downgrade propensity of the agency with respect to each specific borrower. The results in Table 3 remain unchanged.

3.3. Alternative explanations

Our evidence indicates that CRAs are significantly less likely to downgrade the credit rating of their clients 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 fee–based business model of credit ratings. This interpretation is further supported by the fact that the previous result is driven by those instances in which the CRA is the decisive one for the determination of the borrowing costs. In this section, we address a number of potential challenges to our interpretation of the results.

3.3.1 Undisclosed firm information

A first 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 undertake two different approaches. First, 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.[17] 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. If our results are driven by firms hiding 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.[18]

In Table **4**, 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 $cost\ of\ downgrade$.[19] The coefficient on the standalone $cost\ of\ downgrade$ remains statistically significant and similar in magnitude to the estimates in Table **2** in all specifications. Consistent with falling commodity values adversely affecting borrowers, the coefficient on 1(*commodities*) $\times$ 1(*commodities shock*) is always positive and statistically significant, ranging from 3.4–6.4 pp. However, the coefficient on the triple interaction ranges from -4.9–-4.6 pp (always statistically significant), indicating that downgrades were concentrated among borrowers for whom the cost of a downgrade is lower. Since 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 nega-

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

[18]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.

[19]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 also assign a value of 1 to 1(*commodities shock*) for the quarters 2014Q3 to 2015Q4.

tive financial information. In contrast, these results are consistent with conflicts of interest. In Internet Appendix, Table IA.9, we consider the possibility that CRAs lower ratings with a lag, and we extend 1(*commodities shock*) to include 2016. The results in Table 4 remain unchanged.

[Insert Table 4 here]

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 research and development (R&D) expenses as proxies for a firm's "opaqueness" (Wyatt, 2005; Cañibano et al., 2000).[20] In Columns (1) and (2) of Table 5, 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*. While the coefficient on the standalone *cost of downgrade* remains statistically significant and similar in magnitude to the estimates in Table 2 in both columns, the coefficients on both interaction terms are statistically insignificant.[21] Overall, these results are inconsistent with the proposition that our main results are driven by firms hiding negative financial information from the CRAs.

[Insert Table 5 here]

3.3.2 Avoidance of non-investment grade classification

A second potential challenge to our interpretation of the results is that they could be driven by regulatory restrictions on investors that prevent them from investing in non-

[20]Firms with significant intangibles have discretion in determining asset provisions such as goodwill. Likewise, firms have significant flexibility when classifying R&D expenditures.

[21]In the Internet Appendix, Table IA.10, we show that these results remain unchanged when interacting *cost of downgrade* with continuous versions of the proxies for firm opaqueness.

investment grade securities. Thus, CRAs could be less likely to downgrade a client if the credit rating downgrade would change their client's classification from investment grade to non-investment grade, resulting 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). Moreover, since the increase in borrowing costs of PSD contracts is particularly steep at the investment grade threshold (Figure IA.**2**), our point estimates could be driven by these subset of loans.

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 **5**. Consistent with CRAs being particularly hesitant to downgrade their clients to non-investment grade, the point estimate on the interaction term is -0.43 pp, but it is statistically insignificant. In contrast, the point estimate on $cost\ of\ downgrade$ is -0.69 pp. This result is statistically significant at the 1% level and very similar to the point estimates shown in Table **2**.[22] Overall, Column (3) of Table **5** 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.

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

[22]In the Internet Appendix, Table IA.**11**, we show that this result is robust to alternative definitions of $1(border\ junk)$.

aligned because bonds do not adjust their payments based on downgrades.

3.4. Time to downgrade

The previous results indicate that CRAs are less likely to downgrade their clients at times when the downgrade is more costly. A lower probability of downgrade can be explained by CRAs either being slower to downgrade or avoiding downgrades entirely. Next, we investigate whether, conditional on downgrading, CRAs are slower to downgrade their clients when the downgrade is more costly.

Table **6** estimates specifications similar to those in Table **2**, with the main difference being that the dependent variable is *time to downgrade*, which represents the number of quarters between origination and the eventual downgrade.[23] As before, the variable for the cost of downgrade is standardized, and standard errors are clustered by firm.

[Insert Table **6** here]

The coefficient on *cost of downgrade* in Column (1) is 1.14 quarters (statistically significant at the 5% level). This indicates that a one standard deviation increase in the borrowing costs following a one-notch downgrade is associated with 102 additional days (1.14×90) before the borrower is downgraded by a CRA. This is an economically important effect that represents a 22% increase in the time to downgrade compared to the sample mean time to downgrade of 5.08 quarters.

Columns (2) to (4) incorporate loan- and firm-level controls, as well as firm, year, and credit rating at origination fixed effects. The coefficient on *cost of downgrade* ranges from 1.23–2.20 quarters. In particular, the coefficient of 2.20 in the most stringent specification (Column (4)) equals an increase of 198 days (or a 43% increase relative to the mean time to downgrade) in the deferral of a downgrade. To give this result additional context, our sample shows an average downgrade size of 1.3 increments, an average cost per

[23] We limit our sample to a single observation per loan, and we consider only the loans of firms that experience a downgrade within the loan's maturity. In the case of multiple downgrades, we consider only the first downgrade for each loan (i.e., we consider the time from loan origination to the eventual downgrade).

downgrade notch of 13 bp, and an average loan size of $886 million. Thus, 2.2 additional quarters without a credit rating downgrade translates to almost $650,000 in borrower savings ($886\text{m}\times0.0013\times2.2/4=0.633\text{m}$).

Note that one limitation of the analysis in Table **6** is that we are making inferences from a limited number of observations. First, the regressions are at the loan level rather than at the loan–quarter level. Second, the inclusion of firm fixed effects limits us to borrowers that both issue multiple loans and are downgraded during the time in which the loans are still outstanding.[24]

3.5. Survival analysis

In this section, we complement our previous analysis by conducting a nonparametric survival analysis that specifically models the hazard rate of credit rating downgrades (Collett, 2015). This approach relies on the Kaplan–Meier survival curve, which plots the percentage of the sample that has not yet experienced failure over time (i.e., the survival rate).[25] We define *failure* as the occurrence of a credit rating downgrade. Figure **2** compares the survival rate of PSD loans with a high (i.e., above-median) downgrade cost at origination to the survival rate of PSD loans with a low (i.e., below-median) downgrade cost at origination.[26]

[Insert Figure **2** here]

Figure **2** shows that firms with loans that have a high downgrade cost are significantly less likely to be downgraded by CRAs than firms with loans that have a low downgrade cost. This result holds for all time horizons. For example, after eight quarters (i.e., two

[24]There are a total of 451 loans that are associated with a downgrade. This corresponds to about one quarter of the 1,829 loans in our sample. In untabulated results, we find that in simple OLS regressions with no controls in this larger sample, the coefficient estimate on *cost of downgrade* is 1.3 quarters (statistically significant at the 5% level). This is very similar to the estimates in Table **6**.

[25]The Kaplan–Meier estimator is a nonparametric estimator of survival rates that takes into account right censoring. Other applications in finance include Fee, Hadlock, and Thomas (2006), Deyoung et al. (2015), and Malmendier, Opp, and Saidi (2016).

[26]We restrict the analysis to the first five years of each loan's life. Over 90% of the loans in our sample have a maturity of five years or less.

years), 15% of firms with high–downgrade cost loans experience a downgrade. In contrast, the corresponding failure rate for firms with low–downgrade cost loans is almost 25%.

This survival analysis approach also allows us to estimate the expected time before a downgrade for each group.[27] The expected time to downgrade for firms with low–downgrade cost loans is 15 quarters (95% confidence interval is 14.5–15.5), while the expected time before a downgrade for firms with high–downgrade cost loans is 17.1 quarters (95% confidence interval is 16.7–17.6). Thus, the difference in survival times between the two groups is 2.1 quarters, and the difference in the cost of a downgrade is 15.36 bp. Note that the magnitudes of these nonparametric estimates are very similar to those of our most saturated model shown in Table **6**. In that model, we estimate that a one standard deviation increase in the cost of a downgrade variable (11.89 bp) increases the time before a downgrade by 2.20 quarters.

4. 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.

[27] These values are obtained by calculating the area under the Kaplan–Meier survival curves in Figure **2**. Confidence intervals are calculated following Collett (2015).

4.1. 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*, which represents the average cost of a one-notch downgrade during the lifetime of a loan. Thus, this variable is a measure of the *ex post* (i.e., realized) conflicts of interests of CRAs over the life of a loan, as opposed to a measure of the *ex ante* (i.e., expected) conflicts of interest of CRAs that would be captured by the average steepness of the pricing grid.[28] Table 7 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 7 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 7 here]

The point estimates on *average cost of downgrade* are positive and statistically significant at the 1% level in the four specifications, ranging from 6.7–10.1 bp. Thus, the regression results are consistent with borrowers and lenders being aware of and pricing the conflicts of interest of CRAs.

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

[28] In the Internet Appendix (Table IA.12), we show that this analysis is robust even when considering the latter measure of conflicts of interest.

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 3 indicate, CRAs are more reluctant to downgrade their clients when the costs of a downgrade are higher.

4.2. 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).[29] 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 et al., 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.

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.[30] We match these data to our sample of PSD loans using a proprietary linking

[29] 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).

[30] In fact, the main purpose of LPC is to "facilitate trading and investment decisions" (`https://www.`

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.[31] Internet Appendix A provides a detailed description of the matching procedure.

We construct a quarterly panel with quoted prices for the traded loans in our sample. Similar to the analysis in Figure **2**, we 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 **2** (i.e., our most stringent specification) plus loan fixed effects, and we consider the first four years of each loan's lifetime.[32]

Figure **3** 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 as our coefficient of reference. 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

`lsta.org/members/lpc-from-refinitiv/`).

[31] 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 et al. (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.

[32] 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.

associated with loans that have a high cost of downgrade.

[Insert Figure 3 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 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 the coefficient estimates turn positive, consistent with a decrease in the premium associated with high cost of downgrade loans. In fact, on average, these loans become about 2% more expensive than low cost of downgrade loans after three years. Overall, the point estimates in Figure 3 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.

4.3. 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.[33] We then split these 150

[33]These variables include 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). Table IA.13 shows that the matching is successful in finding observationally equivalent loans to the traded loans among the non-traded loans.

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 4.

[Insert Figure 4 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 56% probability of being traded in the secondary market, 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 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 5.

[Insert Figure 5 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 450 days before getting quoted, whereas loans in the other two groups experience their first quote after about 200 days, on average. This is a 150-day difference, equivalent to a 75% 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.

5. 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.[34] 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 3 show that the conflicts of interest of CRAs were pervasive and were not restricted to structured products. S&P and Moody's also 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.**3**).

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.

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

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 8. 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 8 shows a statistically insignificant and negative coefficient on $cost\ of\ downgrade \times 1(post\ settlement)$. In contrast, consistent with the results in Section 3, the coefficient on the standalone variable that represents the cost of a downgrade continues to be statistically significant and negative. In Internet Appendix Figure IA.4, we also consider the possibility that CRAs could have modified their credit rating behavior before the settlement (e.g., after the DOJ investigations started). However, the figure shows that the effect of the cost-of-downgrade variable on the probability of a downgrade is similar for each year throughout the sample period. This is inconsistent with changes in behavior before the settlements. Finally, Column (2) of Table 8 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 8 Here]

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 when rating firms associated with PSD.

6. Conclusion

In this paper, 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. This indicates that CRAs cater to their clients. In the event of a downgrade, 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, second 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.

Our empirical setting allows us to rule out a series of alternative explanations. Our within-firm estimation approach alleviates concerns that firms self-select into PSD contracts as well as concerns about rating shopping. We also find no evidence that our results are driven by firms hiding negative information from CRAs or by investors tacitly agreeing to inflated credit ratings to prevent loans from becoming non-investment grade (and thus unavailable to invest in).

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 fee–based business model of CRAs.

Appendix

A. Variable description

Variable name	Description
Borrower-quarter characteristics	
Assets	Total assets (in billions USD)
Leverage	Total liabilities$\div Assets$
Profitability	EBITDA$\div Assets$
Credit rating	Long-term issuer credit rating. Either from S&P or Moody's, depending on which CRA is decisive.
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$\div Assets$
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(border junk)	Indicator variable that takes the value of 1 if the borrower has a credit rating of BBB- 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.
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.

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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 $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 = $225,000 annual savings

Figure 2
Kaplan–Meier survival curves
This figure shows the Kaplan-Meier survival curves for loans with high (i.e., above-median) and low (i.e., below-median) costs of downgrade at origination. The average cost of a downgrade for the former group is 22.3 bp while the average cost of a downgrade for the latter group is 6.7 bp. The analysis is restricted to the first five years of each loan's life. The shaded areas denote the 95% confidence interval for each estimation.

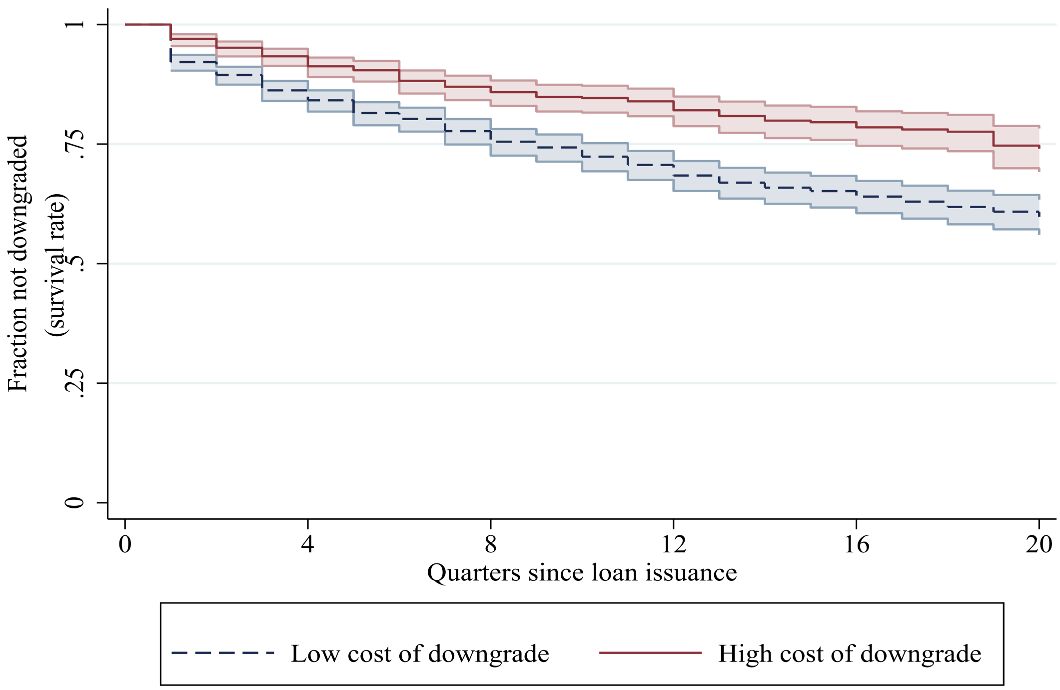

Figure 3
Dynamics of secondary market prices
This figure shows the dynamics of the pricing of loans with high cost of downgrade in the secondary market. *Loan price* (measured as the average of the mid-prices quoted each quarter) is regressed on the interactions of an indicator for above-median cost 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 **2** 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.

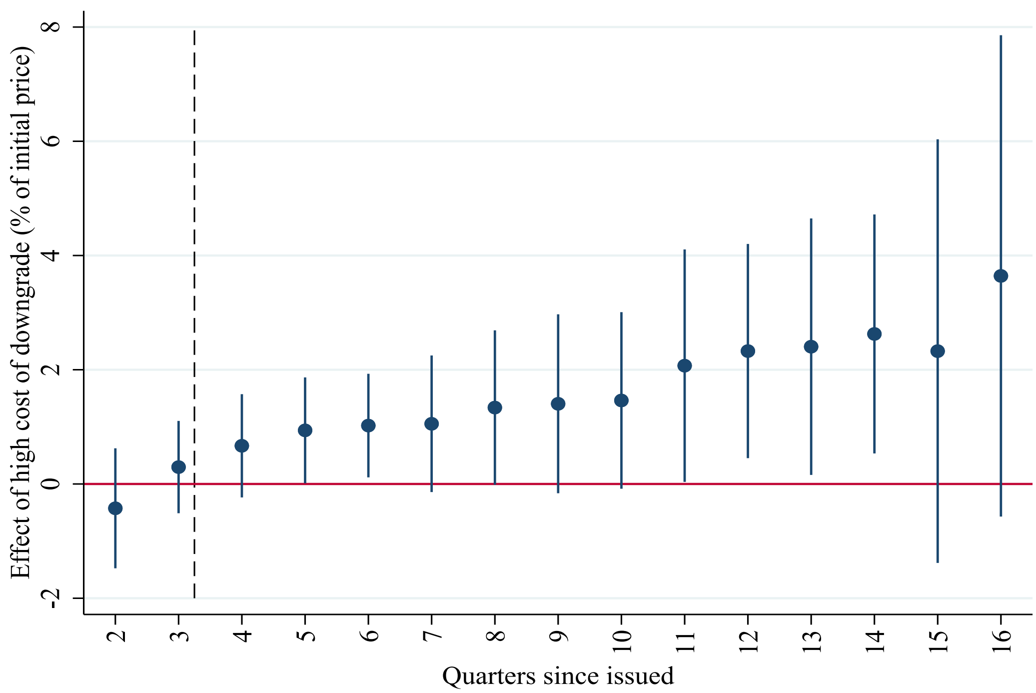

Figure 4
Probability of loan sale
This figure shows the probability of loan trade in the secondary market by terciles of average cost of downgrade. The sample consists of 75 traded loans and 75 non-traded loans. The non-traded loans are selected so that they resemble the traded loans using a nearest neighbor matching framework based on firm characteristics (current credit rating, size, profitability, asset tangibility, and leverage) and loan characteristics (amount, number of financial covenants, and whether the loan is secured or not).

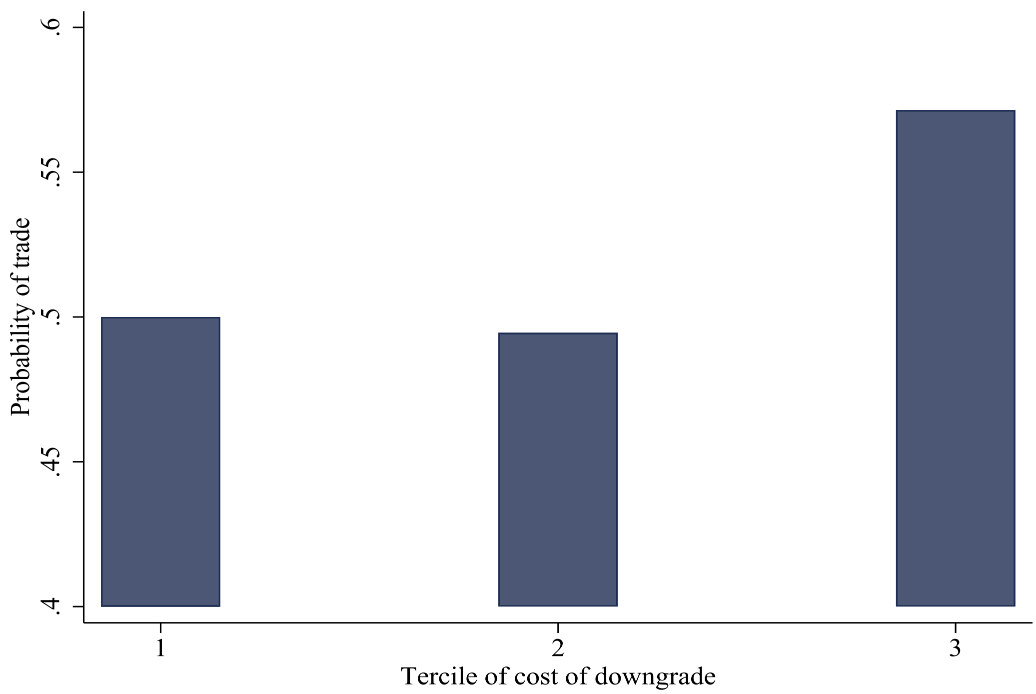

Figure 5
Time to first sale
This figure shows the average time-to-first-trade (days) in the secondary market by terciles of average cost of downgrade. The sample consists of 75 traded loans.

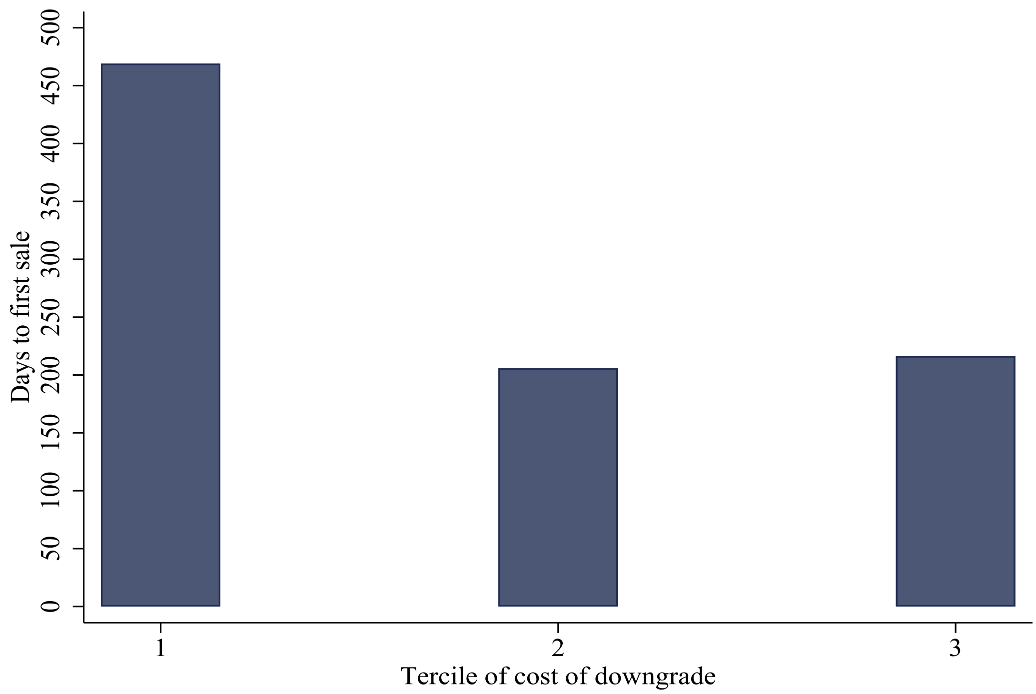

Table 1
Data summary
This table describes the final sample. Panel A shows summary statistics at the borrower–quarter level. Panel B shows summary statistics for the PSD loan contracts contained in the final sample. Panel C shows overall and within-group standard deviations for the main variables in Equation (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 (bp)	20,725	13.26	11.89	0.00	10.80	25.00
Leverage	20,725	0.32	0.16	0.12	0.31	0.51
Total assets ($ billions)	20,725	22.94	57.45	2.15	8.20	45.33
Intangibles over assets	20,725	0.21	0.21	0.00	0.14	0.55
Profitability (ROA)	20,725	0.03	0.07	-0.02	0.04	0.10
1(downgrade) (percent)	20,725	2.93	16.88	0.00	0.00	0.00
Issuer credit rating (numeric)	20,725	9.07	2.61	6.00	9.00	12.00
R&D ($ millions)	9,746	279.47	634.28	0.00	69.00	704.00

Panel B: Loan characteristics

	N	Mean	SD	p10	p50	p90
Number of financial covenants	1,829	1.45	0.82	1.00	1.00	2.00
Loan amount ($ millions)	1,829	886.69	904.33	150.00	550.00	2000.00
1(secured)	1,829	0.15	0.36	0.00	0.00	1.00
Average cost of downgrade	1,829	14.59	8.65	6.50	12.50	25.00
Time to downgrade (quarters)	451	3.99	5.05	0.00	2.00	12.00

Panel C: Variation within groups

	N	Overall SD	SD within credit rating	SD within firm	SD within year
1(downgrade)	20,725	16.88	16.61	15.91	16.74
Cost of downgrade (bp)	20,725	11.89	10.66	8.81	11.71
Time to downgrade (quarters)	2,868	4.50	4.42	3.71	4.25

Table 2
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, 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	-0.786***	-0.863***	-0.753***	-0.826***
	(0.244)	(0.218)	(0.205)	(0.215)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Rating FE	No	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes
N	20,725	20,725	20,725	20,725
$Adj.R^2$	0.10	0.13	0.13	0.14
Mean of dependent variable	2.93	2.93	2.93	2.93

Table 3
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, 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	0.123	0.116	0.043	0.032
	(0.356)	(0.358)	(0.104)	(0.106)
1(decisive rating)	-1.900	-1.746	2.208	2.105
	(1.251)	(1.267)	(1.835)	(1.824)
Cost of downgrade × 1(decisive rating)	-0.955**	-1.010**	-0.820**	-0.854**
	(0.420)	(0.427)	(0.417)	(0.420)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	Yes	Yes	Yes	Yes
N	20,725	20,725	20,725	20,725
$Adj.R^2$	0.10	0.11	0.17	0.17
Mean of dependent variable	1.84	1.84	1.22	1.22

Table 4

Probability and cost of downgrade during an 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 2015, a period in which the Dow Jones Commodity Index fell by 50%. Loan- and firm-level controls, as well as current credit rating, year, 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	-0.706***	-0.848***	-0.712***	-0.810***
	(0.247)	(0.222)	(0.206)	(0.219)
1(commodities) × 1(commodities shock)	6.420**	5.979**	3.738	3.436
	(2.854)	(2.797)	(2.411)	(2.433)
Cost of downgrade × 1(commodities) × 1(commodities shock)	-4.917*	-4.913**	-4.750**	-4.609**
	(2.517)	(2.329)	(2.212)	(2.194)
Firm FE	Yes	Yes	Yes	Yes
Year 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	20,725	20,725	20,725	20,725
$Adj.R^2$	0.10	0.13	0.13	0.14
Mean of dependent variable	2.93	2.93	2.93	2.93

Table 5

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(*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). All regressions include loan- and firm-level controls, as well as current credit rating, year, 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)	0.349		
	(0.473)		
Cost of downgrade × 1(high R&D)		-0.300	
		(0.442)	
Cost of downgrade × 1(border junk)			-0.426
			(0.531)
Cost of downgrade	-0.978***	-0.764***	-0.686***
	(0.254)	(0.237)	(0.237)
1(high intangibles)	0.216		
	(1.046)		
1(high R&D)		-3.286**	
		(1.547)	
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
N	20,725	20,725	20,725
$Adj.R^2$	0.13	0.14	0.14
Mean of dependent variable	2.93	2.93	2.93

Table 6
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, 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	1.137**	1.716**	1.232*	2.204**
	(0.525)	(0.791)	(0.663)	(0.882)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Rating FE	No	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes
N	257	257	257	257
$Adj.R^2$	0.77	0.81	0.80	0.81
Mean of dependent variable	5.08	5.08	5.08	5.08

Table 7
Loan pricing at initiation and average cost of downgrade
This table shows OLS regressions where the dependent variable is the loan spread at origination. The independent variable of interest is *average cost of downgrade*, the average increase in interest rates after a downgrade by one notch over the lifetime of a loan. 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, 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)
Average cost of downgrade	10.139***	6.860***	8.651***	6.708***
	(2.393)	(2.325)	(2.527)	(2.326)
Firm FE	Yes	Yes	Yes	Yes
Year 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	1,814	1,814	1,814	1,814
$Adj.R^2$	0.66	0.75	0.71	0.75
Mean of dependent variable	112.37	112.37	112.37	112.37

Table 8
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. All regressions include loan- and firm-level controls, as well as current credit rating, year, and firm fixed effects. 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	-0.640***	0.421
	(0.175)	(0.257)
Cost of downgrade × 1(post settlement)	-0.465	0.536
	(0.539)	(1.823)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Rating FE	Yes	Yes
Loan controls	Yes	Yes
Firm controls	Yes	Yes
N	20,725	257
$Adj.R^2$	0.10	0.86
Mean of dependent variable	1.84	4.60

Internet Appendix

Credit Rating Inflation: Is It Still Relevant and Who Prices It?

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.**14**, 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.**15**, 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.**13**. We find that there are no economically or statistically significant differences between the firms in the two samples.

B. Supplementary figures and tables

Figure IA.1
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.

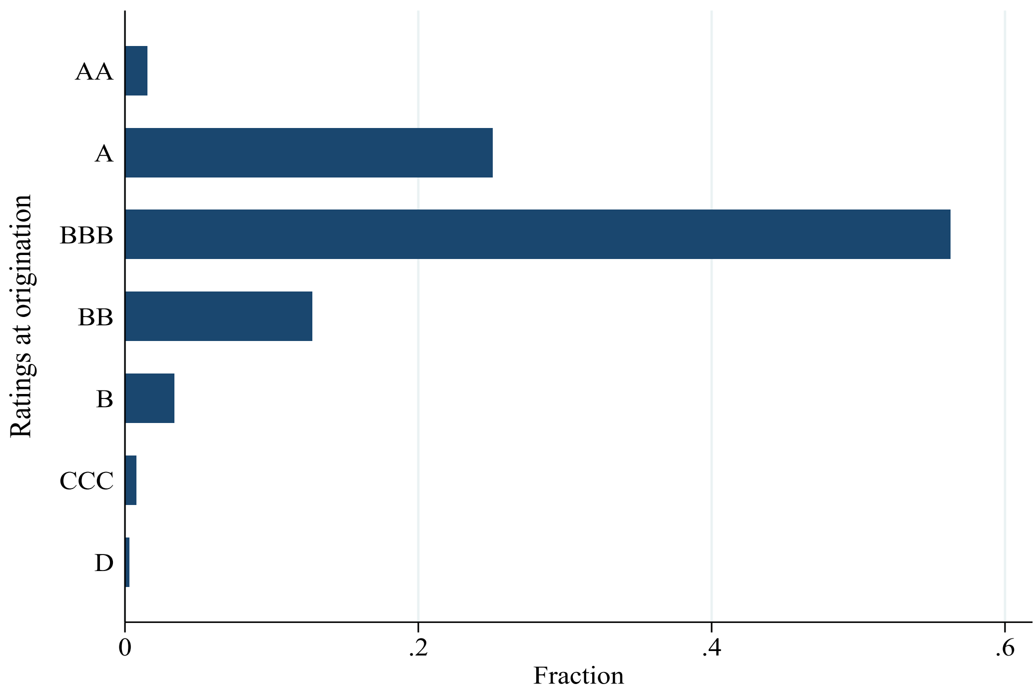

Figure IA.2
Pricing grid steepness
This figure shows the distribution of the average cost of a downgrade for our sample of credit rating–based PSD loans by credit rating at origination. The credit rating scale is simplified by combining the credit ratings within each letter credit rating category. For example, we combine the initial credit ratings of A+, A, and A- into one group, A.

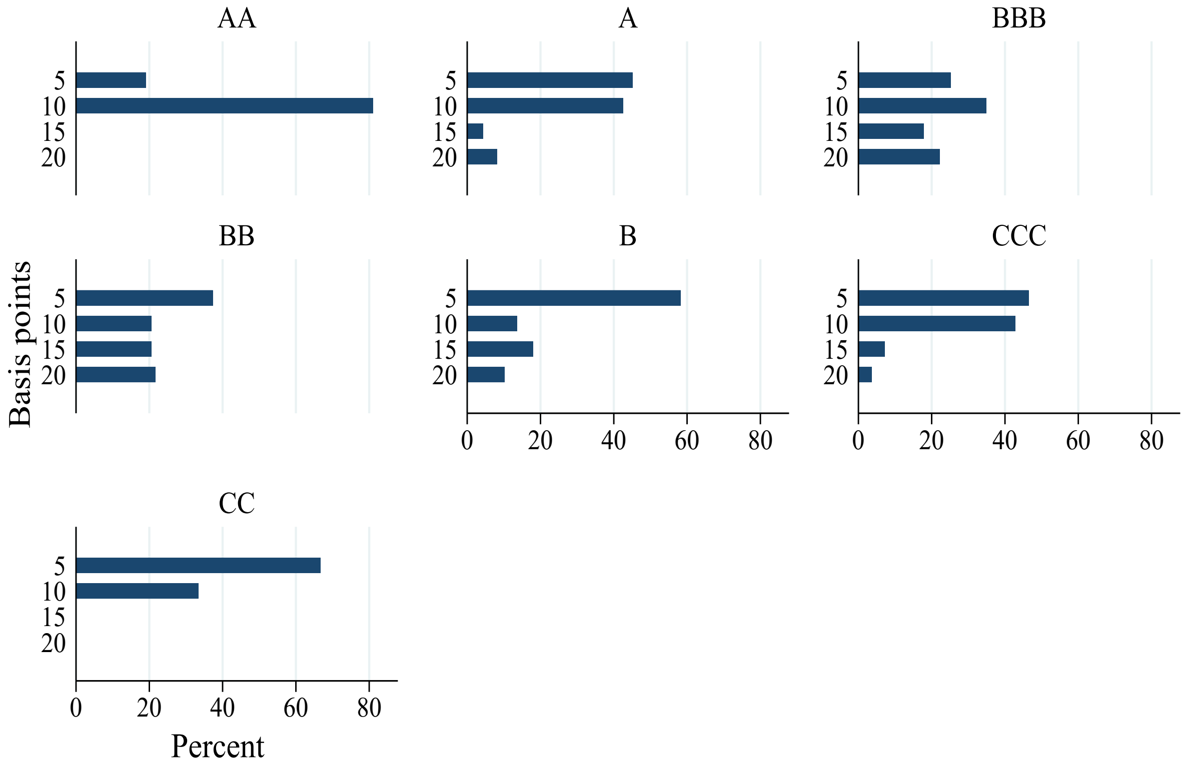

Figure IA.3
Annual volume of newly issued credit rating rating-based PSD
This figure shows the volume of newly issued credit rating–based performance-sensitive debt, by year.

Figure IA.4
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).

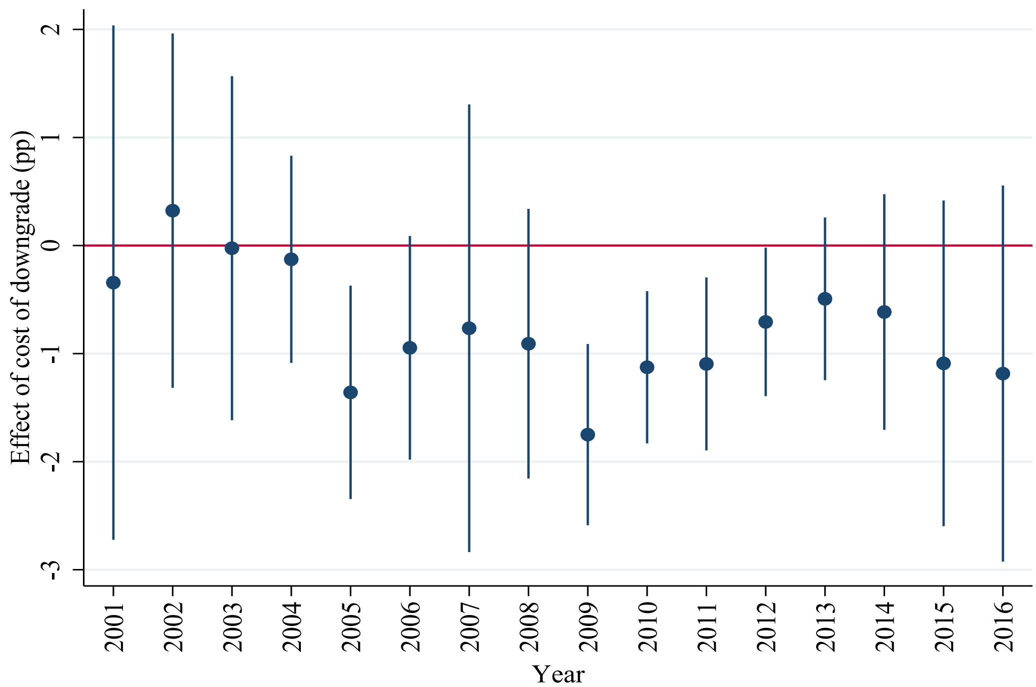

Table IA.1
Accounting ratio–based PSD loans versus credit rating–based PSD loans
This table compares a sample of accounting ratio–based PSD loans with our sample of credit rating–based PSD loans across observable characteristics. Observations are at the loan–year level. $1(\cdot)$ denotes indicator variables. 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	0.40	0.32	0.08***
Total assets ($ billions)	3.46	22.94	-19.47***
Intangibles over assets	0.30	0.21	0.09***
Profitability (ROA)	0.02	0.03	-0.01**
R&D ($ millions)	64.51	279.47	-214.96***
Number of financial covenants	2.76	1.52	1.24***
Loan amount ($ millions)	321.25	868.72	-547.48***
1(secured)	0.88	0.17	0.71***
Cost of one grid (rating or ratio, bp)	16.79	13.26	3.52***
N	17,756	20,725	38,481

Table IA.2

Robustness for Table 2: Year–quarter fixed effects

Regressions reported in this table are identical to Table 2, except that the regressions include year–quarter fixed effects instead of year 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	-0.784***	-0.841***	-0.739***	-0.807***
	(0.243)	(0.220)	(0.206)	(0.216)
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	20,725	20,725	20,725	20,725
$Adj.R^2$	0.11	0.14	0.14	0.15
Mean of dependent variable	2.93	2.93	2.93	2.93

Table IA.3
Robustness for Table 2: Loan fixed effects
Regressions reported in this table are identical to Table 2, except that the 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(downgrade)			
	(1)	(2)	(3)	(4)
Cost of downgrade	-1.885**	-1.835***	-1.723***	-1.723***
	(0.746)	(0.614)	(0.638)	(0.638)
Loan FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Rating FE	No	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes
N	20,625	20,625	20,625	20,625
$Adj.R^2$	0.10	0.13	0.13	0.13
Mean of dependent variable	2.92	2.92	2.92	2.92

Table IA.4
Robustness for Table 2: Cost of downgrade based on two-notch downgrades
Regressions reported in this table are identical to Table 2, 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 downgrade 2 notches	-1.456***	-1.292***	-1.067***	-1.151***
	(0.358)	(0.290)	(0.260)	(0.278)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Rating FE	No	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes
N	20,106	20,106	20,106	20,106
$Adj.R^2$	0.11	0.13	0.13	0.14
Mean of dependent variable	2.98	2.98	2.98	2.98

Table IA.5
Robustness for Table 2: Cost of downgrade as fraction of total assets
Regressions reported in this table are identical to Table 2, 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)	-0.814***	-1.048***	-0.560***	-0.742***
	(0.197)	(0.210)	(0.192)	(0.209)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Rating FE	No	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes
N	20,725	20,725	20,725	20,725
$Adj.R^2$	0.10	0.13	0.13	0.13
Mean of dependent variable	2.93	2.93	2.93	2.93

Table IA.6
Robustness for Table 2: Separate estimation for S&P and Moody's
Regressions reported in this table are identical to Table 2, except that the regressions are estimated separately for borrowers rated by S&P (Columns (1) and (2)) and Moody's (Columns (3) and (4)). 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	-1.107***	-1.201***	-0.639*	-0.759*
	(0.226)	(0.238)	(0.339)	(0.390)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	Yes	Yes	Yes	Yes
N	15,402	15,402	5,316	5,316
$Adj.R^2$	0.11	0.11	0.21	0.21
Mean of dependent variable	2.05	2.05	4.72	4.72

Table IA.7
Placebo test for Table 2: Sample of accounting ratio-based PSD loans

Regressions reported in this table are identical to Table 2, 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	1.423***	1.178***	0.963***	0.977***
	(0.337)	(0.313)	(0.320)	(0.326)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Rating FE	No	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes
N	17,756	17,756	17,756	17,756
$Adj.R^2$	0.15	0.17	0.18	0.18
Mean of dependent variable	3.48	3.48	3.48	3.48

Table IA.8
Robustness for Table 3: CRA–firm fixed effects
Regressions reported in this table are identical to Table 3, except the regressions include CRA–firm 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(downgrade)			
	(1)	(2)	(3)	(4)
Cost of downgrade	-0.144	-0.140	-0.139	-0.152
	(0.255)	(0.251)	(0.243)	(0.255)
Cost of downgrade × 1(decisive rating)	-0.876**	-0.922***	-0.797***	-0.867***
	(0.361)	(0.323)	(0.306)	(0.322)
Firm × CRA FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Rating FE	No	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes
N	20,712	20,712	20,712	20,712
$Adj.R^2$	0.08	0.12	0.12	0.12
Mean of dependent variable	1.83	1.83	1.83	1.83

Table IA.9

Robustness for Table 4: Alternative definition of the commodities shock variable

Regressions reported in this table are identical to Table 4, except that the variable 1(*commodities shock*) is defined to take the value of 1 between 2014Q3 and 2016Q4. 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	-0.675***	-0.846***	-0.697***	-0.799***
	(0.240)	(0.216)	(0.200)	(0.214)
1(commodities) × 1(commodities shock extended)	6.680***	4.742***	2.209	1.750
	(1.975)	(1.756)	(1.908)	(1.902)
Cost of downgrade × 1(commodities) × 1(commodities shock extended)	-5.863***	-4.756***	-4.448**	-4.183**
	(2.023)	(1.768)	(2.052)	(2.022)
Firm FE	Yes	Yes	Yes	Yes
Year 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	20,725	20,725	20,725	20,725
$Adj.R^2$	0.10	0.13	0.13	0.14
Mean of dependent variable	2.93	2.93	2.93	2.93

Table IA.10

Robustness for Columns (1) and (2) of Table 5: Continuous proxies for firm opaqueness

Regressions reported in this table are identical to those in Columns (1) and (2) of Table 5, except the regressions include continuous variables for the firm's intangibles divided by total assets and log(R&D) instead of indicator variables. 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 × Intangibles over assets	0.770	
	(1.375)	
Cost of downgrade × log(R&D)		0.039
		(0.115)
Cost of downgrade	-0.965***	-1.149***
	(0.259)	(0.418)
Intangibles over assets	-7.842*	-10.684**
	(4.133)	(5.406)
log(R&D)		0.358
		(1.378)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Rating FE	Yes	Yes
Loan controls	Yes	Yes
Firm controls	Yes	Yes
N	20,725	9,746
$Adj.R^2$	0.14	0.13
Mean of dependent variable	2.93	3.04

Table IA.11

Robustness for Column (3) of Table 5: Alternative definitions of the border junk variable

Regressions reported in this table are identical to those in Column (3) of Table 5, except the regressions include alternative definitions of 1(*border junk*). 1(*border junk*) (2*notches*) is an indicator that takes the value of 1 if the firm is rated BBB- or BBB (i.e., one or two credit rating notches above the non-investment grade classification threshold). 1(*border junk*)(3*notches*) is an indicator that takes the value of 1 if the firm is rated BBB-, BBB, or BBB+. 1(*border junk*)(4*notches*) is an indicator that takes the value of 1 if the firm is rated BBB-, BBB, BBB+, or 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	-0.599**	-0.613**	-0.917*
	(0.247)	(0.258)	(0.485)
Cost of downgrade × 1(border junk) (2 notches)	-0.636		
	(0.509)		
Cost of downgrade × 1(border junk) (3 notches)		-0.539	
		(0.483)	
Cost of downgrade × 1(border junk) (4 notches)			0.105
			(0.521)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes
Loan controls	Yes	No	Yes
Firm controls	No	Yes	Yes
N	20,725	20,725	20,725
$Adj.R^2$	0.14	0.14	0.14
Mean of dependent variable	2.93	2.93	2.93

Table IA.12
Robustness for Table 7
Regressions reported in this table are identical to Table 7, 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 across all levels of the initial loan contract (as opposed to the realized avgerage cost of a downgrade over the lifetime of the loan). 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	4.806***	4.060***	4.393***	4.011***
	(0.447)	(0.379)	(0.396)	(0.381)
Firm FE	Yes	Yes	Yes	Yes
Year 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	1,736	1,732	1,735	1,732
$Adj.R^2$	0.76	0.81	0.80	0.81
Mean of dependent variable	111.91	111.78	111.96	111.78

Table IA.13
Traded versus non-traded loans

This table compares the subsample 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(·) 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	9.32	0.05
Intangibles over assets	0.28	0.27	0.01
Profitability (ROA)	0.03	0.02	0.01
Issuer credit rating (numeric)	10.05	10.09	-0.04
Number of financial covenants	1.57	1.56	0.01
Loan amount ($ millions)	1339	1317	21
1(secured)	1.17	1.17	0
N	75	75	

Table IA.14
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(·) 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.15
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. $1(\cdot)$ 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	0.32	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	