The Real Costs of Corporate Credit Ratings

Job-Market Paper

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Abstract

Credit rating agencies emphasize the importance of specific financial ratio thresholds in their rating process. Firms on the favorable side of these thresholds are more likely to receive higher ratings than similar firms that are not. I show that firms near these salient thresholds respond to the incentive to improve their appearance on this dimension by distorting real investment activities during periods leading up to bond issuance. These firms are significantly more likely to reduce R&D and SG&A expenditures compared to observationally similar firms not near a threshold. Subsequently, they are more likely to experience declines in innovation output, profitability, and Tobin's Q. These distortions highlight an important cost of arms-length financing and an adverse consequence of transparency in credit rating criteria.

Keywords: credit ratings, transparency, real distortions.

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1 Introduction

Arms-length financing allows firms to access a deeper pool of capital and provides investors with a broader range of investment opportunities. Information intermediaries, such as credit rating agencies (CRAs), facilitate such transactions by mitigating the inherent information asymmetry between these two groups. CRAs bridge this gap by aggregating several pieces of information about a firm into a single measure of creditworthiness. If firms know that CRAs weight specific criteria more than others in the aggregation, they may have an incentive to reallocate some of their resources toward these dimensions to achieve a better rating. Indeed, theoretical models such as Holmstrom and Milgrom (1991) show that agents distort their behavior when they know they will be evaluated based on specific, easily measurable dimensions.[1] Moreover, survey evidence shows that credit ratings are a key focus for CFOs and that the majority of managers are willing to forgo positive NPV projects to meet short-term financial objectives (Graham and Harvey, 2001; Graham, Harvey, and Rajgopal, 2005). Building on these ideas, I ask the following question in this paper: Do firms respond to credit rating criteria by distorting their investment behavior at the expense of long-run performance?

I investigate this question by examining firms' investment behavior during periods when their rating is arguably most important to them: prior to bond issuance. The identification of rating-induced distortions, however, is difficult because a number of confounding factors could affect the firms' investment policies during these time periods. For example, a reduction in R&D expenditures in periods leading up to bond issuance could be driven by changes in a firm's product life cycle or investment opportunity set. Hence, a simple examination of changes in investment during periods prior to issuance stands little chance of separating firms'

[1] Holmstrom and Milgrom (1991) show that principal-agent contracting frictions go beyond the tension between incentives for effort provision and risk sharing. They show that contracts written on easily-measured dimensions (e.g., manufacturing output quantity) can lead to an overprovision of effort by the agent on these dimensions at the expense of more difficult to measure dimensions (e.g., output quality) that are important to the principal (see also Baker, 1992). The theoretical models of Hermalin and Weisbach (2012) and Edmans, Heinle, and Huang (2013) illustrate a similar friction in the context of increased disclosure.

endogenous response to credit rating criteria from other potential factors. To overcome this empirical challenge, I use an institutional feature of the credit rating process that induces cross-sectional variation in the incentives for issuers to improve on a particular dimension that CRAs emphasize, which I describe below.

The CRAs publicly release guidelines and methodologies with specific criteria that they focus on when assessing a given firm's creditworthiness. One primary criterion relates to the firm's Debt/EBITDA ratio. CRAs publish mappings from Debt/EBITDA ratio to potential credit ratings which have jumps at particular ratio thresholds (see Table 1). These thresholds–which the CRAs arbitrarily place at round numbers such as 2.0 and 3.0–are unlikely to systematically coincide with changes in drivers of optimal investment policy. They do, however, generate cross-sectional variation in firms' incentives to improve their Debt/EBITDA ratio in the periods leading up to getting a bond rated. Firms in regions near thresholds the year prior to issuance, which I refer to as *High-Incentive (H-I) Zones*, face a high expected marginal benefit from Debt/EBITDA improvement. To the extent that improvement in the ratio is costly, these firms also face a lower immediate cost to cross a threshold relative to firms farther away.

In my analysis, I compare the pre-issuance investment behavior and post-issuance performance of firms near a salient threshold to firms that are farther away.[2] The identifying assumption is that these two sets of firms face different levels of incentives to improve their ratio while they remain similar on unobserved dimensions that drive optimal investment policy. The presence of multiple economically arbitrary thresholds in my sample produces an alternating sequence of "treatment" (higher incentive to improve Debt/EBITDA) and

[2]Consider the salient thresholds at Debt/EBITDA=1.5, 2.0, and 2.5 as an illustrative example (there are six such thresholds in my sample). For the Debt/EBITDA threshold of 2.0, I classify firms with Debt/EBITDA $\in [1.95, 2.20]$ a year prior to issuance as being in the treatment group (*H-I Zone*). I classify firms with Debt/EBITDA $\in [1.70, 1.95]$ and $[2.20, 2.45]$ as being in the control group since they do not fall in the *H-I Zone* around 2.0 or either of the adjacent thresholds. The timing of the measurement captures the notion that firms typically recognize their financing needs in advance and then face incentives to take actions in the periods leading up to issuance to conform to the rating criteria. Section 2 provides a more thorough description of the classification process and its underlying rationale.

"control" (lower incentive) groups throughout the Debt/EBITDA spectrum which lends credibility to this assumption. In addition, I show that the two groups are well matched on other observable factors that potentially drive investment. This research design allows me to pin down whether firms in *H-I Zones* respond to the rating criteria by distorting their investments in innovation (R&D) and organizational capital (SG&A) in the periods leading up to getting a bond rated as compared to firms that are away from the thresholds.

Reducing these investments in long-term intangible assets provides the immediate benefit of boosting EBITDA, while the costs of forgone investments are borne in the future. This fundamental tension between benefits now and costs later provides incentives for myopic managerial behavior (Narayanan, 1985; Stein, 1989). In my empirical tests, I first examine the effect of ratings-induced incentives on R&D and SG&A investments and then examine the long-run consequences in terms of future innovation output, profitability, and Tobin's Q.

I find that *H-I Zone* issuers are about 40% more likely to reduce R&D and 10% more likely to reduce SG&A expenditures prior to issuance than observationally similar control firms. In terms of the size of the reductions, these firms cut their R&D expenditures by 10% and SG&A expenditures by 3% relative to control firms. After documenting the average treatment effect, I estimate the impact of rating criteria on investment behavior as a continuous function of a firm's distance to a threshold. As the distance to a salient threshold increases, firms face a lower expected marginal benefit from improving their Debt/EBITDA ratio and higher total cost to reach the next threshold. Thus, the overall incentive to reduce these investments diminishes as the distance increases. The results support this notion.

The economic benefit of appearing strong on CRA-emphasized criteria is larger during periods of high yield spreads between ratings classes. Consistent with this view, I show that the main effects discussed above are strongest for periods with high credit spreads. During high-credit-spread periods, defined as above sample median Baa-Aaa spread, the likelihood of reducing investments increases by about 30% for R&D expenditures and 80% for SG&A

expenditures over the baseline estimates. These results lend further credence to my main claim that economic incentives driven by credit rating criteria lead to distortions in firm behavior.

While my results so far establish a link between credit rating criteria and investment behavior, they are silent about the long-run performance effects. Standard and Poor's (S&P) recognize the potential distortions that ratings can create and state the following in their rating methodology handbook (Standard and Poor's, 2008) [emphasis added]:

> "We do not encourage companies to manage themselves with an eye toward a specific rating. The more appropriate approach is to operate for the good of the business as management sees it and to let the rating follow. *Ironically, managing for a very high rating can sometimes be inconsistent with the company's ultimate best interests, if it means being overly conservative and forgoing opportunities.*"

In my next set of tests, I examine firms' post-issuance innovation, profitability, and firm value to study the long-run consequences of the investment changes. First, I focus on innovation because of its long-term nature, its connection to R&D, and because it is an important driver of firm value (Hall, Jaffe, and Trajtenberg, 2005) and overall economic growth (Solow, 1957; Romer, 1990). I find a reduction in the raw quantity of patents produced for the first year after bond issuance for *H-I Zone* issuers, though the effects are short-lived. I next consider patent citations, which are widely considered a better measure of the quality and impact of innovation (see, e.g., Griliches, 1990; Trajtenberg, 1990). I find that issuers near the salient thresholds are about 25% more likely than control firms to see declines in patent citations. This effect persists for multiple years following bond issuance. These results suggest that although declines are not great in the quantity of patents produced, firms facing stronger ratings-induced incentives to improve their Debt/EBITDA ratio have a considerably higher likelihood of declines in the quality of their innovation output. I find similar results for future profitability. Treatment firms are about 12% and 10% more likely to experience declines in ROA (operating income/assets) and ROE (net income/shareholders equity) during the years following issuance than the control group.

To more directly examine the consequences for firm value, I compute the differential changes in industry-adjusted Tobin's Q between treatment and control firms for four years following issuance. The difference-in-differences estimates indicate a treatment effect of a 1.8% decline in industry-adjusted Q in the first year following issuance, which grows to an approximately 3-3.6% decline by year four. Combined with the results on innovation, this decline is consistent with Hall et al. (2005) who find that when a firm's quality of patents increase such that their average patent receives an additional citation, the firm's market value increases by 3%. Overall, these results show that there are real, long-term consequences as a result of incentives to look strong on credit rating criteria in the short term.

Finally, I examine how market participants interpret the issuers' changes in investment behavior around the thresholds. After confirming that crossing a salient threshold is associated with improvements in credit rating, I test whether the reductions in investment around the thresholds are penalized by the CRAs or bond investors by a lower likelihood of rating upgrade or higher at-issuance yields. I find no such evidence.

This paper contributes to several strands of literature. First, it relates to the literature that highlights the importance of credit ratings for firm financial policies. Kisgen (2006) shows that firms issue less debt when they are near a credit rating upgrade or downgrade. Hovakimian, Kayhan, and Titman (2009) and Kisgen (2009) show that firms' financial decisions are consistent with credit rating "targeting." While these papers show that credit ratings have a significant influence on capital structure decisions, my paper focuses on investment decisions. Moreover, this is the first paper to show that firms respond to credit rating *criteria* by distorting behavior on value-relevant dimensions, such as R&D investment, in efforts to look strong on the dimensions emphasized by the CRAs.

This paper also relates to the literature examining the nature of information and the tradeoffs that arise as the informational distance between contracting parties increases. With greater distance between borrower and lender, the incentives to produce soft information declines and lenders rely more on hard information (Stein, 2002; Petersen, 2004; Berger, Miller, Petersen, Rajan, and Stein, 2005).[3] The use of hard information facilitates arms-length transactions and can provide firms with greater access to capital (Faulkender and Petersen, 2006). However, as discussed earlier, Holmstrom and Milgrom (1991) show that high-powered contracts based on easily measurable outputs can have undesirable incentive effects. This issue frequently arises in the context of measuring educational outcomes with the concern that teachers may have incentives to "teach to the test."[4] In the context of this paper, the "contract" between the issuer and CRA puts weight on the hard information dimension of Debt/EBITDA and the issuer endogenously responds by focusing resources on improving this measure at the expense of investments in innovation and organizational capital, which are likely to have a large soft information component.

Finally, this paper also relates to the literature that explores potential adverse effects of increased information disclosure. Hirshleifer (1971) shows that more information can destroy ex-ante welfare-improving risk sharing opportunities and Dang, Gorton, and Holmstrom (2012) show that increased information production can hinder liquidity in money markets. Recent work on disclosure by Hermalin and Weisbach (2012) and Edmans et al. (2013) highlights some costs of providing more information to investors through increased disclosure. Hermalin and Weisbach (2012) show that increased disclosure can lead to greater agency problems in the form of myopic behavior; managers substitute away from long-term investments to boost short-term numbers (see also Stein, 1989). Edmans et al. (2013) present

[3]Rajan, Seru, and Vig (forthcoming) show that as the mortgage market transitioned from an originate-and-hold to originate-to-distribute model, loan originators relied more on hard information such as FICO score and loan-to-value ratios for setting interest rates on loans. Liberti and Mian (2009) show that within a large bank, the sensitivity of loan terms to hard, objective information is greater as the hierarchical distance between the loan officer and the ultimate decision maker increases.

[4]Jacob (2005) shows that teachers in the Chicago Public Schools strategically responded to high-stakes testing by shifting more students into special education, preemptively retaining students and reallocating focus from low-stakes subjects (science and social studies) to high stakes subject (math and reading). Neal (2011) provides a helpful review of this literature.

a theoretical model that shows that an increase in disclosure can produce incentives for managers to improve hard information at the expense of investment. My paper complements these theoretical papers by providing empirical evidence that pressures to appear strong on clearly-delineated rating criteria can lead to investment distortions and to long-run underperformance.

I organize the rest of the paper as follows. Section 2 outlines the empirical strategy and Section 3 describes the sample. Section 4 presents the main results. Section 5 presents additional tests and robustness checks and Section 6 concludes.

2 Research Design and Identification Strategy

Credit ratings represent an opinion of debt issuers' ability and willingness to repay debt. This information about relative creditworthiness plays an important role in allocating capital to firms in the economy. Credit ratings are a key factor for firms' cost of debt capital because of the informational content they supply to investors (Kliger and Sarig, 2000; Jorion, Liu, and Shi, 2005; Tang, 2009) and supply-side frictions induced by ratings-based regulations (Kisgen and Strahan, 2010; Ellul, Jotikasthira, and Lundblad, 2011; Chernenko and Sunderam, 2012; Becker and Ivashina, 2013). In addition to their direct impact on the cost and supply of debt for firms in the bond market, benefits of a higher credit rating include better trade credit terms (Klapper, Laeven, and Rajan, 2012), better access to commercial paper markets, overall financial flexibility, and reputational benefits, to name a few. Further, Jorion et al. (2005) show that stock prices have a positive response to ratings upgrades and negative response to downgrades with the effect particularly strong for downgrades (see also Hand, Holthausen, and Leftwich, 1992; Dichev and Piotroski, 2001). In light of all this, it is not surprising that credit ratings are one of the most important factors affecting firms' financial policies and are a key point of focus for managers (Graham and Harvey, 2001).[5]

[5]See Kisgen (2006) for an extensive discussion of the importance of credit ratings to firms.

In their role as information intermediaries, CRAs condense many different pieces of information into a simple, easy to communicate grade of creditworthiness. Providing a simple measure of debt serviceability and leverage, the Debt/EBITDA ratio is a prominent ratio that CRAs emphasize, and it is the focus in this paper's analysis. In response to this emphasis, firms have an incentive to appear strong on the Debt/EBITDA dimension to economize debt costs.

While there are a number of ways that firms can affect their Debt/EBITDA ratio, I focus on two investment decisions whose payoffs are long term in nature: R&D and SG&A.[6] Because they are fully expensed the period in which they occur, reducing these expenditures allows firms to report higher EBITDA and thus have a more favorable Debt/EBITDA ratio. Because these investments in intangible capital generate benefits that are uncertain and may take years to realize, managers may have an incentive to myopically reduce such expenditures to boost EBITDA even if they would be value-increasing in the long run (Narayanan, 1985; Stein, 1989). Graham et al. (2005) provide survey evidence that 80% of managers report they would decrease discretionary expenses such as R&D, advertising, and maintenance and 55% report that they would delay starting a new project – even if it involved sacrificing NPV – in efforts to meet financial targets. Also, by examining R&D expenditures, I am able to measure the consequences of changes in investment behavior by observing future patent performance.

To study the extent to which the incentive to look strong on CRA-emphasized dimensions affects investment, I focus on firms' behavior during periods when they are likely to care about their credit rating the most: prior to bond issuance. When firms recognize there is an upcoming financing need, they can assess where they stand in relation to the CRAs' rating criteria and respond by taking actions to improve that standing.[7] To empirically identify

[6] SG&A expenditures are often seen as investments in "organizational capital" (e.g., see Lev and Radhakrishnan, 2005; Eisfeldt and Papanikolaou, 2013) and include spending on items such as advertising, information technology, and employee training.

[7] If they wish to have assistance in this assessment, investment banks and consulting firms provide expert advice and institutional knowledge through their "ratings advisory" services.

the effects of the credit ratings process on investment, however, is challenging. Consider the following basic model:

$$Investment_{it} = f(X_{it}) + \psi(ratings\text{-}induced\ incentives_{it}) + \eta_{it}$$

Even after controlling for observable drivers of investment behavior (X_{it}) of firm i at time t, a näive analysis of changes in firm investment leading up to bond issuance is problematic because the effect of ratings-induced incentives is potentially confounded by multiple unobserved factors (i.e., $Cov(ratings\text{-}induced\ incentives_{it}, \eta_{it}) \neq 0$). For example, firms may reduce R&D expenditures simply because they are transitioning from development of a product to commercialization or may reduce SG&A expenditures because they have reached the end of a marketing campaign. To isolate the effect of ratings-induced investment distortions from these and other such factors that influence investment decisions, I exploit multiple discontinuities in the CRAs' mapping from Debt/EBITDA to credit rating which generate cross-sectional variation in incentives for firms to improve their Debt/EBITDA ratio.

CRAs provide specific information about the ranges of Debt/EBITDA that are consistent with different ratings. Table 1A presents an excerpt from S&P's published Corporate Rating Criteria that maps an issuer's Debt/EBITDA ratio to a set of credit ratings (Standard and Poor's, 2012). S&P states that their purpose in providing such guidelines is "to make explicit the rating outcomes that are typical for various business risk/financial risk combinations." Moody's and Fitch also place an emphasis on financial ratio thresholds in their published methodologies. Table 1B presents an example from the Moody's "Global Steel Industry" rating methodology, which shows what ranges of Debt/EBITDA are consistent with particular credit ratings for that industry.

– Table 1: Mapping Debt/EBITDA to Credit Ratings –

While these correspondences are not the sole determinant of the final credit rating,[8] Table 1B makes clear that it behooves steel firms wishing to get an "A" rating to achieve a Debt/EBITDA ratio below 2.0. Firms are keenly aware of the importance of these key financial ratios for their ratings and, in turn, the importance of their rating for their cost and access to capital.[9]

The key to the research design is the cross-sectional variation in firms' incentives to improve their Debt/EBITDA ratio that is induced by the presence of multiple salient Debt/EBITDA thresholds. Drawn from S&P's, Moody's, and Fitch's ratings methodologies and press releases, the salient bin thresholds in the sample are 1.25, 1.50, 2.0, 2.5, 3.0, 4.0, and 5.0.[10] Since the CRAs arbitrarily set these thresholds at round numbers, it is unlikely that the economic primitives that drive optimal investment policy systematically vary at precisely these points throughout the Debt/EBITDA spectrum. That is, for my identification strategy to fail, an omitted variable must drive the optimal R&D policy in this specific alternating sequence around each threshold. While all firms have an incentive to improve and appear strong on this dimension, firms on the cusp of advancing to a better bin face the highest expected marginal benefit from improvement in Debt/EBITDA. To the extent that improvement in the ratio is costly, these firms also face a lower cost since they have less distance to travel to cross a threshold relative to firms farther away.

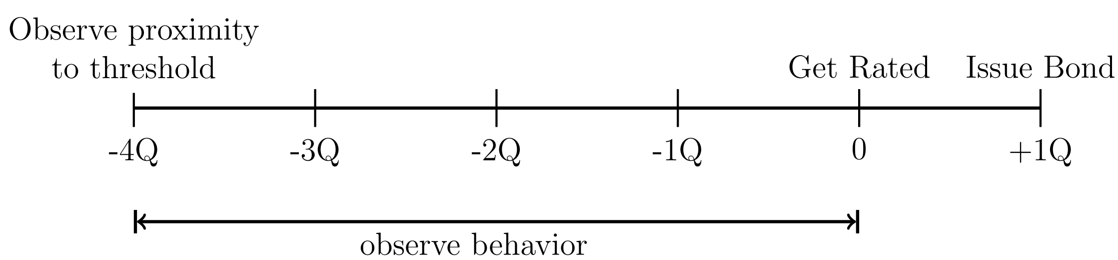
For the empirical tests, I define whether an issuer is in a High-Incentive Zone (*H-I Zone*) in the following simple way. Consider the threshold at Debt/EBITDA = 2.0. I consider the upper bound of the *H-I Zone* around the 2.0 threshold to be 40% of the distance between 2.0

[8]Fracassi, Petry, and Tate (2013) show that credit rating analysts' optimism or pessimism can affect ratings decisions. Griffin and Tang (2012) provide evidence of subjectivity in the ratings for CDOs and its consequences for rating accuracy.

[9]For example, in their 2006 annual report, Textron, Inc. states: "Our credit ratings are predominantly a function of our ability to generate operating cash flow and satisfy certain financial ratios. Since high-quality credit ratings provide us with access to a broad base of global investors at an attractive cost, we target a long-term A rating from the independent debt-rating agencies."

[10]There are some occasions when the rating agencies use guidance for thresholds other than the ones listed here. The presence of such lesser used thresholds in the sample may introduce noise into the estimation and partially mask the true effect.

and the next worse threshold of 2.5. This equals 2.2. To capture the incentives of those with only a slim margin between their current ratio and a worse bin, I consider the lower bound to be 10% of the distance between 2.0 and the next better threshold of 1.5. This equals 1.95. Thus, I consider firms with Debt/EBITDA $\in [1.95, 2.20]$ to be the *H-I Zone* around 2.0. I follow this method for each threshold in the sample based on firms' Debt/EBITDA ratio a year prior to issuance.[11] This timing captures the notion discussed earlier that firms typically recognize their financing needs in advance and then face incentives to take actions in the periods leading up to issuance to conform to the rating criteria. The figure below illustrates the basic timeline of the analysis.



For each firm, I compare the relevant investments during the year leading up to getting a new bond rated to its investments in the prior year. This first difference removes within-firm time invariant unobserved drivers of investment. The timing of this measurement also ensures that results are not driven by seasonality in firm policies. Next, I take the difference between the behavior of the treatment group (those near one of the salient thresholds) and the control group to compute the average treatment effect. Similarly, I use measures of firms' profitability, innovation output, and Tobin's Q a year prior to getting rated as benchmarks for comparison when I investigate the future performance of the firms. The table below summarizes the empirical design for firm policy Y.

[11] The results are robust to reasonable adjustments to this bandwidth scheme.

	$t-4$	t	Difference
Near Threshold (*H-I Zone*=1)	$Y_{t-4}^{treatment}$	$Y_{t}^{treatment}$	$\Delta^{treatment}$
Not Near Threshold (*H-I Zone*=0)	$Y_{t-4}^{control}$	$Y_{t}^{control}$	$\Delta^{control}$
	Average Treatment Effect:		$\Delta^{treatment} - \Delta^{control}$

In addition to the average treatment effects I estimate using the classification approach described above, I also perform tests that exploit finer variation in incentives using a continuous measure of the issuer's proximity to salient thresholds. Specifically, I estimate the likelihood of reducing investment as a function of the distance between the firm's Debt/EBITDA a year prior to getting rated and the next better threshold (for example, 0.15 for a firm with Debt/EBITDA = 2.15, 2.65, 3.15, etc.).

3 Data and Preliminary Tests

3.1 Sample Construction

Firm accounting and stock return data are from Compustat and CRSP. Bond issuance data are from the fixed income securities database (FISD). I merge these data to form a quarterly sample from 1990-2009. Where a firm has multiple financing observations in a single quarter (for example, a firm may issue bonds of various tenors on the same day), I combine them to a single observation by summing the issuance amounts and computing a dollar-weighted average yield.

Patent data are from the National Bureau of Economic Research (NBER) Patent Citation database.[12] This data source contains information on the owner, patent application date, patent grant date, and citation count of over three million patents granted by the United States Patent Trademark Office from 1976-2006 along with matching tables that

[12] See https://sites.google.com/site/patentdataproject/

facilitate merging these data with Compustat. I use two common measures of firm innovation: patent count and citation count. Patent count is the raw number of a firm's patent applications during a given year that are eventually granted. Raw counts, however, do not provide any differentiation in whether the innovations are marginal or new breakthroughs. Trajtenberg (1990) argues that "patents vary enormously in their importance or value, and hence, simple patent counts cannot be informative about innovative output" and proposes citation-weighted patent counts are a better measure of innovation. I correct for bias in this measure due to citation count truncation after 2006 by using the weight factors developed by Hall, Jaffe, and Trajtenberg (2001), who use an obsolesce-diffusion model to estimate future citations based on the patent's year and technology category.

After dropping financial firms, utilities, and observations that are not related to a bond issuance, the main sample contains 1770 observations from 686 firms. The sample size for tests using R&D have fewer observations because many firms do not report R&D expenditures. Tests involving patent productivity have fewer observations because the patent database ends in 2006. I use the maximum number of observations with complete data for each test, but my results are not substantively different if I constrain all tests to observations with complete data across all variables.

I winsorize all variables at 1% to mitigate the effects of outliers. Table A.1 in the appendix provides the details of the construction of variables. Table 2 presents sample summary statistics and Figure 1 presents the distribution of the sample along Debt/EBITDA a year prior to issuance, highlighting the *H-I Zones* near salient thresholds.

– Table 2: Sample Summary Statistics –

– Figure 1: Sample Debt/EBITDA and H-I Zones –

3.2 Comparability of Treatment and Control Groups

Before presenting the main tests, I examine the comparability of the issuers in *H-I Zones* with those that are not. To make meaningful inferences, it is important that issuers in *H-I Zones* (treatment) are observationally similar to those that are not (control) on dimensions that drive investment independent of the incentive effects. To evaluate the comparability, Figure 2 presents kernel densities of several such factors for both groups. The plots show that the sample is well balanced along firm characteristics that represent factors such as firm life cycle (size), financial flexibility and potential debt overhang (debt-to-asset ratio), growth opportunities (Tobin's Q), and ability to generate internal cash flows (cash flow-to-assets); it is also balanced in terms of profitability as measured by ROA (operating income/assets) and ROE (net income/shareholder equity). In unreported results, t-tests fail to reject the null of the equality of means and Kolmogorov-Smirnov tests fail to reject the null of equality of distributions for these characteristics across the two groups.

– Figure 2: Issuer Characteristic Kernel Densities –

4 Results

Firms near salient Debt/EBITDA thresholds face a higher expected marginal benefit from improving on this dimension (i.e., reducing the ratio) because crossing a threshold increases the likelihood of getting a credit rating upgrade.[13] Improving this likelihood gives managers incentives to take actions to increase EBITDA and/or decrease debt. In this section, I exploit the presence of multiple salient Debt/EBITDA thresholds to identify the effect of credit rating criteria on firms' R&D and SG&A investment policies and their subsequent

[13] In later tests, I explicitly show that crossing a salient threshold leads to an average rating upgrade of approximately one-fourth of a rating (see Table 9).

performance.

4.1 The Effect of Rating Criteria on Investment

Figure 3 is a graphical depiction of the main results. It plots the probability that a firm reduces their R&D investment as a function of their Debt/EBITDA ratio one year prior to getting rated. I group firms based on their proximity to the salient thresholds (*H-I Zones* as outlined in Section 2) and plot the mean probability of reducing investment within that group. The alternating nature of the plot highlights the differential behavior of firms that are near salient thresholds from those that are not. For example, about 56% of issuers near the 2.0 threshold reduce their R&D expenditures during the year prior to getting rated, while about 40% and 47% in the adjacent comparison groups not near the threshold (for example, Debt/EBITDA $\approx$ 1.9 and 2.3) do so. This pattern emerges around each salient threshold throughout the Debt/EBITDA spectrum. The pattern for SG&A is similar, though the magnitude of the differences is smaller (not shown).

– Figure 3: Investment Policies along Debt/EBITDA –

Table 3 aggregates the treatment group (*H-I Zone* issuers) and control group and reports the average probability of reducing their R&D or SG&A investment. The first column indicates that roughly half of the firms in the full sample reduce each type of investment in the year leading up to getting rated. The next two columns highlight the difference in investment behavior between those firms near a salient threshold and those that are not. About 64% of *H-I Zone* firms reduced R&D investment as compared to 45% of control firms. The corresponding figures for reducing SG&A are about 56% for *H-I Zone* firms compared to 51% for the controls. The results indicate that issuers in an *H-I Zone*, which face the higher expected marginal benefit of improving their Debt/EBITDA ratio, are about 42% (19 percentage points) more likely to reduce R&D and about 10% (5 percentage points) more likely to reduce SG&A expenditures in the year prior to issuance.

– Table 3: Cut Investment – Mean Differences –

To ensure that any residual differences in the two groups along observable dimensions or time-specific factors are not driving the differences in investment decisions, I estimate the following model.

$$\mathbb{1}\{Cut\ [R\&D, SG\&A]_{i,t\rightarrow t+4}\} = \alpha + \rho(H\text{-}I\ Zone)_{it} + \sum \beta X_{it} + q_t + \epsilon_{it} \tag{1}$$

I regress an indicator of whether the issuer cuts investment (R&D, then SG&A) on the issuer's proximity to a salient threshold. I use an indicator of investment reduction for the main specifications because the magnitude of the reduction is likely a function of the distance to the threshold. Firms closest to the threshold have the strongest incentives to alter their behavior, but have to reduce investment by a smaller amount to achieve their goal. Thus, an indicator variable more sharply captures the change in behavior. I also include a vector of firm characteristics (X_{it}) to control for other potential firm-level drivers of investment and year-quarter fixed effects (q_t) to capture any economy-wide fluctuations that could drive investment decisions. I also include specifications with industry fixed effects to ensure that some unobserved industry factor that is correlated with both firms' pre-issuance investments and their proximity to a salient threshold is not driving the results. I estimate regression equation (1) using a linear probability model[14] and cluster all standard errors at the firm

[14] I present results from estimations using a linear probability model because it does not suffer from the incidental parameters problem in models with fixed effects (conditional logit models rely on stronger assumptions for consistency; see, e.g., Wooldridge (2002)), its parameter estimates are consistent in the face of various forms of heteroskedasticity, and the ease of interpretations of the partial effect estimates. The results are similar using a logistic regression model.

level.[15] Table 4 presents the results.

– Table 4: Cutting Investment Baseline –

The coefficient estimates on *H-I Zone* mirror the results of the simple group mean analysis presented in Table 3. Issuers near a salient Debt/EBITDA threshold one year prior to issuance are about 19 percentage points more likely to reduce their R&D expenditures (Columns 1-2) and 6 percentage points more likely to reduce SG&A (Columns 3-4). The striking similarity of the point estimates from the regression analysis in Table 4 to the simple differences presented in Table 3 supports the notion that the intermittent nature of salient thresholds creates a balanced comparison between firms receiving the high-incentive treatment and the control firms.

The results above highlight the average treatment effect of receiving the high-incentive treatment. The following test exploits heterogeneity in the strength of the treatment by modeling the decision to reduce investment as a function of the issuing firm's distance to the next better Debt/EBITDA threshold. Issuers closest to a salient threshold face the highest expected marginal benefit of an improvement and also the lowest cost because only a relatively small movement is necessary to improve bins. Thus the likelihood of reducing investment should be a decreasing function of distance to the next highest threshold. To test this notion, I estimate the following specification, where *dist* is the distance to the next highest bin (likewise measured a year prior to getting a bond rated) and *dist2* is its square. Columns (1)-(2) in Table 5 present the results.

[15] I find similar results when computing White standard errors or clustering by firm, time, or industry. The relative invariance of the standard error estimates across differing clustering structures indicates that any autocorrelation in the right-hand side variables and/or residuals is likely very small and that there is not a meaningful time-specific correlation effect after controlling for year-quarter fixed effects.

$$\mathbb{1}\{Cut\ Inv_{i,t\rightarrow t+4}\} = \alpha + \delta(dist)_{it} + \gamma(dist2)_{it} + \sum \beta X_{it} + q_t + \epsilon_{it} \quad (2)$$

– Table 5: Cutting Investment – Continuous Measures –

These results indicate that issuers closest to a threshold and thus have the highest incentives to take actions to improve their ratio are most likely to respond by reducing investment. Figure 4 uses the coefficient estimates to plot the change in probability of investment reduction. Similar to the baseline results above, the results are stronger for R&D investments.

– Figure 4: ΔProb(Cut investment) as a continuous function of distance to a threshold –

The next tests examine a continuous measure of changes in investment rather than a discrete outcome of whether firms cuts their investments. Specifically, I re-estimate the baseline regression specification (1) using the percent change in investment policy as the dependent variable. Columns (3)-(4) of Table 5 present the results. The point estimates on *H-I Zone* indicate that the average firm receiving the high-incentive treatment reduces its investments in R&D and SG&A by about 10% and 3%, respectively. For the median firm with Debt/EBITDA $\in [1.25, 1.50]$, this degree of investment reduction, ceteris paribus, translates to an approximate Debt/EBITDA ratio improvement of 0.07. The effect progressively increases with each Debt/EBITDA bin, with the median firm with Debt/EBITDA $\in [4.0, 5.0]$ achieving an improvement of approximately 0.17.

4.2 The Effect When Credit Spreads Are High

The incentives to cross thresholds should be stronger when firms' benefit of improving their credit rating is higher. The economic benefit from an increase in credit rating is greater when the sensitivity of yield spreads to credit quality is high. That is, in high-credit-spread times, the expected benefit of crossing a salient threshold is higher than in low-credit-spread times, and the effects documented above should be stronger. To test this hypothesis, I include in the baseline regression specification an interaction of *H-I Zone* with an indicator, *High Spread*, that equals one when the Baa-Aaa yield spread exceeds the sample period median.

$$\mathbb{1}\{Cut\ Inv_{i,t\rightarrow t+4}\} = \alpha + \rho(H\text{-}I\ Zone)_{it} + \psi(H\text{-}I\ Zone)_{it} \times (High\ Spread)_t + \sum \beta X_{it} + q_t + \epsilon_{it} \quad (3)$$

While there are other differences in the economy that could lead to differential firm investment policies between these two regimes (for example, lower credit spreads could indicate more favorable investment opportunities), the level of such effects will be absorbed by the year-quarter fixed effects–the identifying variation is still in the cross section. Along with the level effects of other macroeconomic shocks, year-quarter fixed effects absorb any level effects of the credit spread on issuers' investment decisions. Table 6 presents the results with Columns (1) and (3) presenting the baseline results from earlier for comparison.

– Table 6: Cutting Investment – High Credit Spread –

For both R&D and SG&A, the point estimate on the interaction of *H-I Zone* and *High Spread* indicates that issuers near salient thresholds are even more likely to respond to incentives to reduce these investments when the economic benefit of a better rating is the higher. Compared to issuers not near a salient threshold a year prior to issuance, issuers in the *H-I Zones* are about 24 percentage points more likely to reduce R&D expenditures and 11 percentage points more likely to reduce SG&A expenditures.

Overall, these results show that issuers with higher incentives to improve their appearance on the CRA-emphasized dimension of Debt/EBITDA ratio are substantially more likely to reduce spending on real investment activities as a means to that end. Further, the likelihood of this response is stronger when the yield spreads between ratings is large and the economic benefit from crossing a salient threshold is greater.

4.3 Future Innovation and Profitability

The evidence thus far documents differential changes in investments for firms near salient Debt/EBITDA thresholds as compared to observationally similar control firms. This section investigates whether these firms experience subsequent declines in innovation and profitability. I use the issuer's performance as of one year prior to issuance as the baseline for comparison and construct an indicator variable equal to one when the firm's performance τ years after bond issuance experiences a decline relative to their benchmark and estimate the following specification.

$$\mathbb{1}\{Perf_{i,t+\tau} < Perf_{i,t-1}\} = \alpha + \rho(H\text{-}I\ Zone)_{i,t-1} + \sum \beta X_{i,t-1} + q_t + \epsilon_{it} \tag{4}$$

Investment in innovation is an important driver of long-run firm value, but its intangible and long-term nature make it particularly vulnerable to short-term cost cutting. The next tests use future patent productivity to measure the consequences of these reductions for innovation output. I use a per annum raw count of new patents and the patent citation counts over the two years prior to bond issuance as a benchmark for the firm's innovation output. To capture the long-run nature of investment on innovation, I follow the literature (see, e.g., Cornaggia, Mao, Tian, and Wolfe, 2013; Seru, 2013) and examine the average innovation output over τ years following the event of interest (bond issuance). Panels A and B of Table 7 present the results.[16]

– Table 7: Future Declines in Innovation and Profitability –

While the sign of the estimated coefficients on *H-I Zone* in Panel A suggest that these firms are more likely to produce less patents in the future, the point estimate is statistically different from zero only in the first year following bond issuance. This result indicates that firms in the *H-I Zone* do see declines in the raw quantity of patents produced, but the effects are relatively short-lived. Panel B presents estimates considering patent citations, which is widely considered a sharper measure of the quality and impact of innovation. These estimates provide evidence that *H-I Zone* issuers are more likely to experience a persistent future decline in innovation. With about 20% of the sample experiencing declines in this measure, the point estimate of about 0.05 indicates that these firms are roughly 25% more likely to see innovation declines that observationally similar firms not near a salient threshold. Together with the results of the tests of raw counts, this suggests though there is not a large decrease in the quantity of patents produced, firms with stronger incentives for improvement in Debt/EBITDA in the short run have a considerably higher likelihood of declines in the quality of their innovation output.

I next examine future operating performance and profitability. To measure operating performance, I use operating income scaled by assets (ROA) as suggested by Barber and Lyon (1996). This ratio measures the productivity of the firm's assets excluding items such

[16]As is typically the case in exercise such as this, the number of observations drop as the time horizon under examination increases.

as interest expense, special items, income taxes, and minority interest. Panel C in Table 7 presents the results. The coefficient estimates on *H-I Zone* indicate that issuers near salient Debt/EBITDA thresholds one year prior to issuance are about 5 percentage points (10%, based on the sample mean of about 0.50) more likely to experience persistent future declines in ROA compared to observationally similar issuers that are not.

In Panel D, I consider return on equity (ROE) to focus on future performance from the perspective of shareholders. Computed as the ratio of net income to shareholder equity, this ratio measures how much profit the firm generates with the money shareholders have invested. The estimates indicate that *H-I Zone* firms are more likely to have lower ROE for three years following bond issuance.

4.4 Future Tobin's Q

The above results highlight some important long-term consequences in terms of depressed innovation and profitability. To more directly assess the firm value implications, I extend the above analysis to examine future changes in industry-adjusted Tobin's Q (Q^{IA}) for *H-I Zone* firms compared to the control firms not near a salient threshold. I compute Q_i^{IA} by subtracting the SIC 2-digit industry median $Q_t^{Industry}$ from firm Q_{it}. Since the sample is well balanced between the treatment and control firms, I begin by computing a simple difference-in-difference estimate. Panel A of Table 8 presents the results.

– Table 8: Future Tobin's Q –

The first column shows both the treatment and control firms have $Q^{IA} = 0.19$. Each following column computes $\Delta Q^{IA} = Q_{t+\tau}^{IA} - Q_t^{IA}$ for each group for four years following issuance. The difference-in-differences estimates indicate that *H-I Zone* firms have lower Q^{IA} in the years following issuance as compared to observationally similar control firms. While the control firms experience a modest increase in Q^{IA}, the differential performance between the groups is driven more by the falling Q^{IA} of the treatment firms. Based on a sample mean of 1.64, the treatment effect of 0.03 to 0.06 in post-issuance years 1 to 4 translates to a 1.8-3.6% decline in Tobin's Q, though the estimate for year 3 is not statistically significant.

I next turn to regression analysis to make sure that any residual differences between the two groups on observable dimensions or time effects are not driving the results. I estimate the following specification:

$$Q^{IA}_{i,t+\tau} = \alpha + \rho(\textit{H-I Zone})_{it} + \sum \beta X_{it} + q_t + \epsilon_{it} \tag{5}$$

Panel B of Table 8 presents the results. The regression estimates present a similar picture to the differences computed in Panel A; *H-I Zone* firms experience a decline in Tobin's Q of about 0.03 to 0.05 relative to control firms.

In sum, reducing investment in R&D and SG&A provides the benefit of an improved Debt/EBITDA in the short term, but it ultimately comes at the cost of reduced innovation, profitability, and long-run value. The results in this section support my main claim that firms respond to credit rating criteria by shifting resources away from value-relevant dimensions to appear strong on the dimensions emphasized by CRAs.

5 Additional Tests

In this section, I examine how credit ratings and at-issuance bond yields respond to the changes in investment behavior documented above. I then examine the effects of rating criteria on investment for bond issuances that are most likely to be planned in advance. Finally, I show that the results are not an artifact of firms cutting investment in response to covenant violations.

5.1 The Market Response to Changes in Investment Behavior

To test whether crossing a Debt/EBITDA threshold is associated with better ratings, I regress changes in credit ratings between one year prior to getting rated and the bond issuance on changes in firm characteristics that are important drivers of default risk (e.g., see Shumway, 2001) and changes in Debt/EBITDA ratio.

$$\Delta Rating_{i,t\rightarrow t+5} = \alpha + \phi(Improve\ bin)_{i,t\rightarrow t+4} + \sum \beta \Delta X_{i,t\rightarrow t+4} + \epsilon_{i,t}$$

The variable of interest is a dummy variable (*Improve bin*) equal to one when the firm has crossed a salient Debt/EBITDA threshold. The coefficient estimate on this variable indicates the additional boost in credit rating a firm receives from crossing a salient threshold above and beyond the general effect of reducing Debt/EBITDA. For example, this estimates the benefit an issuer gets from decreasing Debt/EBITDA from 2.05 to 1.95 (crossing 2.0) above and beyond the effect of an improvement of Debt/EBITDA from 1.9 to 1.8 or 2.2 to 2.1. Columns (1-2) in Table 9 present the results.[17]

– Table 9: Crossing Thresholds and Credit Ratings –

Column (1) presents the results without including the threshold-crossing indicator. Consistent with previous literature, firms with higher stock returns, increases in profitability, and decreases in leverage are more likely to be upgraded. Consistent with intuition, decreases in Debt/EBITDA are also positively related to credit rating upgrades. Column (2) presents the full specification. The coefficient estimate on *Improve bin* of 0.26 indicates that crossing

[17] These estimations require the issuer have an S&P rating five months prior to issuance, which leads to a roughly 12% reduction in sample size.

a salient threshold is associated with a upgrade of about one-fourth of a rating. While it is sufficient that managers believe that improving Debt/EBITDA bin is associated with better ratings, these results show that firms benefit from crossing a salient threshold.

If the CRAs observe that a firm advances to a better Debt/EBITDA bin, but view the behavior that facilitated the move as a poor signal of creditworthiness, then the ratings may not react to the firm crossing a salient threshold. To test this supposition, I regress the changes in credit rating in the periods leading up to bond issuance on fundamental drivers of credit ratings, a variable that indicates an improvement in Debt/EBITDA bin (Improve bin), an indicator of whether the firm cut investment (Cut Inv), and the interaction of the latter two terms in the following specification.

$$\Delta Rating = \alpha + \phi(Improve\ bin) + \rho(Cut\ Inv) + \theta(Improve\ bin \times Cut\ Inv) + \Gamma\Delta X + \epsilon \tag{6}$$

Columns (3-4) of Table 9 present the results. For both R&D and SG&A, firms that are reduce their level of investments are less likely to receive an upgrade. However, the point estimates on the interaction terms ($\hat{\theta}$) indicate the firms that cut investments and crossed a salient threshold were not assigned significantly different ratings than those that cut investments but did not cross a salient threshold. Next, I examine whether at-issuance bond yields respond to this behavior.

If bond market participants observe this behavior and view it as a negative signal, they will demand a higher yield on the bonds. To test this hypothesis, I regress the bond yield at issuance on variables that reflect credit risk including dummy variables for each rating class, Debt/EBITDA bin, and year-quarter fixed effects. Similar to the spirit of the previous test, I include an indicator of whether the firm recently improved their Debt/EBITDA bin, whether the firm recently cut investment, and the interaction of these two variables. If bond buyers identify and penalize this behavior, the point estimate on the interaction term will be positive to indicate a higher demanded yield. Table 10 presents the results.[18]

– Table 10: Crossing Thresholds and Yields –

The point estimates on the interaction terms are not statistically different from zero. These results indicate that firms that cut investment and cross a salient threshold do not receive significantly different yield on their bonds at offering beyond the effects the actions may have on credit rating. Overall, the lack of price response is consistent with the notion that investors rely on credit ratings and that changes in investment policies are not unambiguously interpreted by the bond market. These findings are consistent with those of Cohen, Diether, and Malloy (2013), who provide evidence that stock market investors do not differentiate between high quality and low quality R&D investment.

5.2 Subsample Analysis and Robustness

Refinancing Bonds

An underlying assumption of the tests in the paper is that management knows in advance that there is a financing need. In anticipation of bond issuance, management has some time to take actions to conform to the standards of the CRAs. While issuing a bond is a major financial event for most firms and is typically planned well in advance, there are also cases when firms may issue bonds very quickly to fund, for example, a strategic acquisition. If such an opportunity arises unexpectedly, a firm does not have time to take actions to improve their appearance and simply issues the bond in their current state. The presence of such observations in the data adds noise to the estimations and could mask the true effect. The following test focuses on a subset of observations where management is more likely to be

[18]Some observations are dropped because of missing yield data.

planning the issuance in advance. Specifically, I focus on debt issuances that are more likely to be refinancing transactions by computing a ratio of the amount of debt in current liabilities (debt due within a year) the quarter before issuance to the eventual bond issuance amount. Because of the relatively large amount of debt due soon, firms with a higher ratio are more likely to be planning in advance of their financing need. Table 11A presents the results of the base specification for the subset of observation where $\frac{debt\ in\ current\ liabilities_{t-1Q}}{bond\ amount_t} \geq 1$.

– Table 11: Refinancing Bonds & Covenant Violations –

For this subsample of observations, the point estimates of the coefficient on *H-I Zone* is greater than the estimates from the base specification for each investment category. This finding supports the notion that firms that foresee an approaching financing need are more likely to take actions to strengthen their appearance leading up to getting a bond rated.

Covenant Violations

In addition to being a key metric of creditworthiness in the eyes of CRAs, the Debt/EBITDA ratio is also used in financial covenants in bank loan contracts. When borrowers violate loan covenants, they are in technical default and creditors then have the right to accelerate the loan. This gives creditors a great deal of influence on the actions of the firm during renegotiation. Chava and Roberts (2008) show that capital expenditures decline following violations of financial covenants. In light of their results, a possible concern may be that firms near salient thresholds happen to be firms that have recently violated covenants and the findings in this paper are an artifact of the effects of covenant violations on investment. To rule out this possibility, I augment my dataset with covenant violation data generously provided by Nini, Smith, and Sufi (2012). Their data record whether a firm is in violation of a financial covenant violation data during a given quarter for Compustat non-financial firms from 1996-2009. Because the data begin in 1996 and my sample begins in 1990, these tests have fewer observations than the baseline results.

For each investment variable, I estimate two specifications to examine whether covenant violations drive the findings and present the results in Panel B of Table 11. First, I estimate the base regression specification (1) including an indicator variable, *Cov Violation*, equal to one if the issuer breaches a covenant during the periods leading up to getting rated (columns 1 and 3). Second, I estimate the base specification excluding the observations for which *Cov Violation* equals one (columns 2 and 4).

The coefficient estimate for *Cov Violation* is positive for each investment type indicating that firms in violation of a covenant are more likely to reduce R&D and SG&A investments, but the estimates are not statistically significant. Turning to the coefficient of interest in this paper, the size and statistical significance for coefficient estimates for *H-I Zone* are virtually unaffected by covenant violation considerations.

6 Conclusion

Credit ratings have emerged as a key mechanism to bridge the fundamental information asymmetry problem between firms and investors. Ratings give better access to debt markets for firms, expand the universe of investment opportunities for investors, and are deeply interwoven into financial regulation. Because credit ratings are an important factor in firms' level of access to and cost of debt capital, firms have incentives to take potentially costly actions to improve their rating.

I use an institutional feature of the credit rating process that generates cross-sectional variation in the incentives of firms to improve on a specific dimension that CRAs emphasize: Debt/EBITDA ratio. I show that firms that are near salient Debt/EBITDA thresholds–effectively receiving a high-incentive "treatment" to improve on this dimension–respond by reducing R&D and SG&A investments in the periods leading up to getting a bond rated. Further, I show that these firms are more likely to experience declines in innovation output, profitability, and firm value as measured by Tobin's Q in the years following bond issuance than observationally similar control firms. These results highlight an important cost of arms-length financing and suggest that the benefits of policies requiring increased transparency and disclosure of credit rating criteria should be carefully balanced against the corporate behavioral distortions they may induce.[19]

[19]See the "Credit Rating Agency Reform Act of 2006" and Title XI, Subtitle C – Improvements to the Regulation of Credit Rating Agencies of the "Dodd-Frank Wall Street Reform and Consumer Protection Act."

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Table A.1: Variable Definitions
This table identifies the data sources and describes the construction of variables used in the analysis. Company financial data are from Compustat, returns are from CRSP, and bond data are from the fixed income securities database (FISD). For firm financial data, quarterly data are used if the firm reports at that frequency.

Variable	**Definition**
Assets	Total assets [atq].
Leverage	Total debt [dlcq + dlttq] / assets [atq].
Tobin's Q	(Assets [atq] + market value of equity [prccq * cshoq] - common equity [ceqq] - deferred taxes [txditcq]) / assets [atq].
Debt/EBITDA	Total debt [dlcq + dlttq] / trailing four quarters EBITDA [oibdpq].
Return on Assets	Trailing four quarters of EBITDA [oibdpq] / lagged assets [atq].
Return on Equity	Trailing four quarters net income [niq] / lagged common equity [ceqq]
Cash flow	Trailing four quarters of income plus depreciation [ibq + dpq] / lagged assets [atq].
R&D	Research and development expenditures [xrd] / lagged total assets [atq].
SG&A	Selling, general, and administrative expenditures [xsga] / lagged total assets [atq].
Stock Return	Equity stock return over the past year.
Bond Yield	Yield to maturity of the bond at issuance. When multiple bonds are issued in the same quarter, this is computed as the dollar-weighted yield of the issuances.
Bond Amount	Amount of issuance in millions. When multiple bonds are issued in the same quarter, this is computed as the sum issuances.

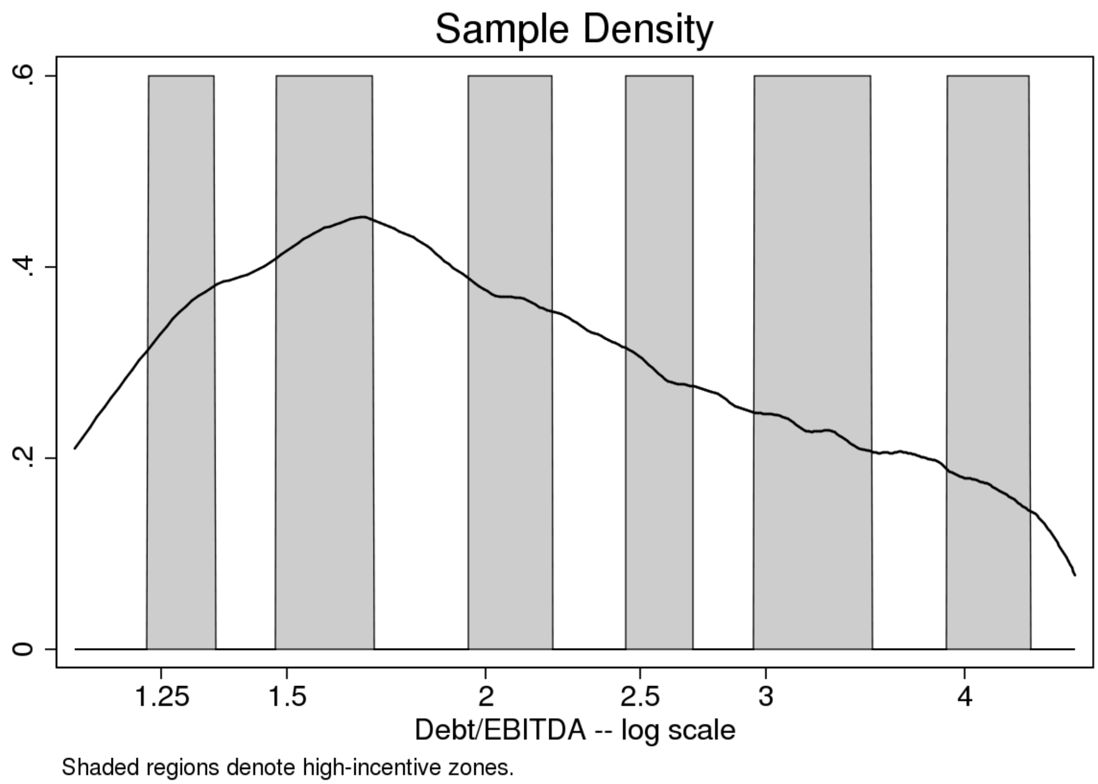

Figure 1: The Distribution of Debt/EBITDA One Year Prior to Getting Rated
This figure presents a kernel density of the sample Debt/EBITDA ratio one year prior to getting rated. The shaded areas indicate regions where issuers are approaching a salient Debt/EBITDA threshold and thus have a high incentive to improve along this dimension, as described in Section 2. In the empirical tests, I refer to the shaded regions as high-incentive zones (*H-I Zones*).

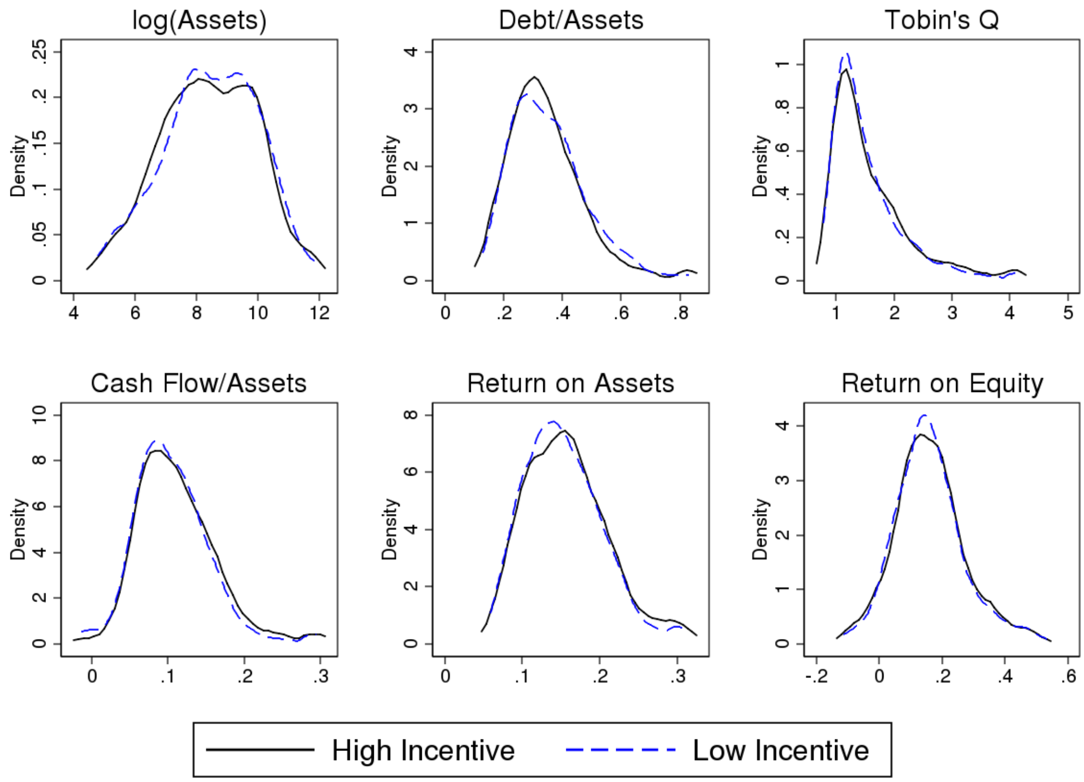

Figure 2: Issuer Characteristics by Whether the Firm Is in the High-Incentive Zone
This figure presents kernel densities of the sample separately for those near salient Debt/EBITDA thresholds (*H-I Zone*=1) and those that are not. Table A.1 in the Appendix outlines the construction of the variables.

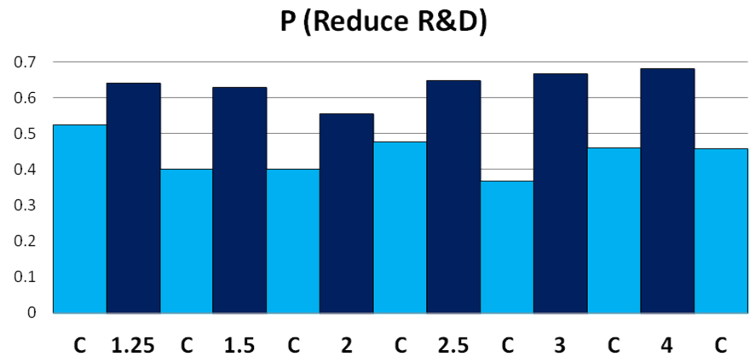

Figure 3: Proximity to a Salient Debt/EBITDA Threshold and Subsequent R&D Investment
This figure presents the mean issuer's decision to reduce R&D investment policies during the year leading up to getting a bond rated, based on issuer's proximity to a salient Debt/EBITDA threshold one year prior to getting rated. Each bin illustrates the mean of the binary behavior response of the issuers in that bin with regard to reducing investment (corresponding to a value of one) or not reducing investment (corresponding to a value of zero). The darker bins represent issuers near a salient threshold (e.g., 2.0, 2.5, etc.), which I refer to as high-incentive zones (*H-I Zones*) throughout the paper, and the lighter bins represent issuers who are not (denoted in the figure with a "C" to represent *Control*).

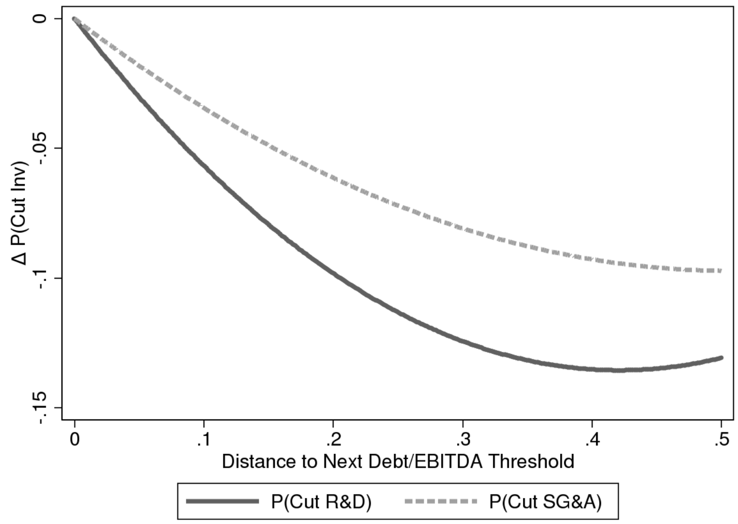

Figure 4: Likelihood of Cutting Investment as a Function of Distance to a Threshold
This figure presents the plot of the change in likelihood of cutting R&D and SG&A investment policies as a function of the issuer's distance to a salient Debt/EBITDA threshold a year prior to getting a bond rated as estimated in Table 5. For example, 0.1 on the x-axis represents firms with Debt/EBITDA = (2.0 + 0.1=) 2.1, 2.6, 3.1, etc.

Table 1: Business and Financial Risk Profile Matrix

This table presents excerpts from the credit ratings methodologies published by major credit rating agencies. Panel A presents Standard & Poor's Corporate Credit Rating Methodology Business Risk/Financial Risk Profile Matrix (Standard and Poor's, 2012) and Panel B presents the Debt/EBITDA to credit rating mapping for the global steel industry by Moody's (Moody's Investor Service, 2012).

Panel A: Standard & Poor's Business Risk/Financial Risk Matrix

	Financial Risk Profile					
	Minimal	Modest	Intermediate	Significant	Aggressive	Highly Leveraged
Debt/EBITDA	< 1.5	1.5-2.0	2.0-3.0	3.0-4.0	4.0-5.0	> 5.0
Business Risk Profile						
Excellent	AAA/AA+	AA	A	A-	BBB	–
Strong	AA	A	A-	BBB	BB	BB-
Satisfactory	A-	BBB+	BBB	BB+	BB-	B+
Fair	–	BBB-	BB+	BB	BB-	B
Weak	–	–	BB	BB-	B+	B-
Vulnerable	–	–	–	B+	B	B- or below

Panel B: Moody's Example Rating Grid from the Global Steel Industry Methodology

Debt/EBITDA	<0.75	0.75-1.25	1.25-2.0	2.0-3.0	3.0-4.0	4.0-5.5	5.5-7.5	>7.5
Rating	Aaa	Aa	A	Baa	Ba	B	Caa	Ca

Table 2: Sample Summary Statistics
This table presents summary statistics for the sample. All variables are winsorized at 1% prior to regression analysis. Table A.1 in the Appendix outlines the construction of the control variables.

	mean	sd	p25	p50	p75	count
Debt/EBITDA	2.47	1.08	1.59	2.24	3.22	1770
log(Assets)	8.32	1.62	7.19	8.31	9.54	1770
Book Leverage	0.35	0.14	0.25	0.33	0.42	1770
Tobin's Q	1.64	0.72	1.15	1.43	1.91	1770
Cash flow/Assets	0.11	0.06	0.08	0.11	0.14	1770
log(Firm Age)	3.39	0.66	2.94	3.61	3.89	1770
Return on Assets	0.16	0.06	0.12	0.16	0.19	1770
Return on Equity	0.18	0.43	0.08	0.16	0.24	1770
R&D/Assets	0.03	0.04	0.01	0.02	0.04	807
SG&A/Assets	0.22	0.20	0.08	0.16	0.29	1770

Table 3: Proximity to Salient Thresholds and Investment – Difference in Means
This table presents the percentage of firms that reduce R&D or SG&A investment policies during the year leading up to getting a bond rated. Column (1) presents overall sample means, Columns (2) and (3) present mean investment decisions for those not near a salient Debt/EBITDA threshold (*H-I Zone* = No) and those that are near a salient threshold (*H-I Zone* = Yes). Columns (4) and (5) present the difference in means for these two groups in percentage points (pps) and percent difference. *H-I Zone* is a dummy variable equal to one if the issuer is near a salient Debt/EBITDA threshold one year prior to getting a bond rated (see Section 2 for details).

	Overall	H-I Zone		Difference	
Investment	$\mathbb{P}$(Cut Investment)	No	Yes	pps	%
R&D	51.4%	44.9%	63.5%	18.6***	41.5%
SG&A	52.4%	50.5%	55.5%	5.0**	9.9%

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Proximity to Salient Thresholds and Investment

This table presents OLS estimates from regressions of an indicator of whether the firm reduces R&D (Columns (1)-(2)) or SG&A (Columns (3)-(4))investment during the year leading up to getting a bond rated on the issuer's proximity to a salient Debt/EBITDA threshold one year prior to getting a bond rated and firm characteristics. *H-I Zone* is a dummy variable equal to one if the issuer is near a salient Debt/EBITDA threshold one year prior to getting a bond rated (see Section 2 for details). Table A.1 in the Appendix outlines the construction of the control variables. Columns (2) and (4) include SIC 2 digit industry code dummies. All standard errors are clustered by issuer.

	Cut R&D		Cut SG&A	
	(1)	(2)	(3)	(4)
H-I Zone	0.184***	0.188***	0.055**	0.062**
	(0.00)	(0.00)	(0.03)	(0.02)
log(Assets)	-0.000	-0.007	0.015	0.009
	(0.98)	(0.69)	(0.21)	(0.49)
Tobin's Q	-0.028	-0.038	0.035*	0.022
	(0.45)	(0.33)	(0.09)	(0.32)
Cash flow	-0.842**	-0.871**	-0.029	0.002
	(0.05)	(0.04)	(0.89)	(0.99)
log(Debt/EBITDA)	-0.082	-0.136	0.030	0.027
	(0.35)	(0.12)	(0.55)	(0.62)
log(Firm Age)	0.067*	0.080**	-0.009	-0.031
	(0.07)	(0.05)	(0.69)	(0.24)
Industry FE	No	Yes	No	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	807	807	1770	1770
R^2	0.186	0.236	0.097	0.129

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Tests Using Continuous Variables

Columns (1)-(2) present OLS estimates from regressions of an indicator of whether the firm reduces R&D or SG&A during the year leading up to getting a bond rated on the issuer's proximity to a salient Debt/EBITDA threshold one year prior to getting a bond rated and firm characteristics. The dependent variables for columns (3)-(4) are the percent change in the relevant investment policy during the year leading up to getting a bond rated. *dist* equals the distance between the firm's Debt/EBITDA and the adjacent better threshold (e.g., for Debt/EBITDA = 2.1, *dist* = 0.1) and *dist2* is its square. *H-I Zone* is a dummy variable equal to one if the issuer is near a salient Debt/EBITDA threshold one year prior to getting a bond rated (see Section 2 for details). Table A.1 in the Appendix outlines the construction of the control variables. All specifications include SIC 2 digit industry code dummies. All standard errors are clustered by issuer.

	$\mathbb{1}$\{Cut Investment\}		%Δ Investment	
	(1) R&D	(2) SG&A	(3) R&D	(4) SG&A
HI_Zone			-0.099***	-0.028***
			(0.00)	(0.00)
dist	-0.644**	-0.382**		
	(0.02)	(0.04)		
dist2	0.765**	0.374		
	(0.04)	(0.15)		
log(Assets)	-0.004	0.010	-0.002	-0.01***
	(0.81)	(0.44)	(0.85)	(0.01)
Tobin's Q	-0.060	0.041**	0.032	-0.019**
	(0.10)	(0.04)	(0.21)	(0.03)
Cash flow	-1.025**	-0.003	0.108	0.183*
	(0.02)	(0.67)	(0.24)	(0.06)
log(Debt/EBITDA)	0.041	0.101*	-0.003	-0.057***
	(0.70)	(0.07)	(0.95)	(0.01)
log(Firm Age)	0.083**	-0.028	-0.027	0.015
	(0.04)	(0.28)	(0.33)	(0.15)
Industry FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	807	1770	807	1770
R^2	0.211	0.129	0.306	0.146

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Proximity to Salient Thresholds and Investment When Credit Spreads Are High

This table presents OLS estimates from regressions of an indicator of whether the firm reduces R&D (Columns (1)-(2)) or SG&A expenditures (Columns (3)-(4)) during the year leading up to getting a bond rated on the issuer's proximity to a salient Debt/EBITDA threshold one year prior to getting a bond rated and firm characteristics. *H-I Zone* is a dummy variable equal to one if the issuer is near a salient Debt/EBITDA threshold one year prior to getting a bond rated (see Section 2 for details), and *High Spread* is a dummy variable equal to one for time periods when the Baa-Aaa spread exceeds the median for the sample period. Table A.1 in the Appendix outlines the construction of the control variables. Columns (1) and (3) reproduce results from Table 4 for comparison. All specifications include SIC 2 digit industry code dummies. All standard errors are clustered by issuer.

	Cut R&D		Cut SG&A	
	(1)	(2)	(3)	(4)
H-I Zone	0.188***	0.007	0.062**	-0.013
	(0.00)	(0.93)	(0.02)	(0.78)
H-I Zone * High Spread		0.241***		0.113**
		(0.01)		(0.04)
Controls, Industry FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	807	807	1770	1770
R^2	0.236	0.246	0.129	0.132

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Future Declines in Operating Performance and Innovation Output

This table presents OLS estimates from regressions of an indicator of future performance declines on whether the issuer is near a salient threshold one year prior to issuing a bond and a vector of firm controls.

$$\mathbb{1}\{Perf_{t+\tau} < Perf_t\} = \alpha + \rho(H\text{-}I\ Zone)_{it} + \sum \beta X_{it} + q_t + \epsilon_{it}$$

The dependent variables in Panels A and B are dummy variables equal to one when the issuers average patent productivity, measured as number of patents and citation-weighted patents, respectively, in the τ years after bond issuance is lower than its average patent productivity one year prior to getting a bond rated. The dependent variable in Panels C and D are dummy variables equal to one when the issuer's ROA (operating income/assets) or ROE (net income/shareholder equity) in τ years is lower than its respective value one year prior to getting a bond rated. *H-I Zone* is a dummy variable equal to one if the issuer is near a salient Debt/EBITDA threshold one year prior to getting a bond rated (see Section 2 for details). The vector of controls includes log(Assets), Tobin's Q, Cash flow/Assets, log(Debt/EBITDA) and SIC 2 digit industry code dummy variables. R&D/Assets is included as a control in Panels A and B. Table A.1 in the Appendix outlines the construction of the control variables. All standard errors are clustered by issuer.

Panel A: P(Lower Future Number of Patents)

	+1yr	+2yr	+3yr	+4yr
H-I Zone	0.085*	0.024	0.006	0.031
	(0.07)	(0.57)	(0.90)	(0.47)
Controls	Yes	Yes	Yes	Yes
Observations	557	548	496	450
R^2	0.161	0.227	0.302	0.323

Panel B: P(Lower Future Patent Citation)

	+1yr	+2yr	+3yr	+4yr
H-I Zone	0.041	0.056**	0.053**	0.052*
	(0.16)	(0.03)	(0.04)	(0.05)
Controls	Yes	Yes	Yes	Yes
Observations	557	548	496	450
R^2	0.454	0.563	0.571	0.521

Panel C: P(Lower Future ROA [operating income/assets])

	+1yr	+2yr	+3yr	+4yr
H-I Zone	0.055**	0.042*	0.052**	0.064**
	(0.01)	(0.09)	(0.04)	(0.03)
Controls	Yes	Yes	Yes	Yes
Observations	1691	1528	1429	1205
R^2	0.162	0.180	0.199	0.219

Panel D: P(Lower Future ROE [net income/shareholder equity])

	+1yr	+2yr	+3yr	+4yr
H-I Zone	0.045*	0.048**	0.051*	0.036
	(0.06)	(0.04)	(0.05)	(0.20)
Controls	Yes	Yes	Yes	Yes
Observations	1691	1528	1429	1205
R^2	0.177	0.195	0.171	0.169

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Future Changes in Tobin's Q

This table presents estimates of changes in future industry-adjusted Tobin's Q (Q^{IA}). Panel A presents the difference in Q^{IA} for the treatment (*HI-Zone*) and control firms for four years following issuance, followed by the difference in differences across these groups. Panel B presents OLS estimates from regressions of future Q^{IA} on whether the issuer is near a salient threshold one year prior to issuing a bond and a vector of firm controls: $Q^{IA}_{i,t+\tau} = \alpha + \rho(H\text{-}I\ Zone)_{it} + \sum \beta X_{it} + q_t + \epsilon_{it}$. Q^{IA} is the firm's Tobin's Q minus the industry median Tobin's Q for that time period. *H-I Zone* is a dummy variable equal to one if the issuer is near a salient Debt/EBITDA threshold one year prior to getting a bond rated (see Section 2 for details). Table A.1 in the Appendix outlines the construction of the variables. All regression specifications include SIC 2-digit industry dummy variables and all standard errors are clustered by issuer.

Panel A: Future Changes in Q – Raw Differences

		ΔQ^{IA}			
	Baseline Q^{IA}	+1yr	+2yr	+3yr	+4yr
Control (*H-I Zone=0*)	0.19	0.01	0.02	0.00	0.01
Treatment (*H-I Zone=1*)	0.19	-0.02	-0.02	-0.03	-0.05
Difference-in-Differences	0.00	-0.03**	-0.04**	-0.03	-0.06**
p-value	(0.97)	(0.03)	(0.04)	(0.15)	(0.04)

Panel B: Future Q – Regression Results

	(1) +1yr	(2) +2yr	(3) +3yr	(4) +4yr
HI-Zone	-0.028*	-0.043**	-0.029	-0.048*
	(0.06)	(0.02)	(0.18)	(0.07)
log(Assets)	-0.001	0.004	0.007	0.009
	(0.95)	(0.73)	(0.59)	(0.56)
Industry-Adjusted Q	0.831***	0.753***	0.714***	0.595***
	(0.00)	(0.00)	(0.00)	(0.00)
log(Debt/EBITDA)	0.014	-0.014	-0.049	-0.115
	(0.74)	(0.79)	(0.39)	(0.14)
log(Firm Age)	0.002	0.012	0.019	0.008
	(0.89)	(0.57)	(0.48)	(0.80)
Leverage	-0.054	0.018	0.123	0.178
	(0.54)	(0.89)	(0.45)	(0.41)
ROA	0.765**	0.659	0.229	0.307
	(0.02)	(0.11)	(0.64)	(0.65)
Industry FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	1691	1528	1429	1205
R^2	0.767	0.664	0.590	0.461

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Crossing Thresholds, Cutting Investment and Credit Rating Improvement
This table presents OLS estimates from regressions of changes in the issuer's credit rating from one year prior to getting rated and bond issuance on the key drivers of corporate credit ratings. 𝟙{Improve Debt/EBITDA bin} is a dummy variable equal to one if the issuer crossed a salient threshold into a better Debt/EBITDA bin during the year leading up to getting a bond rated. *Cut R&D, SG&A* are dummy variables equal to one if the issuer cut the respective investment in the year prior to getting rated. Table A.1 in the Appendix outlines the construction of the control variables. Include SIC 2 digit industry code dummies. All standard errors are clustered by issuer.

	(1) ΔRating	(2) ΔRating	(3) ΔRating	(4) ΔRating
Stock Return	0.339***	0.343***	0.442***	0.365***
	(0.00)	(0.00)	(0.01)	(0.00)
Δlog(Assets)	0.288	0.313	0.312	0.337*
	(0.14)	(0.11)	(0.39)	(0.10)
ΔLeverage	-2.480***	-2.483***	-2.540**	-2.464***
	(0.00)	(0.00)	(0.02)	(0.00)
ΔProfitability	0.599**	0.505**	1.658	0.307
	(0.04)	(0.04)	(0.20)	(0.14)
ΔDebt/EBITDA	-0.061***	-0.053**	-0.064	-0.053**
	(0.00)	(0.01)	(0.23)	(0.01)
𝟙{Improve bin}		0.260***	0.281**	0.270***
		(0.00)	(0.01)	(0.00)
Cut R&D			-0.155*	
			(0.06)	
𝟙{Improve bin} * Cut R&D			-0.031	
			(0.81)	
Cut SG&A				-0.130**
				(0.03)
𝟙{Improve bin} * Cut SG&A				0.053
				(0.58)
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	1498	1498	687	1498
R^2	0.236	0.252	0.311	0.263

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Crossing Thresholds, Cutting Investment and Yields

This table presents OLS estimates from regressions of the yield of newly issued bonds on the key drivers of default risk. For firms that issue multiple bonds in the same quarter, I use a dollar-weighted average yield of the bonds. $\mathbb{1}$\{Improve Debt/EBITDA bin\} is a dummy variable equal to one if the issuer crossed a salient threshold into a better Debt/EBITDA bin during the year leading up to getting a bond rated. *Cut R&D, SG&A* are dummy variables equal to one if the issuer cut the respective investment in the year prior to getting rated. Table A.1 in the Appendix outlines the construction of the control variables. Include SIC 2 digit industry code dummy variables, dummy variables for each credit rating, and dummy variables for each salient Debt/EBITDA bin (described in Section 2. All standard errors are clustered by issuer.

	(1) Yield	(2) Yield	(3) Yield
Log(Assets)	-0.146**	-0.131*	-0.162**
	(0.03)	(0.09)	(0.02)
Leverage	0.027	-0.675	0.083
	(0.96)	(0.33)	(0.88)
Profitability	-2.978***	-2.998	-2.917***
	(0.00)	(0.22)	(0.00)
Stock Return	-0.028	-0.755***	0.011
	(0.88)	(0.01)	(0.95)
log(Bond Amount)	-0.098	-0.276**	-0.067
	(0.35)	(0.02)	(0.53)
$\mathbb{1}$\{Improve bin\}	0.090	0.096	0.177
	(0.31)	(0.60)	(0.16)
Cut R&D		0.059	
		(0.66)	
$\mathbb{1}$\{Improve bin\} * Cut R&D		0.036	
		(0.88)	
Cut SG&A			0.091
			(0.43)
$\mathbb{1}$\{Improve bin\} * Cut SG&A			-0.125
			(0.48)
Debt/EBITDA Bin FE	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Observations	1140	551	1096
R^2	0.619	0.685	0.626

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Additional Tests

This table presents OLS estimates from regressions of an indicator of whether the firm reduces R&D or SG&A expenditures during the year leading up to getting a bond rated on the issuer's proximity to a salient Debt/EBITDA threshold one year prior to getting a bond rated and firm characteristics. Panel A presents estimates using the subsample of bonds that are more likely to be used for refinancing existing debt. These are observations where the debt in current liabilities one quarter prior to issuance is at least as large as the size of the bond issuance. Panel B presents the baseline regression, controlling for whether the issuer is in violation of a financial covenant during the year leading up to getting a bond rated (*Cov Violation*=1). Columns (1) and (3) use all observations that can be matched to the covenant violation data and columns (2) and (4) re-estimate the specification with violating issuers dropped from the sample. *H-I Zone* is a dummy variable equal to one if the issuer is near a salient Debt/EBITDA threshold one year prior to getting a bond rated (see Section 2 for details). All the control variables used in the main specification are included in these regressions. Table A.1 in the Appendix outlines the construction of the control variables. All standard errors are clustered by issuer.

Panel A: Refinancing Bonds

	(1) Cut R&D	(2) Cut SG&A
H-I Zone	0.261***	0.120**
	(0.00)	(0.01)
Controls, Industry FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Observations	417	634
R^2	0.395	0.264

Panel B: Covenant Violations

	Cut R&D		Cut SG&A	
	(1)	(2)	(3)	(4)
H-I Zone	0.198***	0.196***	0.077**	0.080**
	(0.00)	(0.00)	(0.02)	(0.02)
Cov Violation	0.107		0.076	
	(0.36)		(0.36)	
Controls, Industry FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	512	490	1116	1063
R^2	0.259	0.258	0.125	0.127

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$