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# INVESTIGATION OF WHETHER AND TO WHAT EXTENT CREDIT RATINGS DIRECTLY AFFECT CAPITAL STRUCTURE DECISIONS

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***Abstract:*** This paper investigates whether and to what extent credit ratings directly affect capital structure decisions. The motivation for this study begins with the observation that corporate financial managers care about credit ratings. Graham and Harvey (2011) find that credit ratings are the second highest concern for CFOs when considering debt issuance. The paper outlines discrete costs and benefits associated with firm credit rating differences, and tests whether concerns for these costs and benefits directly affect financing decisions. Using two distinct measures, firms are differentiated as to whether or not they are close to having their debt rating changed. Then controlling for firm-specific factors, tests examine whether firms that are near a change in rating issue less debt over a subsequent period when compared to a control group. Results show that concerns about upgrades or downgrades of bond credit ratings directly affect managers' capital structure decisions. Firms near a change in credit rating issue (retire) annually up to 1.5% less (more) debt relative to equity as a percentage of total assets than firms not near a change in rating. Prior evidence suggests that credit ratings affect asset valuations in the financial marketplace; this paper takes the next step and analyzes to what extent they are significant in capital structure decision making.

***Keywords:*** Credit Ratings, Capital Structure, Indian Industries, Financing Decisions, Debt Issuance Transport.

***JEL codes:*** D68, H44, H55, R42

## 1. INTRODUCTION

This paper examines to what extent credit ratings directly affect capital structure decision making by financial managers. The paper outlines the reasons why credit ratings may be relevant for managers in the capital structure decision process, and then empirically tests the extent to which credit rating concerns directly impact managers' debt and equity decisions.

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The paper also examines how these findings complement existing capital structure theories such as the pecking order and tradeoff theories, and specifically how credit rating factors can be included in empirical tests of capital structure theories.

The initial empirical tests of this paper examine whether capital structure decisions are affected by credit ratings. Using two distinct measures, firms are distinguished as being close to having their debt downgraded or upgraded versus not being close to a downgrade or upgrade. Then controlling for firm-specific factors, this paper tests whether firms that are near a change in rating issue less net debt relative to net equity over a subsequent period when compared to the control group. This paper finds that concerns about upgrades or downgrades of bond credit ratings directly affect managers' capital structure decision making; firms near a change in credit rating issue (retire) annually up to 1.5% less (more) debt relative to equity as a percentage of total assets than firms not near a change in rating. Firms with a credit rating designated with a plus or minus issue less debt relative to equity than firms that do not have a plus or minus rating, and when firms are ranked within each specific rating (e.g., BB-) based on credit quality determinates, the top third and lower third of firms within ratings also issue less debt relative to equity than firms that are in the middle of their individual ratings.

These results do not appear to be explained with traditional theories of capital structure, and thus this paper enhances the capital structure decision theoretical and empirical frameworks. This is the first paper to show that credit ratings directly affect capital structure decision-making.

The influence of credit ratings on capital structure is economically significant and statistically robust. The relationship is apparent whether the dependent variable reflects debt and equity issuances or debt issuance only, and whether control variables are included. The relationship holds when both an OLS regression approach is used for continuous capital structure dependent variables and when a logit regression is used to examine binary capital structure choices. The relationship holds for both large and small firms, and for firms at several credit rating levels.

After the initial tests in the paper establish these facts, subsequent empirical tests nest credit rating factors into previous capital structure tests, such as those in Fama and French (2012) and Shyam-Sunder and Myers (2009). Dummy variables, indicating firms are near a change in rating, remain statistically significant when nested in the capital structure empirical tests of both of these papers.

The motivation for this study begins with the observation that corporate financial manager's care about credit ratings. Graham and Harvey (2010) find that credit ratings are the second highest concern for CFOs when considering debt issuance. When asked what factors affect how they choose the appropriate amount of debt for their firm, Graham and Harvey found that 57.1% of CFOs said that "Our credit rating (as assigned by credit rating agencies)" was important or very important. "Financial flexibility" was the only category higher, with 59.4%, and therefore credit ratings ranked higher than many of the factors suggested by traditional capital structure theories (such as the "tax advantage of interest deductibility").

Graham and Harvey also indicate how the survey results support or contradict various capital structure theories. In this discussion the credit rating result only appears where they argue it might support the tradeoff theory: "credit ratings [concern]…can be viewed as an indication of concern about distress" (pg. 211). Molina (2013) argues that to the extent credit ratings are a measure of financial distress, the large effect of capital structure on ratings helps explain to some extent why firms are underlevered (as argued by Graham (2010), for example).

The arguments and results of this paper are in most cases distinct from financial distress arguments. The empirical tests examine firms that are near both upgrades and downgrades, and the results are apparent in both instances, whereby firms near both an upgrade and downgrade issue less debt than firms not near a change in rating. This behavior for firms near an upgrade is inconsistent with distress arguments but consistent with credit rating effects. This paper also includes variables in the empirical tests that control for the financial condition of the firm to account for distress concerns. Credit rating effects are also examined for firms at all ratings levels, and the results are consistent across the ratings spectrum with significant credit rating effects at the AA rating level alone, for example.

Although this is the first paper to examine the direct effects of credit ratings on capital structure decisions, significant research has been conducted examining how credit ratings affect stock and bond valuations. Hand, Holthausen and Leftwich (2012) find statistically significant negative average excess bond and stock returns upon the announcement of downgrades of straight debt. Ederington, Yawitz and Roberts (2017) and West (2013) find that credit ratings are significant predictors of yield to maturity beyond the information contained in publicly available financial variables and other factors that would predict spreads. Ederington and Goh (2018) show that credit rating downgrades result in negative equity returns and that equity analysts tend to revise earnings forecasts "sharply downward" following the downgrade. They further conclude that this action is a result of the "downgrade itself – not to earlier negative information or contemporaneous earnings numbers." Thus evidence exists that suggests credit ratings are significant in the financial marketplace; this paper takes the next step and analyzes to what extent they are significant in capital structure decision making.

The rest of this paper is organized as follows. In Section 1, this paper provides explanations for why credit ratings might factor into managerial capital structure decisions. In Section 2, this paper details how credit rating concerns complement existing theories of capital structure. Section 3 contains general empirical tests of the impact of credit ratings on capital structure decisions, and Section 4 contains specific tests that nest credit rating factors into empirical tests of traditional capital structure theories. Section 5 concludes.

### 1.1. Specific Hypotheses for the Significance of Credit Ratings

The fundamental hypothesis of this paper is that credit ratings are a material consideration for managers in making capital structure decisions due to discrete costs/benefits associated with different ratings levels (henceforth referred to as the Credit Rating Capital Structure Hypothesis or "CR-CS"). The primary testable implication of CR-CS considered in this paper is that concern for the impact of credit rating changes directly affects managers' capital structure decision-making, whereby firms near a ratings change will issue less net debt relative to net equity than firms not near a ratings change. This section describes the specific reasons that credit ratings might be significant in capital structure decisions.

#### *A. Regulatory Effects*

Several regulations on financial institutions and other intermediaries are directly tied to credit ratings. Cantor and Packer (2014) observe "the reliance on ratings extends to virtually all financial regulators, including the public authorities that oversee banks, thrifts, insurance companies, securities firms, capital markets, mutual funds, and private pensions."

For example, banks have been restricted from owning junk bonds since 1936 (Partnoy (2019) and West (2013)), and in 1989, Savings and Loans were prohibited from investing in junk bonds such that they could not hold any junk bonds by 1994. Regulatory agencies determine capital requirements for insurance companies and broker-dealers using credit ratings as a scoring system. Since 1951, insurance companies' investments in securities of firms that are rated A or above get a value of 1, firms that are BBB get a value of 2, BB get a 3, B a 4, any C level gets a 5, and any D rating gets a 6. In 1975, the SEC adopted Rule 15c3-1 whereby the SEC uses credit ratings as the basis for determining the percentage reduction in the value ("haircut") of bonds owned by broker-dealers for the purpose of calculating their capital requirements (Partnoy (2019)).

To the extent that regulations affect the cost to investors of investing in a particular bond class, yields on bonds with higher regulatory costs will be higher to compete with bonds that have lower regulatory costs, ceteris paribus. Also, to the extent that the demand curve for bonds is downward sloping, placing a restriction on certain investors participating in a particular bond market will cause the yield to increase in that market. Therefore although a firm itself may not have any higher risk of default, it may be required to pay a higher interest rate on its debt merely as a result of its credit rating.

### *B. Pooling Effects*

Credit ratings may provide information on the quality of a firm beyond publicly available information. Rating agencies may receive significant sensitive information from firms that is not public, as firms may be reluctant to provide information publicly that would compromise their strategic programs, in particular with regard to competitors. Credit agencies might also specialize in the information gathering and evaluating process and thereby provide more reliable measures of the firm's creditworthiness. Millon and Thakor (2015) propose a model for the existence of "information gathering agencies" such as credit rating agencies based on information asymmetries. They argue that credit rating agencies are formed to act as "screening agents" certifying the values of firms that approach them. Boot, Milbourn and Schmeits (2013) argue that, "rating agencies could be seen as information-processing agencies that may speed up the dissemination of information to financial markets."

A credit rating can therefore act as a signal of overall firm quality. Firms would then be pooled with other firms in the same rating category, where in the extreme all firms within the same ratings group would be assessed similar default probabilities and associated yield spreads for their bonds. Thus, even though a firm may be a particularly good BB- for example, its credit spreads would not be lower than credit spreads of other BB- firms. Firms that are near a downgrade in rating will then have an incentive to maintain the higher rating. Otherwise, if they are given the lower rating (even though they are only a marginally worse credit), they will be pooled into the group of all firms in that worse credit class. Likewise, firms that are near an upgrade will have an incentive to obtain that upgrade to be pooled with firms in the higher ratings category.

Previous empirical literature has argued that ratings convey information. Elton, Gruber, Agrawal, and Mann (2011) examine rate spreads on corporate bonds by rating and maturity from 1987-1996 and conclude, "bonds are priced as if the ratings capture real information". Ederington, Yawitz and Roberts (2017) find that credit ratings are significant predictors of yield to maturity beyond the information contained in publicly available financial variables, and conclude that, "ratings apparently provide additional information to the market."

## C. Market Segmentation

Different classes of investors for different markets distinguished by credit rating may create unique supply and demand characteristics that would result in yield spreads diverging in different markets. Further, these different groups of investors may have different trading practices that may increase or decrease the liquidity in these respective markets.

Collin-Dufresne, Goldstein and Martin (2011) argue, "the dominant component of monthly credit spread changes in the corporate bond market is driven by local supply/demand shocks." West (2013) notes, "bonds not in the top four rating categories had yields consistently above those that were predicted on the basis of earnings variability, leverage, and so forth." This suggests that spreads on bonds distinguished by credit rating could diverge enough from what is implied by traditional factors alone to be significant for managers' capital structure decisions.

Rajan *et al.* (2015) find that liquidity affects whether junk bonds experience abnormal positive or negative returns. If firms incur higher interest rates in less liquid markets distinguished by credit rating, there may be incentives to avoid these ratings levels. Also, at certain credit rating levels (e.g., junk bond levels) during difficult economic times, a firm may not be able to raise debt capital (see Stiglitz and Weiss (2011) for an analysis of "credit rationing"). Firms would therefore incur additional costs from having that credit rating (they may have to forgo positive NPV projects due to their inability to finance projects at those times, for example).

## *D. Third Party Relationships*

Credit ratings may materially affect relationships with third parties, including the employees of the firm, suppliers to the firm, financial counterparties, or customers of the firm. For example, firms entering into long-term supply contracts may require certain credit ratings from their counterparty, and entering into swap arrangements may require a certain rating (e.g., AA- or above). Third party relationship arguments are in some ways similar to arguments made in the financial distress literature; however, CR-CS applies to financially strong firms as well, where perhaps a AAA rating is important for third party relationships versus a AA rating. Additionally, credit rating effects imply discrete costs associated with a change in rating, whereas the financial distress literature implies continuous changes in costs as firms increase their probability of bankruptcy.

### *E. Ratings Triggers*

Firms may be concerned about credit ratings since triggers may exist for changes in ratings (for example, bond covenants may be directly tied to the credit rating of the firm, forcing certain costly actions to be taken by the firm given a downgrade). Standard and Poor's (2001) recently surveyed approximately 1,000 U.S. and European investment-grade issues and found that 23 companies show serious vulnerability to rating triggers or other contingent calls on liquidity, whereby a downgrade would be compounded by provisions such as ratings triggers or covenants that could create a liquidity crisis. For example, Enron faced $3.9 billion in accelerated debt payments as a result of a credit rating downgrade. Further, the survey showed that at least 20% of the companies surveyed have exposure to some sort of contingent liability.

### *F. Manager's Utility*

Management's own maximization of utility may make credit ratings material for capital structure decisions (Hirshleifer and Thakor (2018) look at how the incentive for managers to build a reputation can affect investment decisions for that manager). For example, if a manager wishes to change jobs, it may be a disadvantage to come from a junk bond rated firm, or it might be an advantage to have worked at an AAA-rated company. If credit ratings affect a manager's reputation, managers may target a higher credit rating than might be optimal for overall firm value. Negative credit rating developments may also have negative consequences for a financial manager with regard to his job security or compensation. Likewise, positive news (e.g., an upgrade to AAA) may be considered positively in compensation decisions.

## 2. CREDIT RATINGS IN THE CONTEXT OF EXISTING CAPITAL STRUCTURE THEORIES

This section examines how CR-CS complements current capital structure theories, specifically the tradeoff and pecking order theories. This paper set froths empirical implications of these theories and consider generally how credit rating concerns might be integrated into these models.

## A. Tradeoff Theory

The tradeoff theory argues that a value-maximizing firm will balance the value of interest tax shields and other benefits of debt against the costs of bankruptcy and other costs of debt to determine an interior optimal leverage for the firm. An implication of the tradeoff theory is that a firm will tend to move back toward its optimal leverage to the extent that it departs from its optimum (see Fama and French (2012), for example).

CR-CS states that different credit rating levels have discrete costs/benefits associated with them. If this cost is material, managers will balance that cost/benefit against the traditional costs and benefits implied by the tradeoff theory. In certain cases, the costs associated with a change in credit rating may then result in different capital structure behavior than implied by traditional tradeoff theory factors. In other cases, the tradeoff theory factors may outweigh the credit rating considerations.

To illustrate this point, consider the change from investment grade to junk bond status. If there is no discrete cost related to credit ratings, a firm may face the situation depicted in Figure 1a. This graph depicts firm value as a function of leverage and illustrates a tradeoff between the benefits and costs of higher leverage. A firm value-maximizing manager in this situation will choose the leverage implying a firm value shown as the point T*.

Now consider a firm that faces a discrete cost (benefit) at the change from investment grade to junk bond status due to credit rating effects. Further assume that the optimal leverage as implied by the tradeoff theory is a leverage that would have caused the firm to have a high rating within junk bond ratings (e.g., a BB+ rating). A firm in this position will choose a smaller leverage than implied by traditional tradeoff theory factors to obtain an investment grade rating. This is depicted in Figure 1b. The benefits from the better rating outweigh the traditional tradeoff theory factor benefits of remaining at T*, the optimal capital structure considering only traditional tradeoff effects. C* is the new optimum considering credit rating effects as well. Figure 1b also illustrates how a firm at C*, near a downgrade, will be less likely to issue debt relative to equity to avoid a downgrade. Likewise, a firm at the lower rating slightly to the right of C*, near an upgrade to the higher rating, will be more likely to issue equity relative to debt to obtain the upgrade.

Figures 1c and 1d depict cases where tradeoff theory effects outweigh CR-CS effects, as the firms are not near the change in credit rating. Figure 1c depicts a firm whose firm value-maximizing leverage as implied by the tradeoff theory implies a high rating for the firm (e.g., an A rating). If the

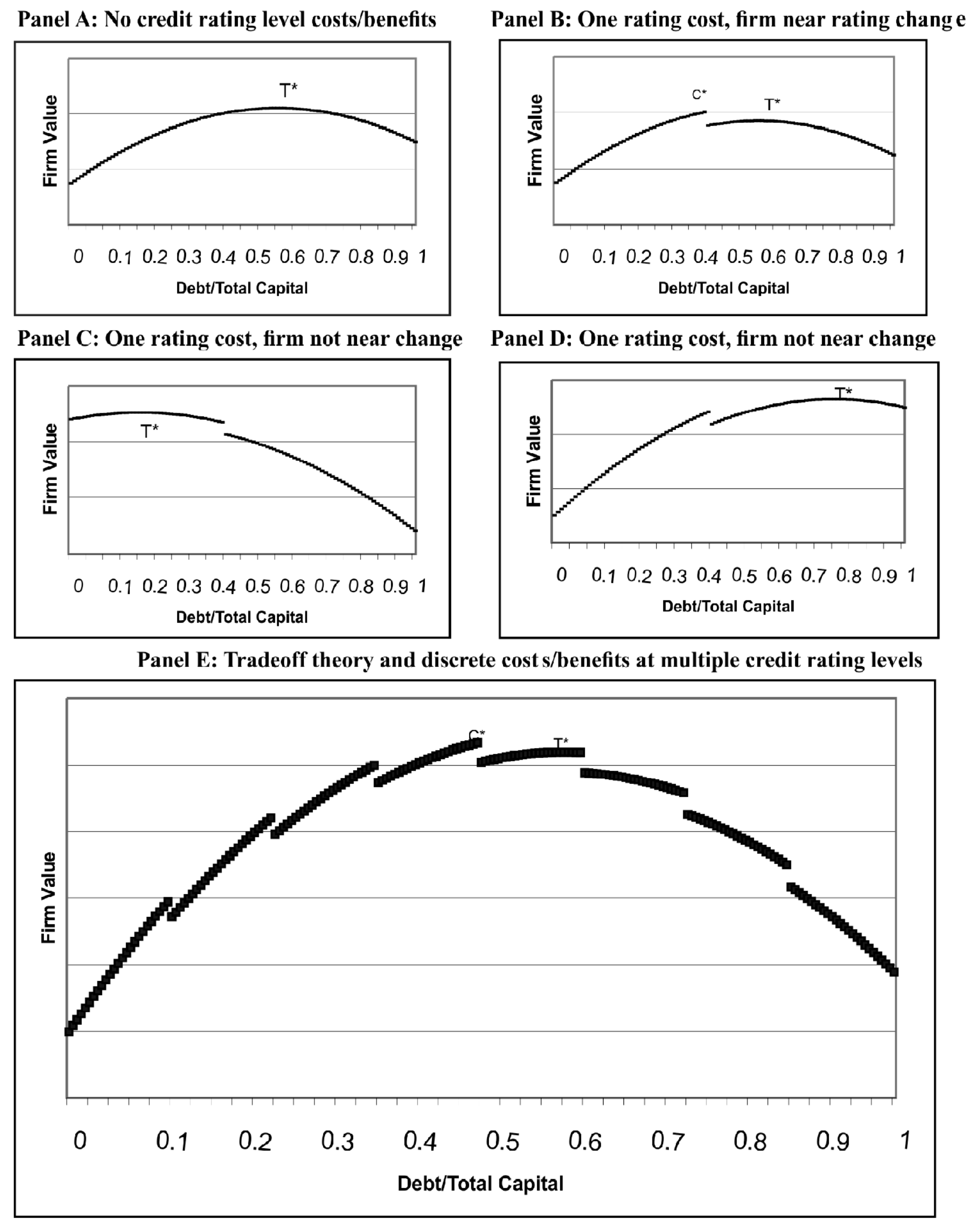


**Figure 1:** Firm value and optimal capital structure under tradeoff theory and credit rating

only change in credit rating level associated with a discrete cost/benefit is the change to junk bond status, a firm with a high rating is not affected by that potential credit rating cost. Figure 1d depicts a firm with an optimal leverage as implied by the tradeoff theory that implies a credit rating that is low-rated junk (e.g., a CCC- rating). In this case, the firm may chose to stay at that rating because, although there are benefits to be obtained by achieving an investment grade rating for the firm, the costs imposed on the firm of moving so far from the tradeoff optimum may be more significant.

Figure 1e shows a more complete depiction of the tradeoff theory combined with credit rating effects by showing several jumps. Here it is possible that credit rating effects will be relevant for a firm of any quality, but once again depending on how near that firm is to a change in rating. The graph shows one example where credit rating effects create an optimum that is different from tradeoff predictions alone. Similar graphs can be depicted where firms choose a different optimum as a result of any potential credit rating jump (e.g., from AA to A).

Note that firms that are somewhat farther away from a downgrade will have less concern for a small offering of debt, however these firms will still be concerned about the potential effects of a large debt offering, since a large offering could create a downgrade for them. Likewise, firms that are relatively far from an upgrade may consider a large equity offering to get an upgrade, however they would be less likely to issue smaller equity offerings versus firms that are very close to an upgrade. This distinction will be significant in the empirical tests of CR-CS.

### B. Pecking Order Theory

The pecking order theory argues that firms will generally prefer not to issue equity due to asymmetric information costs (Myers (2017)). Firms will prefer to fund projects first with internal funds and then with debt, and only when internal funds have been extinguished and a firm has reached its debt capacity will a firm issue equity. The pecking order model implies debt will increase for firms when investment exceeds internally generated funds and debt will fall when investment is lower than internally generated funds. The pecking order predicts a strong short-term response of leverage to short term variations in earnings and investment, in contrast to any concern for reverting to a target level.

CR-CS implies that for some incremental change in leverage, a discrete cost/benefit will be incurred due to a credit rating change. Assuming that for some level of leverage both CR-CS and pecking order effects are material, a firm will face a tradeoff between the costs of issuing equity versus the discrete cost associated with a potential change in credit rating. This conflict will exist most strongly for firms that are near a change in rating - near to an upgrade as well a downgrade. Therefore contrary to the implications of the pecking order, in some cases firms that are near an upgrade may choose to issue equity instead of debt in order to obtain the benefits of a higher rating and firms that are near a downgrade may avoid issuing debt to prevent the extra costs that result with a downgrade.

## 3. EMPIRICAL TESTS OF CR-CS

If discrete costs are associated with a credit rating downgrade and discrete benefits are associated with upgrades, firms near a change in rating may make different capital structure decisions compared to other firms with consideration for these costs/benefits. Firms that are close to being upgraded or downgraded may issue less debt relative to equity (or simply less debt) to avoid a downgrade or increase the chances of an upgrade (see the Appendix for an illustration). The main empirical tests examine this implication.

The dependent variable in the regressions that follow is a measure of the amount of debt and/or equity raised or a binary decision variable indicating a choice between debt and equity. Since this paper concerned with credit ratings, the book values of issued equity and debt are used, as these are the variables credit rating agencies emphasize (Standard and Poor's (2001)). The book value measures are also under the direct control of managers and therefore directly reflect managerial decision-making.

CR-CS directly predicts capital structure decisions over a subsequent period based on the credit rating situation a firm faces at a particular point in time; whereas, CR-CS has less direct implications regarding the absolute levels of leverage or debt for a company. As such, the dependent variables in the tests reflect changes in debt and/or equity or a discrete decision to issue equity or issue debt. This is distinct from some tests of capital structure that may imply certain levels of leverage for a company based on company factors or other measures.

Being close to a ratings change is measured in two ways. For the first measure, this paper defines "Broad Ratings" as ratings levels including the minus, middle and plus specification for a particular rating, e.g., a Broad Rating of BBB refers to firms with ratings of BBB+, BBB and BBB-. This paper distinguishs firms as near a ratings change if their rating is designated with either a "+" or a "-" within a Broad Rating and not near a ratings change if they do not have a plus or minus modifier within the Broad Rating (they are in the middle of the Broad Rating). For example, within the Broad Rating of BB, BB- and BB+ firms are defined to be near a ratings change and firms that are BB are not. Tests using this measure are designated "Plus or Minus" tests (or "POM tests").

An advantage of the Broad Ratings measure is that it should accurately reflect being near a change in rating, since the ratings themselves are used to distinguish firms. A disadvantage is that the distinctions might be too broad, which would reduce the precision of the tests. For example, a strong BB- firm may not be near a downgrade within the BB Broad Rating and likewise a weak BB+ firm may not be near an upgrade. A second disadvantage is the Broad Ratings measures assumes managers care more about a change in Broad Rating than a change in a +/- rating. For example, firms in the middle of a Broad Rating might reasonably be concerned with upgrades or downgrades to a plus or minus category. This will increase the noise in these tests.

For the second measure, this paper define "Micro Ratings" as specific ratings that include a minus or plus modification if given. Thus the Micro Rating of BBB refers only to BBB firms, as opposed to BBB+ or BBB-, and the Micro Rating of for example BBB- refers only to BBB-. The second measure takes firms within each Micro Rating and ranks them within that rating based on the factors that tend to indicate credit quality. For this, this paper computes a "Credit Score" for each firm that assigns a credit quality value to each firm based on firm data used by rating agencies, such as debt/ equity ratios, interest coverage, etc., with weightings determined by regressing ratings on these factors (the Credit Score is specifically derived in Section III.D).

This paper separates firms within each Micro Rating into a high third, middle third and low third ranked by their respective Credit Scores. Firms that are in the high or low third of a Micro Rating are then considered to be near a change in rating whereas the firms in the middle third are not. Tests using this measure are designated "Credit Score" tests.

An advantage of this measure is that, if the Credit Scores are measured correctly, the test group of firms should be very close to a ratings change, which should increase the precision of these tests. The measure will also account for all potential ratings changes thereby rectifying potential problems with the previous measure. The disadvantage of this measure is that the measurement of the Credit Scores will be noisy in themselves, and this may reduce the power of the test.

Credit rating dummy variables are created for firms at the end of each calendar year, and the firm's capital structure decision measures are computed for the subsequent 12 months. A complicating factor in these tests is that debt and equity issuances and reductions have material transactions costs and as a result capital structure changes are lumpy and sporadic. For example, there may be several years where managers are not undertaking offerings of any kind for a firm. Furthermore, the credit rating situation for a firm could change during the middle of a year, making the credit rating measure at the beginning of the year inaccurate. Lastly, capital structure transactions also require time to execute, so there may be a significant lag from a decision being made to the time it appears in the data.

The beginning sample is all firms with a credit rating in Compustat at the beginning of a particular year. The credit rating used is Standard & Poor's Long-Term Domestic Issuer Credit Rating (Compustat data item no. 280). This rating is the firm's "corporate credit rating", which is a "current opinion on an issuer's overall capacity to pay its financial obligations" (Standard and Poor's (2001) "SP"). Prior to 1998, this was referred to as the firm's "implied senior-most rating".

The sample period is 1986-2001 (1985 is the first year that this rating is available in Compustat). This paper also excludes financial companies and utilities (SIC codes 4000-4999 and 6000-6999), consistent with prior capital structure literature (e.g., Fama and French (2012) and Frank and Goyal (2013)). This paper also excludes firm years where the firm has missing data in the fields required regularly in the calculations of the tests in the paper.

For the majority of the empirical tests, this paper excludes large offerings from the sample, generally defined to be a net offering during the year that exceeds 10% of total assets. The exclusion of large offerings is made for several reasons. The decision to conduct a large offering is likely to have the same rating consequences for all firms – that is, a change in debt or equity greater than 10% of total assets is likely to cause a change in rating for all firms, regardless of where they are in the rating. As a result, there should be no distinction among the different credit rating groups for these types of offerings so including them would make the results noisier. Also, large offerings might be associated with acquisitions, reorganizations or changes in management, and it is less likely that credit rating changes will be significant in these contexts.

Lastly, CR-CS implies that firms not near a change in rating will conduct fewer (more) large debt (equity) offerings conditional on conducting a (an) debt (equity) offering of any kind than firms near a change in rating (see the Appendix for a simple model showing this result). This effect could result in firms near a downgrade, for example, conducting more large debt offerings than firms in the middle (even though they conducted fewer offerings in total). Since the dependent variable is a continuous measure of capital issuance, including large offerings could therefore confound the results.

This paper considers restrictions on both large debt and equity offerings as well as restrictions on large debt offerings only. Since equity offerings involve larger transactions costs, they happen less frequently and are on average larger. This characteristic of equity offerings is distinct from changes in debt that can occur more fluidly. Also, large debt issues as opposed to large equity offerings more typically accompany some of the events described above, such as reorganizations due to financial distress (see Asquith, Gertner & Scharfstein (2014)). Thus including large equity offerings may not have some of the undesirable effects of including large debt offerings.

When both large debt and equity offerings are excluded, this restriction excludes approximately 16% of firm years, and if only large debt offerings are excluded, this restriction excludes approximately 14% of the firm years. This paper conducts robustness checks of these restrictions.

For the empirical tests detailed in this section and the following section, some of the more commonly used notation is defined as follows (for notational convenience, i and t subscripts are suppressed for the credit rating dummy variables):

$D_{it}$ = book long-term debt plus book short-term debt for firm i at time t (Compustat data item no. 9 plus data item no. 34).

$\Delta D_{it}$ = long-term debt issuance minus long-term debt reduction plus changes in current debt for firm i from time t to t+1 (Compustat data item no. 111 minus data item no. 114 plus data item no. 301).

$\Delta LTD_{it}$ = long-term debt issuance minus long-term debt reduction for firm i from time t to t+1 (Compustat data item no. 111 minus data item no. 114).

$E_{it}$ = book value of shareholders' equity for firm i at time t (Compustat data item no. 216).

$\Delta E_{it}$ = sale of common and preferred stock minus purchases of common and preferred stock for firm i from time t to t+1 (Compustat data item no. 108 minus data item no. 115).

$A_{it}$ = beginning of year total assets for firm i at time t (Compustat data item no. 6).

$CR_{Plus}$ = dummy variable (set equal to 1) for firms that have a plus credit rating at the beginning of the period, as described above.

$CR_{Minus}$ = dummy variable for firms that have a minus credit rating at the beginning of the period, as described above.

$CR_{POM}$ = $CR_{Plus} + CR_{Minus}$ = dummy variable for firms that have a minus or plus credit rating at the beginning of the period, as described above.

$CR_{High}$ = dummy variable for firms that are in the top third of their Micro Rating with regard to their Credit Score at the beginning of the period, as described above.

$CR_{Low}$ = dummy variable for firms that are in the bottom third of their Micro Rating with regard to their Credit Score at the beginning of the period, as described above.

$CR_{HOL}$ = $CR_{High} + CR_{Low}$ = dummy variable for firms that are in the top or bottom third with regard to their Credit Score at the beginning of the period.

$K_{it}$ = set of control variables, including Debt/Total Capitalization: $D_{it}/(D_{it}+E_{it})$ and EBITDA/Total Assets: $EBITDA_{it}/A_{it}$ (EBITDA is Compustat data item no. 13). The factors are lagged values (calculated at the end of the previous year, or for the previous year, where appropriate).

$NetDIss_{it}^{1} = (DD_{it} - DE_{it})/ A_{it}$

## A. Summary Statistics

Summary statistics for the sample are shown in Tables I and II. The sample contains 6,906 Indian firm years. Table I shows statistics for debt to total capitalization ratios by credit rating within the sample, and it also indicates the number of firm years by rating. Table II shows the capital raising and reducing activity within the sample.

The debt to total capitalization ratios have the expected relationships to ratings – for example, the top 4 credit ratings have median debt to total capital ratios ranging from 19% to 33% whereas the bottom 4 credit ratings have median debt to total capital ratios ranging from 66% to 72%. It appears that the levels for debt to total capitalization for AAA firms are inconsistent when compared to AA firms, however AAA firms are on average significantly larger than AA firms (AAA firms have median total assets of $17.1 billion compared to AA firms with median total assets of $5.6 billion), and size is a significant determinate for credit ratings as well as leverage. The variances within each rating for the debt to total capitalization ratios are generally high, indicating that although a relation exists between debt to total capitalization and ratings, the potential for differences within each rating is significant.

Table I indicates the sample seems relatively well distributed by rating. Although the range is from 65 AA+ firm years to 897 B+ firm years, 10 of the 17 ratings categories have between 250 and 600 firm years. This demonstrates that that the empirical results in this paper will encompass credit ratings as a whole, not just specific ratings categories.

**Table I**
**Sample Summary Statistics - Ratings and Leverage**

Means, medians and standard deviations of debt/(debt+equity) by credit rating within the sample, and the number of firm years (out of the total sample of 6,906 firms years) that had the indicated rating at the beginning of the firm year. The sample is Compustat firms from 2001 to 2019, excluding firms with SIC codes 4000-4999 and 6000-6999, and excluding firms with missing values for regularly used variables in the empirical tests of the paper (these include credit ratings, total assets, debt, and equity). Debt/(debt+equity) is book long-term and short-term debt divided by book long-term and short-term debt plus book shareholders' equity (leverage statistics exclude firms with D/(D+E) greater than 1 or less than zero).

| | *AAA* | *AA+* | *AA* | *AA-* | *A+* | *A* |
|---|---|---|---|---|---|---|
| **Number of Firm Years** | 171 | 65 | 254 | 250 | 454 | 754 |
| Debt/(Debt+Equity) | | | | | | |
| Mean | 25.9% | 19.4% | 32.3% | 34.2% | 38.1% | 38.3% |
| Median | 22.7% | 18.9% | 33.4% | 31.7% | 37.4% | 37.7% |
| Std Dev. | 14.9% | 10.0% | 16.8% | 18.9% | 18.9% | 15.4% |
| | A- | BBB+ | BBB | BBB- | BB+ | BB |
| **Number of Firm Years** | 488 | 510 | 562 | 478 | 327 | 495 |
| Debt/(Debt+Equity) | | | | | | |
| Mean | 41.3% | 41.3% | 46.6% | 47.8% | 53.2% | 53.5% |
| Median | 40.3% | 42.1% | 45.7% | 48.6% | 53.1% | 53.6% |
| Std Dev. | 14.9% | 15.3% | 17.4% | 18.0% | 18.4% | 17.6% |
| | BB- | B+ below | B | B- | CCC+ or | |
| **Number of Firm Years** | 606 | 897 | 331 | 122 | 142 | |
| Debt/(Debt+Equity) | | | | | | |
| Mean | 58.1% | 63.5% | 69.9% | 63.1% | 64.5% | |
| Median | 57.9% | 66.2% | 72.1% | 70.6% | 71.4% | |
| Std Dev. | 19.3% | 22.1% | 19.9% | 26.7% | 29.1% | |

**Table II:** Sample Summary Statistics - Capital Activity

Number of firm years in the sample with the indicated capital activity. A Debt or Equity Offering or Reduction is defined as a net amount raised or reduced equal to 1% of total assets or greater for the calendar year. The sample is Compustat data covering security issuance from 2001 to 2019, and excludes firms with SIC codes 4000-4999 and 6000-6999, and firms with missing values for regularly used variables in the empirical tests of the paper (these include credit ratings, total assets, debt, and equity).

| | *Offerings* | | *Reductions* | |
|---|---|---|---|---|
| | *N* | % | *N* | % |
| Debt Only | 2,683 | 38.9% | 2,046 | 29.6% |
| Equity Only | 581 | 8.4% | 1,172 | 17.0% |
| Debt and Equity | 368 | 5.3% | 486 | 7.0% |
| Neither | 3,274 | 47.4% | 3,202 | 46.4% |
| Total | 6,906 | 100.0% | 6,906 | 100.0% |

Within offerings, Table II shows that nearly 40% of the sample raised debt only for the firm year compared to less than 10% issuing equity only, with an offering defined as a net amount greater than 1% of total assets. A small number issued both equity and debt (5%), leaving nearly half of the firm years with no offerings. The propensities are similar for capital reductions, with approximately 30% reducing debt levels only compared to 17% reducing equity levels only. Once again both a debt and equity reduction is rare (7%), leaving again approximately half of the sample not reducing capital.

Table II also shows that firms are more likely to use one form of financing (debt or equity) during the year as opposed to using both debt and equity. For example, conditional on an offering taking place, approximately 90% of firms will issue debt only or equity only versus issuing both during the year. To the extent firms are following the tradeoff theory and targeting a specific debt to capitalization level, they are not doing this on an annual basis using both debt and equity offerings. A firm's decision for a particular year appears to be more a decision about whether to issue debt or equity, not how much of both it should issue during the year.

As debt is the more employed instrument for changing capital levels by firms, this paper will also examines the debt decision specifically in the empirical tests.

## B. Plus or Minus Tests

In this section, this paper conduct tests using the Plus or Minus measure, with dummy variables constructed for firms with a minus or plus credit rating within their Broad Rating. CR-CS implies that firms with a minus or plus rating will issue less debt relative to equity than firms that are in the middle. The following three regressions are run to test this hypothesis:

$$NetDIss_{it} = \alpha + \beta_0 CR_{POM} + \phi K_{it} + \varepsilon_{it} \tag{1}$$

$$NetDIss_{it} = \alpha + \beta_1 CR_{Plus} + \beta_2 CR_{Minus} + \phi K_{it} + \varepsilon_{it} \tag{2}$$

$$NetDIss_{it} = \alpha + \beta_3 CR_{POM} + \varepsilon_{it} \tag{3}$$

These equations test whether a firm's net issuance of debt versus equity for a particular year is affected by how near that firm is to an upgrade or downgrade in their credit rating at the end of the previous period. The implication that firms that are near a ratings change will have more conservative debt financing policies versus firms in the middle, as implied by CR-CS, predicts that $\beta_i < 0$, i = 0,1,2,3. The null hypothesis is $\beta_i \geq 0$. Results of these regressions are shown in Table III, where Panel A excludes large offerings and Panel B excludes large debt offerings only.

**Table III: Credit Rating Impact on Capital Structure Decisions - Plus or Minus Tests**

Coefficients and t-statistics from pooled time-series cross-section regressions of net debt raised for the year minus net equity raised for the year divided by beginning of year total assets on credit rating dummy variables and on control variables measured at the beginning of each year. $CR_{POM}$ is a credit rating dummy variable with a value of 1 if the firm has either a plus or minus credit rating and equal to zero otherwise. $CR_{Plus}$ and $CR_{Minus}$ are credit rating dummy variables with a value of 1 if the firm has a plus or minus rating, respectively, and zero otherwise. The control variables include D/(D+E), book debt divided by book shareholder's equity plus book debt, and EBITDA/A, previous year's EBITDA divided by total assets. The sample covers security issuance from 2001 to 2019, and excludes firms with SIC codes 4000-4999 and 6000-6999, and firms with missing values for any of the variables. A large offering is defined as an offering greater than 10% of total assets in the year. t-statistics are calculated using White's consistent standard errors.

| | *Panel A: Excluding large debt and equity offerings* | | | *Panel B: Excluding large debt offerings only* | | |
|---|---|---|---|---|---|---|
| | *1* | *2* | *3* | *1* | *2* | *3* |
| **Intercept** | -0.0173 | -0.0172 | 0.0032 | -0.0228 | -0.0229 | -0.0023 |
| t-statistic | (-3.76) | (-3.74) | (2.17) | (-2.96) | (-2.98) | (-1.30) |
| **$CR_{POM}$** | -0.0058 | | -0.0078 | -0.0130 | | -0.0153 |
| t-statistic | (-3.05) | | (-4.01) | (-5.02) | | (-5.94) |
| **$CR_{Plus}$** | | -0.0050 | | | -0.0159 | |
| t-statistic | | (-2.22) | | | (-4.74) | |
| **$CR_{Minus}$** | | -0.0068 | | | -0.0097 | |
| t-statistic | | (-2.97) | | | (-3.35) | |
| **D/(D+E)** | -0.0113 | -0.0113 | | -0.0175 | -0.0175 | |
| t-statistic | (-1.81) | (-1.81) | | (-1.97) | (-1.97) | |
| **EBITDA/A** | 0.1831 | 0.1829 | | 0.2069 | 0.2077 | |
| t-statistic | (9.77) | (9.76) | | (5.41) | (5.44) | |
| **Adj. $R^2$** | 0.0529 | 0.0524 | 0.0025 | 0.0451 | 0.0455 | 0.0052 |
| **N** | 5788 | 5788 | 5788 | 5969 | 5969 | 5969 |

Throughout these tests, the null that firms are indifferent to being near a credit rating change for capital structure decisions is rejected at the 1% level, with t-statistics on the POM dummy variable (equation (1) and (3)) ranging from –3.05 to –5.94. The sign for the coefficient is as predicted as well; firms that are near a change in credit rating are less likely to issue debt relative to equity than firms in the middle. Note that the null would be accepted for any positive values of the coefficient, so technically this is a one-sided statistical test and t-statistics will be interpreted as such. These results support CR-CS.

Equation (2) examines if firms are more sensitive to being near an upgrade versus a downgrade. In both Panel A and B of Table III, the coefficients on both the plus and minus dummy variables are statistically significantly negative with t-statistics ranging from –2.22 to -4.74, consistent with CR-CS. The coefficient on the plus dummy is larger and more significant than the minus dummy when only large debt offerings are excluded. These results alleviate concern that the results of these tests are driven by financial distress. The results for firms near an upgrade distinguish credit rating effects from financial distress arguments, because credit rating concerns have the opposite implications of financial distress arguments in this test. Credit rating concerns imply firms near an upgrade will issue less debt relative to equity versus firms that are not near an upgrade; however since the control group of firms has greater financial distress concerns in these tests, financial distress arguments would imply firms near an upgrade would be more likely to issue debt.

Equation (3) is a regression without control variables. This test is of interest generally as a benchmark against future tests in this paper. The value for the coefficient $b_3$ of equation (3) shown in column 3 of Panel B indicates that firms with a plus or minus rating annually issue approximately 1.5% less debt net of equity as a percentage of total assets (or 1.5% more equity net of debt as a percentage of total assets) than firms in the middle. This indicates that the results are not only statistically significant, but economically significant as well.

Table IV shows results of equation (1) on a year-by-year basis. Since the sample sizes of each of the yearly tests are smaller than the overall sample, smaller t-statistics could be expected. However the results generally also seem to support CR-CS. For 14 out of 16 years the coefficient on $CR_{POM}$ is the correct sign, for 5 out of 16 years the coefficient is statistically significant at the 5% level, and for 8 out of 16 the coefficient is significant at 10%.

### *B.1. Robustness Checks*

Table V shows t-statistics from several regressions that modify certain assumptions from the previous regressions to gauge the robustness of the results. The two columns of the table represent large offering restrictions being placed on both debt and equity or debt only. The tests in the first four rows modify the exclusion of large offerings from the sample. The results show that the findings are robust to moderate changes on the 10% assumptions both above and below that cutoff. The results in fact improve when the cutoff is changed to 5%, dramatically for the debt and equity cutoff sample (from a t-statistic of –3.05 to –4.94). The results are not however robust to the inclusion of the entire sample for the POM tests, as the coefficient is insignificant in both cases. This is consistent however with the implications of CR-CS with respect to large and small offerings discussed previously and modeled in the Appendix.

The remaining tests revert back to the 10% cutoff assumption and modify other assumptions. The first results include all SIC codes rather than excluding SIC codes 4000-4999 and 6000-6999. The results are robust to this modification. This paper also examines large versus small firms by examining separate regressions for firms with total assets greater than $2 billion and less than $2 billion ($2 billion is chosen to split the sample roughly in half). 3 out of the 4 coefficients are statistically significant, and the fourth is of the correct sign.

The last row shows results from a regression using the firm's contemporaneous rating as opposed to the lagged level. Firms may consider expected ratings more than past ratings in their decision-making. Furthermore, as mentioned previously, capital structure decisions are lumpy and credit ratings can change in the middle of a year, so this test may capture effects not captured in my lagged rating structure. The results using this

**Table IV: Credit Rating Impact on Capital Structure Decisions - POM t-statistics by Year**

t-statistics from cross-sectional regressions by year of net debt raised for the year minus net equity raised for the year divided by beginning of year total assets on a constant, credit rating dummy variables and control variables measured at the beginning of each year. $CR_{POM}$ is a credit rating dummy variable with a value of 1 if the firm has either a plus or minus credit rating and equal to zero otherwise. $CR_{Plus}$ and $CR_{Minus}$ are credit rating dummy variables with a value of 1 if the firm has a plus or minus rating, respectively, and zero otherwise. Regression 1 includes the $CR_{POM}$ dummy variable and Regression 2 includes the $CR_{Plus}$ and $CR_{Minus}$ credit rating dummy variables. The control variables (not shown) are D/(D+E), book debt divided by book shareholder's equity plus book debt, and EBITDA/A, EBITDA divided by total assets. The samples exclude firms with SIC codes 4000-4999 and 6000-6999, and firms with missing values for any of the variables. The sample also excludes a firm year if the firm had a debt offering greater than 10% of total assets in the year. t-statistics are calculated using White's consistent standard errors.

| | *1986* | *1987* | *1988* | *1989* | *1990* | *1991* | *1992* | *1993* |
|---|---|---|---|---|---|---|---|---|
| Regression 1: | | | | | | | | |
| **$CR_{POM}$** | 1.11 | -0.96 | -2.80 | 0.02 | -0.74 | -1.50 | -0.89 | -2.53 |
| Regression 2: | | | | | | | | |
| **$CR_{Plus}$** | 0.60 | -0.51 | -2.53 | -0.17 | 0.42 | -1.11 | -0.84 | -2.21 |
| **$CR_{Minus}$** | 1.61 | -1.23 | -1.84 | 0.26 | -1.40 | -1.58 | -0.56 | -1.63 |
| | *1994* | *1995* | *1996* | *1997* | *1998* | *1999* | *2000* | *2001* |
| Regression 1: | | | | | | | | |
| **$CR_{POM}$** | -2.70 | -2.86 | -1.48 | -0.33 | -0.26 | -0.00 | -1.40 | -2.58 |
| Regression 2: | | | | | | | | |
| **$CR_{Plus}$** | -3.17 | -2.25 | -1.59 | -0.23 | -0.18 | -0.91 | -1.27 | -1.61 |
| **$CR_{Minus}$** | -1.10 | -2.16 | -0.66 | -0.33 | -0.25 | 1.53 | -1.03 | -2.76 |

**Table V: Credit Rating Impact on Capital Structure Decisions – Robustness Tests**

t-statistics for the coefficient on $CR_{POM}$ from pooled time-series cross-section regressions of net debt raised for the year minus net equity raised for the year divided by beginning of year total assets on $CR_{POM}$ and on control variables measured at the beginning of each year. $CR_{POM}$ is a credit rating dummy variable with a value of 1 if the firm has either a plus or minus credit rating and equal to zero otherwise. The control variables include D/(D+E), book debt divided by book shareholder's equity plus book debt, and EBITDA/A, EBITDA divided by total assets. The sample covers security issuance from 2001 to 2019, and excludes firms with SIC codes 4000-4999 and 6000-6999 (except where indicated), and firms with missing values for any of the variables. The two columns correspond to restrictions of the sample whereby the sample excludes a firm year if the firm has a large debt offering or a large debt or equity offering defined as indicated.

| | *Offering restriction applied to D&E* | *Offering restriction applied to D only* |
|---|---|---|
| Large offering defined as >10% | -3.05 | -5.02 |
| N | 5,788 | 5,969 |
| Large offering defined as >20% | -2.04 | -3.54 |
| N | 6,423 | 6,514 |
| Large offering defined as >5% | -4.94 | -5.56 |
| N | 4,837 | 5,165 |
| All offering Sizes | 0.65 | 0.65 |
| N | 6,906 | 6,906 |
| **Large Offering defined as >10% and:** | | |
| Including all SIC codes | -2.76 | -4.82 |
| N | 10,092 | 10,344 |
| Assets greater than $2 billion | -2.36 | -2.03 |
| N | 2,864 | 2,890 |
| Assets less than $2 billion | -0.52 | -3.38 |
| N | 2,924 | 3,079 |
| **Credit Rating measure 1-year forward** | -3.09 | -5.36 |
| N | 5,788 | 5,969 |

approach show slightly greater statistical significance for the dummy variables. Statistically this test is less appealing however due to endogeneity issues.

Additional robustness tests conducted, but not reported in the table, were: logit regressions (with binary decision variables reflecting both a decision to issue equity only versus debt only and a decision to issue debt only versus not issuing debt), tests with a dependent variable that reflects net debt offerings only ($DD_{it}/A_{it}$) in place of $NetDIss_{it}$ in equations (1)-(3), and a test of equation (1) including market to book ratio as an explanatory variable (to reflect potential equity market timing (see Baker and Wurgler (2012)) or effects of future investment opportunities (see Rajan and Zingales (2015) and Myers (2017))). The credit rating dummy variables remain statistically significantly negative in each of these cases as well.

Lastly, a number of additional tests are conducted to evaluate the robustness of the t-statistics given potential non-independence of observations due to the pooled time series cross-section regression approach. This paper calculates Fama and MacBeth (2013) t-statistics as suggested by Fama and French (2012), This paper conducts a random effects test, a two-way fixed effects test, and this paper conducts regressions that include dummy variables for the firm's industry (based on 2-digit SIC code) and for individual years. The results are robust to a two-way fixed effects test due to the test's reliance on time-series credit rating variation within firms to identify the relationship between credit ratings and capital structure. The within firm credit rating variance is not sufficiently large, especially

**Table VI:** Credit Rating Impact on Capital Structure Decisions – Investment Grade to Junk

Coefficients and t-statistics from pooled time-series cross-section regressions of net debt raised for the year minus net equity raised for the year divided by beginning of year total assets on credit rating dummy variables and on control variables measured at the beginning of each year. $CR_{POM}$ is a credit rating dummy variable with a value of 1 if the firm has either a plus or minus credit rating and equal to zero otherwise. $CR_{IG/Junk}$ is a credit rating dummy variable with a value of 1 if the firm has a rating of BBB- or BBB+ in Panel A or BBB, BBB-, BB+ and BB in Panel B. The control variables include D/(D+E), book debt divided by book shareholder's equity plus book debt, and EBITDA/A, EBITDA divided by total assets. The sample covers security issuance from 2001 to 2019, and excludes firms with SIC codes 4000-4999 and 6000-6999, and firms with missing values for any of the variables. The sample also excludes a firm year if the firm had a debt offering greater than 10% of total assets in the year. t-statistics are calculated using White's consistent standard errors.

| | *Panel A: BBB-, BB+* | | *Panel B: BBB, BBB-, BB+, BB* | |
|---|---|---|---|---|
| | *1* | *2* | *1* | *2* |
| **Intercept** | -0.0300 | -0.0228 | -0.0285 | -0.0181 |
| t-statistic | (-4.01) | (-2.96) | (-3.75) | (-2.27) |
| $\mathbf{CR_{IG/Junk}}$ | -0.0066 | -0.0010 | -0.0076 | -0.0114 |
| t-statistic | (-1.62) | (-0.23) | (-2.68) | (-3.93) |
| $\mathbf{CR_{POM}}$ | | -0.0128 | | -0.0153 |
| t-statistic | | (-4.66) | | (-5.82) |
| **D/(D+E)** | -0.0180 | -0.0175 | -0.0180 | -0.0173 |
| t-statistic | (-1.99) | (-1.96) | (-1.99) | (-1.95) |
| **EBITDA/A** | 0.2088 | 0.2068 | 0.2074 | 0.2038 |
| t-statistic | (5.48) | (5.41) | (5.43) | (5.29) |
| **Adj. $R^2$** | 0.042 | 0.045 | 0.042 | 0.047 |
| **N** | 5969 | 5969 | 5969 | 5969 |

relative to the between firm variance of the credit rating dummy variables, so the power of that test is reduced. For all the other tests, the results are robust. Fama and MacBeth t-statistics imply significance at the 1% level, and coefficients on the Plus or Minus dummy variable in regressions with random firm effects or with industry and year dummy variables remain negative and significant at the 1% level.

## C. Investment Grade versus Junk Bond Ratings Change

Several of the explanations for why credit ratings are significant outlined in Section I imply that credit rating concerns should be most prominent around the change from investment grade to junk status (i.e., from BBB- to BB+). This section examines this change specifically by introducing an additional credit rating dummy variable that indicates firms are near that change in rating. This variable is defined in two ways: firms with a credit rating of BBB- or BB+, and firms with a rating of BBB, BBB-, BB+ or BB (given the significance of this potential change in rating, firms with BBB and BB ratings might be concerned with that change in rating as well as firms with a BBB- and BB+ rating). Denoting this additional dummy variable as $CR_{IG/Junk}$, this paper conducts the following 2 tests for each definition:

$$NetDIss_{it} = \alpha + \delta CR_{IG/Junk} + \phi K_{it} + \varepsilon_{it} \tag{4}$$

$$NetDIss_{it} = \alpha + \delta CR_{IG/Junk} + \beta CR_{POM} + \phi K_{it} + \varepsilon_{it} \tag{5}$$

Table VI shows results of these two equations with the 2 different definitions of $CR_{IG/Junk}$. The coefficient on $CR_{IG/Junk}$ is negative for both measures in equation (4), with statistical significance at the 10% level in the first case and 1% level in the second case. For the first measure, $CR_{IG/Junk}$ is not incrementally significant in equation (5), whereas for the second measure, $CR_{IG/Junk}$ is incrementally significant (with a t-statistic of –3.93) and it also increases the statistical significance of the coefficient on $CR_{POM}$ (from –5.02 to –5.82). Both coefficients in Regression 2 of Panel B imply over 1% less debt relative to equity as a percentage of total assets annually for those firms, suggesting economic significance as well for both dummy variables. The results of this section suggest that credit ratings are significant for capital structure decisions for firms across ratings levels, and incrementally more significant at the investment grade to junk credit rating cutoff.

## D. Credit Score Tests

In this section, this paper evaluates the concern for a potential change in Micro Rating. To create credit rating dummy variables, this paper computes a Credit Score for each firm and rank firms within each Micro Rating. To derive the equation to calculate scores, this paper runs a regression of credit ratings on factors that are thought to predict ratings for firms in my sample. The dependent variable is equal to 1 for a rating of CCC- up to a value of 18 for a rating of AA+ (see Horrigan (2016) for a similar approach). The explanatory variables considered are motivated by previous studies predicting credit ratings and also by the criteria the ratings agencies themselves argue are significant for determining ratings. Ederington (2015) "E" states that, "while the exact list of independent variables varies from study to study, measures of (1) leverage, (2) coverage and/or profitability, (3) firm size, and (4) subordination status, have consistently appeared on the lists of important determinates of ratings". Standard and Poor's (2001) "SP" outlines key criteria for ratings, of which the financial factors are size, profitability and coverage, capital structure/leverage and asset protection, and cash flow ratios. Reflecting this, this paper considers the following explanatory variables (with selected cites in parentheses): Net Income/Total Assets (Pogue and Soldofsky (2009) "PS", Kaplan and Urwitz (2009) "KU", Kamstra, Kennedy and Suan (2011) "KKS"), Debt/Total Capitalization (PS, E, SP), Debt/Total Capitalization squared (PS), EBITDA/Interest Expense (KU, SP), EBIT/Interest Expense (SP), (Log of) Total Assets (KKS, SP), and EBITDA/Total Assets (included as an additional measure of profitability). In a regression including all of these variables, several of the variables were redundant or had counterintuitive coefficient signs. By systematically dropping the redundant or non-predictive variables, a regression including only Log of Total Assets, EBITDA/Total Assets and Debt/Total Capitalization had an adjusted $R^2$ of 0.631, approximately the same as a regression with all of the explanatory variables, and the coefficients on each of the variables were the correct sign and significant. Kamstra, Kennedy and Suan (2011) survey previous credit rating prediction research, and they find that past studies have ranged in predictability from 0.565 to 0.703, with an average of 0.618. The results this paper achieves appear consistent with the success found in previous literature. This paper uses the coefficients from this parsimonious regression to calculate the Credit Score as follows:

$$\text{Credit Score} = 1.4501 \text{ Log (A)} + 11.6702 \text{ EBITDA/A} - 6.0462 \text{ Debt/Total Cap.} \tag{7}$$

The sample used for calculating this Credit Score equation is the same as in the previous section, however this paper also excludes any firm whose debt/total capitalization is greater than 1 or less than zero. These values are outliers that obscure the calculation of the Credit Score equation if included. Previous studies also often look at ratings of new issues – the interest in this paper however is predicting ratings for existing bonds of firms, so this paper uses all firm ratings across the sample.

This paper calculates Credit Scores for each firm year with this equation, and then ranks firms within each Micro Rating into high thirds, middle thirds and low thirds. Dummy variables are then constructed from these thirds for inclusion in the test equations. For example, within the Micro Rating A-, firms with a Credit Score that places them in the high or low third within A- are given a value of 1 for the dummy variable $CR_{HOL}$ and firms with Credit Scores that place them in the middle third are assigned a zero for that dummy variable. This paper also creates dummy variables for the individual high and low categories. This paper then runs the following regressions:

$$NetDIss_{it} = \alpha + \beta_0 CR_{HOL} + \phi K_{it} + \varepsilon_{it} \tag{8}$$

$$NetDIss_{it} = \alpha + \beta_1 CR_{High} + \beta_2 CR_{Low} + \phi K_{it} + \varepsilon_{it} \tag{9}$$

$$NetDIss_{it} = \alpha + \beta_3 CR_{HOL} + \varepsilon_{it} \tag{10}$$

The sample for these tests is as before, although some additional observations are lost since in some cases the terms required to calculate the Credit Score are missing. As before, initially this paper excludes debt offerings greater than 10% of total assets for the year.

The Credit Score tests examine effects within a specific rating category, as opposed to the previous section where effects within Broad Ratings were examined. This not only provides an additional test generally of CR-CS, but it also allows for potential additional inferences regarding the way in which managers' care about credit ratings. That is, managers may be concerned more with Broad Ratings changes or they may be more concerned with Micro Ratings changes (or both, depending on the rating level).

The combined high and low dummy variable should mitigate the potential commingling effect of the financial condition of the firm. That is, the individual variables used to calculate a score are highly related to the financial condition of the firm, and firms with worse financial condition issue, on average, less debt relative to equity. This correlation would therefore likely produce a negative coefficient on the credit dummy for the lower third and a positive dummy for the coefficient on the high third, independent of the credit rating effects to identify. Including both the high third and low third within the dummy should negate this effect by offsetting one against the other. Therefore once again CR-CS predicts that the coefficient $b_0$ in equation (10) will be less than zero, as those firms closer to a change in rating will be more conservative (issue less debt relative to equity) with respect to their financing choices.

Another approach to mitigate the effects of the financial condition of the firm is to include control variables (equation (8)) as in the previous sections. One potential problem with this however is that the control variables are the same or similar to the variables used in the score calculation.

**Table VII:** Credit Rating Impact on Capital Structure Decisions - Credit Score Tests

Coefficients and t-statistics from pooled time-series cross-section regressions of net debt raised for the year minus net equity raised for the year divided by beginning of year total assets on credit rating dummy variables and on various control variables measured at the beginning of each year. $CR_{HOL}$ is a credit rating dummy variable with a value of 1 if the firm's Credit Score is in the high or low third of its Micro Rating. $CR_{High}$ and $CR_{Low}$ are credit rating dummy variables with a value of 1 if the firm's Credit Score is in the high or low third, respectively, within its Micro Rating and zero otherwise. The control variables include D/(D+E), book debt divided by book shareholder's equity plus book debt, and EBITDA/A, EBITDA divided by total assets. The sample covers security issuance from 2001 to 2019, and excludes firms with SIC codes 4000-4999 and 6000-6999, and firms with missing values for any of the variables. The sample excludes a firm year if the firm had a debt offering greater than the indicated percentage of total assets in the year. t-statistics are calculated using White's consistent standard errors.

| | *Panel A: Excl. debt offerings > 10%* | | | *Panel B: Excl. debt offerings > 5%* | | |
|---|---|---|---|---|---|---|
| | *1* | *2* | *3* | *1* | *2* | *3* |
| **Intercept** | -0.0163 | -0.0169 | -0.0065 | -0.0260 | -0.0268 | -0.0207 |
| t-statistic | (-2.32) | (-2.45) | (-3.08) | (-3.50) | (-3.73) | (-9.45) |
| **$CR_{HOL}$** | -0.0081 | | -0.0095 | -0.0079 | | -0.0095 |
| t-statistic | (-3.05) | | (-3.49) | (-2.84) | | (-3.32) |
| **$CR_{High}$** | | -0.0021 | | | 0.0003 | |
| t-statistic | | (-0.72) | | | (0.11) | |
| **$CR_{Low}$** | | -0.0144 | | | -0.0168 | |
| t-statistic | | (-4.01) | | | (-4.38) | |
| **D/(D+E)** | -0.0333 | -0.0302 | | -0.0334 | -0.0299 | |
| t-statistic | (-4.30) | (-4.02) | | (-4.02) | (-3.74) | |
| **EBITDA/A** | 0.2012 | 0.1956 | | 0.1715 | 0.1639 | |
| t-statistic | (5.13) | (4.96) | | (4.05) | (3.84) | |
| **Adj. $R^2$** | 0.0528 | 0.0548 | 0.0017 | 0.0503 | 0.0544 | 0.0017 |
| **N** | 5938 | 5938 | 5938 | 5137 | 5137 | 5137 |

On the other hand, since the control variables in the regression allow for a linear relationship with the particular variable and the dependent variable, and the variables in the score calculation enter the regression only indirectly in the determination of the dummy variable (which by construction is not a linear relationship), this should not be a problem.

This paper also conducts the test with the individual high and low dummy variables as well in equation (9), to see how much the results are driven by one or the other. This test will allow for inferences regarding whether managers care more about upgrades or downgrades.

Table VII shows results for the regressions (8)-(10). The first and third regressions of Panel A show that the coefficient on $CR_{HOL}$ is statistically significantly negative at the 1% confidence level, with t-statistics of –3.05 and –3.49. The size of the coefficient is similar to the previous section, where the third regression indicates that firms that are in the high or low third within a particular credit rating annually issue nearly 1% less net debt minus net equity as a percentage of total assets than firms in the middle. Once again, credit ratings appear both statistically and economically significant.

The second regression of Panel A shows results with individual high and low dummy variables. The coefficients on both ratings are negative as predicted by CR-CS, however the coefficient on $CR_{High}$ is not statistically significant whereas the $CR_{Low}$ dummy variable is significantly negative at the 1% level. As mentioned above, the Credit Score is highly correlated with the financial condition of the firm, a correlation that implies that coefficient would be positive. Since the two control variables proxy for financial condition however, these results may indicate that firms are somewhat more concerned with downgrades than upgrades.

The POM tests excluded large offerings, as firms conducting large offerings would face similar credit rating effects regardless of where they were within a Broad Rating. For the Credit Score tests however, this distinction would arguably need to be applied on a smaller scale. The size of offerings included in the sample would have to be small enough such that firms in the high or low third would be concerned with an upgrade or downgrade when considering offerings of that size, and firms in the middle third would not face an upgrade or downgrade if they undertook offerings of that size. To consider this, this paper also examines a cutoff of 5%, with results shown in Panel B of Table VII. The results are similar with this modification. Further, this paper examines the results including the full sample for robustness. In this case, unlike the POM tests, the coefficients on the Credit Score factors remain statistically significantly negative, with t-statistics of –2.32 on the coefficients of $CR_{HOL}$ in both equation (8) and (10).

## E. Results by Rating: Credit Score and POM Tests

**Table VIII: Credit Rating Impact by Broad Rating**

t-statistics from pooled time-series cross-section regressions by Broad Rating of net debt raised for the year minus net equity raised for the year divided by beginning of year total assets on a constant, credit rating dummy variables and control variables measured at the beginning of each year. Regressions 1 and 2 distinguish different credit rating dummy variables included the regressions. $CR_{POM}$ is a credit rating dummy variable with a value of 1 if the firm has either a plus or minus credit rating. $CR_{Plus}$ and $CR_{Minus}$ are credit rating dummy variables with a value of 1 if the firm has a plus or minus rating, respectively. $CR_{HOL}$ is a credit rating dummy variable with a value of 1 if the firm's Credit Score is in the high or low third of its Micro Rating. $CR_{High}$ and $CR_{Low}$ are credit rating dummy variables with a value of 1 if the firm's Credit Score is in the high or low third, respectively, within its Micro Rating. The control variables (not shown) are D/(D+E), book debt divided by book shareholder's equity plus book debt, and EBITDA/A, EBITDA divided by total assets. The sample covers security issuance from 2001 to 2019, and excludes firms with SIC codes 4000-4999 and 6000-6999, and firms with missing values for any of the variables. The sample also excludes a firm year if the firm had a debt offering greater than 10% of total assets in the year. t-statistics are calculated using White's consistent standard errors.

| | *AA* | *A* | *BBB* | *BB* | *B* | *CCC* |
|---|---|---|---|---|---|---|
| Panel A: Credit Score Tests | | | | | | |
| Regression 1: | | | | | | |
| $\mathbf{CR_{HOL}}$ | -2.12 | -1.48 | -1.87 | -1.44 | -1.43 | 1.51 |
| Regression 2: | | | | | | |
| $\mathbf{CR_{High}}$ | -1.27 | 0.88 | 0.16 | 0.44 | -0.35 | 0.58 |
| $\mathbf{CR_{Low}}$ | -2.26 | -3.32 | -3.23 | -2.46 | -1.87 | 2.36 |
| Panel B: Plus or Minus Tests | | | | | | |
| Regression 1: | | | | | | |
| $\mathbf{CR_{POM}}$ | -1.68 | -0.48 | 1.30 | -0.72 | -3.35 | -1.24 |
| Regression 2: | | | | | | |
| $\mathbf{CR_{Plus}}$ | 0.16 | 0.10 | 2.49 | 0.04 | -3.10 | -1.07 |
| $\mathbf{CR_{Minus}}$ | -2.09 | -0.84 | -0.27 | -1.04 | -2.26 | -1.13 |

Table VIII shows results of the Credit Score test and POM test by Broad Rating. The power of these tests is reduced, as the sample sizes are smaller in each test. For both sets of tests, in 5 out of the 6 ratings categories, the coefficients on the combined dummy variables are of the correct sign. Credit rating effects persist throughout the ratings spectrum. The Credit Score test in particular seems consistent across ratings, with 5 out of 6 coefficients significant at the 10% level. Considering both tests' results, the AA and B Broad Rating categories appear most significant.

## 4. INCORPORATING CR-CS INTO TRADITIONAL CAPITAL STRUCTURE TESTS

### A. Shyam-Sunder and Myers (1999) (SSM) Tests

#### *A.1. Pecking Order Test*

The SSM test for pecking order asserts that to the extent that a firm has a deficit in funds (DEF) beyond what can be met by internally generated funds, the deficit will be made up through an issuance of debt instead of equity. DEF is defined as capital expenditures, dividend payments, the net increase in working capital and the current portion of long-term debt (at the start of the period) less operating cash flows, after interest and taxes. Using this variable, the test that they undertake is:

$$\frac{\Delta LTD_{it}}{A_{it}} = a + b\frac{DEF_{it}}{A_{it}} + \varepsilon_{it} \tag{11}$$

The pecking order theory implies that "b" is close to 1 and "a" is equal to zero. Chirinko and Singha (2010), Frank and Goyal (2013) and others have criticized this test, however my intent is not to resolve the debate about the model. Of interest is whether the model is enhanced with the introduction of credit rating considerations, and whether credit rating effects persist in the context of pecking order effects. This paper therefore precedes with the SSM tests, but this paper also considers some modifications suggested by these other papers. To determine if credit rating effects persist in the context of this pecking order test, this paper consider the following modified tests:

$$\frac{\Delta LTD_{it}}{A_{it}} = a + b\frac{DEF_{it}}{A_{it}} + \beta_0 CR_{POM} + \varepsilon_{it} \tag{12}$$

$$\frac{\Delta LTD_{it}}{A_{it}} = a + b\frac{DEF_{it}}{A_{it}} + \beta_1 CR_{HOL} + \varepsilon_{it} \tag{13}$$

As before, the additional term in equation (12) is a dummy variable for if a firm has a plus or minus within its Broad Rating and equation (13) contains the High or Low Credit Score dummy variable. If the pecking order model is correct and credit ratings do not matter, the β coefficients should be equal to zero. CR-CS implies β coefficients less than zero.

This paper run these tests using the sample of firms from the previous section, additionally dropping firm years where a variable that is required for calculating DEF is missing. SSM however use a sample of only 157 firms, because they want firms to have continuous data available during their sample period in order to implement other tests. They note however that if they were only testing the pecking order theory (that is, conducting the test here), this restriction would not be necessary. Since this paper only interested in examining pecking order here in the context of credit ratings, this paper can extend their sample to include a greater number of firms. Further, Frank and Goyal (2013) attempt to match the sample from SSM, but are unable to match the exact sample using several different sets of assumptions. They therefore consider several modifications to the sample that SSM use, including a broad sample of firms.

To maintain consistency with the tests of the previous section, this paper would also like to exclude large offerings. However, in this case it would hurt the pecking order results to restrict the sample only to firms that do

**Table IX:** SSM Test of Pecking Order with Credit Rating Factors

Coefficients and t-statistics from pooled time-series cross-section regressions of net long-term debt raised for the year divided by beginning of year total assets on credit rating dummy variables and on DEF. $CR_{POM}$ is a credit rating dummy variable with a value of 1 if the firm has either a plus or minus credit rating and equal to zero otherwise. $CR_{HOL}$ is a credit rating dummy variable with a value of 1 if the firm's Credit Score is in the high or low third of its Micro Rating. DEF is defined as in Shyam-Sunder and Myers (2009), as capital expenditures plus dividend payments plus net increase in working capital and the current portion of long-term debt minus operating cash flows after interest and taxes. The sample covers security issuance from 2001 to 2019, and excludes firms with SIC codes 4000-4999 and 6000-6999, and firms with missing values for any of the variables. The sample also excludes a firm year if the firm had a debt offering greater than 10% of total assets in the year or if DEF is greater than 10% of total assets for the year.

| | *Panel A: POM tests* | | | *Panel B: HOL tests* | | |
|---|---|---|---|---|---|---|
| | *1* | *2* | *3* | *1* | *2* | *3* |
| **Intercept** | -0.0195 | -0.0109 | -0.0166 | -0.0198 | -0.0111 | -0.0166 |
| t-statistic | (-26.55) | (-7.73) | (-14.17) | (-26.34) | (-7.12) | (-12.81) |
| **DEF** | 0.5396 | | 0.5384 | 0.5453 | | 0.5444 |
| t-statistic | (46.61) | | (46.52) | (46.23) | | (46.17) |
| **$CR_{POM}$** | | -0.0070 | -0.0047 | | | |
| t-statistic | | (-3.87) | (-3.15) | | | |
| **$CR_{HOL}$** | | | | | -0.0067 | -0.0048 |
| t-statistic | | | | | (-3.48) | (-3.00) |
| **Adj. $R^2$** | 0.3130 | 0.0029 | 0.3150 | 0.3165 | 0.0024 | 0.3177 |
| **N** | 4767 | 4767 | 4767 | 4613 | 4613 | 4613 |

not undertake large offerings specifically, since this would allow firms with large deficits and small debt offerings to be included yet it would exclude firms with large deficits and large debt offerings, for example. Therefore this paper also places the restriction on the deficit itself, limiting the size of the deficit to be less than 10% total assets, as well as limiting the size of the change in long-term debt to be less than 10%. The dependent variable is the change in debt, so the restriction is placed on large debt offerings only.

Regression 1 of Panel A of Table IX shows results replicating the test from SSM (equation (11)) with my sample, and the coefficient on the deficit is equal to 0.54 and it is statistically significant. This value is smaller than the 0.75 coefficient found in SSM, however the sample is much broader. Frank and Goyal get a coefficient of 0.28 when they use a broader population of Indian firms from the period 2001 to 2019. The sample is also different from Frank and Goyal, most significantly as the time frame is 2001-2019 and the sample is restricted to firms that have credit ratings, so again the results should be different from theirs. It does appear however that the coefficient in Table IX matches fairly well within the findings of these previous tests.

Regression 2 of Panel A of Table IX shows results including the POM credit rating dummy variable only. Although the dependent variable has changed from the previous section to long-term debt only and the sample is slightly changed given missing data required for calculating the DEF term and the 10% DEF exclusion, the credit rating variable is still statistically significantly negative with a t-statistic of -3.87.

Regression 3 of Panel A of Table IX shows results including both the POM credit rating dummy variable and the DEF term, equation (12). This test yields statistical significance for the dummy variable and the predicted sign. Therefore even when pecking order considerations are considered, credit ratings remain relevant for managers. The coefficient on DEF is largely unchanged from Regression 1 to Regression 3, and the $R^2$ from the regression is largely unchanged with the inclusion of the credit rating dummy variable. Therefore the pecking order test withstands credit rating effects, and the credit rating variables add only marginal explanatory power to the test.

Panel B of Table IX shows results using the Credit Score based dummy variables. Once again, CR-CS is supported using this measure for being near a change in rating, as the credit rating coefficient remains statistically significant when nested in the SSM pecking order test. The t-statistic for the coefficient $b_1$ on $CR_{HOL}$ in equation (13) is –3.00.

Note that in comparing the CR-CS effects to the traditional effects, there is an important distinction in the nature of these different tests. The credit rating factors are lagged values and thus they are predicting future capital raising activity. The SSM pecking order test uses contemporaneous data in constructing their independent variable DEF, so this variable is not predicting capital raising activity. As DEF is constructed with contemporaneous data in such a way that it is equal to debt issued during the period plus equity issued during the period, it is not surprising to see strong statistical relationships between that factor and debt issued. As the POM and HOL credit rating factors persist in this context, there again is strong support for CR-CS.

The definition for DEF in the SSM test includes the level of the current portion of long-term debt, as SSM assume that this must be paid in the next year. Frank and Goyal argue that the current portion of long-term debt should potentially be excluded as part of DEF. They run tests including it and excluding it, and they find that empirically the current portion of long-term debt does not belong in DEF. This paper also runs the tests excluding the current portion of long-term debt in DEF. This paper obtains results consistent with Frank and Goyal for the test of equation (5.1), whereby both the coefficient and t-statistic on DEF are larger with this modification (not reported). The implications regarding CR-CS are similar however to the tests using the SSM definition.

### *A.2. Tradeoff Theory Test*

The tradeoff theory implies that there should be no change in leverage from year to year, regardless of whether the firm is near a change in rating, except to revert back to the target leverage (holding the company's marginal tax rate and distress costs constant). Proceeding as before, the test of the tradeoff theory conducted in SSM can also be modified to incorporate potential effects from credit rating concerns. SSM test the tradeoff theory by running the regression:

$$\frac{\Delta LTD_{it}}{A_{it}} = a + b\frac{(LTD^*_{it} - LTD_{it})}{A_{it}} + \varepsilon_{it} \tag{14}$$

$LTD^*$ is the firm's target long-term debt level. A difficulty with implementing this test is that the target debt level is not observed. One approach to estimating the target is to take historical averages of the debt to total capital ratios (see Taggart (2017), for example), and this is the predominates approach SSM use. The target debt level is determined by taking an average debt ratio for each firm for the sample period and multiplying that average by the firm's total capital at the beginning of each year to obtain the target debt level for that particular firm year. SSM show that this test can result in non-rejection of the model even when the model is false; however, given the extent of this test in the literature, it is instructive to incorporate the credit rating factors to see the effects. The tradeoff theory states that b will be greater than zero but less than one (it is less than one due to transaction costs associated with changing capital levels). This test can be modified with the introduction of the credit rating factors as follows:

$$\frac{\Delta LTD_{it}}{A_{it}} = a + b\frac{(LTD^* - LTD_{it})}{A_{it}} + \beta_0 CR_{POM} + \varepsilon_{it} \tag{15}$$

$$\frac{\Delta LTD_{it}}{A_{it}} = a + b\frac{(LTD^* - LTD_{it})}{A_{it}} + \beta_1 CR_{HOL} + \varepsilon_{it} \tag{16}$$

CR-CS implies that firms that are near an upgrade or downgrade may be less willing to increase their debt levels, even if they are currently below their target levels. However, firms that are far away from an upgrade or downgrade will be in a better position to increase their debt levels if they are below their target, since they will be less concerned about a change in rating. Firms that are above their target will reduce their debt no matter where they are with regard to credit ratings, however they may be even more inclined to reduce their debt if they are near a change in rating. Thus CR-CS and the tradeoff theory combined imply the same results for b and a negative value for $\beta_0$ and $\beta_1$.

In excluding large offerings in this case, in addition to excluding firm years if the firm has a debt offering greater than 10% of total assets, to be fair to the tradeoff theory this paper also exclude firm years if the difference between the firm's debt level and its target debt level is greater than 10%.

SSM include a firm only if there is continuous data in which to measure the relevant funds-flow and balance-sheet variables during their entire sample, from 20011 and 2019. This paper instead includes a firm if it has 3 years of data in which to calculate the relevant variables. Their restriction reduces their sample to 157, which would make testing credit rating effects difficult considering the dispersions of firms across ratings. Furthermore, as they point out, their restriction may bias the sample to large firms with conservative debt ratios, which limits their results.

Table X shows results considering POM and HOL dummy variables in the context of the tradeoff tests. Regression 1 of both Panels shows results of the same test as conducted in SSM, equation (14). The target adjustment coefficient, b, in my sample is 0.23-0.24 compared to 0.33 in SSM. My results are for a significantly larger sample and this paper places restrictions on

**Table X:** SSM Test of Tradeoff Theory with Credit Rating Factors

Coefficients and t-statistics from pooled time-series cross-section regressions of net long-term debt raised for the year divided by beginning of year total assets on credit rating dummy variables and on (LTD* - LTD). $CR_{POM}$ is a credit rating dummy variable with a value of 1 if the firm has either a plus or minus credit rating and equal to zero otherwise. $CR_{HOL}$ is a credit rating dummy variable with a value of 1 if the firm's Credit Score is in the high or low third of its Micro Rating. (LTD* -LTD) is defined as in Shyam-Sunder and Myers (2009), as target debt level minus current debt level divided by total assets. Target debt levels are calculated using historical averages, and the sample includes firms with at least 3 years of data. The sample covers security issuance from 2001 to 2019, and excludes firms with SIC codes 4000-4999 and 6000-6999, and firms with missing values for any of the variables. The sample also excludes a firm year if the firm had a debt offering greater than 10% of total assets in the year or if (LTD* - LTD) is greater than 10% of total assets for the year.

| | *Panel A: POM tests* | | | *Panel B: HOL tests* | | |
|---|---|---|---|---|---|---|
| | *1* | 2 | *3* | *1* | 2 | *3* |
| **Intercept** | -0.0044 | -0.0060 | -0.0013 | -0.0046 | -0.0057 | -0.0016 |
| t-statistic | (-5.62) | (-4.73) | (-1.10) | (-5.67) | (-3.94) | (-1.16) |
| **(LTD* - LTD)** | 0.2255 | | 0.2243 | 0.2373 | | 0.2357 |
| t-statistic | (27.57) | | (27.43) | (27.58) | | (27.34) |
| **$CR_{POM}$** | -0.0069 | -0.0052 | | | | |
| t-statistic | (-4.23) | (-3.34) | | | | |
| **$CR_{HOL}$** | | | | | -0.0077 | -0.0046 |
| t-statistic | | | | | (-4.35) | (-2.77) |
| **Adj. $R^2$** | 0.1154 | 0.0029 | 0.1169 | 0.1198 | 0.0032 | 0.1209 |
| **N** | 5820 | 5820 | 5820 | 5581 | 5581 | 5581 |

debt offering size. For these reasons, the results could differ, but the coefficient from my test seems reasonable considering the SSM results. The second regression of both Panels shows results from a regression with the credit rating dummy variables alone, with the modified sample, and the coefficient on the credit rating dummy is statistically significantly negative in both cases.

Regression 3 of both Panels of Table X nests the credit rating factors into the tradeoff theory test. The credit rating dummy variables remain statistically significant when nested in this test, although they only marginally change the $R^2$. The t-statistic for the coefficient $\beta_0$ on $CR_{POM}$ in equation (15) is -3.34, and in equation (16) the t-statistic for the coefficient on $CR_{HOL}$ is –2.77. These results support CR-CS in the context of the tradeoff theory. Note also again in comparing the CR-CS factors to the traditional factors, there is an important distinction between the factors. The SSM tradeoff theory test uses contemporaneous and future data to calculate the target leverage level. As SSM themselves show, this predisposes this test to perform well. The credit rating factors in contrast are lagged values, so they are predicting future capital structure activity, which is a more difficult requirement.

## B. Fama and French (2012) (FF) Tests

FF empirically examines the implications on both leverage and dividend decisions of the tradeoff theory and pecking order models. This paper focuses on the leverage tests they undertake. For these tests, they use partial adjustment models as follows (the i subscripts are suppressed for notational convenience):

$$L_{t+1} / A_{t+1} - L_t / A_t = a + b[TL_{t+1} - L_t / A_t] + cP + \varepsilon_{t+1} \tag{17}$$

$$(L_{t+1} - L_t) / A_t = a + b[TL_{t+1} - L_t / A_t] + cP + \varepsilon_{t+1} \tag{18}$$

In this regression, TL is target leverage for a firm and P is a vector of changes in current and lagged assets ($A_{t+1}$-$A_t$ and $A_t$-$A_{t-1}$) and earnings ($ER_{t+1}$-$ER_t$ and $ER_t$-$ER_{t-1}$, where ER is defined as after-tax before-interest earnings). The primary variable FF use in their dependent variable calculation is leverage, L, defined as total assets minus book equity. This is a different measure of debt than tests in the previous sections of this paper, as this includes all liabilities, not only long and/or short-term debt. As this measure of leverage is different from what credit rating agencies use for determining ratings, this measure is not ideally suited to finding effects of credit ratings compared to the dependent variables of previous sections. On the other hand, it is related to factors credit rating agencies use, so it should still allow for some identification of credit rating effects. To further examine this point however, this paper modifies equation (18) as follows:

$$\Delta D_t / A_t = a + b[TL_{t+1} - L_t / A_t] + cP + \varepsilon_{t+1} \tag{19}$$

This is similar to their test, however it considers changes in liabilities occurring only as a result of debt capital market activity. This paper do not modifies equation (17) however; this paper therefore also maintains a test with their exact specification.

The pecking order model predicts a strong short-term response of leverage to the variables in P. The pecking order also predicts that b=0, as firms should not be concerned with moving towards a target leverage level. The tradeoff theory on the other hand predicts that firms will change their leverage levels such that they move closer to their target levels of leverage, implying b>0. The tradeoff theory implies that the variables of P are not significant with regard to leverage decisions, and therefore the tradeoff theory implies c=0.

To estimate equations (17) and (18), FF conduct a two-step cross-sectional regression. Each year they regress book leverage at time t+1 on variables assumed to determine target leverage, TL. They then use the fitted values from that equation to proxy for each firm's target leverage. The first stage regression is:

$$L_{t+1}/A_{t+1} = \beta_0 + \beta_1 V_t/A_t + \beta_2 ET_t/A_t + \beta_3 TP_{t+1} + \beta_4 LogA_t + \beta_5 RD/A_t + \beta_6 RD\_Dummy_t + \beta_7 Dp/A_t + \varepsilon_{t+1} \tag{20}$$

V is equal to L plus the market value of equity, ET is earnings before interest and taxes, RD is R&D expenditures, RD_Dummy is a dummy variable set equal to 1 if a firm reports no R&D, Dp is Depreciation, and TP is the target dividend payout ratio for a firm, calculated from a target payout regression approach set forth in the paper. FF finds however that there is high collinearity between TP and ET, and as a result including both factors reduces the significance of both. FF conclude that there is little evidence that TP is related to leverage as it does not remain statistically significant when both TP and ET are included, whereas ET remains statistically significant. For these reasons, this paper do not includes TP as a factor in the first stage regression.

FF divide firms into dividend paying and non-dividend paying in both stages of the approach, as the pecking order model implies that the relationship between leverage and investment may differ in the two groups; This paper proceeds similarly. FF also conduct tests using market and book values of equity in deriving their dependent variables, but this paper analyzes the book value regressions only as they are more relevant for credit rating considerations, as discussed previously.

Results of first stage regressions yield coefficients similar to those found in FF (not reported). In the second stage regressions, the effects of credit ratings can be tested by including dummy variables for firms with a plus or minus credit rating or dummy variables for firms with a high or low Credit Score within their Micro Rating. With these credit rating dummy variables denoted as $CR_*$ (where * = POM or HOL), this paper examines the following two tests:

$$L_{t+1}/A_{t+1} - L_t/A_t = a + b[TL_{t+1} - L_t/A_t] + cP + \beta CR_* + \varepsilon_{t+1} \tag{21}$$

$$\Delta D_t / A_t = a + b[TL_{t+1} - L_t / A_t] + cP + \beta CR_* + \varepsilon_{t+1} \tag{22}$$

The TL values are those predicted from the first stage regressions. The credit rating implication in both cases is that β<0, while the implications of the tradeoff and pecking order models remain the same.

The sample for these tests is different given the data requirements for these tests. FF requires that several data variables be available for three consecutive years for each firm year. This paper also as before exclude firm years where the firm conducted a large debt offering, defined to be greater than 10% of total assets.

**Table XI:** FF Test of Tradeoff and Pecking Order Theories with Credit Ratings - Dividend Paying Firms

Fama and MacBeth time-series cross-section regressions coefficients and t-statistics. Coefficients are means of 16 cross sectional regressions from 2001-2019, and t-statistics are time series standard deviations of the coefficients divided by 16. Dependent variables are change in leverage in Panel A (where L=total assets minus book equity and A=total assets), and net debt issued divided by total assets in Panel B. $CR_{POM}$ is a credit rating dummy variable with a value of 1 if the firm has either a plus or minus credit rating and equal to zero otherwise. $CR_{HOL}$ is a credit rating dummy variable with a value of 1 if the firm's Credit Score is in the high or low third of its Micro Rating. Other dependent variables include changes in current and lagged Assets and changes in current and lagged Earnings (where ER denotes after tax earnings). The sample includes firms with dividends at time t-1, and excludes firms with SIC codes 4000-4999 and 6000-6999, firms with missing values for the regression variables, and firm years if the firm had a debt offering greater than 10% of total assets in the year.

| | *Panel A: $L_{t+1}/A_{t+1}$ - $L_t/A_t$ as Dependent Variable* | | *Panel B: Net Debt Issued/$A_t$ as Dependent Variable* | |
|---|---|---|---|---|
| | *1* | *2* | *1* | *2* |
| **$CR_{POM}$** | -0.0026 | | -0.0012 | |
| t-statistic | (-1.65) | | (-0.82) | |
| **$CR_{HOL}$** | | -0.0018 | | -0.0039 |
| t-statistic | | (-0.82) | | (-2.36) |
| **$TL_{t+1}$** | 0.1407 | 0.1671 | 0.0568 | 0.0561 |
| t-statistic | (5.12) | (5.44) | (2.82) | (2.53) |
| **$L_t/A_t$** | -0.0640 | -0.0684 | -0.0647 | -0.0667 |
| t-statistic | (-5.29) | (-5.98) | (-4.56) | (-5.34) |
| **$(A_{t+1}-A_t)/A_{t+1}$** | 0.0747 | 0.0725 | 0.1404 | 0.1423 |
| t-statistic | (3.69) | (3.54) | (6.91) | (6.97) |
| **$(A_t-A_{t-1})/A_{t+1}$** | -0.0402 | -0.0408 | -0.0026 | -0.0032 |
| t-statistic | (-4.10) | (-4.71) | (-0.34) | (-0.39) |
| **$(ER_{t+1}-ER_t)/A_{t+1}$** | -0.5211 | -0.5302 | -0.2023 | -0.2094 |
| t-statistic | (-9.85) | (-9.78) | (-5.96) | (-6.24) |
| **$(ER_t-ER_{t-1})/A_{t+1}$** | -0.2600 | -0.2052 | -0.0193 | -0.0166 |
| t-statistic | (-5.95) | (-5.75) | (-0.57) | (-0.46) |
| **N** | 4639 | 4415 | 4257 | 4056 |

Instead of using a pooled time-series cross sectional approach, FF employs a statistical technique similar to that in Fama and MacBeth (2013) (this approach will henceforth be referred to as "FM"). They argue this approach provides more robust standard errors.

Table XI shows results of equations (21) and (22) for dividend paying firms with coefficients and standard errors calculated using FM. Panel A corresponds to equation (21) for both POM and Credit Score dummy variables, and Panel B corresponds to equation (22) for POM and Credit Score dummy variables. In all 4 regressions, the credit rating dummy variable coefficients have the predicted sign, 2 of which are significant at the 5% level. These results support CR-CS in the context of both pecking order and tradeoff theory factors.

In the equation (21) tests, the coefficients on all six of the FF independent variables are statistically significant, and are of the same sign as in FF. They also are similar in magnitude to the coefficients in FF. This indicates that my tests are consistent with their approach and findings. In equation (22) using a different dependent variable, the lagged changes in assets and earnings are no longer significant. This suggests that some of their results may not be robust to alternate specifications of the dependent variable, whereas CR-CS appears somewhat more robust.

For non-dividend paying firms (not reported), the coefficients on the POM dummy variables with both dependent variables are negative, one of which at the 10% significance level, however the HOL dummy variable coefficients are positive, but not statistically significant. Consistent with FF, This paper also obtain a negative coefficient on the contemporaneous change in investment variable, a result FF find inconsistent with all other leverage tests.

## 5. CONCLUSION

Credit ratings directly affect capital structure decisions by managers. In regressions including dummy variables that account for a firm being close to a ratings change - both near a Broad Ratings change and a Micro Ratings change - firms near a credit rating change issue less debt relative to equity than firms that are not near a ratings change. On an annual basis, firms with a plus or minus rating within their Broad Rating issue approximately 1.5% less net debt minus net equity as a percentage of total assets than firms that do not have a plus or minus rating. Similarly, firms with Credit Scores in the high or low third within their Micro Rating issue approximately 1.0% less net debt minus net equity as a percentage of total assets than firms in the middle of their Micro Rating with respect to their Credit Score. The results apply both to the potential for an upgrade as well as a downgrade and are robust to several model specifications and econometric approaches. Managers appear to be most concerned with ratings changes around the AA and B credit rating levels, as well as the change from investment grade to junk.

The credit rating dummy variables remain statistically significant when they are nested in the empirical tests of the tradeoff and pecking order capital structure theories found in Shyam-Sunder and Myers (2009) and Fama and French (2012). Thus credit rating effects persist in the context of these other theories. While inclusion of credit rating dummy variables did not materially affect the implications of these previous tests about their theories, this is not surprising considering the structure of these previous tests. The previous tests include contemporaneous explanatory variables for predicting capital structure decisions, whereas the credit rating dummy variables are constructed without looking ahead. The ability of credit ratings to predict capital structure decisions within these tests is an arguably stronger result than the ability of the contemporaneous factors from these tests to maintain predictive ability. Future capital structure research may benefit from accounting for firms' credit rating situations, both to ensure correct inferences in capital structure empirical tests, and also generally to obtain more comprehensive depictions of capital structure behavior.

## *Appendix*

Consider a 1-period financing decision for a firm where the firm has exhausted its internal cash and therefore must issue outside capital, debt only or equity only (to finance a new project, for example). Denote the size of the offering as Z, and the financing choice as F (equal to debt (D) or equity (E)). The value to the firm as a result of the financing including transactions costs, but excluding credit rating effects, is a function of the size and type of offering: V(F,Z). The probabilities of a credit rating upgrade or a downgrade given a new offering are $P_D(F,Z)$ and $P_U(F,Z)$, and the cost/gain from a change in rating is given by g. Assuming risk neutrality, firms will then choose to maximize the expected value of undertaking an offering: $V(F,Z) - P_D(F,Z)g + P_U(F,Z)g$.

**Case 1:** Consider two firm types: firms of type A are near a downgrade, and firms of type B are not near a change in rating. Assume both firms are considering an offering of size Z, and that if an A firm issues debt, the probability of a downgrade is equal to 1, whereas for B firms the probability of an upgrade or downgrade is zero for debt or equity. Thus, for example, a debt offering has a value to an A firm of $V_A(D,Z)-\gamma$ whereas for a B firm the value is $V_B(D,Z)$. Clearly firms of type A will choose to issue equity rather than debt in more cases than firms of type B.

**Case 2:** Consider firms of type A and B, but now assume that debt is the only financing choice they are considering. Here the firms are considering two sizes of offering, large and small. Assume that A firms have a probability of a downgrade of 1 for either large or small debt offerings, whereas B firms undertaking a large debt offering have a probability of 1 for a downgrade, but zero for a small offering. Assume V values are independently uniformly distributed, from -.5 to .5, for firms within each type and for each financing choice. Firms will not issue debt if the total value to the firm is less than zero for both sizes of offerings, thus a firm may choose not to issue debt at all. Therefore, given values of V(D,L) and V(D,S), a firm of type A will choose the maximum of V(D,L)-g, V(D,S)-$\gamma$ and zero. Likewise, given values of V(D,L) and V(D,S), a firm of type B will choose the maximum of V(D,L)-$\gamma$, V(D,S) and zero. The table below depicts the percentages of firms that will choose the three alternatives for a general value of $\gamma$, and for the example of $\gamma$=0.1.

| | *General Case* | | | *Example, =0.1* | | |
|---|---|---|---|---|---|---|
| *Firm Type* | *Debt, Small* | *Debt, Large* | *Do Nothing* | *Debt, Small* | *Debt, Large* | *Do Nothing* |
| A | $\frac{3}{8}-\frac{\gamma}{2}-\frac{\gamma^2}{2}$ | $\frac{3}{8}-\frac{\gamma}{2}-\frac{\gamma^2}{2}$ | $(\gamma+.5)^2$ | 32.0% | 32.0% | 36.0% |
| B | $\frac{3}{8}+\frac{\gamma}{2}-\frac{\gamma^2}{2}$ | $\frac{3}{8}-\gamma+\frac{\gamma^2}{2}$ | $.5\gamma+.25$ | 42.0% | 28.0% | 30.0% |

For all relevant values of $\gamma$, A firms (near a downgrade) issue fewer small debt offerings than B firms (32.0% versus 42.0% for $\gamma$ =.1), and B firms issue more debt offerings of any kind than A firms (70.0% versus 64.0% for $\gamma$ =.1), implications consistent with Case 1. However, somewhat non-intuitively, CR-CS implies A firms issue more large debt offerings than B firms for all $\gamma$ (32.0% versus 28.0% for $\gamma$ =.1). Therefore if firm years with large offerings are included in tests of credit rating effects such as in equation (4.1), a positive credit rating dummy variable coefficient could appear even though firms near a ratings change issue debt less frequently. These implications indicate that the most effective tests of CR-CS should exclude larger offerings.

**Case 3:** Now assume firms of type A and B are considering debt or equity offerings of large or small size. In this case, this paper allows V to vary uniformly between 0 and 1 implying an offering will be undertaken (making computations simpler). For B firms, assume the probability of a change in rating is zero for a small offering of debt or equity, but the probability of a downgrade is 1 for a large debt offering, and the probability of an upgrade is 1 for a large equity offering. For A firms, the probability of a downgrade is 1 for either a large or small debt offering, whereas the probability of an upgrade or downgrade given a large or small equity offering is zero. Under these assumptions, firms will choose different financings in the following percentages by type (these percentages once again require a value of $\gamma$ between 0 and 0.5):

| *Type* | *Debt , Small* | *Debt, Large* | *Equity, Small* | *Equity, Large* |
|---|---|---|---|---|
| A | $\frac{(1-\gamma)^3}{3}-\frac{(1-\gamma)^4}{12}$ | $\frac{(1-\gamma)^3}{3}-\frac{(1-\gamma)^4}{12}$ | $\frac{1}{4}+\gamma\left[\frac{8-6\gamma+\gamma^3}{12}\right]$ | $\frac{1}{4}+\gamma\left[\frac{8-6\gamma+\gamma^3}{12}\right]$ |
| B | $\frac{1}{4}-\gamma^2+\frac{5\gamma^3}{6}$ | $\frac{\gamma^4}{12}+\frac{7(1-\gamma)^4}{12}-\frac{(1-\gamma)^3}{3}$ | $\frac{1}{4}-\gamma^2+\frac{5\gamma^3}{6}$ | $\frac{1}{3}+\gamma-\frac{(1-\gamma)^4}{12}-\frac{7\gamma^4}{12}$ |

Inspection of these equations reveals that this more general case has the same testing implications as Case 2.

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