Exogenous Credit Rating Changes and the Provision of Voluntary Disclosure

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Abstract

We provide evidence suggesting that corporate credit rating changes have an effect on firms' voluntary disclosure behavior that is independent of the information they convey about firm fundamentals. Our analyses exploit two separate quasi-experimental settings that generate either exogenous credit rating downgrades or credit rating upgrades that allow us to isolate the effect of the credit rating label from changes in firms' credit quality. We find evidence of a negative relation between the direction of the credit rating change and the provision of voluntary disclosure in both settings—firms respond to exogenous downgrades by increasing voluntary disclosure and to exogenous upgrades by decreasing voluntary disclosure. Overall, our analyses indicate that credit rating agencies as information intermediaries influence firms' provision of voluntary disclosure.

Keywords: Credit ratings, voluntary disclosure, information intermediaries.

JEL codes: G15, G18, M41.

Data Availability: Data are available from the public sources cited in the text.

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1. Introduction

Many studies have examined the association between quantitative financial disclosures and credit ratings (e.g., Kraft, 2015; Basu and Naughton, 2017). A smaller number of studies have investigated whether aspects of firms' qualitative disclosures affect credit ratings (e.g., Bonsall and Miller, 2017; Bozanic and Kraft, 2017). The implication of these studies is that firm disclosures have a causal effect on credit ratings—holding constant the credit quality of the firm, enhanced disclosures can improve the firm's credit rating. We hypothesize that causality does not only go from disclosure to credit ratings. Rather, we posit that in the absence of a change in credit quality, a firm may respond to a change in its credit rating label by changing its disclosure practices. Thus, the certification role provided by credit rating agencies as information intermediaries (e.g., Sufi, 2009) could influence firms' voluntary disclosure behavior.

Empirically identifying a causal relation between credit rating labels and corporate disclosure is difficult in part due to an omitted variables problem whereby unobservable changes in firm fundamentals may jointly affect both credit ratings and corporate disclosure. Our proposed solution to this endogeneity problem is to focus on two quasi-experimental settings with credit rating changes that are plausibly exogenous to firm fundamentals, thus allowing us to attribute changes in voluntary disclosure behavior to changes in credit rating labels rather than changes in firm fundamentals. These quasi-experimental settings also mitigate the concern that our results are a manifestation of the reverse-casual effect of disclosure on credit ratings documented in prior research.

While the existence of a relation between changes in the firm's credit rating label and its voluntary disclosure behavior could be established with either setting, we use two complementary settings because it allows us to provide a more complete picture of how credit rating labels influence disclosure choices. We suggest that the firm may respond to an exogenous credit rating change in one of two ways. First, the firm could view the credit rating label to be unimportant because interested parties focus on the underlying credit quality of the firm, thus leading to no association between changes in the firm's credit rating label and its provision of voluntary disclosure. In contrast, the firm could view the credit rating label as an important public signal about the firm's prospects. In this case, we follow the analytical framework in Penno (1996) and suggest that changes in credit rating labels will influence the extent of the firm's information production. More specifically, Penno (1996) predicts that firms will respond to an exogenous credit rating downgrade with an increase in voluntary disclosure (a "back-to-the-wall" policy) and to an exogenous credit rating upgrade with a reduction in voluntary disclosure (a "don't-rock-the-boat" policy).[1] Our use of separate downgrade and upgrade settings allows us to investigate both of these disclosure policies.

Our downgrade setting exploits rating agencies' sovereign ceiling rule, which generally doesn't allow a firm to have a credit rating higher than its home country (Almeida et al., 2017). The implementation of this rule increases the likelihood of a credit rating downgrade for bound firms (i.e., those firms with a credit rating at or above the sovereign rating of its home country) in response to a sovereign downgrade. For identification, we use a difference-in-differences framework that compares the change in voluntary disclosure in response to a sovereign downgrade for bound versus non-bound firms. This approach controls for firm fundamentals to the extent that bound firms do not experience a greater deterioration in credit quality than non-bound firms in response to the sovereign downgrade. Empirically, our data are consistent with this identification

[1] An analytical study of the strategic timing of information releases in a dynamic disclosure model by Acharya, DeMarzo and Kremer (2011) generates similar predictions. Their model predicts that bad market news can trigger the immediate release of information by firms, consistent with the empirical findings in Sletten (2012). In addition, their model also predicts that good market news slows the release of information by firms.

strategy. The probability that a firm receives a downgrade during the same period as the sovereign downgrade is strongly discontinuous at the sovereign bound, with bound firms experiencing an incremental reduction in their credit rating of 0.82 notches relative to non-bound firms. However, we do not find a statistically significant difference in the change in CDS spreads for bound versus non-bound firms, indicating that the observed difference in rating changes is unlikely to be attributable to differential changes in credit quality.

Our upgrade setting takes advantage of the implementation of Financial Accounting Standards Board Statement No. 158 ("SFAS158"), which increases the likelihood of a credit rating upgrade for firms with Additional Minimum Liability ("AML") reporting requirements attributable to underfunded defined benefit pension plans (Basu and Naughton, 2017). These credit rating upgrades are unrelated to firm fundamentals, and are simply a function of a correction to the credit rating process.[2] Once again, we use a difference-in-differences framework that compares the change in voluntary disclosure after the adoption of SFAS158 for high versus low AML firms. As with the sovereign setting, our data indicates that this setting generates differential changes in credit ratings without differential changes in credit quality. We find that high AML firms experience a statistically significant rating upgrade of 0.27 notches relative to low AML firms. However, there is not a statistically significant difference in the change in CDS spreads for high versus low AML firms, consistent with the notion that SFAS158 did not differentially affect the credit quality of high versus low AML firms.

[2] Prior to the implementation of SFAS158, there were potentially two liabilities, the Accrued Pension Cost and the Additional Minimum Liability ("AML"). Basu and Naughton (2017) find that the major credit rating agencies were only aware of the Accrued Pension Cost, and not the AML. As a result, the credit rating agency adjustments overstated the net pension liability by the amount of the AML. SFAS158 eliminated the AML, thus exogenously correcting the error in the rating agency adjustments.

Across both settings, we find a negative relation between the direction of the credit rating change and the provision of voluntary disclosure, which we proxy for using the likelihood and frequency of management forecasts. In the sovereign setting, we find that firm-year observations subject to the sovereign ceiling increased both the likelihood and frequency of management forecasts during sovereign downgrade years. This result is consistent with a "back-to-the-wall" policy, whereby the firm exerts effort to respond to and potentially mitigate negative public news about the firm. In the SFAS158 setting, we find that firms with AML reporting requirements above the median decreased both the likelihood and frequency of management forecasts in response to SFAS158. This result is consistent with a "don't-rock-the-boat" policy, whereby the firm does not increase its own information production in response to positive public news.

The complementary nature of these results is reassuring, because the data employed in each setting are substantially different. While the sovereign ceiling rule setting focuses on a small number of foreign firms where exogenous rating downgrades are distributed over time, the SFAS158 setting uses a large sample of US firms where exogenous rating upgrades are at a single point in time. It is also reassuring that the results across both settings are robust to a variety of fixed effects specifications,[3] and that we find consistent evidence in additional tests that consider the firm's overall information environment and variation in the strength of the negative news. In general, the coefficients in our analyses suggest that the effects we document are economically meaningful. For example, firms with AML reporting requirements above the median are 15.7 percent less likely to provide management forecasts during the SFAS158 implementation year.

[3] For example, in the sovereign ceiling setting, our results are robust to country-industry-year fixed effects. This particular specification implies that within a particular year, a bound firm in the same country and industry as a non-bound firm increases its provision of voluntary disclosure relative to the non-bound firm in response to a sovereign downgrade.

We make several contributions to the literature. First, we contribute to the emerging literature that examines how credit rating agencies as information intermediaries shape a firm's disclosure choices. The most closely related paper to ours is Sethuraman (2018), who finds that firms increase disclosure during periods where credit rating agency reputations are lower to aid investors' assessment of credit risk. Our study complements Sethuraman (2018) by finding that firms also adjust their disclosure policies in response to changes in credit rating labels. More broadly, we contribute to the literature that examines how outside forces shape a firm's disclosure choices. Within this broader literature, our results are related to Sletten (2012), who documents an increase in management forecasts in response to exogenous stock price declines, as the disclosed firm-value-related information withheld prior to the decline became more favorable at the lower stock price.

Our study also relates to prior studies that examine whether improved disclosure has an effect on firms' credit ratings. For example, Bonsall and Miller (2017) find that less readable annual reports are associated with less favorable credit ratings and more frequent and larger magnitude disagreements about the initial rating of a new bond. Similarly, Bozanic and Kraft (2017) find that qualitative disclosures are associated with soft credit rating adjustments, indicating that effective disclosures can justify favorable adjustments to credit ratings determined using quantitative financial inputs. Our analyses complement these prior studies by providing evidence consistent with the reverse causality result that credit rating changes that are unrelated to changes in credit quality have an effect on firms' disclosure practices.

Lastly, we contribute to the literature that examines the effects of credit ratings. Within this literature, prior studies have shown that corporate credit ratings affect a firm's cost of capital (Kisgen and Strahan, 2010), its capital structure (Kisgen, 2006), and the level of firm investment

(Lemmon and Roberts 2010; Chernenko and Sunderam 2012; Almeida et al., 2017). This literature has also shown that credit markets are influenced by the certification role of rating agencies (e.g., Sufi, 2009) and that sophisticated investors vary their reliance on credit rating in response to changes in the reputation of credit rating agencies (e.g., deHaan, 2017). We add to this literature by showing that credit ratings influence the firm's disclosure policy.

This paper proceeds as follows. In Section 2, we discuss existing literature and present our hypotheses. We then outline the data and sample selection in Section 3. We present our research design and results in Section 4. We conclude in Section 5.

2. Related Research and Hypothesis Development

We examine the effect of exogenous credit rating changes on firms' voluntary disclosure behavior. Our study is related to recent work that has examined how firms and investors respond to variation in the reputation of the credit rating agencies. deHaan (2017) finds that sophisticated market participants decrease their reliance on corporate credit ratings after the 2008 global financial crisis, consistent with the notion that the perceived usefulness of corporate credit ratings declined in response to the reputational consequences of the financial crisis for rating agencies. Sethuraman (2018) finds that firms increase voluntary disclosure during periods where the reputation of the rating agencies is low, to help investors who are not as willing to rely on the credit rating itself to assess the firm's credit risk. Our study is also related to work that has examined whether firm disclosure has an effect on the firm's credit rating. Bonsall and Miller (2017) find that less readable annual reports are associated with less favorable credit ratings and Kraft and Bozanic (2017) find evidence suggesting that effective disclosures can justify favorable soft adjustments to firm credit ratings. The implication of these two studies is that firm disclosures have a causal effect on credit ratings— more effective disclosures produce higher credit ratings.

We examine the opposite causal relation to these studies by examining whether exogenous credit rating changes affect the provision of voluntary disclosure. Even though prior studies have not investigated how credit rating labels influence disclosure choices, there are some closely related studies in the debt contracting literature. In particular, Vashishtha (2014) finds that firms reduce the provision of management forecasts following covenant violations, as enhanced bank monitoring substitutes for shareholder monitoring and hence the need for management forecasts. To the extent that covenant violations are contemporaneous with credit rating downgrades or that credit rating downgrades otherwise shift control rights to the firm's creditors (e.g., Manso et al., 2010; Adelino and Ferreira, 2016), then Vashishtha (2014) predicts that credit rating downgrades should reduce the provision of management forecasts, consistent with a positive association between the direction of the credit rating change and the provision of management forecasts.

Beyond the credit rating and debt contracting literatures, there are studies that examine the consequences of public signals for the firm's information production. For example, the analytical model in Acharya, DeMarzo and Kremer (2011) predicts that bad market news can trigger the immediate release of information by firms, and that good market news slows the release of information by firms. Sletten (2012) documents an increase in management forecasts in response to exogenous stock price declines, as the favorability of the disclosed news depends, in part, on the firm's stock price. Within this literature, the framework that is most closely aligned with our setting is Penno (1996), which examines how the firm's information production responds to public signals about the firm's future prospects. There are two potential types of public signals—positive and negative. For the negative signal, Penno (1996) finds that firms will adopt a "back-to-the-wall" policy, which means that public signal will be followed by extensive information production. For the positive signal, Penno (1996) finds that firms will adopt a "don't-rock-the-boat" policy, which means that the public signal will not be followed by information production.

The implication of these two policies is that firms will increase the provision of voluntary disclosure in response to a negative external signal, but will not increase the provision of voluntary disclosure in response to a positive external signal. In our setting, these disclosure policies predict that credit rating downgrades (i.e., a negative public signal) will be associated with increases in voluntary disclosure. While this prediction is in contrast with Vashishtha (2014), it is consistent with Sletten (2012). In addition, these disclosure policies predict that credit rating upgrades (i.e., a positive public signal) will not be associated with increases in voluntary disclosure—the level of disclosure could remain the same or decrease, but it will not increase. Overall, this discussion highlights the uncertainty of predictions based on prior studies. Thus, while the actions of credit rating agencies as information intermediaries could have an effect on the firm's voluntary disclosure behavior, we cannot predict the direction of the effect ex ante nor can we predict whether it is the same for both credit rating upgrades and credit rating downgrades. Therefore, we state our main hypothesis separately for credit rating upgrades and downgrades, and state both in null form:

H1a: Exogenous credit rating downgrades have no effect on firms' provision of voluntary disclosure.

H1b: Exogenous credit rating upgrades have no effect on firms' provision of voluntary disclosure.

Any relation between exogenous credit rating changes and firms' voluntary disclosure suggests that credit rating agencies, as information intermediaries, have an effect on firms' voluntary disclosure behavior. A negative association between the direction of the credit rating change and the change in voluntary disclosure is consistent with Penno (1996).

3. Institutional Settings and Sample Selection

3.1 The Sovereign Ceiling Rule Setting

The sovereign ceiling rule applies to any highly rated firm domiciled in a downgraded country. Therefore, as a starting point, we collect data on all non-US firms with non-missing foreign currency long-term issuer credit ratings from the S&P Capital IQ database. We use the foreign currency rating because it is more likely to be tied to the sovereign rating than the local currency ratings (Almeida et al., 2017). We follow other studies (e.g., Adelino and Ferreira, 2016) and focus on S&P's ratings history over other agencies' history because S&P tends both to be more active in making ratings revisions and to lead other agencies in re-rating (Kaminsky and Schmukler, 2002). In addition, rating announcements by S&P also seem to convey a greater own-country stock market impact and seem not to be fully anticipated by the market (Reisen and von Maltzan, 1999).

The initial sample consists of 19,655 firm-years with 2,509 unique firms from fiscal years 2000 through 2015. We exclude firms from countries that did not experience a sovereign downgrade during the 2000 through 2015 period, resulting in 11,494 firm-years with 1,442 unique firms. We exclude Japanese firms because management forecasts are considered a mandatory disclosure for those firms, financial firms (SIC codes “60-69”), utilities (SIC code “49”), and all observations with insufficient requisite data described below. The final sample consists of 2,313 firm-years with 370 unique firms.

The main challenge in using the sovereign ceiling rule setting is the connection between the creditworthiness of firms in downgraded countries and the overall credit quality of those countries. To address this challenge, we follow Almeida et al. (2017) and adopt an empirical strategy that compares firm-years where the credit rating downgrade is more likely to be attributable to the sovereign ceiling rule rather than firm fundamentals to other firm-years. More specifically, we identify firms as bound by the sovereign ceiling rule if the credit rating of the firm is at or above the credit rating of the sovereign in the prior year. For these firm-year observations, the variable *BOUND* takes the value of one. Firm-years where the firm is more likely to be downgraded due to the sovereign ceiling are those years where the firm is bound and there is a sovereign downgrade. We use the variable *DOWNGRADE*, which is an indicator variable that takes the value of one for the years in which the sovereign downgrades occur, to identify downgrade years. In our empirical tests, which we describe in detail in Section 4.1, treatment firm-years are those where both *BOUND* and *DOWNGRADE* are equal to one. The empirical strategy is illustrated in Figure 1 for Titan Cement Company. For this Greek firm, there are two firm-years (2011 and 2015) where the firm is bound (i.e., the credit rating of the firm is at or above the sovereign rating in the prior year) *and* there is a sovereign downgrade. These are the treatment firm-year observations in our analyses. All other years are used as control firm-year observations.

This research design ensures that we are identifying treatment and control observations using ex-ante characteristics. This is preferable to simply identifying ex-post downgraded firms and examining the disclosure response of those firms for two reasons. First, construction of the sample using ex-ante characteristics provides more assurance that the OLS assumption of random sampling is not violated due to sample formation based on ex-post outcomes. Second, an examination of downgraded firms would likely provide insights into a slightly different research question. In particular, the likely comparison in that case would be between firms that were downgraded for economic reasons and firms that were downgraded for exogenous reasons. As a result, we would be providing insights into whether there is a difference in disclosure based on the reason for the downgrade rather than providing insights into whether exogenous downgrades generate different disclosure practices. This type of analysis would be complicated by the fact that it is not clear how to identify economic versus exogenous downgrades ex-post at the firm level.

Table 1 Panel A provides the sample composition by country. The bound (non-bound) sample consists of 102 (2,211) firm-years with 23 (347) unique firms. Consistent with Almeida et al. (2017), this distribution of firms indicates that the vast majority of firms have a credit rating that is below the sovereign rating. Almeida et al. (2017) report that 88.2% of firms receive a rating below the sovereign, compared with 93.7% in our sample. Within the bound sample, there is a sovereign rating downgrade for 35 firm-years. This sample of 35 firm-year observations originates from nine countries: Argentina, Brazil, Greece, Hungary, Italy, Portugal, Russia, Sri Lanka and Turkey. For the other countries in Table 1, the sovereign rating exceeded the firm credit rating for each firm-year observation, and thus none of those firm-year observations were bound by the sovereign ceiling rule. While small, our sample of treatment firm-year observations is consistent with Almeida et al. (2017) who identify 73 treatment firm-year observations using a sample that extends over a longer time period (1990—2013 compared with 2000—2015) and includes utilities (SIC code "49").

Even though the sovereign ceiling is not an absolute rule, the data indicate that the probability that a corporate issuer will obtain a rating downgrade during the same period as the sovereign downgrade is discontinuous at the sovereign bound. In Table 1 Panel B, we report the percentage of bound versus non-bound firm-year observations in our sample that experience a credit rating upgrade, no change in credit rating, or a credit rating downgrade during a sovereign downgrade year. Bound firm-year observations have a 51.4% chance of obtaining a downgrade during the year, compared with only 20.6% for non-bound firm-year observations. Conversely, bound firm-year observations have only a 2.3% chance of obtaining an upgrade during the year, compared with 12.9% for non-bound firm-year observations.[4] Overall, Table 1 Panel B shows that the credit rating of bound firm-year observations declines by approximately one notch in response to a sovereign downgrade (*RATING* increases from 9.40 to 10.34, where higher values indicate lower credit ratings), compared to virtually no change for non-bound firm-year observations.

To ensure that the observed changes in credit ratings are not accompanied by corresponding changes in the credit quality of the firm, we compare changes in the average five-year CDS spread across the groups of firms in Table 1 Panel C. The CDS spread is the periodic payment to the seller of a CDS contract, who in turn promises to buy the reference bond at its par value when a predefined default event occurs. The CDS spread is usually expressed as a percentage (in basis points) of the bond's notional value. By construction, this spread provides a pure measure of the default risk of the reference entity and higher values of the CDS spread reflect higher default risk. We use five-year CDS spreads because these contracts are the most liquid; thus they provide the most reasonable pricing estimate of the default risk for the underlying entity (Micu, Remelona, and Woolridge, 2006; Zhang, Zhou, and Zhu, 2009; Ham and Koharki, 2016). The results in Panel C indicate that there is not a statistically significant difference in the change in CDS spreads for bound versus non-bound firms, suggesting that the observed difference in rating changes is unlikely to be driven by changes in credit quality.

[4] These results are similar to Almeida et al. (2017) who report that, conditional on a sovereign downgrade, firms whose rating is at the sovereign ceiling have a 59% chance of obtaining a rating downgrade within the month, compared to only 9% and 4% for firms who are, respectively, one and two notches below the sovereign rating.

For each firm, we obtain financial data from Compustat, stock return data from Datastream, management forecast data from RavenPack, analyst forecast data from I/B/E/S, and institutional investor data from FactSet LionShares.[5] We use RavenPack rather than I/B/E/S because our sample consists of foreign firms, and management forecast data on I/B/E/S is primarily for US firms.[6] For the RavenPack data, we require that novelty=100 and relevance=100 to ensure that the earnings forecast news is strictly for the concerned firm only. A firm is categorized as providing management earnings forecast if the RavenPack category is "earnings-estimate", "earnings-guidance", or "earnings-per-share-guidance." Frequency is the count of forecasts.

We use the entropy balanced matching technique to match treatment and control observations (Hainmueller 2012; McMullin and Schonberger 2017; Shroff, Verdi, and Yost, 2017; Bonsall and Miller 2017). In our setting, this matching approach provides another way to reduce noise in our estimation that would otherwise be present due to fact that the average treatment observation may not be easily comparable to the average control observation. The entropy balancing technique preserves the full sample and ensures covariate balance between treatment and control observations by re-weighting observations such that the post-weighting mean and variance for treatment and control observations are virtually identical along rating controls. This approach ensures that our treatment and control samples are similar in credit quality, thus allowing us to more comfortably interpret changes in disclosure in response to rating changes in our treatment group as arising from the rating change as opposed to inherent and unobservable differences in fundamentals across the treatment and control firms. Entropy matching is well suited

[5] RavenPack (http://www.ravenpack.com/) is one of the most well known providers of news analytics data. It measures the news sentiment and news flow of the global equity market based on all major investable equity securities.
[6] In robustness tests, we use management earnings forecast from S&P's Capital IQ database (see, e.g., Li and Yang, 2016) and obtain similar results.

to this setting because there is a small number of treatment observations, and these observations are not easily matched to a single control firm (Bonsall and Miller, 2017).

As we discuss in more detail in Section 4, our use of a difference-in-differences research design provides some assurance that our inferences are robust to broad changes that would be expected to affect all the firms in our sample. For example, a deterioration in macroeconomic fundamentals could only generate the discontinuity in credit rating changes across treatment and control subsamples if credit risk increases for bound firms but not for non-bound firms. Consistent with Almeida et al. (2017), we suggest that if there were any differential macro effects, better-quality firms (the treatment group) should be less affected than poorer-quality firms (the control group). Within our differences-in-differences framework, we also employ a variety of fixed effect structures, including country-industry-year fixed effects, to provide additional assurance that our inferences are not due to correlated omitted variables. These tests are described in more detail in Section 4.

The entropy matching variables are a group of variables that prior research has found to be associated with the creditworthiness of the firm. We follow Baghai, Servaes, and Tamayo (2014) in selecting these variables because the financial statement variables employed in that study are comprehensive with regard to prior research and are well suited to analyses over a long time-series. The specific entropy matching variables we use are: *DEBTCOV* (sum of long-term debt and debt in current liabilities scaled by EBITDA. If this number is negative, we set it equal to zero), *NEG_DEBTCOV* (indicator variable equals to one if *DEBTCOV* is negative, and zero otherwise),[7] *RENT* (rental payments divided by total assets), *CASH FLOW* (cash and short-term investments

[7] We do not allow DEBTCOV to be negative because large ratios of debt to EBITDA increases default risk while small ratios decrease default risk. When EBITDA is negative, the ratio becomes negative, while default risk actually increases further. Because we limit DEBTCOV to be positive, we capture the effect of negative values with the binary indicator variable NEG_DEBTCOV.

divided by total assets), *INTCOV* (EBITDA divided by net interest paid), *PROFIT* (EBITDA divided by sales), *PROFITVOL* (standard deviation of *PROFIT* over the last five years, or at least the last two years if data is not available for the last five years), *SIZE* (log of total assets), *LEVERAGE* (long-term debt plus debt in current liabilities divided by total assets), *TANGIBILITY* (net property, plant, and equipment divided by total assets), and *CAPEX* (capital expenditures divided by total assets).

Table 1 Panel D provides the mean and variance of each variable across our bound and non-bound subsamples both before and after the entropy matching technique is employed. Pre-matching, there are modest differences across the two groups of observations. For example, the bound group appear to be slightly larger (mean *SIZE* of 9.313 for the bound group compared with 9.021 for the non-bound group) and have more property, plant and equipment (mean *TANGIBILITY* of 0.511 for the bound group compared with 0.360 for the non-bound group). However, post-matching there are no differences in either the mean or variance of any of the 11 variables across the two groups of observations. Table 1 Panel E presents the descriptive statistics for all variables used in the regression. All explanatory variables are winsorized at the 1^{st} and 99^{th} percentile. The average forecast probability is about 23.7% and the forecast frequency is about 28% in our final sample.

3.2 The SFAS158 Setting

The second setting we employ is the implementation of SFAS158, which generated exogenous improvements in credit ratings for firms with additional minimum liability reporting requirements under the prior accounting regime (Basu and Naughton, 2017). Prior to the implementation of SFAS158, there were potentially two liabilities, the Accrued Pension Cost and the Additional Minimum Liability ("AML"). The latter liability only exists for firms with pension plans that are underfunded on an accrued basis. Basu and Naughton (2017) find that the major credit rating agencies were only aware of the Accrued Pension Cost, and not the AML. As a result, the credit rating agency adjustments overstated the net pension liability by the amount of the AML. SFAS158 eliminated the AML, thus automatically correcting the error in the rating agency adjustments. Basu and Naughton (2017) note that neither S&P nor Moody's was aware of this error, nor did either agency examine changes in credit ratings for firms affected by SFAS158 which would have potentially shed light on the error.

For this setting, we start with all US firms with non-missing long-term issuer credit ratings in the S&P Capital IQ database for the period 2004 to 2007. We merge these firms with the Fundamental File and Pension Item in Compustat. We eliminate firms that do not have pension plans, as our empirical approach relies on the magnitude of the AML, which is an accounting item that only exists for firms with pension plans. We also want to ensure that our treatment and control firms are similar, and we believe this objective is best achieved by focusing on firms with pension plans. We exclude all financial institutions (SIC codes "60-69"), utilities (SIC codes "49"), and governmental enterprises (SIC codes that begin with "9"). The resulting sample consists of 5,076 firm-quarters from 346 unique firms, all of which sponsor a pension plan. Table 2 Panel A provides the industry composition for the sample.

We use this setting to test the effect of credit ratings on disclosure by exploiting the fact that the correction to the rating process generated by SFAS158 is exogenous to firm fundamentals, and the probability that a corporate issuer will obtain a rating upgrade following the implementation of SFAS158 is discontinuous based on the size of the AML reporting requirement. Our treatment firms are those with an AML above the median for all the firms in our sample (*HIGHAML*=1) and the remaining firms are the control firms (*LOWAML*=1). Across these two groups of firms, our data indicates that there is a significant difference in how credit ratings responded in the year SFAS158 was effective. In Table 2 Panel B, we report the percentage of *HIGHAML* and *LOWAML* firms in our sample that experience a credit rating upgrade, no change in credit rating, or a credit rating downgrade during 2007 (i.e., the year that SFAS158 became effective). *HIGHAML* firms have a 28.4% chance of obtaining an upgrade during the year, compared with only 22.9% for *LOWAML* firms. Conversely, *HIGHAML* firms have only a 29.5% chance of obtaining a downgrade during the year, compared with 35.3% for *LOWAML* firms. Overall, Table 2 Panel B shows that the credit rating of *HIGHAML* firms relative to *LOWAML* firms increases by approximately one-third of a notch in response to SFAS158. Importantly, the analyses of the CDS spreads in Panel C indicate that even though there is a difference with regard to changes in credit ratings, there is no difference- with regard to changes in CDS spreads and hence credit quality.

As with the sovereign ceiling rule setting, we ensure that there is balance across the treatment and control subsamples by using the entropy matching procedure. We use the same variables to capture the credit worthiness of the firm as we did for the sovereign ceiling rule setting in Section 3.1. The results of the entropy matching procedure are provided in Table 2 Panel D. Pre-matching, there are visible differences in *DEBTCOV*, *INTCOV*, *PROFITVOL*, and *TANGIBILITY*. These differences indicate that the treatment firms have, on average, higher debt, lower interest coverage on debt, more volatile profits, and fewer tangible assets. The entropy matching procedure eliminated these differences, thus providing some comfort that our subsequent analyses are not influenced by inherent differences in the credit worthiness of the treatment and control subsamples. Table 2 Panel E presents the descriptive statistics for all variables used in the regression. All explanatory variables are winsorized at the 1st and 99th percentile.

4. Research Design and Results

4.1 The Sovereign Ceilings Rule Setting

We examine the effect of credit ratings on disclosure in the sovereign ceiling rule setting using the following difference-in-differences specification:

$$VOL\_DISC_{i,t} = \alpha + \beta_1 BOUND_{i,t} + \beta_2 DOWNGRADE_t + \beta_3 BOUND{*}DOWNGRADE_{i,t} + \sum \gamma_j \, Controls + Fixed\ Effects + \varepsilon_{i,t} \qquad (1)$$

We proxy for voluntary disclosure using the provision of management forecasts for two reasons. First, there is an extensive prior literature that provides evidence suggesting that management forecasts represent broad disclosure events that facilitate the monitoring of the firm (e.g., Ruland, Tung, and George, 1990; Nagar, Nanda, and Wysocki, 2003; Karamanou and Vafeas, 2005). Second, the amount of private information revealed by managers through earnings forecasts is economically large. For example, Beyer, Cohen, Lys, and Walther (2010) note that, on average, management forecasts account for 16% of the variation in quarterly stock returns. In addition, credit markets react significantly to management forecast news as evidenced by credit default swap (CDS) spreads (e.g., Shivakumar, Urcan, Vasvari, and Zhang, 2011).

We use two different variables to proxy for voluntary disclosure behavior: *FORECAST* and *FREQUENCY*. *FORECAST* is an indicator variable set to one if the firm issues at least one management earnings forecast during the fiscal year. *FREQUENCY* is the natural logarithm of one plus the number of times management issues earnings forecast during the fiscal year. We use the natural logarithm of one plus the number of forecasts to calculate *FREQUENCY* because the distribution of forecasts is skewed. *BOUND* is an indicator variable that takes the value one for firm-years where the firm's rating is equal to or above the sovereign rating in the prior year. This variable identifies those firms where the probability of downgrade is substantially higher than other firms in the event of a sovereign downgrade. *DOWNGRADE* is an indicator variable that takes the value one for all country-years if the country experiences a sovereign ratings downgrade during the year.

We control for various factors identified in prior research as determinants of voluntary disclosure behavior (e.g., Lang and Lundholm, 1993; Li and Yang, 2016). These control variables are: *BTM* (the ratio of book value of equity divided by market value of equity); *SURPRISE* (the absolute change in earnings per share scaled by beginning price per share); *RETVOL* (the annual standard deviation of monthly stock returns); *RETURN* (the annual buy-and-hold return); *ROA* (the ratio of earnings before extraordinary items divided by total assets); *ACCRUALS* (which equals discretionary accruals calculated based on modified Jones model); *ANALYST* (the number of analysts providing an EPS forecast each month averaged over the entire fiscal year); and *INSTOWNERSHIP* (the percentage of stock held by institutional investors). We also include each of the variables used in the entropy matching procedure as controls to absorb residual variation not captured by the matching process. We include either country and industry fixed effects or firm fixed effects to control for time-invariant unobserved correlated variables. We also include year-fixed effects to capture the influence of aggregate time-series trend. Finally, we include country-industry-year fixed effects so that the effect is attributable only to variation within a given country-industry-year. We cluster all the standard errors by country-industry groups to account for any correlation structure among similar firms (i.e., firms in the same industry) in a given country over the entire sample period.

The coefficient of interest in equation (1) is β_3, the coefficient on the interaction term *BOUND*DOWNGRADE*, which captures the change in voluntary disclosure behavior across the treatment firm-years (i.e., high probability of a downgrade in response to the sovereign ratings downgrade) and control firm-years (i.e., low probability of a downgrade). To the extent that an exogenous credit rating decline leads to a decrease (increase) in the provision of management forecasts, we expect $\beta_3 < 0$ ($\beta_3 > 0$).

We present our results using an OLS specification for both continuous as well as binary outcome variables for three reasons. First, nonlinear models tend to produce biased estimates in panel data sets with a short time series and many fixed effects, leading to an incidental parameters problem and inconsistent estimates. Second, nonlinear fixed effects models generate biased estimates for interaction terms, which are the main coefficients of interest in our study (see e.g., Duchin and Sosyura, 2014). Lastly, it is straightforward to interpret the economic magnitude of the coefficients in an OLS specification when the variables of interest are binary variables. In robustness tests, we confirm that our conclusions are the same when we use a logit (for the *FORECAST* specification) and ordered logit (for the *FREQUENCY* specification) model instead of OLS.

The results from equation (1) are presented in Table 3. Panel A provides the univariate results and Panel B provides the multivariate results. In Panel A, we separate the firm-year observations in our sample into two groups: bound and non-bound. Because of the sovereign ceiling rule, the observations in the bound group have a substantially higher probability of downgrade in the event of a sovereign ratings downgrade relative to the other observations. We further separate the bound and non-bound observations into sovereign downgrade (non-downgrade) years based on whether the country experienced a sovereign ratings downgrade. We then compare, across each of these two groups, whether there are differences in voluntary disclosure behavior between downgrade and non-downgrade years. The results in Panel A indicate that there was an increase in both the likelihood and frequency of management forecasts for firms subject to the sovereign ceiling in downgrade years when compared with non-downgrade years. For example, in the *FORECAST* specification, there was a statistically significant increase for the bound firm-years of 18.0 percent. Similarly, in the *FREQUENCY* specification, there was a statistically significant increase for the bound group of 27.8 percent.[8] In contrast, there was no measurable change in either specification for the non-bound group. Most importantly, the difference-in-differences estimator is positive and highly significant in both specifications.

The multivariate results in Panel B also show that the bound group increased both the likelihood and frequency of management forecasts during sovereign downgrade years. In columns (1) and (2), we estimate the effect on *FORECAST* and *FREQUENCY* using a specification that includes country, industry and year fixed effects. Across the two columns, the coefficient on the *BOUND*DOWNGRADE* interaction term is significantly positive, indicating that firms that are more likely to experience exogenous credit rating downgrades respond by providing management forecasts or by increasing the frequency of management forecasts. These coefficients are also economically meaningful. For example, the coefficient in Column (1) of 0.182 indicates that bound firm-years are 18.2 percent more likely to provide management forecasts during sovereign downgrade years when compared to other firm-year observations. In columns (3) and (4), we replace the country and industry fixed effects with firm fixed effects and obtain results similar to those in columns (1) and (2), albeit weaker magnitude. These results indicate that, holding the firm constant, there is a statistically significant increase in voluntary disclosure during sovereign downgrade years only for the bound group. In columns (5) and (6), we use country-industry-year fixed effects so that the effect is attributable only to variation within a given country-industry-year and obtain economically strong and statistically significant results in this most restrictive model.

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[8] More precisely, because we use the natural logarithm of one plus the number of forecasts, the difference in logs represents an approximate percentage change in one plus the number of forecasts.

For example, the coefficient in Column (5) of 0.452 indicates that bound firm-years are 45.2 percent more likely to provide management forecasts during sovereign downgrade years when compared to other firm-year observations.

Overall, these results indicate that a credit rating decline unrelated to firm fundamentals is associated with an increase in voluntary disclosure, thus providing evidence that credit rating agencies, as information intermediaries, have an effect on firms' voluntary disclosure behavior. The direction of the association is consistent with Penno (1996), which predicts a negative association between the direction of the credit rating change and the change in voluntary disclosure behavior. Next, we examine the nature of the relation between credit rating changes and voluntary disclosure in the context of exogenous rating upgrades, thus providing a more complete picture of the relation between credit rating changes and voluntary disclosure.

4.2 The SFAS158 Setting

We examine the effect of credit ratings on disclosure in the SFAS158 setting using the following difference-in-differences specification:

$$VOL\_DISC_{i,t} = \alpha + \beta_1 HIGHAML_{i,t} + \beta_2 HIGHAML*POST_{i,t} + \sum \gamma_j \, Controls + Fixed\ Effects + \varepsilon_{i,t} \quad (2)$$

HIGHAML is an indicator variable that takes the value of one for firms whose average additional minimum liability scaled by total assets pre-SFAS158 is above the median of the firms in our sample. This variable identifies those firms where the probability of an upgrade generated by the rating agency correction is highest (Basu and Naughton, 2017). *POST* is an indicator variable that takes the value of one for firm-quarters after the implementation of SFAS158 (i.e., calendar year 2007).

Our remaining research design choices mirror those used in equation (1). We use two different variables to proxy for voluntary disclosure behavior: *FORECAST* and *FREQUENCY*. We use the same set of control variables included in equation (1) as determinants of disclosure behavior as well as all the same entropy matching variables. In addition, we include *PENSIONSIZE*, measured as pension assets scaled by total assets, as a control variable to ensure that our inferences are robust to potential differences in the size of the pension plan across *HIGHAML* and *LOWAML* firms. We include industry fixed effects or firm fixed effects to control for time-invariant unobserved correlated variables and year- and quarter- fixed effects to capture the influence of aggregate time-series trend. The main effect for *POST* is suppressed due to the inclusion of year fixed effects.

The coefficient of interest in equation (1) is β_2, the coefficient on the interaction term *HIGHAML*POST*. This coefficient captures the difference in the change in voluntary disclosure behavior between the treatment firms (i.e., those firms with a higher probability of a rating upgrade in response to the SFAS158) and the control firms (i.e., those firms with a lower probability of a rating upgrade in response to the SFAS158). To the extent that an exogenous credit rating upgrade leads to a decrease (increase) in the provision of management forecasts, we expect $\beta_2 < 0$ ($\beta_2 > 0$).

The results from equation (2) are presented in Table 4. Panel A provides the univariate results and Panel B provides the multivariate results. In Panel A, we separate the firms in our sample into two groups: *HIGHAML* and *LOWAML*. Within these two groups of firms, we separate firm-year observations into pre- and post-SFAS158. We then compare, across each of the *HIGHAML* and *LOWAML* groups of firms, how the provision of management forecasts changes with the implementation of SFAS158. The results in Panel A indicate that *HIGHAML* firms experienced a statistically significant decline in both the likelihood and frequency of management forecasts. In contrast, there was no statistically significant change in either the likelihood or frequency of management forecasts for *LOWAML* firms. Most important, the difference-in-differences estimate is significantly negative in both specifications.

The results in Panel A are also economically meaningful. For example, in the *FORECAST* specification, there was a statistically significant decline for *HIGHAML* relative to *LOWAML* firms of 8.0 percent. Similarly, in the *FREQUENCY* specification, there was a statistically significant decline for *HIGHAML* relative to *LOWAML* firms of 16.4 percent.[9] The fact that the economic magnitude of these coefficients is less than those in the sovereign ceiling rule setting is reassuring, as prior research has found that the market response to credit rating downgrades is typically stronger than the response to credit rating upgrades (e.g., Dichev and Piotroski, 2001). In addition, our descriptive results showed that change in the average credit rating of the treatment firm-year observations was greater in the sovereign ceiling rule setting relative to the SFAS158 setting. Finally, as was the case in Table 3, the univariate results suggest that the variation in disclosure behavior is attributable to changes for firms subject to the exogenous change in its credit rating (i.e., the *HIGHAML* firms).

The multivariate results in Panel B also show that *HIGHAML* firms decreased both the provision of and frequency of management forecasts post-SFAS158. In columns (1) and (2), we estimate the effect on *FORECAST* and *FREQUENCY* using a specification that includes industry and year fixed effects. In columns (3) and (4), we replace the industry fixed effects with firm fixed effects. Across each of the four columns, the coefficient on the *HIGHAML*POST* interaction term is significantly negative, indicating that firms respond to credit rating upgrades that are unrelated to firm fundamentals by reducing the likelihood and frequency of management forecasts. These

[9] More precisely, because we use the natural logarithm of one plus the number of forecasts, the difference in logs represents an approximate percentage change in one plus the number of forecasts.

coefficients are also economically meaningful. For example, the coefficient on the interaction term in Column (1) of 0.116 indicates that there is a decline in the provision of management forecasts for *HIGHAML* firms that is 11.6 percent less than the change in the provision of management forecasts for *LOWAML* firms in response to SFAS158. *HIGHAML* is suppressed in columns (3) and (4) when we include firm fixed effects, as that variable is constant over time for each firm. The results in columns (3) and (4) are consistent with those in columns (1) and (2), albeit weaker magnitude. Holding constant the firm, we find that *HIGHAML* firms reduce the likelihood and frequency of management forecasts post-SFAS158 relative to *LOWAML* firms. In economic terms, the additional decline in the provision of management forecasts is 7.4 percent and the decline in the frequency of management forecasts is 10.3 percent.

Overall, these results indicate that a credit rating upgrade is associated with a decrease in voluntary disclosure, which mirrors our previous result that a credit rating downgrade is associated with an increase in voluntary disclosure. Therefore, both the sovereign ceiling rule and the SFAS158 settings document a negative association between the direction of the credit rating change and the change in voluntary disclosure behavior. These findings suggest that both the "back-to-the-wall" and "don't-rock-the-boat" policies seem to describe how the firm responds to exogenous credit rating changes, with the former explaining the increase in disclosure in response to downgrades and the latter explaining the decrease in disclosure in response to upgrades. Collectively, our results across both settings provide strong evidence that credit rating agencies influence firms' voluntary disclosure behavior.

4.3 Additional Analyses

We conduct two sets of cross-sectional tests to provide some additional evidence consistent with the conclusions we draw from our main analyses. First, we examine whether the firm's information environment influences how it responses to the exogenous change in its credit rating. For the "back-to-the-wall" policy, Penno (1996) predicts that the increase in the firm's information production is accentuated for firms with worse information environments. The intuition for this prediction is that firms have to do more to respond to exogenous negative news when there is more uncertainty about the firm's prospects. Similarly, in the upgrade setting, firms with worse information environments adopting a "don't-rock-the-boat" policy are more likely to curtail disclosures so as not to distract from the external positive signal. In an extreme setting where there is perfect transparency, neither the "back-to-the-wall" nor the "don't-rock-the-boat" policies would exist. Empirically, we examine this cross-sectional conjecture using Size (measured as the natural log of the firm's Market Cap) to proxy for the firms' information environment. We implement these tests by adding this cross-sectional variable to equations (1) and (2). The results are presented in Table 5.

The analysis using the sovereign setting are provided in Panel A, and the analysis using the SFAS158 setting are provided in Panel B. For ease of display, we have not presented the coefficients for the main effects, 2-way interaction, the matching variables or the control variables. For the sovereign setting, the coefficient on the triple interaction term, *BOUND*DOWNGRADE*SMALL*, is significantly positive in each column, with magnitudes that are substantially higher than those in our main specification in Table 3 Panel B. In contrast, the coefficients on the triple interaction term, *BOUND*DOWNGRADE*BIG*, are not statistically significant in columns (1) through (4), and are of much lower magnitude in each column. For example, Column (1) indicates that *FORECAST* increases by 35.7 percent for the subset of bound firm-years where the bound firm has a market capitalization above the sample median, whereas there is no statistically significant change for the observations below the sample median. Tests of the difference in the coefficients across BIG versus SMALL firms had statistically significant p-values in columns (1), (3), (5) and (6). As expected, the analysis of the SFAS158 setting in Panel B does not generate similarly stark differences. While the coefficients on the triple interaction term, *HIGHAML*POST*SMALL*, are significantly negative, these coefficients are not statistically different to the coefficients on the triple interaction term, *HIGHAML*POST*BIG*.

Second, we examine whether the relevance of the public news influences the firm's response. In particular, since an exogenous rating downgrade could be more material for firms that are financially constrained, we examine whether the results in the sovereign setting are attributable to the subset of firms that are more financially constrained. As with the prior analysis, we implement these tests by adding this cross-sectional variable to equation (1). We use two different cross-sectional variables, both of which are proxies for financial constraints. The first cross-sectional variable is a binary variable that partitions the sample based on the firm's level of free cash flows (operating cash flows less capital expenditures scaled by total assets) for the year prior to the sovereign ratings downgrade. *LOWFCF* (*HIGHFCF*) indicates firm-years with free cash flows below (above) the sample median. The second cross-sectional variable is a binary variable that partitions the sample based on the firm's KZ Index, developed by Kaplan and Zingales (1997). Companies with a higher KZ-Index scores are more likely to experience difficulties when financial conditions tighten since they may have difficulty financing their ongoing operations. *HIGHKZ* (*LOWKZ*) indicates firm-years with the value of the KZ index above (below) the sample median.

The analyses using both of these cross-sectional variables is presented in Table 6. The free cash flow partition is provided in Panel A. Once again, for ease of display, we have not presented the coefficients for the main effects, 2-way interaction, the matching variables or the control variables. The coefficient on the triple interaction term, *BOUND*DOWNGRADE*LOWFCF*, is significantly positive in each column, with magnitudes that are substantially higher than those in our main specification in Table 3 Panel B. In contrast, the coefficients on the triple interaction term, *BOUND*DOWNGRADE*HIGHFCF*, are not statistically significant, and of much lower magnitude. For example, Column (1) indicates that *FORECAST* increases by 30.7 percent for the subset of bound firm-years with lower free cash flow during downgrade years, whereas there is no statistically significant change for the subset of bound firm-years with higher lower free cash flow (coefficient of 0.133, which corresponds to 13.3 percent increase in economic terms, and a t-statistic of 1.026). In general, these tests do not find that there is a statistically significant difference in the coefficients across the *LOWFCF* and *HIGHFCF* triple interaction terms. Therefore, we cannot claim that the effect of a credit rating downgrade is stronger for *LOWFCF* firms.

We find similar results for the KZ index cross-sectional test in Panel B. The coefficient on the triple interaction term, *BOUND*DOWNGRADE*HIGHKZ*, is significantly positive in each column, with magnitudes that are substantially higher than those in our main specification in Table 3 Panel B. For example, Column (1) indicates that *FORECAST* increases by 33.9 percent for the bound sample that have a higher KZ index during the sovereign downgrade year. In contrast, the coefficients on the triple interaction term, *BOUND*DOWNGRADE*LOWKZ*, are not statistically significant, and of much lower magnitude. As with our prior analyses, these tests do not consistently find that there is a statistically significant difference in the coefficients across the *HIGHKZ* and *LOWKZ* triple interaction terms. The p-values are statistically significant in columns (1) and (3), but not in the other specifications. Therefore, we cannot convincingly claim that the effect of a credit rating downgrade is stronger for *HIGHKZ* firms.

Overall, the results in Table 5 and Table 6 provide some insights into the drivers of firms' disclosure choices. In Table 5, the decline in disclosure in response to a credit rating downgrade is primarily attributable to those firms that have poor information environments. Similarly, in Table 6, the decline in disclosure in response to a credit rating downgrade is primarily attributable to those firms that are financially constrained, and hence those firms where an exogenous credit rating downgrade is potentially more salient.

5. Conclusion

We find a negative association between the direction of the credit rating change and the likelihood and frequency of management forecasts. We find consistent results across two very different settings—the sovereign ceiling rule setting focuses on a small sample of foreign firms and rating downgrades, whereas the SFAS158 setting focuses on a large sample of US firms and rating upgrades. Overall, our findings suggest that credit rating agencies influence firms' voluntary disclosure behavior.

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APPENDIX A: Variable Descriptions and Data Sources

Variable	Description	Data Source
Voluntary Disclosure Variables		
FORECAST	Indicator variable set to one for firm-years or firm-quarters where the firm issues at least one management earnings forecast during the fiscal year or fiscal quarter	RavenPack, I/B/E/S
FREQUENCY	Natural logarithm of one plus the number of times management issues earnings forecast during the fiscal year or fiscal quarter	RavenPack, I/B/E/S
Treatment and Cross-sectional Variables		
BOUND	Indicator variable set to one for firm-years where the firm's rating is equal to or above the sovereign rating in the prior year	S&P
DOWNGRADE	Indicator variable set to one for firm-years where the country experiences a sovereign rating downgrade	S&P
HIGH(LOW)AML	Indicator variable set to one for firms where the size of the firm's Additional Minimum Liability adjustment pre-SFAS158 is above (below) the sample median (see Basu and Naughton, 2017)	Constructed
POST	Indicator variable set to one for firm-quarters post-SFAS158	Constructed
HIGH(LOW)FCF	Indicator variables set to one for firm-years or firm-quarters where free cash flow is above (below) the sample median; free cash flows is defined as operating cash flows less capital expenditures scaled by total assets	Constructed
HIGH(LOW)SA	Indicator variables set to one for firm-years or firm-quarters where the SA index is above (below) the sample median; the SA index is defined as $-0.737 * SIZE + 0.043 * SIZE^2 - 0.040 * AGE$ (see Hadlock and Pierce, 2010)	Constructed
Entropy Balanced Matching Variables		
SIZE	Log of total assets	Compustat
LEVERAGE	Sum of long-term debt and debt in current liabilities scaled by total assets	Compustat
CASHFLOW	Operating cash flow scaled by total assets	Compustat
DEBTCOV	Sum of long-term debt and debt in current liabilities scaled by EBITDA, or zero if the ratio is negative	Compustat
NEG_DEBTCOV	Indicator variable set to one if the DEBTCOV ratio is negative	Compustat
INTCOV	EBITDA scaled by net interest paid	Compustat
PROFIT	EBITDA scaled by sales	Compustat
PROFITVOL	Standard deviation of PROFIT over the last five years or quarters, or at least the last two years or quarters if insufficient data	Compustat
TANGIBILITY	Net property, plant, and equipment scaled by total assets	Compustat
CAPEX	Capital expenditures scaled by total assets	Compustat
RENT	Rental payments scaled by total assets	Compustat
PENSIONSIZE	Pension assets scaled by total assets	Compustat

Other Control Variables		
BTM	Ratio of book value of equity divided by market value of equity	Compustat
SURPRISE	The absolute change in earnings per share scaled by beginning price per share	Compustat
RETVOL	Annual or quarterly standard deviation of monthly stock returns	Datastream, CRSP
RETURN	Annual or quarterly buy-and-hold return	Datastream, CRSP
ROA	Ratio of earnings before extraordinary items divided by total assets	Compustat
ACCRUALS	Discretionary accruals calculated based on the modified Jones model	Compustat
ANALYST	Number of analysts providing an EPS forecast each month averaged over the entire fiscal year or fiscal quarter	I/B/E/S
INSTOWNERSHIP	Percentage of shares held by institutional investors	Worldscope

Figure 1: Illustrative Coding for the Sovereign Ceiling Rule Setting

Country: Greece
Firm: Titan Cement Company

	2007	2008	2009	2010	2011	2012	2013	2014	2015
Sovereign rating	A	A	BBB+	BB+	CC	B-	B-	B	CCC+
Firm rating	BBB	BB+	BB+	BB+	BB-	BB-	BB	BB	BB
Bound (firm-year)	0	0	0	0	1	1	1	1	1
Downgrade (country-year)	0	0	1	1	1	0	0	0	1
Bound * Downgrade	0	0	0	0	1	0	0	0	1
Guide	0	0	0	1	1	0	0	0	0
Frequency	0	0	0	1	2	0	0	0	0

Figure 1 illustrates the coding and our identification strategy for the sovereign ceiling rule setting using Titan Cement Company in Greece. We use the sovereign rating and firm's foreign currency long-term issuer credit rating from S&P. Bound is an indicator variable set to one for firm-years where the firm's rating is equal to or above the sovereign rating in the prior year. Downgrade is an indicator variable set to one for country-years where the country experiences a sovereign rating downgrade. Bound*Downgrade identifies the average effect of the treatment on the treated.

Table 1: Descriptive Statistics for the Sovereign Ceiling Rule Setting

Panel A: Sample Composition by Country

		Bound Sample			*Non-bound Sample*			*Total*	
Country	Sovereign Rating Downgrade Years	Unique Firms	Downgrade Firm-Years	Non-downgrade Firm-Years	Unique Firms	Downgrade Firm-Years	Non-downgrade Firm-Years	Unique Firms	Firm-Years
Argentina	2000;2001;2008;2012	2	4	12	0	0	0	2	16
Austria	2012	0	0	0	5	3	29	5	32
Belgium	2011	0	0	0	6	4	36	6	40
Brazil	2002;2014;2015	4	4	18	30	48	140	35	210
Bulgaria	2014	0	0	0	1	1	1	1	2
Chile	2015	0	0	0	15	11	67	15	78
Cyprus	2012	0	0	0	1	1	3	1	4
Czech Republic	2002;2004	0	0	0	1	2	11	1	13
Egypt	2001	0	0	0	1	0	3	1	3
Finland	2014	0	0	0	7	6	78	7	84
France	2012;2013	0	0	0	48	73	352	48	425
Greece	2004;2009;2010;2011;2015	5	7	11	2	5	6	7	29
Hungary	2002;2005;2006;2008;2009;2011;2012	2	2	3	3	8	5	5	18
India	2001;2002	0	0	0	13	1	82	13	83
Indonesia	2001	0	0	0	27	3	130	27	133
Ireland	2009;2010;2011	0	0	0	7	9	35	7	44
Israel	2002;2013	0	0	0	3	2	15	3	17
Italy	2004;2006;2011;2012;2013;2014	4	11	11	11	32	34	15	88
Kazakhstan	2007;2015	0	0	0	3	2	10	3	12
Malaysia	2011	0	0	0	7	4	47	7	51
Mexico	2009;2011	0	0	0	28	24	163	28	187
Mongolia	2014;2015	0	0	0	1	1	1	1	2
Netherlands	2013	0	0	0	25	14	197	25	211
New Zealand	2011	0	0	0	7	3	48	7	51

		Bound Sample			Non-bound Sample			Total	
Country	Sovereign Rating Downgrade Years	Unique Firms	Downgrade Firm-Years	Non-downgrade Firm-Years	Unique Firms	Downgrade Firm-Years	Non-downgrade Firm-Years	Unique Firms	Firm-Years
Oman	2015	0	0	0	1	1	1	1	2
Philippines	2003;2004;2005	0	0	0	4	5	11	4	16
Poland	2002;2003	0	0	0	7	4	33	7	37
Portugal	2005;2009;2010;2011;2012	2	2	2	3	8	9	5	21
Russia	2008;2014;2015	2	2	0	25	32	59	27	93
Saudi Arabia	2015	0	0	0	1	1	6	1	7
South Africa	2011;2012;2014	0	0	0	5	10	18	5	28
Spain	2009;2010;2011;2012	0	0	0	14	16	41	14	57
Sri Lanka	2008;2012	1	2	8	1	0	1	1	11
Taiwan	2002	0	0	0	17	2	79	17	81
Thailand	2009	0	0	0	8	6	67	8	73
Turkey	2001;2015	1	1	2	9	8	43	10	54
Total		23	35	67	347	350	1,861	370	2,313

(*continued*)

Table 1 (continued)

Panel B: Ex-post Changes in Credit Ratings

		Long-term Credit Ratings		
		Pre-Downgrade Year	Downgrade Year	
		(a)	(b)	(b)-(a)
Bound	(i)	9.16 *N=25*	10.34 *N=35*	1.18***
Non-bound	(ii)	10.28 *N=319*	10.64 *N=350*	0.36***
	(i)-(ii)	1.12	0.35	0.82*

		% (Count) Of firms that experienced credit ratings changes in the sovereign downgrade year		
		# Upgrades	# No Change	# Downgrades
		(a)	(b)	(c)
Bound	(i)	2.3% *N=1*	45.7% *N=16*	51.4% *N=18*
Non-bound	(ii)	12.9% *N=45*	66.6% *N=233*	20.6% N=72

Panel C: Ex-post Changes in CDS Spreads (Unweighted)

		5-Year CDS Spreads		
		Pre-Downgrade Year	Downgrade Year	
		(a)	(b)	(b)-(a)
Bound	(i)	1.36 *N=10*	1.32 *N=10*	-0.04
Non-bound	(ii)	2.54 *N=110*	2.41 *N=103*	-0.13
	(i)-(ii)	1.18**	1.09*	0.09

Table 1 (continued)

Panel D: Entropy Balanced Matching

	Pre-Matching				*Post-Matching*			
	Bound Mean	Non-bound Mean	Bound Variance	Non-bound Variance	Bound Mean	Non-bound Mean	Bound Variance	Non-bound Variance
SIZE	9.313	9.021	3.044	2.007	9.313	9.313	3.044	3.044
LEVERAGE	0.323	0.318	0.032	0.025	0.323	0.323	0.032	0.032
CASH FLOW	0.137	0.099	0.005	0.005	0.137	0.137	0.005	0.005
DEBTCOV	2.503	3.209	4.167	8.705	2.503	2.502	4.167	4.167
NEG_DEBTCOV	0.000	0.022	0.000	0.021	0.000	0.000	0.000	0.000
INTCOV	17.269	16.886	271.766	984.667	17.269	17.268	271.766	271.804
PROFIT	0.319	0.213	0.020	0.025	0.319	0.319	0.020	0.020
PROFITVOL	0.035	0.028	0.001	0.001	0.035	0.035	0.001	0.001
TANGIBILITY	0.511	0.360	0.035	0.046	0.511	0.511	0.035	0.035
CAPEX	0.088	0.061	0.002	0.002	0.088	0.088	0.002	0.002
RENT	0.067	0.048	0.002	0.002	0.067	0.067	0.002	0.002

(*continued*)

Table 1 (continued)

Panel E: Descriptive Statistics for Variables Used in the Regression Analyses

Variable (N=2,313)	*Mean*	*Std. Dev.*	*Min*	*P25*	*Median*	*P75*	*Max*
Dependent Variables:							
FORECAST	0.237	0.425	0	0	0	0	1
FREQUENCY	0.279	0.555	0	0	0	0	2.565
Entropy Balanced Matching Variables:							
SIZE	9.319	1.740	5.718	7.976	9.250	10.636	12.327
LEVERAGE	0.321	0.177	0.004	0.195	0.290	0.428	0.828
CASH FLOW	0.137	0.069	-0.072	0.089	0.130	0.175	0.337
DEBTCOV	2.488	2.022	0.000	1.027	1.906	3.466	20.351
NEG_DEBTCOV	0.000	0.005	0.000	0.000	0.000	0.000	1.000
INTCOV	17.330	16.458	-0.861	6.939	16.306	16.306	274.676
PROFIT	0.319	0.141	-0.066	0.209	0.325	0.413	0.784
PROFITVOL	0.035	0.029	0.001	0.014	0.025	0.047	0.177
TANGIBILITY	0.511	0.185	0.006	0.410	0.544	0.644	0.900
CAPEX	0.088	0.043	0.003	0.058	0.081	0.115	0.260
RENT	0.067	0.043	0.000	0.012	0.100	0.100	0.100
Other Control Variables:							
BTM	1.666	4.591	-0.159	0.412	0.675	1.252	28.130
SURPRISE	0.171	0.433	0.000	0.009	0.036	0.098	2.080
RETVOL	0.313	0.215	0.011	0.155	0.255	0.412	1.200
RETURN	0.079	0.418	-0.950	-0.136	0.033	0.247	2.766
ROA	0.045	0.068	-0.244	0.013	0.045	0.085	0.262
ACCRUALS	0.000	0.058	-0.389	-0.024	0.000	0.023	0.490
ANALYST	11.606	10.601	0.000	2.000	8.000	18.000	40.000
INSTOWNERSHIP	0.209	0.154	0.000	0.124	0.194	0.282	1.000

The table presents descriptive statistics for the sovereign ceiling rule setting. Our sample contains a maximum of 370 unique firms and 2,313 firm-year observations from 36 countries that experienced a sovereign rating downgrade during the period 2000 to 2015 listed in Panel A. The bound (non-bound) sample includes firm-years where the firm's rating is equal to or above (below) the sovereign rating in the prior year, hence will be affected (unaffected) by rating agencies' sovereign ceiling policies, which requires that firms' ratings remain at or below the sovereign rating of their country of domicile. Panel B presents the ex-post changes in long-term credit ratings for bound (non-bound) samples around the sovereign downgrade years. Panel C presents the ex-post changes in 5-year CDS spreads for bound (non-bound) samples around the sovereign downgrade years. Panel D reports the comparisons of mean and variance for various firm characteristics (i.e., firm-level determinants of corporate credit rating) between the bound and non-bound samples, pre- and post- entropy balanced matching. Panel E presents descriptive statistics for the variables used in the regression analyses. All variables are defined in Appendix A.

Table 2: Descriptive Statistics for the SFAS158 Setting

Panel A: Sample Composition by Industry

Fama-French 12 Industries Code	*Unique Firms*	*Firm-Quarters*
Consumer NonDurables -- Food, Tobacco	39	615
Consumer Durables -- Cars, TV's, Furniture	22	298
Manufacturing -- Machinery, Trucks, Plants	107	1,535
Oil, Gas, and Coal Extraction and Products	29	443
Chemicals and Allied Products	42	594
Business Equipment -- Computers, Software	30	463
Wholesale, Retail, and Some Services	31	461
Healthcare, Medical Equipment, and Drug	23	341
Other -- Mines, Constr, BldMt, Trans	23	324
Total	346	5,074

Panel B: Ex-post Changes in Credit Ratings

		Long-term Credit Ratings		
		Pre-SFAS158	Post-SFAS158	
		(a)	(b)	(b)-(a)
HIGHAML	(i)	9.81 *N=1,982*	10.00 *N=659*	0.19*
LOWAML	(ii)	9.99 *N=1,819*	10.45 *N=614*	0.46***
	(i)-(ii)	-0.18	-0.45	-0.27*

		% (Count) Of firms that experienced credit ratings changes in the year 2007		
		# Upgrades	# No Change	# Downgrades
		(a)	(b)	(c)
HIGHAML	(i)	28.4% *N=50*	42.0% *N=74*	29.5% *N=52*
LOWAML	(ii)	22.9% *N=39*	41.8% *N=71*	35.3% N=60

(*continued*)

Table 2 (continued)

Panel C: Ex-post Changes in CDS Spreads (Unweighted)

		5-Year CDS Spreads		
		Pre-SFAS158	Post-SFAS158	
		(a)	(b)	(b)-(a)
HIGHAML	(i)	1.03 *N=1,181*	1.03 *N=414*	0.00
LOWAML	(ii)	0.99 *N=1,088*	1.02 *N=374*	0.03
	(i)-(ii)	-0.04	-0.01	-0.03

Panel D: Entropy Balanced Matching

	Pre-Matching				*Post-Matching*			
	HIGHAML Mean	LOWAML Mean	HIGHAML Variance	LOWAML Variance	HIGHAML Mean	LOWAML Mean	HIGHAML Variance	LOWAML Variance
SIZE	8.369	8.453	1.636	1.509	8.369	8.369	1.636	1.637
LEVERAGE	0.276	0.287	0.025	0.026	0.276	0.276	0.025	0.025
CASH FLOW	0.024	0.025	0.001	0.001	0.024	0.024	0.001	0.001
DEBTCOV	15.900	17.492	600.067	701.590	15.900	15.899	600.067	600.043
NEG_DEBTCOV	0.015	0.011	0.015	0.010	0.015	0.015	0.015	0.015
INTCOV	0.137	0.174	0.007	0.023	0.137	0.137	0.007	0.007
PROFIT	0.008	0.009	0.000	0.000	0.008	0.008	0.000	0.000
PROFITVOL	15.314	14.245	760.204	558.564	15.314	15.314	760.204	760.212
TANGIBILITY	0.276	0.311	0.025	0.049	0.276	0.276	0.025	0.025
CAPEX	0.011	0.013	0.000	0.000	0.011	0.011	0.000	0.000
RENT	0.014	0.015	0.000	0.000	0.014	0.014	0.000	0.000

(*continued*)

Table 2 (continued)

Panel E: Descriptive Statistics for Variables Used in the Regression Analyses

Variable (N=5,074)	*Mean*	*Std. Dev.*	*Min*	*P25*	*Median*	*P75*	*Max*
Dependent Variables:							
FORECAST	0.546	0.498	0	0	1	1	1
FREQUENCY	0.602	0.623	0	0	0.693	1.099	2.079
Entropy Balanced Matching Variables:							
SIZE	8.418	1.253	5.566	7.562	8.315	9.297	11.902
LEVERAGE	0.281	0.16	0	0.178	0.262	0.363	0.916
CASH FLOW	0.024	0.028	-0.149	0.008	0.024	0.039	0.125
DEBTCOV	16.697	25.552	0	4.55	7.995	14.73	102.438
NEG_DEBTCOV	0.013	0.112	0	0	0	0	1
INTCOV	14.84	25.84	-4.745	4.707	9.216	15.619	220.542
PROFIT	0.155	0.124	-0.226	0.083	0.135	0.195	0.709
PROFITVOL	0.009	0.013	0	0.002	0.005	0.011	0.137
TANGIBILITY	0.293	0.192	0	0.146	0.242	0.399	0.901
CAPEX	0.012	0.011	0	0.005	0.009	0.015	0.084
RENT	0.015	0.02	0	0.006	0.009	0.016	0.169
PENSIONSIZE	0.15	0.164	0	0.037	0.100	0.200	0.802
Control Variables:							
BTM	0.438	0.313	-0.708	0.255	0.403	0.579	2.385
SURPRISE	0.011	0.034	0	0.001	0.003	0.008	0.322
RETVOL	0.12	0.072	0	0.074	0.105	0.147	0.665
RETURN	0.041	0.153	-0.786	-0.046	0.039	0.124	1.592
ROA	0.013	0.021	-0.419	0.006	0.014	0.022	0.07
ACCRUALS	0.088	0.144	-0.489	0	0.056	0.151	0.844
ANALYST	10.016	6.549	0	5	9	14	38
INSTOWNERSHIP	0.714	0.295	0	0.641	0.794	0.897	1

The table presents descriptive statistics for the SFAS158 setting. Our sample contains a maximum of 346 unique U.S. firms and 5,074 firm-quarter observations during the period 2004 to 2007. Panel A presents the breakdown of the sample based on industry classification in fiscal year 2005. Panel B presents the ex-post changes in long-term credit ratings for the high AML and low AML samples around SFAS158 implementation. *HIGHAML* (*LOWAML*) is an indicator variable set to one for firms where the size of the firm's Additional Minimum Liability adjustment pre-SFAS158 is above (below) the sample median (see Basu and Naughton, 2017). We transform the categorical long-term credit ratings in to a continuous measure where higher value represents lower ratings. Panel C presents the ex-post changes in 5-year CDS spreads for the high (low) AML samples around SFAS158 implementation. Panel D reports the comparisons of mean and variance for various firm characteristics (i.e., firm-level determinants of corporate credit rating) between the treatment and control firms, pre- and post- entropy balanced matching. Panel E presents descriptive statistics for the variables used in the regression analyses. All variables are defined in Appendix A.

Table 3: Changes in Voluntary Disclosure Behavior around Sovereign Rating Downgrades

Panel A: Difference-in-Differences Analysis of Management Forecasts

		Management Forecast		
		Non-Downgrade Years	Downgrade Years	
		(a)	(b)	(b)-(a)
Bound	(i)	0.134 *N=67*	0.314 *N=35*	0.180***
Non-bound	(ii)	0.287 *N=1,861*	0.236 *N=350*	-0.051
	(i)-(ii)	-0.153**	0.078	0.231***

		Forecast Frequency		
		Non-Downgrade Years	Downgrade Years	
		(a)	(b)	(b)-(a)
Bound	(i)	0.147 *N=67*	0.424 *N=35*	0.277***
Non-bound	(ii)	0.325 *N=1,861*	0.270 *N=350*	-0.055
	(i)-(ii)	-0.178**	0.154	0.332***

(*continued*)

Table 3 (continued)

Panel B: Regression Analysis of Management Forecasts around Sovereign Rating Downgrades

Dependent variable	(1) Mgmt. Forecast	(2) Forecast Frequency	(3) Mgmt. Forecast	(4) Forecast Frequency	(5) Mgmt. Forecast	(6) Forecast Frequency
BOUND*DOWNGRADE	0.182**	0.221**	0.157	0.173*	0.452**	0.561**
	(2.245)	(2.514)	(1.626)	(1.708)	(2.376)	(2.354)
BOUND	-0.009	0.044	0.075	0.111	-0.065	-0.127
	(0.141)	(0.505)	(0.456)	(0.527)	(0.412)	(0.674)
DOWNGRADE	-0.010	0.029	0.010	0.060	-0.057	-0.020
	(0.217)	(0.444)	(0.205)	(0.831)	(0.603)	(0.159)
Entropy Balanced Matching Variables:						
SIZE	0.051***	0.066***	-0.047	0.004	0.093**	0.132**
	(2.936)	(2.879)	(0.502)	(0.042)	(2.086)	(2.298)
LEVERAGE	-0.031	0.053	0.215	0.464	0.252	0.166
	(0.187)	(0.193)	(0.760)	(1.054)	(0.871)	(0.579)
CASHFLOW	-0.119	-0.418	-0.251	-1.253	-0.434	-0.288
	(0.194)	(0.413)	(0.333)	(1.014)	(0.581)	(0.350)
DEBTCOV	-0.016	-0.030	-0.048*	-0.075*	-0.022	-0.015
	(0.894)	(0.891)	(1.889)	(1.724)	(1.083)	(0.649)
NEG_DEBTCOV	0.052	0.029	0.156	0.241	-0.147	-0.172
	(0.295)	(0.104)	(0.449)	(0.469)	(0.494)	(0.547)
INTCOV	0.001	0.001	-0.001	-0.002	0.004	0.002
	(0.604)	(0.856)	(0.929)	(1.256)	(0.922)	(0.811)
PROFIT	-0.096	-0.080	0.257	0.500	-0.411	-0.584*
	(0.612)	(0.321)	(0.660)	(1.106)	(1.434)	(1.660)
PROFITVOL	0.677	0.240	1.360	1.383	0.161	0.599
	(1.100)	(0.362)	(1.388)	(1.100)	(0.129)	(0.462)
TANGIBILITY	0.078	0.005	0.491*	0.621**	0.115	-0.006
	(0.705)	(0.029)	(1.727)	(2.111)	(0.522)	(0.021)
CAPEX	-0.231	-0.172	-0.369	0.194	0.371	0.966
	(0.537)	(0.296)	(0.508)	(0.276)	(0.441)	(1.273)
RENT	-0.471	-0.212	0.851	1.137	-0.619	-0.696
	(0.866)	(0.248)	(0.867)	(0.790)	(1.266)	(1.033)
Other Control Variables:						
BTM	0.004	0.003	0.020*	0.027**	-0.014*	-0.014
	(0.438)	(0.305)	(1.728)	(2.308)	(1.896)	(1.441)
SURPRISE	0.100	0.129*	0.043	0.056	0.218**	0.195
	(1.534)	(1.880)	(0.717)	(0.969)	(2.134)	(1.410)
RETVOL	0.023	-0.051	0.086	-0.008	-0.088	-0.165
	(0.204)	(0.395)	(0.551)	(0.048)	(0.645)	(0.965)
RETURN	-0.028	-0.013	-0.058	-0.023	0.039	0.098
	(0.850)	(0.261)	(1.302)	(0.374)	(0.601)	(0.980)
ROA	-0.132	-0.158	-0.496	-0.370	-0.707	-1.055*
	(0.353)	(0.343)	(0.838)	(0.493)	(1.638)	(1.834)
ACCRUALS	0.357	0.088	0.309	0.054	1.149	1.302
	(1.372)	(0.293)	(1.026)	(0.167)	(1.575)	(1.330)
ANALYST	0.006*	0.008	0.002	-0.001	0.001	0.000
	(1.687)	(1.654)	(0.376)	(0.144)	(0.173)	(0.060)
INSTOWNERSHIP	0.009	0.000	0.198	0.001	0.062	0.232
	(0.087)	(0.002)	(0.812)	(0.004)	(0.139)	(0.520)

Firm Fixed Effects	-	-	Yes	Yes	-	-
Industry Fixed Effects	Yes	Yes	-	-	-	-
Country Fixed Effects	Yes	Yes	-	-	-	-
Year Fixed Effects	Yes	Yes	Yes	Yes	-	-
Country-Industry-Year Fixed Effects	No	No	-	-	Yes	Yes
Adjusted R-squared	0.345	0.344	0.428	0.467	0.764	0.828
Number of Firm-Years	2,313	2,313	2,313	2,313	2,313	2,313

The table reports analyses of changes in firms' voluntary disclosure behavior following sovereign rating downgrade. Panel A reports the mean values of the voluntary disclosure behavior variables across bound and non-bound firm-years, in the downgrade year and outside of the downgrade year. We indicate statistical significance of differences across cells with t-tests. Panel B reports OLS coefficient estimates and (in parentheses) t-statistics based on robust standard errors clustered by country-industry. *BOUND* is an indicator variable set to one for firm-years where the firm's rating is equal to or above the sovereign rating in the prior year. *DOWNGRADE* is an indicator variable set to one for country-years where the country experiences a sovereign rating downgrade. All variables are defined in Appendix A. We include firm-, country-, industry-and year-fixed effects in the regressions as indicated, but do not report the coefficients. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% p-levels (two-tailed), respectively.

Table 4: Changes in Voluntary Disclosure Behavior around SFAS158

Panel A: Difference-in-Differences Analysis of Management Forecasts around SFAS158

		Management Forecast		
		Pre-SFAS158	Post-SFAS158	
		(a)	(b)	(b)-(a)
HIGHAML	(i)	0.586 *N=1,982*	0.539 *N=659*	-0.047**
LOWAML	(ii)	0.518 *N=1,819*	0.551 *N=614*	0.033
	(i)-(ii)	0.068	-0.012	-0.080***

		Forecast Frequency		
		Pre-SFAS158	Post-SFAS158	
		(a)	(b)	(b)-(a)
HIGHAML	(i)	0.681 *N=1,982*	0.542 *N=659*	-0.139***
LOWAML	(ii)	0.573 *N=1,819*	0.548 *N=614*	-0.025
	(i)-(ii)	0.108*	-0.006	-0.164***

(*continued*)

Table 4 (continued)

Panel B: Regression Analysis of Management Forecasts around SFAS158

Dependent variable	(1) *Management Forecast*	(2) *Forecast Frequency*	(3) *Management Forecast*	(4) *Forecast Frequency*
HIGHAML*POST	-0.116***	-0.161***	-0.074***	-0.103***
	(3.990)	(4.161)	(2.801)	(2.920)
HIGHAML	0.044	0.080		
	(0.881)	(1.255)		
Entropy Balanced Matching Variables:				
SIZE	0.001	0.029	0.042	0.052
	(0.040)	(1.244)	(1.193)	(0.777)
LEVERAGE	-0.052	-0.035	-0.169*	-0.344**
	(0.408)	(0.224)	(1.748)	(2.498)
CASH FLOW	0.894***	1.484***	0.308*	0.578**
	(2.613)	(3.353)	(1.766)	(2.371)
DEBTCOV	-0.001	-0.000	0.000	0.001
	(0.868)	(0.219)	(0.236)	(1.108)
NEG_DEBTCOV	-0.012	0.059	0.075	0.140*
	(0.142)	(0.579)	(1.222)	(1.861)
INTCOV	-0.000	-0.001***	-0.001**	-0.001***
	(1.058)	(2.863)	(2.006)	(2.847)
PROFIT	0.152	0.368	0.069	0.150
	(0.561)	(1.079)	(0.398)	(0.700)
PROFITVOL	-5.420***	-6.802***	-0.431	-1.042
	(4.173)	(4.308)	(0.595)	(1.220)
TANGIBILITY	-0.488***	-0.545***	-0.288	-0.511**
	(3.352)	(3.054)	(1.586)	(2.200)
CAPEX	1.528	2.585	1.317	2.076
	(0.584)	(0.835)	(1.214)	(1.529)
RENT	2.164**	3.196**	-3.181*	-5.024**
	(2.379)	(2.318)	(1.650)	(2.023)
Other Control Variables:				
BTM	-0.025	-0.038	-0.020	-0.033
	(0.462)	(0.604)	(0.382)	(0.527)
SURPRISE	-0.549	-0.660	-0.584*	-0.871*
	(1.397)	(1.460)	(1.805)	(1.879)
RETVOL	-0.945***	-0.936***	-0.136	-0.002
	(4.969)	(4.157)	(0.927)	(0.010)
RETURN	-0.075	-0.120**	-0.069*	-0.117**
	(1.503)	(1.998)	(1.717)	(2.377)
ROA	0.843	1.121	0.523	0.779*
	(1.444)	(1.498)	(1.309)	(1.689)
ACCRUALS	-0.108	-0.145	0.033	0.046
	(0.980)	(1.005)	(0.590)	(0.561)
ANALYST	0.009**	0.010**	0.008*	0.012*
	(2.474)	(2.030)	(1.832)	(1.729)
INSTOWNERSHIP	0.266***	0.332***	-0.180**	-0.215*
	(3.697)	(3.993)	(1.994)	(1.908)
PENSION ASSETS	0.062	0.075	-0.190	-0.216
	(0.417)	(0.368)	(0.736)	(0.753)

Firm Fixed Effects	-	-	Yes	Yes
Industry Fixed Effects	Yes	Yes	-	-
Quarter Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R-squared	0.203	0.201	0.694	0.681
Number of Firm-Years	5,074	5,074	5,074	5,074

The table reports analyses of changes in firms' voluntary disclosure behavior following SFAS158 implementation. Panel A reports the mean values of the voluntary disclosure behavior variables across the high AML and low AML firms, pre and post SFAS158. *HIGHAML* (*LOWAML*) is an indicator variable set to one for firms where the size of the firm's Additional Minimum Liability adjustment pre-SFAS158 is above (below) the sample median (see Basu and Naughton, 2017). We indicate statistical significance of differences across cells with t-tests. Panel B reports OLS coefficient estimates and (in parentheses) t-statistics based on robust standard errors clustered by firm. *Post* is an indicator variable that takes the value of one for fiscal-quarters ending during calendar year 2007 (i.e., post SFAS158 implementation). All variables are defined in Appendix A. We include firm-, industry-, quarter- and year-fixed effects in the regressions as indicated, but do not report the coefficients. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% p-levels (two-tailed), respectively.

Table 5: Cross-Sectional Analyses of the Changes in Voluntary Disclosure

Panel A: Sovereign Rating Downgrades Setting

Dependent variable	(1) *Mgmt. Forecast*	(2) *Forecast Frequency*	(3) *Mgmt. Forecast*	(4) *Forecast Frequency*	(5) *Mgmt. Forecast*	(6) *Forecast Frequency*
BOUND *DOWNGRADE*SMALL	0.357***	0.281***	0.352***	0.278***	1.552***	2.185***
	(3.790)	(2.618)	(3.140)	(2.616)	(6.206)	(6.487)
BOUND *DOWNGRADE*BIG	0.062	0.183	0.013	0.092	0.639***	0.755***
	(0.696)	(1.564)	(0.128)	(0.748)	(3.092)	(2.765)
F-test for Differences across Coefficients [p-value]	[0.009]	[0.510]	[0.013]	[0.174]	[0.000]	[0.000]
Main Effects, 2-way Interaction, Matching and Control Variables	Included	Included	Included	Included	Included	Included
Firm Fixed Effects	-	-	Yes	Yes	-	-
Industry Fixed Effects	Yes	Yes	-	-	-	-
Country Fixed Effects	Yes	Yes	-	-	-	-
Year Fixed Effects	Yes	Yes	Yes	Yes	-	-
Country-Industry-Year F.E.	-	-	-	-	Yes	Yes
Adjusted R-squared	0.345	0.339	0.446	0.474	0.777	0.841
Number of Firm-Years	2,313	2,313	2,313	2,313	2,313	2,313

Panel B: SFAS158 Implementation Setting

Dependent variable	(1) *Management Forecast*	(2) *Forecast Frequency*	(3) *Management Forecast*	(4) *Forecast Frequency*
HIGHAML*POST*SMALL	-0.098**	-0.119**	-0.146***	-0.186***
	(2.499)	(2.444)	(3.267)	(3.537)
HIGHAML*POST*BIG	-0.053	-0.088*	-0.080**	-0.132**
	(1.486)	(1.712)	(2.175)	(2.437)
F-test for Differences across Coefficients [p-value]	[0.409]	[0.664]	[0.253]	[0.461]
Main Effects, 2-way Interaction, Matching and Control Variables	Included	Included	Included	Included
Firm Fixed Effects	-	-	Yes	Yes
Industry Fixed Effects	Yes	Yes	-	-
Quarter Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R-squared	0.693	0.681	0.209	0.207
Number of Firm-Years	5,074	5,074	5,074	5,074

The table presents cross-sectional analyses of changes in firms' voluntary disclosure behavior following a sovereign rating downgrade (Panel A) and around SFAS158 implementation (Panel B). In both panels, we use total market cap to proxy for the firms' information environment. *SMALL* (*BIG*) indicates firm-years with total market cap below (above) the sample median. The panels only report the OLS coefficient estimates and (in parentheses) t-statistics of the main variables of interest but include all the main effects, 2-way interaction terms and the full set of matching variables, controls and fixed effects. All variables are defined in Appendix A. We use robust standard errors clustered by country-industry (Panel A) and firm (Panel B). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% p-levels (two-tailed), respectively.

Table 6: Additional Analyses of the Changes in Voluntary Disclosure around Sovereign Rating Downgrades

Panel A: Partition based on Free Cash Flow

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	*Mgmt. Forecast*	*Forecast Frequency*	*Mgmt. Forecast*	*Forecast Frequency*	*Mgmt. Forecast*	*Forecast Frequency*
BOUND *DOWNGRADE*LOWFCF	0.307**	0.489**	0.301**	0.468*	1.169***	1.553***
	(2.341)	(2.044)	(2.034)	(1.859)	(2.891)	(2.940)
BOUND *DOWNGRADE*HIGHFCF	0.133	0.143	0.099	0.097	0.275	0.307
	(1.026)	(0.922)	(0.648)	(0.549)	(1.088)	(0.948)
F-test for Differences across Coefficients [p-value]	[0.418]	[0.310]	[0.417]	[0.305]	[0.001]	[0.001]
Main Effects, 2-way Interaction, Matching and Control Variables	Included	Included	Included	Included	Included	Included
Firm Fixed Effects	-	-	Yes	Yes	-	-
Industry Fixed Effects	Yes	Yes	-	-	-	-
Country Fixed Effects	Yes	Yes	-	-	-	-
Year Fixed Effects	Yes	Yes	Yes	Yes	-	-
Country-Industry-Year F.E.	-	-	-	-	Yes	Yes
Adjusted R-squared	0.353	0.384	0.435	0.507	0.777	0.842
Number of Firm-Years	2,313	2,313	2,313	2,313	2,313	2,313

Panel B: Partition based on the KZ Index

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	*Mgmt. Forecast*	*Forecast Frequency*	*Mgmt. Forecast*	*Forecast Frequency*	*Mgmt. Forecast*	*Forecast Frequency*
BOUND *DOWNGRADE*HIGHKZ	0.339***	0.306**	0.330**	0.251	0.469**	0.584**
	(2.944)	(2.182)	(2.471)	(1.532)	(2.267)	(2.354)
BOUND *DOWNGRADE*LOWKZ	-0.024	0.065	-0.061	0.025	0.317	0.512
	(0.272)	(0.598)	(0.564)	(0.204)	(1.519)	(1.384)
F-test for Differences across Coefficients [p-value]	[0.009]	[0.162]	[0.020]	[0.261]	[0.440]	[0.821]
Main Effects, 2-way Interaction, Matching and Control Variables	Included	Included	Included	Included	Included	Included
Firm Fixed Effects	-	-	Yes	Yes	-	-
Industry Fixed Effects	Yes	Yes	-	-	-	-
Country Fixed Effects	Yes	Yes	-	-	-	-
Year Fixed Effects	Yes	Yes	Yes	Yes	-	-
Country-Industry-Year F.E.	-	-	-	-	Yes	Yes
Adjusted R-squared	0.359	0.354	0.438	0.472	0.770	0.831
Number of Firm-Years	2,313	2,313	2,313	2,313	2,313	2,313

(*continued*)

Table 6 (continued)

The table presents cross-sectional analyses of changes in firms' voluntary disclosure behavior following a sovereign rating downgrade based on two proxies of financial constraints. In Panel A, we divide the firm-years based on the level of free cash flows (operating cash flows less capital expenditures scaled by total assets) for the year prior to the sovereign rating downgrades. *LOWFCF* (*HIGHFCF*) indicates firm-years with free cash flows below (above) the sample median. In Panel B, we divide the firm-years based on the KZ index for the year prior to the sovereign rating downgrades. The KZ index is calculated based on Kaplan and Zingales (1997). *HIGHKZ (LOWKZ)* indicates firm-years with KZ index above (below) the sample median. The panels only report the OLS coefficient estimates and (in parentheses) t-statistics of the main variables of interest but include all the main effects, 2-way interaction terms and the full set of matching variables, controls and fixed effects. All variables are defined in Appendix A. We use robust standard errors clustered by country-industry. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% p-levels (two-tailed), respectively.