Rating Agency Beliefs and Credit Market Distortions*

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Abstract

The beliefs of credit rating agencies (CRAs) induce mispricing in bond markets which in turn affect firms' financial and investment decisions. We measure CRA beliefs as the difference in forecasts of future aggregate credit spreads between CRAs and a consensus of other financial institutions. We show that when CRAs are relatively more optimistic, they issue higher credit ratings even though their forecasts do not contain additional information regarding future aggregate yields. Moreover, this optimism leads to lower initial yields and subsequent negative returns for newly issued bonds. In response to this mispricing, firms increase their debt levels, leverage and investment, where the effects are most pronounced among rated firms. Finally, when CRAs are more optimistic, firms are more likely to be rated. Our results are consistent with investors being overly reliant on the beliefs of rating agencies, causing mispricing in credit markets, which firms then take advantage of. Overall, our analysis shows how CRA beliefs drive aggregate financing and investment behavior through mispricing in credit markets.

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1 Introduction

Credit rating agencies (CRAs) play a central role in credit markets. Investors rely on CRA credit assessments for the pricing and structuring of bonds and other credit agreements and CRAs' credit assessments can influence firms' financing and investment decisions.[1] Given the importance of CRAs' credit assessments, a burgeoning strand of literature has studied rating quality mainly through the lens of institutional frictions and agency issues. Yet there has been little attention to the CRA belief formation process through which rating decisions are made. For example, not much is known about how CRAs form their beliefs about future credit market conditions and, more importantly, how or if these beliefs affect their credit rating decisions, asset prices, and firm behavior. In this paper, we attempt to fill this void by creating a direct measure of CRA beliefs based on their forecasts of future aggregate corporate bond yields and find that these beliefs induce mispricing in credit markets which in turn strongly influences firms' financing and investment decisions.

An empirical challenge to testing how the beliefs of CRAs affect asset prices and firm behavior is that ratings themselves may be correlated with aggregate outcomes. For example, observing that a CRA issues lower average credit ratings during a particular period may not mean that CRA was abnormally pessimistic, as others may be equally pessimistic (for instance, when economic conditions are expected to deteriorate). Hence, it is difficult to disentangle aggregate conditions from the subjective beliefs of CRAs. A solution to this problem is to analyze differences in ratings across credit rating agencies (e.g., Fracassi, Petry, and Tate, 2016, Kempf and Tsoutsoura, Forthcoming). However, this approach cannot distinguish the aggregate beliefs of CRAs, thereby limiting the ability to analyze their impact on bond prices and firm-level behavior. In this paper, we address this issue by using CRA forecasts of aggregate corporate bond credit spreads. In particular, Moody's, S&P, and other financial institutions report monthly forecasts of various corporate bond credit

[1] e.g., Begley (2013), Kisgen (2019) and Fracassi and Weitzner (2020).

spreads, such as the one-quarter-ahead Aaa and Baa credit spreads. This survey data allows us to isolate differences between the CRA beliefs and beliefs from other prominent financial institutions such as large banks and asset managers (i.e., the "consensus"). By analyzing the differences between CRA and the consensus forecasts, we control for the unobserved common information set—which, for example, may consist of expectations of different aggregate outcomes—or common beliefs distortions.

We begin by constructing a variable that reflects the difference in beliefs between CRAs and the consensus regarding aggregate credit risk, which we refer to as *AaaDev*, by taking the average CRA forecasts of the one-year-ahead Aaa credit spread and subtracting the consensus forecast of the same variable.[2]

We first examine the impact of CRA forecasts on their credit assessments. In particular, we test whether *AaaDev* affects bond-level credit ratings. Consistent with CRAs incorporating their forecasts of future aggregate credit spreads in their bond ratings, we find that when CRAs are relatively more optimistic, their bond ratings are higher. This result suggests that CRA beliefs about aggregate credit spreads have a meaningful impact on their credit assessments.

If *AaaDev* drives CRAs' credit rating decisions, it would be natural to expect that CRA forecasts are informative about future realized credit spreads. We test this hypothesis by estimating a linear regression with both *AaaDev* and the consensus forecast as the independent variable and the future realized Aaa spread as the dependent variable. Despite *AaaDev* driving CRA credit ratings, we find that it contains no additional information regarding future realized credit spreads beyond the consensus forecast. In contrast, the consensus forecast on its own strongly predicts future realized credit credit spreads.

The previous tests suggest we have identified a component of credit ratings that is unrelated to fundamentals, given that it affects ratings but is not informative about future

[2]Specifically, the credit spread forecast is obtained as the difference between yield forecasts of Aaa bond index (ICE BofA AAA US Corporate Index) and the yield of the 10-year Treasury note. We use the 10-year yield because it is the closest match to the average maturity of the Aaa index among all forecast variables.

aggregate credit spreads. If markets are perfectly rational, we would expect that these inflated ratings would not affect bond prices. However, credit investors often rely on credit ratings for information (e.g., Tang, 2009) and may not be able to disentangle the component of credit ratings that are due to CRAs' subjective beliefs. If this is the case, we would expect CRA optimism would lead to higher initial bond yields and lower subsequent returns as the information regarding aggregate conditions is revealed over time. We directly test this hypothesis by regressing initial yields and subsequent bond returns on $AaaDev$. Consistent with the mispricing hypothesis, we find that higher CRA pessimism leads to higher initial yields and subsequent negative excess returns among newly issued bonds.

We then explore whether CRA beliefs affect firms' financing and investment behavior through their effects in the credit markets. If firm managers have a more accurate assessment of their own creditworthiness in markets due in part to their superior information, they are likely to take advantage of their higher ratings and lower yields by issuing more debt and increasing their leverage. Consistent with this hypothesis, we find that when CRAs are relatively more optimistic, firms respond by increasing their debt and leverage levels. Moreover, this effect is concentrated among rated firms and is completely absent from firms' bank debt issuance. This evidence suggests that CRA beliefs affect rated firms' debt issuance decisions through the ratings firms receive and that the corporate bond market does not seem to undo the effect.

Next, we test whether CRA beliefs affect the asset side of the balance sheet through firms' investment decisions. We find that firms increase their assets and property plant and equipment (PP&E) when CRAs are relatively more optimistic than the consensus. Hence, the optimism in CRA beliefs also affects the real decisions of firms.

Finally, we study firms' credit rating "shopping" behavior by testing whether the relative pessimism of CRAs affects firms' decisions to get rated. Intuitively, as CRAs become more pessimistic we would expect firms to be less likely to get rated.[3] Consistent with this

[3]A caveat is that issuer level ratings are usually not paid for; however, CRAs do not usually provide issuer ratings without having provided bond ratings.

hypothesis, we find that the more pessimistic CRAs are, the less likely firms are to be rated.

Taken together, our results are consistent with CRA forecasts inducing mispricing in bond markets, which firms then take advantage of through their issuance, leverage and investment decisions. This story fits nicely within the framework of rational manager and irrational bond investors (e.g., Baker, Stein, and Wurgler, 2003, Shleifer and Vishny, and Stein, 2005). However, we cannot fully determine whether firms are rational. For example, firm managers may interpret their higher ratings (and lower initial bond yields) as a signal about the profitability of their investment opportunities, thereby inducing more investment.

Related literature. Our paper contributes to a broader literature analyzing the effects of ratings on firm financing and investment decisions (e.g., Graham and Harvey, 2001, Kisgen, 2006, Sufi, 2007, Kisgen, 2009, Hovakimian, Kayhan, and Titman, 2009, Begley, 2013, Almeida et al., 2017, Kisgen, 2019 and Fracassi and Weitzner, 2020). To our knowledge, this is the first paper showing that CRAs influence firms' financing and investment decisions by inducing mispricing in credit markets via their aggregate beliefs.

We build on the literature that shows CRAs credit assessments can be subjective (Griffin and Tang, 2012, Fracassi, Petry, and Tate, 2016, Cornaggia, Cornaggia, and Xia, 2016, Kempf and Tsoutsoura, Forthcoming, Fracassi and Weitzner, 2020). Our main contribution to this literature is showing how these aggregate beliefs affect CRA credit assessments which in turn create distortions in credit markets and firm behavior.

Relatedly, there is a large empirical and theoretical literature on credit rating inflation (e.g., Skreta and Veldkamp, 2009, Griffin and Tang, 2011, Bolton, Freixas, and Shapiro, 2012), Goldstein and Huang, 2020). We contribute to this literature by showing that CRA beliefs can cause credit ratings to be either inflated or deflated.

Our paper also relates to the literature analyzing how CRA standards evolve over time. Becker and Milbourn (2011) find that S&P relaxed their rating standards as Fitch gained market share. Jiang, Stanford, and Xie (2012) find that S&P's ratings improve once it switched from an investor-pay to an issuer-pay model. Alp (2013) finds that investment-grade ratings tightened while speculative-grade ratings loosened over the period of 1985-2002. Similarly, Baghai, Servaes, and Tamayo (2014) find that credit rating agencies have become more conservative over time. We differ from this literature by analyzing an explicit measure of CRA beliefs' effect on credit markets and firm behavior.[4]

The second related strand of literature that we contribute to is the behavioral finance and economics literature that studies realistic, and potentially irrational, beliefs from the economic agents (e.g., Greenwood and Shleifer, 2014, Coibion and Gorodnichenko, 2015 and Bordalo et al., 2020). Similar to several recent works on subjective beliefs of the interest rates such as Cieslak (2018), Wang (2021), Singleton (2021), we also use survey expectation of interest rates elicited from Blue Chip Financial Forecasts. However, different from these previous papers studying short rates and Treasury yields, we are the first to explore the subjective beliefs in the credit market by focusing on the corporate bond yields and credit spreads. In our main results, we establish a strong link between the stated beliefs from the two CRAs and their credit rating decisions, joining a small set of recent papers in answering the open question in belief study that whether people behave in accordance with their elicited beliefs (e.g., Giglio et al., 2021 and Wang, 2021). Lastly, we characterize CRA beliefs using the difference in beliefs between CRAs and the consensus. This approach is similar to that used in papers that study disagreement in interest rate and inflation expectations (Giacoletti, Laursen, and Singleton, 2021).

On the corporate finance side, our paper relates to the broader literature on firm behavior when there is mispricing in asset markets. For example, Dong et al. (2006) show that mispricing drives the takeover market and Ma (2019) shows that firms take advantage of mispriced securities in financial markets. Our evidence is also consistent with the idea of Ma (2019) who shows that firms act as cross-market arbitrageurs of their own securities. A key contribution of our paper is identifying a specific source of mispricing stemming from CRA

[4]Another important distinction between our paper and the existing literature is we are able to analyze CRAs' *ex-ante* beliefs rather than attempting to infer their credit rating standards *ex-post*.

beliefs.

2 Data

In this section, we describe the datasets we use in this paper.

Survey expectation data. The main dataset that enables us to study CRA beliefs is survey expectations data from the Blue Chip Financial Forecasts (BCFF). BCFF is a monthly survey of professional forecasters. It maintains a stable and large panel of forecasters over the years and has a long sample that dates back to the 1980s. Each month, the BCFF survey collects forecasts from a group of, on average, over 40 economists from leading financial institutions and economic consulting firms. The surveyed economists are asked to provide point forecasts of future financial and macroeconomic variables at horizons ranging from the current quarter ("nowcast") to four quarters ahead (five quarters since January 1997). The forecast variables include Aaa, Baa corporate bond yields, and Treasury bill and bond yields across the entire yield curve. The forecasts are collected over a two-day period, usually between the 23rd and 27th of each month, and published on the first day of the following month. A sample BCFF survey questionnaire is presented in the Appendix.

Apart from its long history, another major advantage of the BCFF survey is that the identity of each forecaster, names of the economist and his/her affiliated institution, is revealed.[5] This unique feature allows us to keep track of the time series of each firm's forecasts and hence make the BCFF forecasts a panel dataset. Moreover, following the procedure in Wang (2021), we manually adjust for firm name changes due to corporate restructuring such as mergers and acquisitions[6]. This gives us 86 unique forecasters with more than 60 monthly forecasts, among which 26 are banks, 15 are broker-dealers, and 17 are primary dealers of

[5] As the forecasts mostly reflect collective expectations of the institutions, for the rest of the paper, we use "forecaster" to refer to the institution.

[6] Specifically, we manually check the name changes of the forecasters using the information provided by the Federal Financial Institutions Examinations Council (FFIEC) and concatenate the observations that belong to the same entity.

the Federal Reserve Bank of New York[7].

Specific to this study, we focus on forecasts from two of the "Big Three" CRAs—namely Moody's Investors Service (MR) and S&P Global Ratings (SPR)—that participate in BCFF surveys continuously since 2001. The variables of interest are Aaa and Baa corporate bond yields which are based on Aaa and Baa corporate bond indices published by Bank of America-Merrill Lynch[8]. Since these corporate bond indices are maintained by a third party, their construction is not directly influenced by neither CRA and the realized value can be treated as exogenous to the CRAs. Furthermore, to construct forecasts of credit spreads, we use forecasts of the 10-year Treasury yield, which is the closest Treasury yield in maturity from the survey. For each forecast variable at each forecast horizon, we obtain individual forecasts from the two CRAs and recalculate the consensus forecast as the cross-sectional average forecast, excluding those from Moody's and S&P.

One may naturally question how informative are the BCFF survey forecasts. In addition to the immediate reputation and career concerns given the wide circulation of the BCFF survey among financial market participants, Wang (2021) shows that, for a subset of BCFF forecasters that are banks, their allocations to the Treasuries of a given maturity vary positively with their expectation of bond returns for that maturity. This evidence suggests that BCFF forecasters treat the surveys seriously such that several of them are willing to put their money behind their forecasts.

In order to maintain consistency across the frequency of our data, we resample the monthly forecasts at the quarterly level by taking the first observation of each quarter (typically available at the beginning of the quarter) as that quarter's forecast.

[7]Refer to the Online Appendix for a complete list of institutions that participate in BCFF surveys for more than five years.

[8]Names of the two corporate bond indices change over the years. Their current names are ICE BofA AAA (BBB) US Corporate Index. The indices track the performance of US dollar-denominated Aaa (or Baa) investment-grade rated corporate debt publicly issued in the US domestic market. The average maturity of the tracked bonds is over 15 years.

Corporate bond, ratings, and firm financial data. Data on corporate bond ratings are drawn from Mergent Fixed Income Securities Database (FISD), from which we obtain issue (bond)-specific ratings from S&P, Moody's, and Fitch. Mergent FISD also provides mostly static bond issuance information such as offering yield, date, and maturity. We additionally obtain issuer (firm)-level ratings from Thomson Eikon, Capital IQ, and Compustat. We follow Becker and Milbourn (2011) to convert the letter ratings from Moody's and S&P to numerical ratings. The numerical ratings are in descending order, ranging from Aaa (28) to C (4). Refer to Table 2 in Becker and Milbourn (2011) for details on the conversion.

Quarterly firms financial information is obtained from Compustat Fundamentals Quarterly.

We obtain monthly bond returns data from the WRDS Bond Returns data, which is a cleaned dataset of corporate bond returns compiled by WRDS and sourced from TRACE Standard and TRACE Enhanced datasets. Following the literature, we apply a few additional filtering criteria: We focus on non-convertible corporate bonds with fixed coupons. We exclude asset-backed securities, Yankee bonds, bonds issued by Canadian issuers, junior bonds and bonds denominated in foreign currencies. Since our analysis is at the quarterly level, we aggregate monthly bond returns into quarterly returns.

Lastly, financial firms issue a large share of the corporate bonds and notes in the FISD dataset. However, financial firms are likely to be fundamentally different from non-financial ones (Becker and Milbourn 2011). Hence, we exclude all bonds issued by financial firms by using FISD's industry classification.[9]

Final sample and summary statistics. We merge BCFF forecasts with corporate bond and firm level data at the quarterly level. Notice that BCFF forecasts are available at the beginning of each quarter while other bond and firm level variables are typically available at the end of the quarter. Merging these data at the same quarter ensures that forecasts are

[9] We use the industry group variable provided by FISD to identify financial firms. In Compustat, we remove any firms with SIC codes beginning with 6.

unlikely to be influenced by bond and firm level outcomes such as ratings or issuance in the same quarter, mitigating concerns that forecasts are reversely engineered by CRA and other forecasters from bond prices or ratings. By doing this, we establish that forecasts elicited by BCFF surveys are likely to reflect forecasters' true subjective beliefs of the forecasters. Since valid forecasts of Aaa, Baa, and 10-year Treasury yields from both Moody's and S&P are available from September 2009 onward, our final sample period is 2001:Q3-2018:Q4, spanning a total of 69 quarters.

In the empirical analyses of this paper, we explore how CRA credit assessment embedded in their forecasts impacts various aspects of the credit market. It is therefore necessary to isolate the part of their forecasts directly related to credit risk. Following a long strand of literature on corporate bond (e.g., Gilchrist and Zakrajšek, 2012 and Nozawa, 2017), we focus on the credit spread and its forecasts as our main gauge of credit market conditions as credit spread reflects both expected credit loss and corporate bond risk premium and it excludes interest rate risk associated with default-risk Treasuries. In particular, we define forecaster i's forecast of credit spread as the difference between her forecasts of the Aaa and 10-year Treasury yields[10]:

$$\mathbb{E}_t^i(CS_{t+h}^{Aaa}) \equiv \mathbb{E}_t^i(Aaa_{t+h}) - \mathbb{E}_t^i\left(y_{t+h}^{(10)}\right).$$

As discussed earlier, our main analyses center on the differences in beliefs between CRAs and other financial institutions, not the heterogeneity among CRAs, hence we aggregate the CRAs beliefs by averaging forecasts from Moody's and S&P for variable X_{t+h} as

$$\mathbb{E}_t^{CRA}(X_{t+h}) \equiv 0.5\left[\mathbb{E}_t^{MR}(X_{t+h}) + \mathbb{E}_t^{SPR}(X_{t+h})\right].$$

[10]Though the credit spread is not the actual variable that the forecasts make forecasts about, it is derived only through a simple subtraction. As long as BCFF forecasters have internally consistent forecasting models—a reasonable low requirement for these professional economists, the constructed credit spread forecasts reflect forecasters' assessment of future credit market conditions.

2.1 Summary Statistics.

Table 1 provides an overview of the main variables used in this paper. Panel A reports summary statistics for CRA forecasts $\mathbb{E}^{CRA}(.)$, consensus forecasts $\mathbb{E}^{Con}(.)$ and their differences $\mathbb{E}^{CRA-Con}(.)$. We include one-quarter-ahead forecasts for Aaa corporate bond yield, 10-year Treasury yield and the credit spread. Comparing forecasts from CRAs and the consensus, we find that, on average, they are comparable in most moments that we report in the table. Notably, CRAs' forecasts of the 10-year Treasury yields are very close to those from the consensus, with only 2 basis point (bps) differences in the mean forecasts. On the other hand, CRAs' forecasts of Aaa corporate bond yields and credit spreads are on average around 10 bps lower than those from the consensus. These full-sample statistics indicate that CRAs have a slightly more optimistic outlook for future credit market condition than the other financial institution, but they have similar forecasts of the future path of the default-free interest rates. It is worth noting that the average differences in forecasts are small in magnitude—for example, the average difference in Aaa forecasts is less than three percent of the level of Aaa yields.

Figure 1 displays the time series of the credit spread forecasts of CRAs, the consensus and their difference. The credit spread forecast of CRAs and the consensus, as shown in Panel A, exhibit business cycle frequency variations; they are high typically in recessions. In Panel B, the differences in credit spread forecasts do not feature such a low frequency trend, but rather fluctuate around zero with a slightly lower level after 2015.

Panels B and C of Table 1 summarize bond-level characteristics and firm-level financials, respectively. One thing to notice is that ratings from S&P and Moody's—both at the bond level and the firm level—are very close on average, suggesting that the two CRAs usually reach the same conclusion in their credit assessments of numerous bonds and firms.

3 Empirical Analysis

We define our main variable of interest $AaaDev$ as follows:

$$AaaDev_t = \mathbb{E}_t^{CRA}(CS_{t+1}^{Aaa}) - \mathbb{E}_t^{CON}(CS_{t+1}^{Aaa}), \tag{1}$$

where $\mathbb{E}_t^{CRA}(CS_{t+1}^{Aaa})$ and $\mathbb{E}_t^{CON}(CS_{t+1}^{Aaa})$ are the average CRA and consensus forecast for the Aaa one quarter ahead credit spread. It will also be helpful to define the consensus forecast of the Aaa credit spread:

$$AaaCon_t \equiv \mathbb{E}_t^{CON}(CS_{t+1}^{Aaa}) \tag{2}$$

Throughout our analysis, we test how $AaaDev$ affects various bond-level and firm-level outcomes. Note that we always report all interest rate variables in percentage points.

3.1 CRA Forecast Deviations and Credit Ratings

We first test if individual CRA forecast deviations from the consensus predict the ratings they provide. If $AaaDev$ reflects differences in CRA beliefs and the consensus, $AaaDev$ should affect CRAs credit assessments. To test this, we estimate the following regression:

$$Rating_{b,c,t} = \beta(\mathbb{E}_t^{c}(CS_{t+1}^{Aaa}) - \mathbb{E}_t^{Con}(CS_{t+1}^{Aaa})) + \alpha_b + \gamma Z_b + u_{b,c,t}, \tag{3}$$

where $Rating_{b,c,t}$ is the the rating of bond b by CRA c at time t, $\mathbb{E}_t^{c}(CS_{t+1Q}^{Aaa}) - \mathbb{E}_t^{Con}(CS_{t+1Q}^{Aaa})$ is the difference between CRA c's forecast of the Aaa credit spread and the consensus at time t, Z_b is a vector of bond-level controls and α_b are issue fixed effects. We also double cluster our standard errors by issue and quarter. The main coefficient of interest is β which represents how an increase in an individual CRA forecast relative to the consensus affects the bond ratings that CRA's provides. The results are displayed in Column (1) of Table 2. The point estimate is -0.20 and statistically significant, which implies that if the CRA forecast deviates 1pp from the consensus, this results in a -0.20 reduction in bond-level rating. In Column (2) we also include CRA fixed effects and find similar results. This result suggests that CRA forecast deviations affect the credit ratings they provide for bonds.

Because most of our analysis is at the bond and firm level, we also estimate the following bond-level regression where we aggregate CRA ratings across bonds and use the average CRA forecast deviation ($AaaDev$) as the main independent variable:

$$AverageRating_{b,t} = \beta AaaDev_t + \gamma Z_b + \alpha_b + u_{b,t}, \tag{4}$$

where $AverageRating$ is calculated by averaging the numerical value of ratings for a single bond across Moody's and S&P. The estimates, which are displayed in Column (3) of Table 2, show that when CRAs are relatively more optimistic bonds have on average lower ratings.

3.2 Do CRA Forecast Deviations Predict Future Realized Credit Spreads?

As we have just shown, CRA beliefs influence the bond ratings they provide. However, this could simply reflect CRAs having additional information regarding future aggregate credit spreads that the consensus does not. To test this hypothesis, we estimate the following time-series regression:

$$CS_{t+1}^{Aaa} = \beta AaaDev_t + \alpha_t + u_t, \tag{5}$$

where Aaa_{t+1} is the realized Aaa credit spread in quarter $t+1$. If the estimated coefficient β is positive, this would suggest that CRAs forecasts have additional predictive content beyond the consensus. We also estimate 5with the consensus forecast as its own independent variable. The results are displayed in Table 3, where we estimate Newey-West standard errors using three lags. In Column (1) the estimated coefficient for $AaaDev$ is close to zero and statistically insignificant. Moreover, the R-squared is effectively zero. This suggests that CRA credit spread forecast deviations do not contain information regarding future realized credit spreads. In Column (2) we reestimate (5), but also include the consensus forecast $AaaCon$. Once again, the estimated coefficient for $AaaDev$ is close to zero and statistically insignificant. On the other hand, the consensus forecast is both economically and statistically significant with a point estimate of 0.766. Moreover, the R-squared increases from 0.000 to 0.521. This result suggests that the consensus forecast contains substantial information regarding future credit spreads, while CRA deviations from the consensus do not.

3.3 The Asset Pricing Implications of CRA Forecast Deviations

So far we have shown that CRAs forecast deviations affect the credit ratings they apply to bonds but do not contain any additional information regarding future aggregate credit spreads. We now examine whether CRA forecasts ultimately affect initial bond pricing. If investors are rational and realize that CRAs' forecasts do not predict future aggregate credit spreads beyond the consensus, we would expect there to be no relationship between $AaaDev$ and bond prices. However, if investors are not able to disentangle the effects of CRAs' potentially biased beliefs about aggregate outcomes, they may provide more favorable pricing to bonds when CRAs are more optimistic. In order to test this, we estimate the following regression:

$$Yield_{b,t} = \beta AaaDev_t + \gamma Z_b + \alpha_i + u_{i,b,t}, \tag{6}$$

where the dependent variable, $Yield_{b,t}$, is the initial yield on bond b at time t and α_i are issuer fixed effects and standard errors are double clustered by issuer and quarter. If CRA forecasts influence the initial yields, we would expect the estimate of β to be positive. The results are displayed in Table 4, and consistent with CRA deviations affecting initial bond yields, we find that the coefficient estimate is positive and statistically in specifications with and without bond-level controls (Columns (1) and (2)). In Columns (3) and (4) we find similar results if we include the initial credit spread as the dependent variable.

If CRA optimism, i.e., lower $AaaDev$, drives initial yields higher, we would also expect that higher optimism would lead to new bonds underperforming as this initial optimism is proven to be unwarranted over time.[11] In this regression, we include all bonds rather than just new issues to compare the returns across new and old issues. To test this hypothesis we estimate the following regression:

$$Return_{b,t,t+1} = \beta_0 AaaDev_t + \beta_1 (AaaDev_t \times New_b) + \gamma Z_b + \alpha_b + u_{b,i,t}, \tag{7}$$

Where $Return_{b,t,t+1}$ is the realized quarterly bond-level return over the following quarter and New_b is a dummy variable that equals one if the bond has been issued over the past two quarters. Once again, we double cluster our standard errors by issuer and quarter. The results are displayed in Table 5. In Columns (1) and (2), we exclude the interaction between $AaaDev$ and New and estimate the regression with and without controls. In both specifications the point estimate for $AaaDev$ is positive but not statistically significant. However when we include the interaction term in Columns (3) and (4) we find that the coefficient is highly significant and positive across both specifications. This result suggests that new bonds underperform relative to old bonds when CRAs are more optimistic.

Why are the asset pricing effects concentrated in new bonds? We argue that investors in new issues are more likely to be less sophisticated than investors actively trading existing bonds. More sophisticated investors are better able to disentangle the true credit risk of the bond from its rating. Moreover, the fact that new bonds appear to be initially overpriced but then have negative excess returns following CRA optimism, is consistent with the fact that CRA optimism does not predict lower future aggregate credit spreads among the broader set of outstanding bonds.

[11]It is unwarranted because as shown earlier, CRA optimism does not lead to lower aggregate bond yields.

3.4 Firm Level Analysis

We have established that CRAs beliefs regarding future aggregate credit spreads affects the ratings they provide bonds as well as the yields and returns of those bonds. In this section, we explore whether the rating and asset pricing implications of CRA forecasts impact firms financing and investment decisions.

We divide our analysis into two sets of tests. In the first set of tests we estimate how CRA forecast deviations affect firms' financing and investment decisions. To do so we estimate the following regression

$$y_{i,t} = \beta AaaDev_t + \gamma X_{i,t} + \alpha_i + u_{i,t}, \tag{8}$$

where $y_{i,t}$ is a quarterly firm-level outcome variable, $X_{i,t}$ is a vector of firm characteristics which include size (log of total assets), leverage ratio (total debt to total assets), profitability ratio (EBITDA to net sales), and tangibility ratio (tangible assets to total assets)[12] and α_i are firm fixed effects. In all regressions in this section, we double cluster our standard errors at the firm and quarter level.

In order to show that the effects we identify are occur through the rating channel, as opposed to broader market sentiments, we also would like to show the effects are concentrated among rated firms. To do so, we estimate the following regression:

$$y_{i,t} = \beta_0 AaaDev_t + \beta_1 Rated_{i,t} + \beta_2 (AaaDev_t \times Rated_{i,t}) + \gamma X_{i,t} + \alpha_i + u_{i,t}, \tag{9}$$

where $Rated_{i,t}$ is a dummy variable that equals one if the firm is rated by either Moody's or S&P at the issuer level at time t. If CRA forecasts affect firm behavior through the ratings they provide firms, we would expect β_2 to be positive. This test is particularly useful because we would expect the effects we identify to be stronger among rated firms whose debt pricing and ratings are affected by CRA forecasts.

[12] These controls are the most common controls in the capital structure literature (e.g. Rajan and Zingales, 1995 and DeAngelo and Roll, 2015).

3.4.1 CRA Deviations and Firms' Capital Structure

We begin by testing whether CRA forecast deviations predict firms' debt and leverage decisions. To do so, we first estimate (9) with Total Debt (defined as the log of total debt) as the dependent variable. The results are displayed in Table 6. In Column (1), the coefficient $AaaDev_t$ is negative and statistically significant with a point estimate of -0.46. This estimate suggests that a 1pp increase in Moody's and S&P's credit spread forecast relative to the consensus, results in firms' using 0.46pp less debt. In Column (2) we estimate (10) by interacting $AaaDev_t$ with $Rated_{i,t}$ and the corresponding coefficient is negative and statistically significant, which suggests that rated firms' debt decisions are more sensitive to CRA deviations than unrated firms. In Columns (3) and (4) we estimate the same regressions but with leverage as the dependent variable. The estimated coefficients are also negative and statistically significant, suggesting that the lower debt levels following CRA pessimism lead to lower leverage ratios, especially among rated firms. Note that we still find a small effect among unrated firms for debt levels but not leverage. This result could be explained by the fact that firms may have rated securities, which means they are affected by CRA forecast deviations, but may not necessarily be rated at the issuer level.

We next test whether the changes in debt and leverage are driven by active issuance decisions by firms by estimating the same regressions as in Table 6 with equity issuance and long-term debt issuance as dependent variables. The results are displayed in Table A.1. In Columns (1) and (2) we estimate regression with long-term debt issuance as the dependent variable. $AaaDev$ is negative and statistically significant by itself in Column (1). Moreover, the interaction between $AaaDev$ and $Rated$ is negative and statistically significant. In Columns (3) and (4) we perform the same tests with equity issuance as the dependent variable. Although $AaaDev$ is not statistically significant on its own, the interaction between $AaaDev$ and $Rated$ is positive and statistically significant, suggesting that rated firms are more likely to issue equity when CRAs are more pessimistic in their forecasts.

3.4.2 CRA Deviations and Firms' Investment Decisions

After having established that CRAs projections affect firms' leverage and issuance decisions, we now test whether they affect firms' investment decisions by once again estimating (9) and (10) with different investment outcome variables. In particular, in Columns (1) and (2) of Table 8 the results are displayed with total assets as the dependent variable, while Columns (3) and (4) we use PP&E. Across the different specifications we find a negative relationship between $AaaDev$ and investment which is also concentrated among rated firms. This result implies the beliefs of the CRAs have real effects on firm behavior and firms do not only adjust their capital structures in response to CRA forecast deviations. A potential explanation could that firms also look to the information in credit ratings and are not able to undo the effect of excess optimism or pessimism by the CRAs. For instance, firms may believe their investment opportunities are less risky based on the credit ratings they receive which could induce higher investment levels. An alternative explanation could be that the CRAs' projections can tighten or relax rating-based covenants which affect firms' investment decisions (Fracassi and Weitzner, 2020).

3.4.3 CRA Deviations and the Likelihood of Firms' Being Rated

If CRAs are more generous in their ratings when they are relatively more optimistic than the consensus, i.e., when $AaaDev$ is lower, we expect that firms have a higher incentive to be rated to take advantage of favorable bond market conditions. To test this hypothesis, we estimate the following regression

$$Rated_{i,t} = \beta AaaDev_t + \gamma X_{i,t} + \alpha_i + u_{i,t}, \tag{10}$$

where the dependent variable, $Rated_{i,t}$, is a dummy that equals one if the firm is rated. The results are displayed in Table 9. In Column (1) the estimated coefficient of β is negative and statistically significant. This implies that the more pessimistic the rating agencies are relative to the consensus, the likely firms have issuer level ratings. Note, a caveat to these results is they may also be partially driven by the fact that firms are more likely to be rated at the issuer level as they issue more debt and their leverage increases. Hence, the effect we identify may be partially driven by the results in Section 3.4.1.

4 Conclusion

In this paper, we show that the subjective beliefs of CRAs have a pervasive effect on credit markets and firm behavior. We identify CRA beliefs by comparing their forecasts of future aggregate credit spreads to the consensus. When CRAs are relatively more optimistic about future aggregate credit spreads, they issue higher ratings on bonds, which in turn lead to lower yields and subsequent negative excess returns. This occurs despite the fact that CRA forecasts do not contain information about future realized credit spreads. Firms appear to take advantage of this mispricing by issuing more debt and increasing their leverage and investment. Overall, our results highlight the effect of CRA beliefs on both credit markets and firm behavior. In the current paper, we take CRA beliefs as given; however, but future work could analyze whether this is driven by CRA incentives or is driven by behavioral biases.

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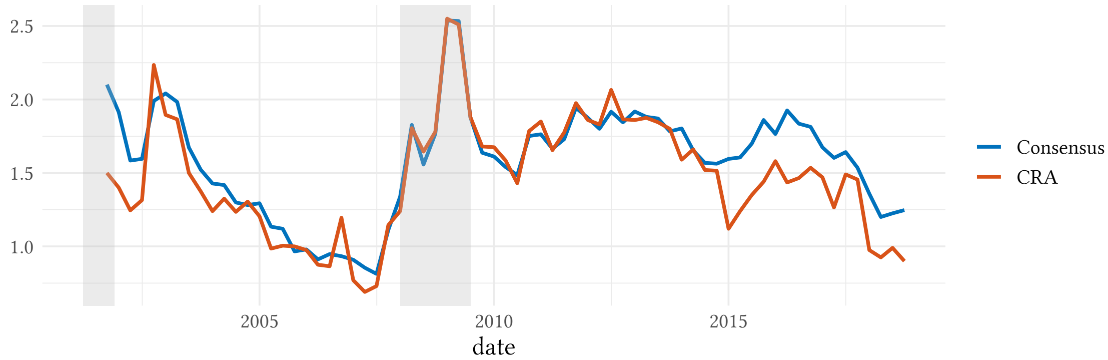
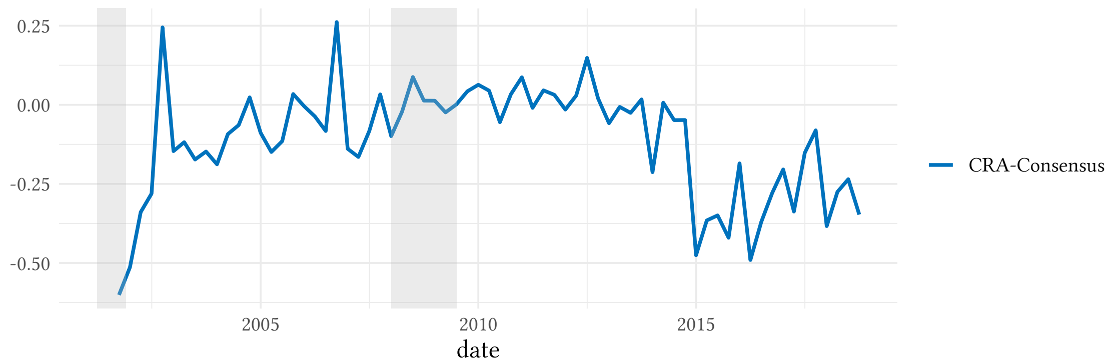
5 Figures



A. Consensus and CRA Forecasts



B. Consensus-CRA

Figure 1 This figure plots the time series of the consensus, CRA and CRA-consensus forecast ($AaaDev$) of Aaa credit spreads at the quarterly frequency.

6 Tables

Table 1 Summary Statistics

This table contains summary statistics for one-quarter-ahead forecasts (Panels A), bond-level (Panel B) and firm-level characteristics (Panel C). We report the number of observations (N), mean, median, standard deviation (SD), 5th and 95th percentile for each variable. In Panel A, we report average forecasts from CRAs, the consensus forecasts and their differences. The forecast variables include Aaa corporate bond yield, 10-year Treasury yield and Aaa credit spread. In Panel B, we report bond characteristics, while in Panel C, we report firm financial variables. Section A.1 of the Appendix includes detailed definitions of all of our variables and filters. Interest rates, credit spreads, and coupon rates are reported in percentage points.

	N	Mean	Median	SD	P5	P95
Panel A: Forecasts						
$\mathbb{E}_t^{Con}(Aaa_{t+1})$	69	5.13	5.28	0.90	3.84	6.61
$\mathbb{E}_t^{CRA}(Aaa_{t+1})$	69	4.99	5.25	1.01	3.53	6.41
$\mathbb{E}_t^{CRA-Con}(Aaa_{t+1})$	69	-0.13	-0.13	0.23	-0.52	0.23
$\mathbb{E}_t^{Con}(y_{t+1}^{(10)})$	69	3.54	3.58	1.06	1.96	5.16
$\mathbb{E}_t^{CRA}(y_{t+1}^{(10)})$	69	3.52	3.48	1.14	1.97	5.16
$\mathbb{E}_t^{CRA-Con}(y_{t+1}^{(10)})$	69	-0.02	-0.04	0.17	-0.25	0.22
$\mathbb{E}_t^{Con}(CS_{t+1}^{Aaa})$	69	1.59	1.64	0.37	0.92	2.02
$\mathbb{E}_t^{CRA}(CS_{t+1}^{Aaa})$	69	1.47	1.47	0.40	0.87	2.03
$\mathbb{E}_t^{CRA-Con}(CS_{t+1}^{Aaa})(AaaDev)$	69	-0.11	-0.08	0.18	-0.45	0.09
Panel B: Bond-Level Characteristics						
Return	247860	0.02	0.01	0.05	-0.05	0.09
S&P Rating	290736	18.68	19.00	3.76	12.00	24.00
Moody's Rating	289326	18.52	19.00	3.91	11.00	24.00
Average Rating	299490	18.67	19.00	3.79	12.00	24.00
Time to Maturity	299124	10.03	6.43	10.64	0.67	28.50
Bid-Ask Spread	279080	0.01	0.00	0.01	0.00	0.02
Coupon	299490	6.36	6.50	2.05	2.75	9.75
Duration	297227	6.06	5.03	4.21	0.65	14.25
Panel C: Firm-Level Characteristics						
Profitability	304030	-0.15	0.01	0.70	-0.60	0.06
Tangibility	306942	0.24	0.14	0.25	0.00	0.79
Market to Book	306942	8.65	1.40	39.72	0.49	18.74
Sales	305436	591.02	34.73	3134.80	0.00	2241.11
Assets	306942	3033.61	167.38	17689.73	0.53	11527.72
PPE	306942	995.01	21.65	5766.94	0.00	3638.00
Book Leverage	306942	0.30	0.21	0.32	0.00	1.00
Rated	306942	0.23	0.00	0.42	0.00	1.00
IG	306942	0.09	0.00	0.29	0.00	1.00
Junk	306942	0.14	0.00	0.34	0.00	1.00
S&P Rating	67729	16.93	17.00	3.35	12.00	22.00
Moody's Rating	45948	16.01	15.00	3.64	11.00	22.00

Table 2 CRA Forecast Deviations and Credit Ratings

This table tests whether CRA credit spread forecast deviations affect their bond-level credit ratings. In Columns (1) and (2), the dependent variable is the rating for bond b issued by agency c at time t and the main independent variable is the differences in credit spread forecasts between agency j and the consensus. In Column (3), the dependent variable is the average rating for bond b from Moody's and S&P at time t and the main independent variable is the differences in credit spread forecasts between CRAs and the consensus ($AaaDev$). Issue (bond) fixed effects are included in all regressions and CRA fixed effects are included in Column (2). Robust standard errors double clustered by bond (issue) and year-quarter are shown below the parameter estimates in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	$Rating_{b,c,t},\ c \in \{MR, SPR\}$		$AverageRating_{b,t}$
	(1)	(2)	(3)
$\mathbb{E}_t^c(CS_{t+1}^{Aaa}) - \mathbb{E}_t^{Con}(CS_{t+1}^{Aaa})$	-0.1992***	-0.1015*	
	(0.0603)	(0.0536)	
$AaaDev$			-0.3563***
			(0.1211)
Maturity	-0.0474***	-0.0495***	-0.0358***
	(0.0103)	(0.0104)	(0.0105)
Bid-Ask Spread	-4.142***	-4.145***	-4.220***
	(0.9973)	(1.001)	(0.9814)
Duration	0.2136***	0.2129***	0.1901***
	(0.0152)	(0.0154)	(0.0160)
R^2	0.91203	0.91237	0.92193
N	591,947	591,947	277,344
Issue FE	✓	✓	✓
CRA FE		✓	

Table 3 CRA Forecast Deviations and Future Aggregate Credit Spreads

This table evaluates whether CRA credit spread forecast deviations helps predict future realized credit spreads. The dependent variable is one-quarter-ahead realized Aaa credit spread CS_{t+1}^{Aaa} measured in percentage points. The independent variables include CRA credit spread forecast deviations $AaaDev_t$ and consensus credit spread forecast $AaaCon_t$ measured in percentage points. Newey-West standard errors with three lags are shown below the parameter estimates in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	CS_{t+1}^{Aaa}	
	(1)	(2)
$AaaDev_t$	0.041	0.176
	(0.3515)	(0.2835)
$AaaCon_t$		0.766***
		(0.1223)
Constant	1.381***	0.180
	(0.1004)	(0.1923)
Quarters	69	69
R^2	0.000	0.521

Table 4 CRA Forecast Deviations and Initial Bond Pricing

This table tests whether CRA credit spread forecast deviations ($AaaDev$) affect initial bond yields and credit spreads. The dependent variables are corporate bond yield to maturity at issuance (Columns (1) and (2)) and credit spread at issuance (Columns (3) and (5)), both measured in percentage points. Credit spreads are calculated by matching the bond yield with the Treasury yield with the closest maturity. Robust standard errors double clustered by issuer and quarter are shown below the parameter estimates in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Yield at Issuance		Credit Spread at Issuance	
	(1)	(2)	(3)	(4)
$AaaDev$	1.011***	1.011***	0.3413***	0.2962***
	(0.2254)	(0.2194)	(0.1022)	(0.0980)
Maturity		0.0707***		0.0236**
		(0.0142)		(0.0094)
Bid-Ask Spread		17.72***		-0.6465
		(4.634)		(1.367)
Duration		-0.1229***		-0.0358
		(0.0339)		(0.0264)
R^2	0.66085	0.62719	0.79562	0.63434
N	19,045	8,654	18,084	8,407
Issuer FE	✓	✓	✓	✓

Table 5 CRA Forecast Deviations and Subsequent Bond Returns

This table tests whether CRA credit spread forecast deviations (*AaaDev*) forecast subsequent bond returns. The dependent variable is one quarter ahead corporate bond returns. New bonds are defined as bonds issued during the most recent two quarters. Robust standard errors double clustered by bond (issue) and year-quarter are shown below the parameter estimates in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	$Return_{t+1}$			
	(1)	(2)	(3)	(4)
AaaDev	0.0135	0.0123		
	(0.0175)	(0.0174)		
AaaDev × New			0.0423***	0.0435***
			(0.0157)	(0.0159)
AaaDev × Old			0.0110	0.0097
			(0.0179)	(0.0178)
Maturity		-0.0004**		-0.0004**
		(0.0002)		(0.0002)
Bid-Ask Spread		-0.1238		-0.1278
		(0.1267)		(0.1265)
Coupon		0.0018***		0.0018***
		(0.0005)		(0.0005)
Duration		0.0020***		0.0020***
		(0.0007)		(0.0007)
R^2	0.04912	0.06012	0.04986	0.06099
N	247,860	239,789	247,860	239,789
Issuer FE	✓	✓	✓	✓

Table 6 CRA Forecast Deviations and Firms' Debt and Leverage Decisions

This table reports results testing whether CRA credit spread forecast deviations (*AaaDev*) affect firms' debt and leverage decisions. The dependent variables are total debt (Columns (1) and (2)) and leverage (Columns (3) and (4)). Robust standard errors double clustered by firm and year-quarter are shown below the parameter estimates in parenthesis *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Total Debt		Leverage	
	(1)	(2)	(3)	(4)
AaaDev	-0.458***	-0.360***	-0.056***	-0.037***
	(0.1046)	(0.0836)	(0.0116)	(0.0089)
Rated		1.604***		0.154***
		(0.0718)		(0.0087)
AaaDev x Rated		-0.219**		-0.061***
		(0.0893)		(0.0140)
Profitability	-0.058***	-0.048***	0.032***	0.033***
	(0.0061)	(0.0058)	(0.0023)	(0.0023)
Tangibility	0.694***	0.690***	0.200***	0.200***
	(0.0635)	(0.0602)	(0.0145)	(0.0144)
Sales	0.736***	0.654***	0.035***	0.027***
	(0.0234)	(0.0209)	(0.0029)	(0.0028)
Market-to-Book	-0.001***	-0.001***	-0.000***	-0.000***
	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Firm FE	✓	✓	✓	✓
Firm Quarters	303563	303563	303564	303564
R^2	0.146	0.203	0.031	0.048

Table 7   CRA Forecast Deviations and Firms' Issuance Decisions

This table reports results testing whether CRA credit spread forecast deviations (*AaaDev*) affect firms' issuance decisions. The dependent variables are long-term debt issuance (Columns (1) and (2)) and equity issuance (Columns (3) and (4)). Robust standard errors double clustered by firm and year-quarter are shown below the parameter estimates in parenthesis *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	LT Debt Issuance		Equity Issuance	
	(1)	(2)	(3)	(4)
AaaDev	-0.236***	-0.139***	0.080	0.026
	(0.0599)	(0.0455)	(0.0739)	(0.0527)
Rated		0.503***		0.069**
		(0.0560)		(0.0270)
AaaDev x Rated		-0.345***		0.236**
		(0.0995)		(0.1035)
Profitability	-0.032***	-0.028***	0.031***	0.031***
	(0.0027)	(0.0025)	(0.0038)	(0.0038)
Tangibility	0.092**	0.092**	-0.383***	-0.383***
	(0.0440)	(0.0433)	(0.0368)	(0.0366)
Sales	0.326***	0.298***	0.067***	0.065***
	(0.0164)	(0.0155)	(0.0132)	(0.0130)
Market-to-Book	-0.000***	-0.000***	0.000***	0.000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Firm FE	✓	✓	✓	✓
Firm Quarters	303564	303564	301954	301954
R^2	0.017	0.021	0.004	0.005

Table 8 CRA Forecast Deviations and Firms' Investment Decisions

This table reports results testing whether CRA credit spread forecast deviations (*AaaDev*) affect firms' investment decisions. The dependent variables are Assets (Columns (1) and (2)) and PP&E (Columns (3) and (4)). Robust standard errors double clustered by firm and year-quarter are shown below the parameter estimates in parenthesis *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Assets		PPE	
	(1)	(2)	(3)	(4)
AaaDev	-0.236***	-0.139***	0.080***	0.001
	(0.0599)	(0.0455)	(0.0089)	(0.0054)
Rated		0.503***		0.022***
		(0.0560)		(0.0053)
AaaDev x Rated		-0.345***		0.013
		(0.0995)		(0.0251)
Profitability	-0.032***	-0.028***	0.031***	0.001***
	(0.0027)	(0.0025)	(0.0040)	(0.0003)
Tangibility	0.092**	0.092**	-0.383***	0.002
	(0.0440)	(0.0433)	(0.0167)	(0.0034)
Sales	0.326***	0.298***	0.067***	-0.002
	(0.0164)	(0.0155)	(0.0030)	(0.0021)
Market-to-Book	-0.000***	-0.000***	0.000**	0.000
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Firm FE	✓	✓	✓	✓
Firm Quarters	303564	303564	302006	303564
R^2	0.017	0.021	0.004	0.000

Table 9 CRA Forecast Deviations and the Likelihood of Firms' Being Rated

This table contains results testing whether CRA forecast deviations affect the likelihood of firms being rated. The dependent variable is an indicator variable that equals one when the firm is rated by either S&P or Moody's at time *t* (Rated). Robust standard errors double clustered by firm and quarter are shown below the parameter estimates in parenthesis *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Rated
	(1)
AaaDev	-0.028***
	(0.0068)
Profitability	-0.006***
	(0.0005)
Tangibility	0.003
	(0.0097)
Sales	0.051***
	(0.0034)
Market-to-Book	-0.000***
	(0.0000)
Firm FE	✓
Firm Quarters	303564
R^2	0.030

Appendix

A.1 Variable Definitions

AaaCon: The one-quarter ahead consensus forecast of the aggregate Aaa credit spread (based on the 10-year treasury), excluding Moody's and S&P, from Blue Chip Financial Forecasts.

AaaDev: The difference in the average of Moody's and S&P's one-quarter ahead forecast of the aggregate Aaa credit spread (based on the 10-year treasury) and the consensus, from Blue Chip Financial Forecasts.

New: Dummy variable that equals one if the bond is issued in that quarter, from FISD.

Assets: log(assets[atq]), from Compustat.

PPE: log(1 + PP&E[ppentq]), from Compustat.

Sales: log(1+sales[saleq]), winsorized at [1%, 99%], from Compustat.

Total Debt: log(1+ short-term debt[dlcq] +long-term debt[dlttq]), from Compustat.

Tangibility: tangible assets/assets, winsorized at [1%, 99%], from Compustat.

Leverage: short-term debt[dlcq] +long-term debt[dlttq] /assets [atq], winsorized at [0, 1], from Compustat.

Tangibility: tangible assets/assets, winsorized at [1%, 99%], from Compustat.

Profitability: EBITDA[oiadpq]/assets[atq], winsorized at [1%, 99%], from Compustat.

Market-to-Book: (Market equity[prccq $\times$ cshoq] + total debt [dlcq +dlttq] + preferred [pstkq] + deferred taxes [txditcq]) / total assets [atq], winsorized at [1%, 99%], from Compustat.

Rated: Dummy variable that equals one if the firm is rated by either S&P or Moody's, issuer ratings data is collected from Thomson Eikon, Compustat and Capital IQ.

Total Debt: log(1+total debt [dlcq +dlttq]), from Compustat.

LT Debt Issuance: log(1+dltisy), from Compustat.

Equity Issuance: log(1+ [sstky]), from Compustat.

BD Issuance: The log of 1 plus a firm's quarterly bank debt issuance, from Dealscan.

BD Issuance Dummy: Dummy variable that equals one if the firm issues bank debt in the quarter, from Dealscan.

A.2 Additional Tables and Figures

Table A.1 CRA Forecast Deviations and Firms' Bank Debt Issuance Decisions

This table contains results testing... Robust standard errors double clustered by firm and quarter are shown below the parameter estimates in parenthesis *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	BD Issuance		BD Issuance Dummy	
	(1)	(2)	(3)	(4)
AaaDev	0.087	0.045	0.004	0.001
	(0.2031)	(0.0953)	(0.0106)	(0.0054)
Rated		0.483***		0.022***
		(0.1056)		(0.0053)
AaaDev x Rated		0.234		0.013
		(0.5110)		(0.0251)
Profitability	0.013**	0.015***	0.001***	0.001***
	(0.0051)	(0.0049)	(0.0003)	(0.0003)
Tangibility	-0.008	-0.009	0.002	0.002
	(0.0669)	(0.0667)	(0.0034)	(0.0034)
Sales	0.018	-0.005	-0.000	-0.002
	(0.0436)	(0.0421)	(0.0022)	(0.0021)
Market-to-Book	0.000	0.000	0.000	0.000
	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Firm FE	✓	✓	✓	✓
Firm Quarters	303564	303564	303564	303564
R^2	0.000	0.000	0.000	0.000

Table A.2 Blue Chip Financial Forecasts participants, grouped by institution types

Firms' commonly used names are reported, which may slightly differ from their legal names. I manually check the name changes of the forecasters—due to mergers and acquisitions or other reasons—using the information provided by the Federal Financial Institutions Examinations Council (FFIEC) and concatenate the observations that belong to the same entity. Only participants with more than 60 months of observations are reported. For institutions with multiple classifications, I report its primary type.

	Count	Institution Names
Asset Manager	13	ASB Capital Management, Sanford C. Bernstein, J.W. Coons, ING Aeltus, JPMorgan Chase Wealth Management, Loomis Sayles, Mesirow, Northern Trust, RidgeWorth, Stone Harbor, US Trust Company, Wayne Hummer, Wells Capital
Bank	26	Banc One Corp, Bankers Trust, First National Bank of Chicago/Bank One (Chicago), Barnett Banks, Bank of America, Comerica Bank, CoreStates Financial, First Fidelity Bancorp, First Interstate Bank, Fleet Financial Group, Huntington National Bank, JPMorgan, LaSalle National Bank, MUFG Bank, National City Bank of Cleveland, PNC Financial Corp, Bank of Nova Scotia, SunTrust, Tokai Bank, Valley National Bank, Wachovia, Wells Fargo
Broker/Dealer	15	Amherst Pierpont, Barclays, Bear Stearns, BMO, Chicago Capital, Daiwa, Deutsche Bank, Goldman Sachs, Lanston, Merrill Lynch, Nomura Securities, Prudential Securities, RBS, Societe Generale, UBS
Mortgage	2	Fannie Mae, Mortgage Bankers Association
Insurance	5	Kemper, Metropolitan Insurance Companies, New York Life, Prudential Insurance, Swiss Re
Rating	2	Moody's, Standard & Poor's
Research	21	Action Economics, Investor's Briefing, Chmura Economics & Analytics, ClearView, Cycledata, DePrince & Associates, Economist Intelligence Unit, Genetski & Associates, GLC Financial Economics, Independent Econ Advisory, Kellner Economic Advisers, MacroFin Analytics, MMS International, Moody's Economy.com, Naroff Economic Advisors, Oxford Economics, Maria Fiorini Ramirez, RDQ Economics, Technical Data, Thredgold Economic, Woodworth Holdings
Others	3	National Association of Realtors, US Chamber of Commerce, Georgia State University

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	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
	Effective Federal Funds Rate[1]	Prime Rate[2]	LIBOR 3-Mo Rate[3]	Commercial Paper 1-Mo Rate[4]	Treasury Bill 3-Mo Yield[5]	Treasury Bill 6-Mo Yield[5]	Treasury Bill 1-Yr Yield[5]	Treasury Note 2-Yr Yield[5]	Treasury Note 5-Yr Yield[5]	Treasury Note 10-Yr Yield[5]	Treasury Bond 30-Yr Yield[5]	Corporate Aaa Bond Yield[6]	Corporate Baa Bond Yield[7]	State & Local Bond Yield[8]	Mortgage Rate 30-Yr Fixed[9]	Fed's Advanced Foreign Economies (AFE) Index[10]	Real GDP (Q/Q %Chg, SAAR)[11]	GDP Price Index (Q/Q %Chg, SAAR)[12]	Consumer Price Index (Q/Q % Chg, SAAR)[13]
Q4 2019																			
Q1 2020																			
Q2 2020																			
Q3 2020																			
Q4 2020																			
Q1 2021																			

[1] Federal Funds Rate: Charged on loans of uncommitted reserve funds among banks; Federal Reserve Statistical Release (FRSR) H.15
[2] Prime Rate: One of several base rates used by banks to price short term business loans; FRSR H.15.
[3] London Interbank Offered Rate (LIBOR): The interbank offered rate for 3-month dollar deposits in the London market. The Wall Street Journal publishes a LIBOR quote on a daily basis, The Economist on a weekly basis.
[4] Commercial Paper: Financial; 1-month bank discount basis; Interest rates interpolated from data on certain commercial paper trades settled by The Depository Trust Company; The trades represent sales of commercial paper by dealers or direct issuers to investors; FRSR H.15
[5] Treasury Bills, Notes, and Bonds: 3-month, 6-month, 1-year bills, 2-year, 5-year, 10-year notes and 30-year bond; Yields on actively traded issues, adjusted to constant maturities; U.S. Treasury; FRSR H.15
[6] Aaa Corporate Bonds: BofA Merrill Lynch Corporate Bonds: AAA-AA: 15+ Years; Yield to Maturity (%)
[7] Baa Corporate Bond: BofA Merrill Lynch Corporate Bonds: A-BBB: 15+ Years; Yield to Maturity (%)
[8] State & Local Bonds: BofA Merrill Lynch Municipals: A Rated: 20-year; Yield to Maturity (%)
[9] Conventional Mortgages: Contract interest rates on commitments on 30-year fixed rate first mortgages; FreddieMac
[10] Federal Reserve Board's Advanced Foreign Economies (AFE) Nominal Dollar Index. FRB H.10
[11] Real Gross Domestic Product (Chain-type): Percent change (SAAR) Economic Indicators; BEA
[12] Chained Gross Domestic Product Price Index: Percent change (SAAR) Economic Indicators; BEA
[13] Consumer Price Index (All Urban Consumers): Percent change (SAAR); Economic Indicators; BLS

Figure A.1 Blue Chip Financial Forecasts sample survey questionnaire

This figure presents a screenshot of the latest iteration of the Blue Chip Financial Forecasts survey questionnaire. The definition of each target variable is specified in the footnote.