The Impact of Beliefs on Credit Markets: Evidence from Rating Agencies*

Chen Wang[†] Gregory Weitzner[‡]

March 2023

Abstract

An open question in finance and economics is how the beliefs of agents affect the credit cycle and real economic activity. We analyze the impact of beliefs on credit market conditions in the context of credit rating agencies (CRAs). We measure CRAs' subjective beliefs as the difference between their predictions of future aggregate credit spreads and the consensus forecasts of other financial institutions. When CRAs are relatively more optimistic, they issue higher credit ratings even though their forecasts do not contain additional information regarding future credit market conditions. This optimism leads to lower initial yields and subsequent negative returns for newly issued bonds. In response to this mispricing, firms increase their debt, leverage, and investment, where the effects are concentrated among rated firms. A one standard deviation increase in CRA optimism results in a 3.5% increase in leverage and a 2% increase in investment among rated firms. Our analysis shows how subjective beliefs drive aggregate financing and investment behavior through mispricing in credit markets.

*We thank Patrick Augustin, Zhi Da, Adolfo De Motta, Cesare Fracassi, Stefano Giglio, Huseyin Gulen, Zhiguo He, Kelly Shue, Dragon Tang, Sheridan Titman, Jinming Xue and seminar and conference participants at Notre Dame, McGill, Shanghai University of Finance and Economics, Peking University, AsianFA Annual Meeting, CICF, the Office of the Comptroller of the Currency and the Chinese University of Hong Kong, Shenzhen for helpful comments and discussions. Chen Wang acknowledges financial support from a Whitebox Advisors research grant from the International Center for Finance at Yale School of Management.

[†]Mendoza College of Business, University of Notre Dame. Email: chen.wang@nd.edu.

[‡]McGill University. Email: gregory.weitzner@mcgill.ca.

1 Introduction

How do people's beliefs affect credit market conditions and aggregate economic activity? This question dates back to Minsky's financial instability hypothesis, whereby debt levels can build up over time as agents become more optimistic (Minsky, 1977).[1] Despite the intuitive appeal of this type of theory, it is extremely difficult to directly test the impact of beliefs on credit market conditions. First, measuring beliefs is challenging. The most common approach is to use survey data; however, survey respondents' answers may not reflect the beliefs they act on.[2] Second, it is difficult to i) distinguish whether beliefs deviate from rationality and ii) isolate the impact of this non-rational component of beliefs on credit market conditions.

In this paper, we attempt to address these issues by investigating the relationship between beliefs and credit market conditions in the context of credit rating agencies (CRAs). CRAs are central players in credit markets as firms use CRAs to rate their debt securities and investors rely on credit ratings to price these same securities. We create a measure of CRAs' beliefs based on their forecasts of future aggregate corporate bond credit spreads and find that CRA beliefs deviate from rationality. We then isolate the subjective component of these beliefs by comparing CRA forecasts to a consensus of other financial institutions. First, CRAs act on their subjective beliefs through the credit ratings they issue. Second, these subjective beliefs do not contain any information regarding future aggregate credit spreads. Third, CRA subjective beliefs induce mispricing in newly issued bonds. Fourth, firms respond to inflated ratings and bond prices by increasing their leverage and investment. Finally, we show that CRA's beliefs are strongly related to their forecasters' experienced housing market returns. Overall, our findings connect the subjective beliefs of key actors in credit markets to aggregate market conditions and real economic activity.

Our analysis uses survey expectations data from the Blue Chip Financial Forecasts. Specifically, Moody's, S&P, and other financial institutions report monthly forecasts of various corporate

[1] See also Geanakoplos (2010) for a similar mechanism.

[2] See Brunnermeier et al. (2021) for a review of this challenge; see also Giglio et al. (2021) for recent evidence that links stated beliefs with investors' portfolio decisions.

bond and treasury yields. This survey data allows us to compare the CRA beliefs to those of other prominent financial institutions such as large banks and asset managers (i.e., the "consensus"). We create a measure of CRA beliefs based on the average one-quarter ahead Aaa credit spreads across Moody's and S&P.[3]

We start by examining if CRAs deviate from rationality in their forecasts. Using the methodology proposed by Coibion and Gorodnichenko (2015), we show that when updating their forecasts of future credit spreads, CRAs significantly overreact to the new information, indicating a departure from rationality. In contrast, the consensus forecast exhibits no significant deviation from rationality.

Having established a departure from rationality in CRAs' forecasts of credit spreads, we attempt to isolate the subjective component of CRA beliefs. To do so, we construct a variable *AaaDev* which equals the difference between the CRAs' Aaa credit spread forecast and the consensus forecast of the same variable.[4] We then estimate a regression with both *AaaDev* and the consensus forecast as the independent variables and the future realized Aaa spread as the dependent variable. While the consensus on its own strongly predicts future realized credit spreads, we find that *AaaDev* contains no additional information regarding future realized credit spreads.

In order for *AaaDev* to meaningfully reflect the subjective component of CRA beliefs, CRAs must act on these beliefs. Hence, we examine whether *AaaDev* affects bond-level credit ratings. Consistent with CRAs incorporating their beliefs regarding future aggregate credit spreads into their bond ratings, we find that bond ratings are higher when CRAs are relatively more optimistic—that is, when they forecast a narrower credit spread than the consensus forecast. Hence, CRA beliefs about aggregate credit spreads have a material impact on their actions in the form of their credit assessments.[5]

[3]Specifically, the credit spread forecast is obtained as the difference between yield forecasts of the 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.

[4]Our approach of comparing forecasts to the consensus is similar to papers studying disagreement in interest rate and inflation expectations (e.g., Giacoletti, Laursen, and Singleton, 2021).

[5]As we discuss later, this is consistent with CRAs' guidance to incorporate aggregate economic forecasts into their individual credit ratings.

The previous tests suggest we have identified a component of credit ratings related to the beliefs of CRAs that is unrelated to fundamentals. If markets are perfectly rational, we would not expect this subjective component of ratings to affect bond prices. However, credit investors often rely on credit ratings for information (e.g., Kliger and Sarig, 2000 and Tang, 2009) and may not be able to disentangle the component of credit ratings that are due to CRAs' subjective beliefs. If this were the case, we would expect CRA optimism to 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 mispricing, we find that higher CRA pessimism leads to higher initial yields and subsequent negative excess returns among newly issued bonds.

Next, we explore whether CRA beliefs affect firms' financing and investment behavior. If firm managers have a more accurate assessment of their own creditworthiness than the financial market, they can take advantage of their higher ratings and lower bond yields by issuing more debt and increasing their leverage. Consistent with this "rational manager-irrational market" 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 entirely absent in firms' bank debt issuance decisions. 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.

We further test whether CRA beliefs affect the asset side of the balance sheet through firms' investment decisions. Firms increase their investment when CRAs are relatively more optimistic than the consensus. Hence, the subjectivity in CRA beliefs also affects the real side of the economy by influencing the investment decisions of firms.

The effects we identify are large. When the CRAs are 20bps more optimistic than the consensus regarding future credit spreads (approximately one standard deviation), this leads to a 1.8pp (3.5%) increase in firm leverage and a 2% decrease in total assets among rated firms. Hence, over half of the proceeds raised through the firms' increase in leverage are invested in new assets.

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 managers and irrational bond investors (e.g., Baker, Stein, and Wurgler, 2003, Shleifer and Vishny, 2003, and Stein, 2005). However, we cannot fully determine whether firms are rational. For example, firm managers may wrongly interpret their higher ratings (and lower initial bond yields) from CRA optimism as a signal about the profitability of their investment opportunities, thereby inducing more investment. In either case, we have identified a subjective component of beliefs of key actors in credit markets that strongly affects firms' financing and investment decisions through mispricing in credit markets.

What drives CRAs' deviation from the consensus forecast? One explanation is that CRAs may choose forecasts that are intentionally biased to maximize their expected profits (e.g., Griffin and Tang, 2011). An alternative explanation is that these forecasts stem from the subjective beliefs of the individual forecasters employed by the CRAs. Inconsistent with the first channel, we find no relationship between measures of CRA performance and their forecasts. However, we do find that the individual economists, i.e., economist fixed effects, explain a substantial portion of CRA subjective beliefs. To further explore this link between economists' idiosyncratic beliefs and their deviation from the consensus we construct a proxy for returns to each economist's financial wealth using their experienced local housing market returns based on hand-collected property ownership information. Interestingly, when economists experience higher (lower) housing returns their forecasts regarding future credit spreads are more optimistic (pessimistic). This result suggests that economists' idiosyncratic subjective beliefs are an important driver of CRAs' documented impact on credit markets.

One concern is that our measure of CRA beliefs is simply correlated with aggregate "sentiment" in credit markets (e.g., Greenwood and Hanson, 2013, López-Salido, Stein, and Zakrajšek, 2017, and Gulen, Ion, and Rossi, 2021). First, our measure is based on the *difference* between CRAs and the consensus of other financial institutions. Hence, we are differencing out any market-wide sentiment that affects the CRAs and other financial institutions equally. Second, our measure of CRA subjective beliefs has a low correlation with many commonly used credit market sentiment proxies. For example, the correlation between $AaaDev$ and the high-yield share HYS from Greenwood and Hanson (2013) is merely -0.1 and not significantly different from zero. Third, we find that our documented effects are heavily concentrated in rated firms and entirely absent in bank debt markets, suggesting the results are driven by the actual ratings CRAs provide. Finally, our main results are robust to controlling for many of the main sentiment measures established in the literature. Thus, we believe that we have truly captured a component of subjective CRA beliefs that strongly affects credit market conditions and real activity.

Related literature Our paper makes several contributions to the behavioral finance and economics literature that studies agents' beliefs of financial and macroeconomic variables.

First, we establish a strong link between the stated beliefs of CRAs and their credit rating decisions. The paper joins a small but growing literature that studies the relationship between beliefs and actions (e.g., Giglio et al., 2021, Wang, 2021 and Ma, Paligorova, and Peydro, 2021). Most closely, Ma, Paligorova, and Peydro (2021) analyze the relationship between bank expectations and their lending decisions. An open issue in this literature is that differences in beliefs could reflect either behavioral biases or differences in private information. By showing that the subjective component of CRA beliefs does not predict future credit spreads and that these beliefs are strongly related to the forecasters' experienced housing returns, we arguably are able to make this distinction. Hence, a key innovation in our paper relative to the existing literature is that we are able to isolate a component of agents' beliefs unrelated to fundamentals and analyze how they impact credit market conditions and firm behavior through CRAs' rating decisions.

Second, by exploring the beliefs of CRAs, we shed some light on an important question raised by Brunnermeier et al., 2021—that is, whose beliefs matter for asset prices. Just because agents act on their beliefs does not mean these agents are driving asset prices. Since CRAs decide credit ratings themselves, their beliefs are clearly relevant credit market and firm-level outcomes. Hence, this paper i) identifies certain agents whose beliefs matter for asset prices and ii) shows that the idiosyncratic component of these beliefs exert a large impact on credit market conditions and real activity.

Because we focus our analysis on CRAs' beliefs, our paper also 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, Fracassi and Weitzner, 2020 and Liu and Shivdasani, 2013). 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.

Relatedly, we also 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). For example, Kempf and Tsoutsoura (Forthcoming) show that credit rating analysts' partisan beliefs affect the credit ratings they assign. To identify the effects of CRA subjectivity, these papers typically analyze differences across or within credit rating agencies for a given firm or bond at a particular point in time. While this approach helps identify subjective beliefs, it limits the ability to analyze how these beliefs affect bond and firm-level outcomes. In contrast, we compare the average beliefs of CRAs to a consensus of financial institutions allowing us to test how these beliefs affect bond and firm-level outcomes.[6]

Our paper also relates to the literature analyzing how CRA standards evolve over time. (e.g., Becker and Milbourn, 2011, Jiang, Stanford, and Xie, 2012, Alp, 2013 and Baghai, Servaes, and Tamayo, 2014). 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

[6]Our paper also contributes to the 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), by showing that CRA beliefs can cause credit ratings to be either inflated or deflated.

behavior. 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*.

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. Rather than taking mispricing as given, a key contribution of our paper is identifying a specific source of mispricing stemming from CRAs' subjective beliefs.

2 Data

In this section, we describe various datasets we use in this paper. We also explain how we measure the expectations of CRAs and other financial institutions.

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 has maintained a stable and large panel of forecasters over the years and has an extended 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 and 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 time series, another major advantage of the BCFF survey is that it contains the identity of each forecaster, i.e., the names of the economist and his/her affiliated institution.[7] 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 restructurings such as mergers and acquisitions[8]. This gives us 86 unique forecasters who made more than 60 monthly forecasts, among which 26 are banks, 15 are broker-dealers, and 17 are primary dealers of the Federal Reserve Bank of New York[9].

We focus on forecasts from the two largest CRAs, Moody's Investors Service (MR) and S&P Global Ratings (SPR), which have participated in BCFF surveys continuously since 2001. The key variable of interest is Aaa corporate bond yields which are based on Aaa corporate bond indices published by Bank of America-Merrill Lynch.[10][11] Since these corporate bond indices are maintained by a third party, their construction is not directly influenced by either 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.

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.

One may naturally question how informative are the measured BCFF survey forecasts about

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

[8] 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.

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

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

[11] BCFF provides forecasts of both Aaa and Baa corporate bond yields. For our main results, we focus only on Aaa forecasts due to their much longer availability.

agents' beliefs. First, there are immediate reputation and career concerns for the forecasters, given the wide circulation of the BCFF survey among financial market participants. Additionally, Wang (2021) shows that, for a subset of BCFF forecasters, their allocations to the Treasuries of a given maturity vary significantly and positively with their expectation of bond returns for that maturity. This evidence suggests that BCFF forecasters treat the surveys seriously enough that they are willing to put their money behind their forecasts.

Another concern is that credit analysts at CRAs may not rely on the projections provided by the macroeconomics team, headed by the chief economists. Fortunately, CRAs explicitly require that credit analysts use them as key inputs in their credit assessment. For example, Moody's guidance for the credit rating process states:

> "*Moody's Macroeconomic Board provides a consistent set of macroeconomic forecasts for use in the rating process; facilitating analyst access to these forecasts; and encouraging the development of macroeconomic sensitivity analysis within each sector.*"[12]

Thus the institutional setting we analyze ensures a formal information flow from the macroeconomists to the credit analysts in the same agency. When credit analysts are making rating decisions, the current macroeconomic forecasts are not only readily available to them but also embedded in their rating models.

Firm and bond data. We obtain data on corporate bond ratings and issuance information, e.g., bond issuance information such as offering yield, date, and maturity from Mergent Fixed Income Securities Database (FISD). 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).[13] We obtain firms' quarterly financial information from Compustat Fundamentals Quarterly.

We obtain monthly bond returns data from the WRDS Bond Returns data, a cleaned dataset of corporate bond returns compiled by WRDS and sourced from TRACE Standard and TRACE

[12] Similar requirements are articulated in the rating guidance of S&P.

[13] Refer to Table 2 in Becker and Milbourn (2011) for details on the conversion.

Enhanced datasets. Following the literature, we apply a few additional filtering criteria: We focus on non-convertible corporate bonds with fixed coupons. We also 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.[14]

CRA and Economist data. We collect stock prices, earnings and earnings forecasts of publicly traded CRAs or their parent companies from CRSP, Compustat, and I/B/E/S respectively. For S&P Global Ratings, we use stock information from The McGraw-Hill Companies, McGraw Hill Financial and S&P Global Inc., which are its successive parent companies. For Moody's Investors Service, we use stock information from Moody's Corporation, which is its sole parent company.

We also manually collect information about the head economists who are responsible for the forecasts at the two CRAs. We identify each economist in the LexisNexis Public Records Database and obtain data on his/her property transactions from the deeds records. To proxy for their housing returns, we compute economists' experienced local housing returns using the Zillow Home Value Index (ZHVI) for single-family homes at the zip code level.

Final sample and summary statistics. We merge BCFF forecasts at the beginning of each quarter with corporate bond and firm-level data at the end of the quarter.[15] Since valid forecasts of Aaa, Baa, and 10-year Treasury yields from both Moody's and S&P are available from September 2001 onward, our final sample period is 2001:Q3-2018:Q4, spanning a total of 69 quarters.

[14]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.

[15]Merging the forecast data in this way helps mitigate concerns that forecasts may be reversely engineered from outcome variables such as bond prices or credit ratings.

Following a long strand of literature on corporate bonds (e.g., Gilchrist and Zakrajšek, 2012 and Nozawa, 2017), we focus on credit spreads as our main gauge of credit market conditions. Specifically, we define forecaster j's forecast of credit spreads as the difference between their forecast of the Aaa and 10-year Treasury yields:

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

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 CRA beliefs by averaging forecasts from Moody's and S&P for variable X_{t+h} as

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

To simplify the notation, we define forecasts of one-quarter-ahead Aaa credit spread from the consensus and the CRAs, respectively:

$$AaaCon_t \equiv \mathbb{E}_t^{Con}(CS_{t+1}^{Aaa}) \quad \text{and} \quad AaaCRA_t \equiv \mathbb{E}_t^{CRA}(CS_{t+1}^{Aaa}) \tag{1}$$

Based on these notations, we define our primary variable of interest $AaaDev$ as follows:

$$AaaDev_t \equiv AaaCRA_t - AaaCon_t. \tag{2}$$

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

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. The Aaa credit spread forecast made by the CRAs is, on average, 11bps lower than the consensus (147bps versus 159bps), suggesting on average CRAs are just under 3% more aggressive in their forecasts.

Figure A.1 displays the time series of the credit spread forecasts of CRAs, the consensus, and their difference. As expected, the individual credit spread forecast of the CRAs and the consensus, as shown in Panel A, are typically high in recessions. However, in Panel B, the differences in credit spread forecasts do not appear to exhibit any relationship with the business cycle 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.

3 CRA Beliefs

In this section, we evaluate the rationality and accuracy of the forecasts from CRAs and the consensus.

3.1 Rationality of CRA Beliefs

We start by testing whether the forecasts from the CRAs and the consensus are consistent with rational expectations. To do so, we apply a methodology developed by Coibion and Gorodnichenko (2015, CG), which examines the predictability of future forecast errors from current forecast revisions. Under full-information rational expectations (FIRE), the forecast errors are not predictable, and the coefficient should be zero. Therefore, any significant relationship implies a deviation from FIRE. A negative (positive) sign means that an upward revision in the forecast is followed by a lower (higher) outcome than expected, implying overreaction (underreaction).[16] Additionally, it

[16] One noticeable advantage of this error-on-revision test is that it does not require us to observe or measure the information set of the forecasters directly, as we can infer their reaction to new information from their forecast revisions.

is worth stressing that an overreaction cannot be attributed to a violation of "full information" in FIRE, as theories based on information frictions such as rational inattention (e.g., Sims, 2003) or sticky information (e.g., Mankiw and Reis, 2002) all predict an underreaction. As a consequence, such a departure from FIRE indicates a departure from rational expectations.

Formally, we apply the CG regression to the forecasts of the Aaa credit spread:

$$\underbrace{CS_{t+h} - \mathbb{E}_t^j CS_{t+h}}_{\text{Forecast Error, } FE_t(CS_{t+h})} = \alpha + \beta \underbrace{\left(\mathbb{E}_t^j CS_{t+h} - \mathbb{E}_{t-1}^j CS_{t+h}\right)}_{\text{Forecast Revision, } FR_t(CS_{t+h})} + \epsilon_{t+h}, \tag{3}$$

where $j \in \{CRA, Con\}$, the data is at a quarterly frequency, and forecast revision is measured as the quarterly updates in the forecasts. We fix the forecast horizon to one quarter $h = 1$. The results of this regression are reported in Table 2. column (1) shows that CRA beliefs overreact to news about the credit market, as indicated by a negative and significant β coefficient at the 5% level. As discussed earlier, this overreaction supports a departure from rational expectations in CRA forecasts of credit spreads. In contrast, the β coefficient for the consensus is slightly negative but not significantly different from zero, failing to reject FIRE in consensus forecasts. This holds true whether we construct the consensus with or without forecasts from the two CRAs (columns (2) and (3)). Taken together, CRA forecasts of credit spreads deviate from rational expectations in the form of overreaction, while the consensus forecasts of credit spread do not deviate significantly from rational expectations.

3.2 CRA Beliefs and Future Realized Credit Spreads

Despite overreacting to news, CRAs' forecasts may still be informative about future credit spreads beyond what is contained in the consensus, as they may have some private information stemming from their expertise in forecasting credit market conditions. To test this hypothesis, we estimate the following time-series regression:

$$CS_{t+1}^{Aaa} = \alpha + \beta_0 AaaCon_t + \beta_1 AaaDev_t + u_{t+1}, \tag{4}$$

where Aaa_{t+1} is the realized Aaa credit spread in quarter $t+1$. If the estimated coefficient β_1 is positive, this would suggest that CRAs' forecasts have additional predictive content beyond the consensus. We also estimate (4) with 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 (4), 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 Properties of CRA Subjective Beliefs

Since CRAs' forecast deviation from the consensus, $AaaDev$, carries little information regarding future credit market conditions, it is likely to reflect the subjectivity in CRAs' beliefs. Henceforth, we refer to this subjective component as CRA subjective beliefs. IThe last row of Panel A, Table 1 reports the summary statistics and Panel B of Figure A.1 plots a time series of CRA subjective beliefs. A few notable features emerge. First, the average and median of $AaaDev$ are slightly negative. Though the mean is small in magnitude (-0.11%), it is statistically significant from zero at the 1% level, suggesting a meaningful difference between the CRA and the consensus forecasts. Second, $AaaDev$ features both positive and negative values, indicating that CRAs' beliefs are not always pessimistic or optimistic. Lastly, CRAs' forecasts are very close to the consensus during the Global Financial Crisis, suggesting that the deviation is not driven by one specific episode.

Next, since the variation of $AaaDev$ is in the time series, one may be concerned that it is driven by credit market-wide sentiments, not from the subjective beliefs of the economists at the CRAs.

To address this concern, we examine the correlation of our measure of CRA subjective beliefs with other commonly used measures of credit market sentiments in the literature. Specifically, we consider four measures of credit market sentiments. The high-yield share, HYS, and Credit Growth are from Greenwood and Hanson (2013). Easy Credit is the three-year average of the percentage of the Reserve's Senior Loan Office Opinion Survey. $-EBP$ is negative one times excess bond premium from Gilchrist and Zakrajšek (2012). More broadly, we also include the stock market sentiment from Baker and Wurgler (2006), BW Sentiment. The correlations are reported in Table A.3. As the first column indicates, $AaaDev$ is not significantly correlated with most credit market sentiments, including HYS, Easy Credit, and $-EBP$; it is only weakly correlated with Credit Growth (0.2). This suggests that the variation in $AaaDev$ is unlikely to be attributed to sentiments in the overall credit market. However, $AaaDev$ has a significant correlation of 0.3 with BW Sentiment, the stock market sentiment measure.

4 CRA Beliefs and Rating Actions

The tests in the previous section suggest that CRA forecasts of credit spread deviate from rationality and do not contain any additional information regarding future credit spreads beyond the consensus.

Fortunately, as we have discussed in Section 2, the rating protocols in major CRAs require that the forecasts made by macroeconomists be explicitly incorporated by the credit analysts in the rating decisions. Since credit analysts and macroeconomists in the same firm are likely to share a similar incentive structure and information set regarding the future aggregate credit market conditions, any bias or deviation from rationality in the macroeconomists' forecasts is not likely to be corrected by the credit analysts. Therefore, it is reasonable to claim that the subjective beliefs we documented also represent the beliefs of the credit analysts in the same CRA.

We formally test whether CRAs act on their forecasts in credit rating actions by estimating the following regression:

$$Rating_{b,j,t} = \beta \times \left[\mathbb{E}_t^c(CS_{t+1}^{Aaa}) - \mathbb{E}_t^{Con}(CS_{t+1}^{Aaa})\right] + \alpha_b + \Gamma Z_b + u_{b,j,t}, \tag{5}$$

where $Rating_{b,j,t}$ is the rating of bond b by CRA j at time t, $\mathbb{E}_t^j(CS_{t+1Q}^{Aaa}) - \mathbb{E}_t^{Con}(CS_{t+1Q}^{Aaa})$ is the difference between CRA j'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 match the ratings immediately after the most recent quarter's $AaaDev$ to mitigate the impact of reverse causality. We double-cluster our standard errors by issue and quarter. The main coefficient of interest is β, representing how an increase in an individual CRA forecast relative to the consensus affects the bond ratings that CRAs provide. The results are displayed in column (1) of Table 4. 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 the consensus forecast of credit spread $AaaCon$ to check if the decision is actually driven by the average forecast of the future credit spread. We find that β in column (2) barely changes and is highly significant and that the coefficient of $AaaCon$ is not significant. This indicates that the rating decisions are determined more by the CRA's own subjective beliefs, not the market-wide aggregate beliefs. In columns (3) and (4), 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:

$$AverageRating_{b,t} = \beta AaaDev_t + \Gamma Z_b + \alpha_b + u_{b,t}, \tag{6}$$

where $AverageRating_{b,t}$ 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 4, show that when CRAs are relatively more optimistic, bonds have on average lower ratings.

Alternative explanations. The evidence so far indicates that more optimistic subjective beliefs from CRAs lead to higher ratings. Here we discuss a few alternative explanations that may explain this result. First, because CRAs act in accordance with their subjective beliefs, we can safely rule out that their stated beliefs are purely measurement errors or noise. Second, the relationship between subjective beliefs and rating decisions is also unlikely to be driven by aggregate credit market sentiments. The correlation between $AaaDev$ and other measures of credit market sentiment is very low. Furthermore, we explore the between CRAs variations in credit spread forecasts and ratings. Specifically, we regress the rating difference between Moody's and S&P, $Rating_{i,t}^{MR} - Rating_{i,t}^{SPR}$, on their difference in forecasts, $\left(\mathbb{E}_t^{MR} - \mathbb{E}_t^{SPR}\right)(x_{t+1Q})$. The results are reported in Table **??** in the Appendix, where we still obtain a significant and negative coefficient for credit spread forecasts. Since any impact from aggregate credit market sentiments is already differenced out, this further eliminates the possible common influence of aggregate credit market sentiments. Finally, we have documented a similar relationship between optimism ($AaaDev < 0$) and pessimism ($AaaDev > 0$). The latter helps at least partially rules out a concern that the relationship is determined by credit analysts' incentive to issue more favorable ratings to their corporate clients, as the incentive explanation only predicts inflated ratings across the board.

5 CRA Beliefs and Bond Pricing

Thus far, we have shown that CRA's 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 expect no relationship between $AaaDev$ and bond prices. However, if investors cannot disentangle the component of CRAs' beliefs that affects ratings and is unrelated to fundamentals, they may price bonds more favorably when CRAs are more optimistic. To test this hypothesis, we estimate the following regression:

$$CS_{b,t} = \beta_0 AaaCon_t + \beta_1 AaaDev_t + \Gamma Z_b + \alpha_i + u_{b,t}, \tag{7}$$

where the dependent variable, $CS_{b,t}$, is the initial credit spread on bond b issued at time t, calculated using the Treasury yield of the closest maturity; Z_b is a set of bond-level control variables, including bond issue size (in logarithms), maturity, covenants, and duration; and α_i are issuer fixed effects. Standard errors are double clustered by issuer and quarter. If CRA forecasts influence the initial credit spread, we would expect the estimate of β_1 to be positive. The results are displayed in Table 5, and consistent with CRA deviations affecting initial bond pricing, we find that the coefficient estimate is positive and statistically in specifications with and without consensus forecasts $AaaCon$ (column 2) and bond-level controls (columns 3). Specifically, a one percentage point increase (decrease) in CRA forecasts deviation leads to around 0.3 percentage point increase in credit spread at issuance, indicating that CRA optimism (a negative deviation) leads to higher bond prices at issuance.

If CRA optimism drives initial yields higher, we would also expect higher optimism to lead to new bonds underperforming, as this initial optimism is proven to be unwarranted over time.[17] In this regression, we include all bonds rather than just new issues to compare the returns across new and old bond issues. To test this hypothesis, we estimate the following regression:

$$\begin{aligned} Return_{b,t,t+1} = {} & \beta_0 AaaCon_t + \beta_1 (AaaCon_t \times New_{b,t}) \\ & + \beta_2 AaaDev_t + \beta_3 (AaaDev_t \times New_{b,t}) + \Gamma Z_b + \alpha_i + u_{b,t,t+1}, \end{aligned} \tag{8}$$

Where $Return_{b,t,t+1}$ is the realized quarterly bond-level return over the next quarter, and $New_{b,t}$ is a dummy variable that equals one if the bond has been issued over the past two quarters.[18] Once

[17] It is unwarranted because, as shown earlier, CRA optimism does not lead to lower aggregate credit spreads.

[18] We match BCFF forecasts at the beginning of each quarter to quarter-end TRACE pricing data. Therefore, defining new bonds as issued in the last two quarters ensures that each bond has a minimum of one quarter of pricing data available in TRACE.

again, we double-cluster our standard errors by issuer and quarter. The results are displayed in Table 6. In columns (1) and (2), we exclude the interaction between $AaaDev$ (and $AaaCon$) 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, with no prior pricing information, investors have to rely more on credit ratings to assess credit risk when they purchase newly issued bonds. Moreover, there are more buy-and-hold investors, such as bond ETFs, pension funds and insurance companies, investing in new issues, who are on average likely to be less sophisticated than investors who trade existing bonds actively. Moreover, sophisticated investors are likely better able to disentangle the true credit risk of the bond from its rating. Additionally, the pattern that new bonds appear to be initially overpriced but experience negative subsequent returns following CRA optimism is consistent with the result that CRA optimism does not predict lower future *aggregate*-level credit spreads.[19]

6 Firm-Level Analysis

We have established that CRAs' beliefs regarding future aggregate credit spreads affect 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 analyses 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

[19]Specifically, the Aaa index is based on existing bonds.

following regression

$$y_{i,t} = \beta_0 AaaCon_t + \beta_1 AaaDev_t + \Gamma X_{i,t} + \alpha_i + u_{i,t}, \tag{9}$$

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)[20] and α_i are firm fixed effects. In all regressions in this section, we double-cluster our standard errors at the firm and quarter levels.

In order to show that the effects we identify operate through credit ratings specifically, we also test whether the effects are concentrated among rated firms. Specifically, we estimate the following regression:

$$y_{i,t} = \beta_0 AaaDev_t + \beta_1 Rated_{i,t} + \beta_2(AaaDev_t \times Rated_{i,t}) + \Gamma X_{i,t} + \alpha_i + u_{i,t}, \tag{10}$$

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 instrumental because we would expect the effects we identify to be stronger among rated firms whose debt pricing and ratings are affected by CRA forecasts.

6.1 CRA Beliefs 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 7. In column (1), the coefficient $AaaDev_t$ is negative and statistically significant with a point estimate of -0.44. This estimate suggests that a 1pp

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

increase in Moody's and S&P's credit spread forecast relative to the consensus results in firms' using 0.44pp less debt. In column (2), we estimate (11) 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 7 with equity issuance and long-term debt issuance as dependent variables. The results are displayed in Table 8. 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.

6.2 CRA Beliefs 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 (11) with different investment outcome variables. In particular, in columns (1) and (2) of Table 9, the results are displayed with total assets as the dependent variable, while in 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 CRAs have real effects on firm behavior and that firms do not only adjust their capital structures in response to CRA forecast deviations. A potential explanation could be that firms also look to the information in credit ratings and cannot undo the effect of excess optimism or pessimism by the CRAs. For instance, firms may believe their investment opportunities are less risky based on their credit ratings, 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).

6.3 CRA Beliefs and Firms' Likelihood of Being Rated

If CRAs give higher 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

$$Rated_{i,t} = \beta_0 AaaCon_t + \beta_1 AaaDev_t + \Gamma X_{i,t} + \alpha_i + u_{i,t}, \tag{11}$$

where the dependent variable, $Rated_{i,t}$, is a dummy that equals one if the firm is rated. The results are displayed in Table 10. 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 more likely firms are to have issuer-level ratings. In terms of economic magnitudes, a one standard deviation increase in CRA optimism (18bp) leads to a 2.3% increase in the likelihood of a firm being rated. A caveat to this interpretation is 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 6.1.

7 Determinants of the CRA Beliefs

In this section, analyze the determinants of CRAs' subjective beliefs of CRAs. While in our main analysis we focus on the average of CRAs' forecasts, here we focus on individual CRA estimates to better hone in on the sources of these forecasts.

One potential rationale for CRAs being more optimistic or pessimistic in their forecast of credit spreads could be attributed to their incentives For example, if a CRA is performing poorly, it may find it advantageous to be more optimistic to attract more business from clients.

To test this hypothesis, we regress the difference between rating agency j's forecast of the Aaa credit spread and the consensus forecast, i.e., $\left[\mathbb{E}_t^j(CS_{t+1}^{Aaa}) - \mathbb{E}_t^{Con}(CS_{t+1}^{Aaa})\right]$ on various lagged measures of CRA performance such as earnings surprises and stock returns. The results are displayed in Table 11. None of the performance measures have a statistically significant effect on the forecast deviations. Moreover, the F-statistics range from 0.68 to 1.01 (p-values of 0.411 - 0.609) across the models, indicating that we cannot reject the null hypothesis that CRA performance does not affect their forecast deviations from the consensus.

An alternative source for variation in CRA forecasts is the individual biases of the economists who are responsible for making the forecasts. To test this hypothesis, we further collapse the forecast data to the economist level. Notably, S&P has three different economists (David M. Blitzer, David Wyss, and Beth Ann Bovino), while Moody's has John Lonski over the entire sample period. In Table 12, we use the difference in forecasts of the Aaa credit spread between economist f of rating agency j and the consensus as the dependent variable and we include economist fixed effects. As references, in columns (1) - (3), we include quarter fixed effects, CRA fixed effects and both, respectively. In columns (4) - (5), we include specifications with economist fixed effects alone and economist fixed effects plus year-quarter fixed effects.[21] In both specifications, the F-statistic is above 5. In terms of R^2, economist fixed effects alone explain around 20% of the variation in forecast deviations and they add an additional 13% to the explanatory power

[21]Since Moody's has only one economist over the sample, CRA fixed effects are equivalent to the John Lonski dummy in the economist fixed effects.

of the year-quarter fixed effects, suggesting that idiosyncratic characteristics of the individual economists indeed account for a sizable portion of CRAs' forecast deviations.

We next investigate whether economists' forecasts are influenced by their financial wealth and exposure to local economic activities through the returns from their housing portfolios. We consider housing for two reasons. First, houses likely represent a sizable portion of the CRA economists' financial wealth. Second, because we do not have access to these economists' entire financial portfolios, housing returns remain our best proxy for their financial performances.

We use the LexisNexis Public Records Database to manually collect data on all properties owned and sold by economists from the deeds records. To proxy for economists' own housing returns, we compute their experienced local housing returns based on the zip codes of all properties they own at time t. Specifically, for each property owned by economist f, we compute its local housing return as the one-year change in the Zillow Home Value Index (ZHVI) for single-family homes. We then calculate economist f's experienced housing return, $\Delta ZHVI_{f,t}$, by averaging across all the properties she owns.

We then examine how their experienced housing returns affect their deviations from the consensus forecast of credit spreads. We regress economist f's forecast deviation on her experienced housing return and its lagged values, controlling for year-quarter and CRA fixed effects. Table 13 reports the results. The coefficients on both current and lagged experienced returns are negative and significant, indicating that higher returns are associated with more optimistic forecasts for future credit markets. Using coefficients from the lagged return, which is much less subject to reverse causality issues, a 10% increase in experienced housing return implies that economist f's forecast is about 0.24pp lower than the consensus, which is more than half of the standard deviation of that deviation. Taken together, these results imply that personal, idiosyncratic factors such as behavioral biases significantly influence their deviations from the consensus and, to a large extent, determine their belief formation.

8 Conclusion

In this paper, we show that subjective beliefs have a pervasive effect on credit markets and firm behavior. Specifically, we analyze the beliefs of key players in credit markets: credit rating agencies (CRAs). 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 even though 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. Rather than CRA forecasts being driven by incentive problems, we find evidence consistent with CRA beliefs being driven by the idiosyncratic beliefs of the individual economists the CRAs employ.

In order to identify subjective beliefs, our analysis focuses on a specific aspect of CRA beliefs tied to aggregate conditions. Hence, we are not able to identify subjectivity at the individual firm level. Given the large effects we see at the aggregate level, we expect the subjective beliefs of CRAs (and potentially other agents) to be an extremely important driver of credit and real decisions at the individual firm level.

Overall, our results show how beliefs of key players in credit markets impact credit market conditions and firms' capital structures and investment decisions. More broadly, our analysis highlights how beliefs can affect aggregate credit issuance and real economic activity.

References

Almeida, Heitor, Igor Cunha, Miguel A Ferreira, and Felipe Restrepo, 2017, The real effects of credit ratings: The sovereign ceiling channel, *Journal of Finance* 72, 249–290.

Alp, Aysun, 2013, Structural shifts in credit rating standards, *Journal of Finance* 68, 2435–2470.

Baghai, Ramin P, Henri Servaes, and Ane Tamayo, 2014, Have rating agencies become more conservative? implications for capital structure and debt pricing, *Journal of Finance* 69, 1961–2005.

Baker, Malcolm, Jeremy C Stein, and Jeffrey Wurgler, 2003, When does the market matter? stock prices and the investment of equity-dependent firms, *The Quarterly Journal of Economics* 118, 969–1005.

Baker, Malcolm and Jeffrey Wurgler, 2006, Investor sentiment and the cross-section of stock returns, *The journal of Finance* 61, 1645–1680.

Becker, Bo and Todd Milbourn, 2011, How did increased competition affect credit ratings?, *Journal of Financial Economics* 101, 493–514.

Begley, Taylor A, 2013, The real costs of corporate credit ratings, Working paper.

Bolton, Patrick, Xavier Freixas, and Joel Shapiro, 2012, The credit ratings game, *Journal of Finance* 67, 85–111.

Brunnermeier, Markus, Emmanuel Farhi, Ralph S.J. Koijen, Arvind Krishnamurthy, Sydney C Ludvigson, Hanno Lustig, Stefan Nagel, and Monika Piazzesi, 2021, Review Article: Perspectives on the Future of Asset Pricing, *Review Of Financial Studies* 34, 2126–2160.

Coibion, Olivier and Yuriy Gorodnichenko, 2015, Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts, *American Economic Review* 105, 2644–2678.

Cornaggia, Jess, Kimberly J Cornaggia, and Han Xia, 2016, Revolving doors on wall street, *Journal of Financial Economics* 120, 400–419.

DeAngelo, Harry and Richard Roll, 2015, How stable are corporate capital structures?, *Journal of Finance* 70, 373–418.

Diebold, Francis X. and Roberto S. Mariano, 1995, Comparing Predictive Accuracy, *Journal of Business and Economic Statistics* 13, 253–263.

Dong, Ming, David Hirshleifer, Scott Richardson, and Siew Hong Teoh, 2006, Does investor misvaluation drive the takeover market?, *Journal of Finance* 61, 725–762.

Fracassi, Cesare, Stefan Petry, and Geoffrey Tate, 2016, Does rating analyst subjectivity affect corporate debt pricing?, *Journal of Financial Economics* 120, 514–538.

Fracassi, Cesare and Gregory Weitzner, 2020, What's in a debt? rating agency methodologies and firms' financing and investment decisions, *Rating Agency Methodologies and Firms' Financing and Investment Decisions (March 18, 2020)* .

Geanakoplos, John, 2010, The leverage cycle, *NBER macroeconomics annual* 24, 1–66.

Giacoletti, Marco, Kristoer T. Laursen, and Kenneth J. Singleton, 2021, Learning From Disagreement in the U.S. Treasury Bond Market, *Journal of Finance* 76, 395–441.

Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Steve Utkus, 2021, Five Facts about Beliefs and Portfolios, *American Economic Review* 111, 1481—-1522.

Gilchrist, Simon and Egon Zakrajšek, 2012, Credit spreads and business cycle fluctuations, *American Economic Review* 102, 1692–1720.

Goldstein, Itay and Chong Huang, 2020, Credit rating inflation and firms' investments, *Journal of Finance* 75, 2929–2972.

Graham, John R and Campbell R Harvey, 2001, The theory and practice of corporate finance: Evidence from the field, *Journal of Financial Economics* 60, 187–243.

Greenwood, Robin and Samuel G Hanson, 2013, Issuer quality and corporate bond returns, *The Review of Financial Studies* 26, 1483–1525.

Griffin, John M and Dragon Yongjun Tang, 2011, Did credit rating agencies make unbiased assumptions on cdos?, *American Economic Review* 101, 125–30.

Griffin, John M and Dragon Yongjun Tang, 2012, Did subjectivity play a role in cdo credit ratings?, *Journal of Finance* 67, 1293–1328.

Gulen, Huseyin, Mihai Ion, and Stefano Rossi, 2021, Credit Cycles, Expectations, and Corporate Investment, Working paper.

Hovakimian, Armen, Ayla Kayhan, and Sheridan Titman, 2009, Credit rating targets, Working paper.

Jiang, John Xuefeng, Mary Harris Stanford, and Yuan Xie, 2012, Does it matter who pays for bond ratings? historical evidence, *Journal of Financial Economics* 105, 607–621.

Kempf, Elisabeth and Margarita Tsoutsoura, Forthcoming, Partisan professionals: Evidence from credit rating analysts, *Journal of Finance* .

Kisgen, Darren J, 2006, Credit ratings and capital structure, *Journal of Finance* 61, 1035–1072.

Kisgen, Darren J, 2009, Do firms target credit ratings or leverage levels?, *Journal of Financial and Quantitative Analysis* 44, 1323–1344.

Kisgen, Darren J, 2019, The impact of credit ratings on corporate behavior: Evidence from moody's adjustments, *Journal of Corporate Finance* 58, 567–582.

Kliger, Doron and Oded Sarig, 2000, The information value of bond ratings, *Journal of Finance* 55, 2879–2902.

Liu, Tim and Anil Shivdasani, 2013, Do credit ratings matter? evidence from s&p's 2013 methodology revision, *Evidence from S&P's* .

López-Salido, David, Jeremy C Stein, and Egon Zakrajšek, 2017, Credit-market sentiment and the business cycle, *The Quarterly Journal of Economics* 132, 1373–1426.

Ma, Yueran, 2019, Nonfinancial firms as cross-market arbitrageurs, *Journal of Finance* 74, 3041–3087.

Ma, Yueran, Teodora Paligorova, and José-Luis Peydro, 2021, Expectations and bank lending, *University of Chicago, Unpublished Working Paper* .

Mankiw, N. Gregory and Ricardo Reis, 2002, Sticky Information versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve, *Quartely Journal of Economics* 117, 1295–1328.

Minsky, Hyman P, 1977, The financial instability hypothesis: An interpretation of keynes and an alternative to "standard" theory, *Challenge* 20, 20–27.

Nozawa, Yoshio, 2017, What Drives the Cross-Section of Credit Spreads?: A Variance Decomposition Approach, *Journal of Finance* 72, 2045–2072.

Rajan, Raghuram G and Luigi Zingales, 1995, What do we know about capital structure? some evidence from international data, *Journal of Finance* 50, 1421–1460.

Shleifer, Andrei and Robert W. Vishny, 2003, Stock Market Driven Acquisitions, *Journal of Financial Economics* 70, 295–311.

Sims, Christopher A., 2003, Implications of Rational Inattention, *Journal of Monetary Economics* 50, 665–690.

Skreta, Vasiliki and Laura Veldkamp, 2009, Ratings shopping and asset complexity: A theory of ratings inflation, *Journal of Monetary Economics* 56, 678–695.

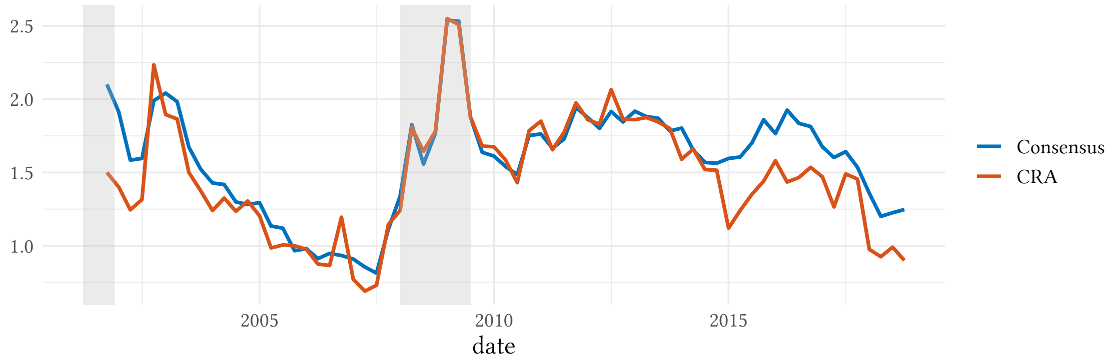
Stein, Jeremy C, *Rational capital budgeting in an irrational world* (Princeton University Press 2005).

Sufi, Amir, 2007, The real effects of debt certification: Evidence from the introduction of bank loan ratings, *Review of Financial Studies* 22, 1659–1691.

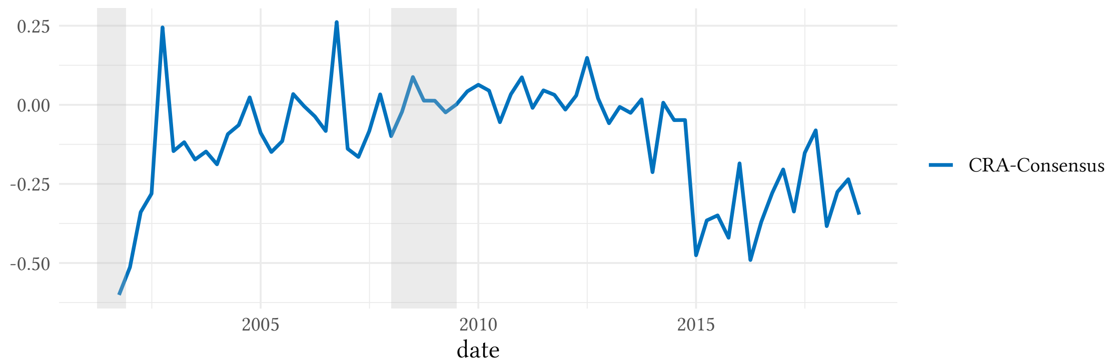
Tang, Tony T, 2009, Information asymmetry and firms' credit market access: Evidence from moody's credit rating format refinement, *Journal of Financial Economics* 93, 325–351.

Wang, Chen, 2021, Under- and Overreaction in Yield Curve Expectations, Working paper, Working Paper.

West, Kenneth D., 1996, Asymptotic Inference about Predictive Ability, *Econometrica* 64, 1067–1084.



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.

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), and 5th and 95th percentile for each variable. In Panel A, we report average forecasts from CRAs, the consensus forecasts, and their differences. The forecast variable is the 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						
AaaCon	69	1.59	1.64	0.37	0.92	2.02
AaaCRA	69	1.47	1.47	0.40	0.87	2.03
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 Coibion and Gorodnichenko (2015) **Regressions for CRA and Consensus Forecasts**

This table reports, for each group of forecasters, the regression coefficients from regressing of forecast errors on forecast revisions and credit rating agencies (CRA) forecast deviations from the consensus:

$$FE_{i,t}\left(CS_{t+1}^{Aaa}\right) = \alpha_i + \beta FR_{i,t}\left(CS_{t+1}^{Aaa}\right) + \varepsilon_{i,t},$$

where forecasts are pooled across various forecasts horizon h, and standard errors are clustered by date. Columns (1)-(3) use CRA forecasts, consensus forecasts (excluding CRAs), and consensus forecasts (including CRAs), respectively. The underlying variable is the Aaa credit spread (CS^{Aaa}). The data are quarterly and cover the period 2001Q4 to 2018Q4. *, **, and *** indicate statistical significance at 10, 5, and 1% levels, respectively.

	Dependent Variable: Forecast Error $FE_{i,t}\left(CS_{t+1}^{Aaa}\right)$		
i =	CRA (1)	Consensus, incl. CRA (2)	Consensus, excl. CRA (3)
Constant	-0.115***	-0.204***	-0.209***
	(0.035)	(0.030)	(0.030)
$FR_{i,t}\left(CS_{t+1}^{Aaa}\right)$	-0.238**	-0.094	-0.098
	(0.117)	(0.171)	(0.177)
Observations	69	69	69
R^2	0.043	0.005	0.005

Table 3   CRA Forecast Deviations and Future Aggregate Credit Spreads

This table evaluates whether CRA credit spread forecast deviations help predict future realized credit spreads. The dependent variable is one-quarter-ahead realized Aaa credit spread CS^{Aaa}_{t+1} 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^{Aaa}_{t+1}		
	(1)	(2)	(3)
$AaaDev_t$	0.048		-0.019
	(0.398)		(0.317)
$AaaCRA_t$		0.588***	
		(0.125)	
$AaaCon_t$			0.700***
			(0.125)
Constant	1.380***	0.486**	0.256
	(0.093)	(0.200)	(0.195)
Observations	69	69	69
R^2	0.000	0.399	0.470

Table 4 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.

	$Rating_i^j,\ j \in \{MR, SPR\}$				$AverageRating_i$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}^j(CS) - \mathbb{E}^{Con}(CS)$	-0.199***	-0.198***	-0.102*	-0.099*		
	(0.060)	(0.060)	(0.054)	(0.053)		
$AaaDev$					-0.356***	-0.367***
					(0.121)	(0.118)
$AaaCon$		-0.013		-0.021		0.046
		(0.045)		(0.045)		(0.046)
Maturity	-0.047***	-0.048***	-0.050***	-0.050***	-0.036***	-0.035***
	(0.010)	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)
Bid-Ask Spread	-4.14***	-4.105***	-4.145***	-4.084***	-4.220***	-4.352***
	(0.997)	(0.936)	(1.000)	(0.933)	(0.981)	(0.962)
Duration	0.214***	0.214***	0.213***	0.213***	0.190***	0.190***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)
Issue FE	✓	✓	✓	✓	✓	✓
CRA FE			✓	✓		
Observations	591,947	591,947	591,947	591,947	277,344	277,344
R^2	0.912	0.912	0.912	0.912	0.922	0.922

Table 5 CRA Forecast Deviations and Initial Bond Pricing

This table tests whether CRA credit spread forecast deviations (*AaaDev*) affect bond credit spreads at issuance. The dependent variables are corporate bond credit spread at issuance, which is measured in percentage points. Credit spreads are calculated by matching the bond yield with the Treasury yield with the closest maturity. Control variables include bond characteristics at issue such as bond size, maturity, covenant and duration. Size refers to the log of the total amount issued (in thousands of dollars). Maturity refers to the initial tenor in years. No covenant is an indicator for bonds with no covenants reported in Mergent. Duration is modified duration. 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.

	Credit Spread at Issuance		
	(1)	(2)	(3)
AaaDev	0.341***	0.224**	0.179**
	(0.102)	(0.097)	(0.083)
AaaCon		1.22***	1.06***
		(0.163)	(0.211)
Maturity			0.059***
			(0.012)
Size			0.108***
			(0.040)
Duration			-0.123***
			(0.033)
No Covenant			0.037
			(0.061)
Issuer FE	✓	✓	✓
Observations	18,084	18,084	8,557
R^2	0.796	0.825	0.707

Table 6 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.

	Next Quarter Return			
	(1)	(2)	(3)	(4)
AaaDev	1.354	1.124		
	(1.751)	(1.660)		
AaaDev × New			4.225***	2.873**
			(1.567)	(1.399)
AaaDev × Old			1.102	0.9797
			(1.791)	(1.714)
AaaCon		2.252**		2.228**
		(0.9011)		(0.9138)
Maturity		-0.000**		-0.000**
		(0.000)		(0.000)
Bid-Ask Spread		-0.199*		-0.200*
		(0.118)		(0.118)
Coupon		0.002***		0.002***
		(0.000)		(0.001)
Duration		0.002***		0.002***
		(0.001)		(0.001)
Issuer FE	✓	✓	✓	✓
Observations	247,860	239,789	247,860	239,789
R^2	0.049	0.081	0.050	0.081

Table 7 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	-0.439***	-0.349***	-0.053***	-0.035***
	(0.108)	(0.086)	(0.012)	(0.009)
AaaCon	0.080**	0.045	0.015***	0.009**
	(0.035)	(0.030)	(0.004)	(0.004)
Rated		1.404***		0.113***
		(0.093)		(0.013)
AaaDev × Rated		-0.194**		-0.056***
		(0.095)		(0.014)
AaaCon × Rated		0.126***		0.026***
		(0.045)		(0.006)
Profitability	-0.057***	-0.047***	0.033***	0.034***
	(0.006)	(0.006)	(0.002)	(0.002)
Tangibility	0.676***	0.675***	0.197***	0.197***
	(0.062)	(0.059)	(0.014)	(0.014)
Sales	0.738***	0.655***	0.035***	0.027***
	(0.024)	(0.021)	(0.003)	(0.003)
Market-to-Book	-0.001***	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm FE	✓	✓	✓	✓
Observations	303563	303563	303564	303564
R^2	0.147	0.204	0.032	0.049

Table 8 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	-0.235***	-0.145***	0.037	-0.008
	(0.061)	(0.044)	(0.066)	(0.044)
AaaCon	0.003	-0.028	-0.188***	-0.142***
	(0.025)	(0.017)	(0.032)	(0.023)
Rated		0.305***		0.389***
		(0.095)		(0.085)
AaaDev × Rated		-0.317***		0.200*
		(0.099)		(0.104)
AaaCon × Rated		0.126**		-0.201***
		(0.049)		(0.053)
Profitability	-0.032***	-0.028***	0.029***	0.029***
	(0.003)	(0.002)	(0.004)	(0.004)
Tangibility	0.092**	0.092**	-0.341***	-0.344***
	(0.044)	(0.044)	(0.035)	(0.035)
Sales	0.326***	0.298***	0.065***	0.063***
	(0.016)	(0.016)	(0.012)	(0.012)
Market-to-Book	-0.000***	-0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm FE	✓	✓	✓	✓
Observations	303564	303564	301954	301954
R^2	0.017	0.021	0.010	0.012

Table 9 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	-0.105**	-0.076*	-0.128***	-0.112***
	(0.047)	(0.041)	(0.032)	(0.021)
AaaCon	-0.020	-0.048**	0.047***	0.035***
	(0.020)	(0.022)	(0.013)	(0.011)
Rated		0.137***		0.282***
		(0.040)		(0.039)
AaaDev × Rated		-0.086		-0.025
		(0.054)		(0.054)
AaaCon × Rated		0.116***		0.048***
		(0.022)		(0.018)
Profitability	0.470***	0.472***	0.013***	0.015***
	(0.013)	(0.013)	(0.005)	(0.005)
Tangibility	0.139**	0.140**	2.338***	2.338***
	(0.061)	(0.061)	(0.056)	(0.056)
Sales	0.740***	0.723***	0.620***	0.601***
	(0.017)	(0.017)	(0.013)	(0.012)
Market-to-Book	-0.009***	-0.009***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm FE	✓	✓	✓	✓
Observations	303559	303559	303564	303564
R^2	0.538	0.543	0.514	0.524

Table 10 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***
	(0.007)
$AaaCon$	0.004
	(0.003)
Profitability	-0.006***
	(0.001)
Tangibility	0.002
	(0.010)
Sales	0.051***
	(0.003)
Market-to-Book	-0.000***
	(0.000)
Firm FE	✓
Observations	303564
R^2	0.030

Table 11 Does CRA Performance Affect Their Forecasts

This table contains results testing whether CRA forecast deviations are affected by the performance of each rating agency. The dependent variable is the difference between rating agency j's forecast of the 10-year Aaa credit spread and the consensus forecast: $\mathbb{E}^j(CS) - \mathbb{E}^{Con}(CS)$. Robust standard errors clustered by quarter are shown below the parameter estimates in parenthesis *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	$\mathbb{E}^j(CS) - \mathbb{E}^{Con}(CS)$		
	(1)	(2)	(3)
Earnings Surprise	0.022	-0.004	-0.017
	(0.019)	(0.030)	(0.028)
Quarterly Stock Return	0.256	0.603	0.586
	(0.179)	(0.525)	(0.514)
Annual Stock Return	-0.115	-0.276	-0.383
	(0.084)	(0.256)	(0.259)
Quarter FE		✓	✓
CRA FE			✓
Observations	124	114	114
R^2	0.022	0.477	0.539
F-stat	0.90	0.84	1.25
p-value	0.446	0.480	0.301

Table 12 Economist Fixed Effects

This table contains results testing whether CRA forecast deviations are affected by the economist making the forecast. The dependent variable is the difference between rating agency j's forecast of the 10-year Aaa credit spread and the consensus forecast: $\mathbb{E}^j(CS) - \mathbb{E}^{Con}(CS)$. John Lonski was Moody's forecasting economist for our entire sample. S&P economists were David Blitzer from the beginning of our sample until 2004Q2, David Wyss from 2004Q3 to 2011QQ1 and Beth Ann Bovino from 2011Q2 to the end of our sample. David M. Blitzer (S&P) is the omitted economist in columns (4) and (5). Robust standard errors clustered by quarter are shown below the parameter estimates in parenthesis *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	$\mathbb{E}^f(CS) - \mathbb{E}^{Con}(CS)$				
	(1)	(2)	(3)	(4)	(5)
David Wyss (S&P)				0.233*	0.041
				(0.123)	(0.166)
Beth Ann Bovino (S&P)				-0.047	-0.234
				(0.140)	(0.171)
John Lonski (Moody's)				0.207	0.044
				(0.124)	(0.158)
Year-Quarter FE	✓		✓		✓
CRA FE		✓	✓		
Economist FE					
Observations	116	127	116	127	116
R^2	0.462	0.061	0.519	0.202	0.591
F-stat	.	.	.	5.61	5.88
p-value	.	.	.	0.002	0.001

Table 13 CRA Subjective Beliefs and Economists' Experienced Housing Price Changes

This table reports the relationship between CRA economists' subjective beliefs and their experienced local housing market returns. The dependent variable is the difference in Aaa credit spread forecasts made by economist f and the consensus. The independent variables are economist f's experienced local housing market returns and its lagged values. Economist j's experienced housing return, $\Delta ZHVI_t^f$, is calculated as the one-year changes in the Zillow Home Value Index (ZHVI) for single family homes, averaged across all zip codes where economist f owns a property. The property information is hand-collected from the deeds records via the LexisNexis Public Records Database. The data is at the quarterly frequency. The standard errors are clustered by economist and date. *, ** and *** indicate statistical significance at 10, 5, and 1% levels, respectively.

	$\mathbb{E}_t^f(CS_{t+1}) - \mathbb{E}_t^{Con}(CS_{t+1})$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta ZHVI_t^f$		-2.125**		0.023		-1.921**		0.1047
		(0.565)		(0.747)		(0.494)		(0.7865)
$\Delta ZHVI_{t-1}^f$			-2.402**	-2.422*			-2.250**	-2.340*
			(0.573)	(1.008)			(0.5206)	(0.9274)
Year-Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
CRA FE					✓	✓	✓	✓
Observations	139	139	136	136	139	139	136	136
R^2	0.505	0.627	0.659	0.659	0.550	0.632	0.662	0.662

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.

Annual Stock Return: Annual stock return of Moody's or S&P, from CRSP

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

Bank Debt: The log of total bank debt from CapIQ.

Bid-Ask:

Duration:

Earnings Surprise: Earnings surprise for Moody's or S&P, eps-eps$_{(t-4)}$/std(past 8 eps-eps$_{(t-4)}$), from IBES.

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

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

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

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

Maturity:

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

Next Quarter Return:

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

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

Quarterly Stock Return: Quarterly stock return of Moody's or S&P, from CRSP.

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.

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.

A.2 Additional Tables and Figures

Table A.1 Summary statistics of 1-quarter-ahead raw forecasts and forecast errors (in percentage points)

	N	Mean	Median	SD	P5	P95
Panel A: Raw Forecasts						
Aaa: MR	69	5.02	5.19	1.02	3.63	6.65
Aaa: SPR	64	5.06	5.45	1.06	3.33	6.37
Aaa: CRA	69	4.99	5.25	1.01	3.53	6.41
Aaa: Consensus	69	5.12	5.28	0.91	3.82	6.60
Aaa: Consensus ex. CRAs	69	5.13	5.28	0.90	3.84	6.61
$y^{(10)}$: MR	69	3.47	3.48	1.18	1.72	5.15
$y^{(10)}$: SPR	69	3.57	3.36	1.12	2.13	5.18
$y^{(10)}$: Consensus	69	3.54	3.58	1.06	1.95	5.16
$y^{(10)}$: Consensus ex. CRAs	69	3.54	3.58	1.06	1.96	5.16
$y^{(10)}$: CRA	69	3.52	3.48	1.14	1.97	5.16
CS^{Aaa}: MR	69	1.54	1.59	0.43	0.76	2.09
CS^{Aaa}: SPR	64	1.44	1.44	0.44	0.77	2.05
CS^{Aaa}: Consensus	69	1.58	1.64	0.37	0.92	2.02
CS^{Aaa}: Consensus ex. CRAs	69	1.59	1.64	0.37	0.92	2.02
Panel B: Forecasts Errors						
Aaa: MR	69	-0.21	-0.19	0.44	-1.00	0.50
Aaa: SPR	64	-0.18	-0.17	0.56	-1.12	0.63
Aaa: CRA	69	-0.18	-0.17	0.46	-0.92	0.55
Aaa: Consensus	69	-0.31	-0.30	0.40	-0.90	0.31
Aaa: Consensus ex. CRAs	69	-0.32	-0.31	0.40	-0.90	0.31
$y^{(10)}$: MR	69	-0.04	-0.03	0.53	-0.77	0.82
$y^{(10)}$: SPR	69	-0.14	-0.13	0.56	-0.99	0.77
$y^{(10)}$: Consensus	69	-0.11	-0.13	0.53	-0.82	0.86
$y^{(10)}$: Consensus ex. CRAs	69	-0.11	-0.14	0.53	-0.82	0.86
$y^{(10)}$: CRA	69	-0.09	-0.08	0.53	-0.82	0.80
CS^{Aaa}: MR	69	-0.17	-0.10	0.34	-0.75	0.24
CS^{Aaa}: SPR	64	-0.04	-0.09	0.43	-0.76	0.77
CS^{Aaa}: Consensus	69	-0.20	-0.20	0.30	-0.76	0.26
CS^{Aaa}: Consensus ex. CRAs	69	-0.21	-0.20	0.30	-0.77	0.26
CS^{Aaa}: CRA	69	-0.09	-0.12	0.34	-0.55	0.46

Table A.2 Diebold-Mariano-West Predictive Ability Test: CRA vs. consensus forecasts

This table reports the Diebold and Mariano (1995) and West (1996) statistics of equal predictive ability, with p-values of the test statistics in parentheses. We compare the predictive ability of credit rating agencies (CRA) forecasts and consensus forecasts. The underlying variables are Aaa corporate bond yields (Aaa), 10-year Treasury note yields ($tn10y$), and Aaa credit spread (CS^{Aaa}). A positive statistic indicates that CRAs have higher forecast errors than the consensus and vice versa. We report statistics for one-quarter-ahead forecasts (1Q) ahead and pooled across all horizons. The "Pooled" column represents statistics that pool all three variables together.

	Aaa	$y^{(10)}$	CS^{Aaa}	Pooled
1Q	1.78	2.97	2.29	5.72
	(0.08)	(0.00)	(0.02)	(0.00)

Table A.3 CRA Subjective Beliefs and Credit Market Sentiment Measures

This table reports correlations between CRA subjective beliefs ($AaaDev$) and other commonly used credit market sentiment measures. $AaaDev$ is the difference in Aaa credit spread forecasts between CRA and the consensus forecasts, $AaaCon$. HYS, from Greenwood and Hanson (2013), is the fraction of nonfinancial corporate bond issuance with a high-yield rating from Moody's. Credit Growth is the percentage change in outstanding corporate credit computed using Table L103 from the Financial Accounts of the United States (formerly Flow of Funds). Easy Credit is the three-year average of the percentage of the Reserve's Senior Loan Office Opinion Survey. −*EBP* is negative one times excess bond premium from Gilchrist and Zakrajšek (2012). BW Sentiment is Baker and Wurgler (2006) composite investor sentiment measure. *, ** and *** indicate statistical significance at 10, 5, and 1% levels, respectively.

	$AaaDev$	$AaaCon$	HYS	Credit Growth	Easy Credit	−*EBP*	BW Sentiment
$AaaDev$	1.00						
$AaaCon$	-0.13	1.00					
HYS	-0.10	-0.06	1.00				
Credit Growth	0.20^{*}	0.07	-0.06	1.00			
Easy Credit	0.07	0.53^{***}	-0.09	-0.04	1.00		
−*EBP*	-0.06	-0.28^{***}	0.43^{***}	-0.14	-0.31^{***}	1.00	
BW Sentiment	0.32^{***}	-0.14	-0.09	0.36^{***}	-0.08	-0.10	1.00

Table A.4 CRA Forecast Deviations and Credit Ratings: Controlling for Sentiment Measures

This table tests whether CRA credit spread forecast deviations affect their bond-level credit ratings, This table controls for commonly used credit and stock market sentiment measures: HYS, from Greenwood and Hanson (2013), is the fraction of nonfinancial corporate bond issuance with a high-yield rating from Moody's. Credit Growth is the percentage change in outstanding corporate credit computed using Table L103 from the Financial Accounts of the United States (formerly Flow of Funds). Easy Credit is the three-year average of the percentage of the Reserve's Senior Loan Office Opinion Survey. $-EBP$ is negative one times excess bond premium from Gilchrist and Zakrajšek (2012). BW Sentiment is Baker and Wurgler (2006) composite investor sentiment measure. 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.

	$Rating_{i,j,t},\ j \in \{MR, SPR\}$				$AverageRating_{i,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}_t^j(CS_{t+1Q}^{Aaa}) - \mathbb{E}_t^{Con}(CS_{t+1Q}^{Aaa})$	-0.1732**	-0.1795**	-0.1057*	-0.1121**		
	(0.0733)	(0.0693)	(0.0558)	(0.0522)		
$AaaDev_t$		0.1373*		0.1202*	-0.3988***	-0.4241***
		(0.0704)		(0.0695)	(0.1335)	(0.1236)
$AaaCon_t$						0.1691**
						(0.0698)
Maturity	-0.0554***	-0.0501***	-0.0555***	-0.0509***	-0.0394***	-0.0330***
	(0.0110)	(0.0119)	(0.0112)	(0.0121)	(0.0114)	(0.0122)
Bid-Ask Spread	-3.725***	-3.749***	-3.724***	-3.745***	-4.012***	-4.040***
	(0.8764)	(0.8741)	(0.8764)	(0.8741)	(0.9366)	(0.9353)
Duration	0.2282***	0.2261***	0.2276***	0.2258***	0.2140***	0.2115***
	(0.0175)	(0.0176)	(0.0175)	(0.0176)	(0.0183)	(0.0184)
HYS	-0.1491	-0.1973	-0.2074	-0.2487	-0.0107	-0.0633
	(0.1578)	(0.1595)	(0.1654)	(0.1654)	(0.1531)	(0.1547)
Credit Growth	-1.816	-3.220*	-1.682	-2.913	-0.5186	-2.099
	(1.703)	(1.788)	(1.764)	(1.805)	(1.523)	(1.600)
Easy Credit	-0.0022*	-0.0030***	-0.0021*	-0.0028**	-0.0024*	-0.0032***
	(0.0012)	(0.0011)	(0.0012)	(0.0010)	(0.0012)	(0.0010)
$-EBP$	-0.0357	-0.0157	-0.0285	-0.0110	-0.0580**	-0.0337
	(0.0239)	(0.0236)	(0.0247)	(0.0243)	(0.0233)	(0.0226)
BW Sentiment	0.0429	0.1069	0.0410	0.0970	-0.0509	0.0305
	(0.0587)	(0.0645)	(0.0568)	(0.0640)	(0.0579)	(0.0616)
Issue FE	✓	✓	✓	✓	✓	✓
CRA FE			✓	✓		
Observations	511,765	511,765	511,765	511,765	233,484	233,484
R^2	0.91602	0.91607	0.91636	0.91639	0.92414	0.92421

Table A.5 CRA Forecast Deviations and Firms' Debt and Leverage Decisions, Controlling for Sentiments

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)
$AaaDev$	-0.397***	-0.334***	-0.052***	-0.038***
	(0.090)	(0.076)	(0.012)	(0.010)
$AaaCon$	0.143***	0.092***	0.016***	0.008*
	(0.037)	(0.032)	(0.005)	(0.004)
Rated		1.419***		0.111***
		(0.090)		(0.012)
$AaaDev$ × Rated		-0.061		-0.038***
		(0.086)		(0.013)
$AaaCon$ × Rated		0.132***		0.027***
		(0.042)		(0.006)
Profitability	-0.035***	-0.026***	0.034***	0.035***
	(0.005)	(0.005)	(0.002)	(0.002)
Tangibility	0.751***	0.748***	0.203***	0.203***
	(0.060)	(0.058)	(0.015)	(0.015)
Sales	0.627***	0.555***	0.026***	0.019***
	(0.021)	(0.018)	(0.003)	(0.003)
Market-to-Book	-0.001***	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
HYS	0.198	0.174	0.022	0.019
	(0.133)	(0.120)	(0.014)	(0.013)
Credit Growth	4.256***	4.038***	0.215	0.193
	(1.300)	(1.152)	(0.154)	(0.142)
Easy Credit	-0.006***	-0.005***	-0.000***	-0.000***
	(0.001)	(0.001)	(0.000)	(0.000)
$-EBP$	0.061***	0.062***	0.009***	0.009***
	(0.018)	(0.016)	(0.002)	(0.002)
BW Sentiment	-0.087***	-0.080***	-0.010***	-0.009***
	(0.023)	(0.021)	(0.003)	(0.003)
Firm FE	✓	✓	✓	✓
Observations	267699	267699	267700	267700
R^2	0.131	0.188	0.030	0.045

Table A.6 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	-0.137**	-0.069	-0.086	-0.095
	(0.055)	(0.053)	(0.076)	(0.066)
AaaCon	0.102***	0.068**	-0.116***	-0.056
	(0.029)	(0.028)	(0.042)	(0.041)
Rated		0.287***		0.475***
		(0.100)		(0.071)
AaaDev × Rated		-0.220**		0.038
		(0.105)		(0.090)
AaaCon × Rated		0.122**		-0.259***
		(0.052)		(0.043)
Profitability	-0.021***	-0.019***	0.020***	0.021***
	(0.003)	(0.002)	(0.003)	(0.003)
Tangibility	0.138***	0.138***	-0.357***	-0.359***
	(0.040)	(0.040)	(0.038)	(0.038)
Sales	0.250***	0.228***	0.085***	0.083***
	(0.015)	(0.014)	(0.012)	(0.012)
Market-to-Book	-0.000***	-0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
HYS	0.017	0.007	0.351**	0.354**
	(0.088)	(0.084)	(0.141)	(0.140)
Credit Growth	2.808***	2.736***	-0.477	-0.454
	(0.947)	(0.907)	(1.372)	(1.365)
Easy Credit	-0.005***	-0.005***	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
−EBP	0.006	0.006	-0.075***	-0.074***
	(0.013)	(0.012)	(0.019)	(0.019)
BW Sentiment	-0.003	0.001	0.043*	0.041*
	(0.016)	(0.015)	(0.022)	(0.021)
Firm FE	✓	✓	✓	✓
Observations	267700	267700	266298	266298
R^2	0.016	0.019	0.023	0.026

Table A.7 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	-0.054	-0.041	-0.091***	-0.092***
	(0.047)	(0.046)	(0.033)	(0.028)
AaaCon	0.021	-0.011	0.071***	0.054***
	(0.022)	(0.022)	(0.017)	(0.015)
Rated		0.127***		0.272***
		(0.035)		(0.035)
AaaDev × Rated		-0.016		0.050
		(0.044)		(0.051)
AaaCon × Rated		0.116***		0.053***
		(0.019)		(0.015)
Profitability	0.466***	0.467***	0.022***	0.024***
	(0.014)	(0.014)	(0.005)	(0.005)
Tangibility	0.185***	0.185***	2.299***	2.298***
	(0.063)	(0.063)	(0.056)	(0.056)
Sales	0.698***	0.685***	0.581***	0.565***
	(0.016)	(0.016)	(0.013)	(0.012)
Market-to-Book	-0.009***	-0.009***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
HYS	0.086	0.080	0.050	0.045
	(0.072)	(0.070)	(0.059)	(0.056)
Credit Growth	3.872***	3.820***	2.710***	2.658***
	(0.784)	(0.764)	(0.599)	(0.571)
Easy Credit	-0.003***	-0.003***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.000)	(0.000)
−EBP	0.022*	0.022*	0.015*	0.015*
	(0.011)	(0.011)	(0.009)	(0.008)
BW Sentiment	-0.011	-0.009	-0.014	-0.013
	(0.013)	(0.012)	(0.010)	(0.009)
Firm FE	✓	✓	✓	✓
Observations	267695	267695	267700	267700
R^2	0.535	0.539	0.505	0.515

Table A.8 CRA Forecast Deviations and Credit Ratings: Split by Investment Grade

This table tests whether CRA credit spread forecast deviations affect their bond-level credit ratings. 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*). Bonds are classified into investment grade (IG) bonds with a rating of Baa and above, and high yield grade (HY) bonds. 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.

	AverageRating			
	HY		IG	
	(1)	(2)	(3)	(4)
AaaDev	-0.1982	-0.2260	-0.2219***	-0.2253***
	(0.1525)	(0.1463)	(0.0755)	(0.0744)
AaaCon		0.1029*		0.0154
		(0.0544)		(0.0384)
Maturity	-0.0742***	-0.0746***	-0.0022	-0.0018
	(0.0241)	(0.0236)	(0.0072)	(0.0074)
Bid-Ask Spread	-2.901***	-3.055***	-1.704***	-1.778***
	(0.9343)	(0.9584)	(0.4839)	(0.4120)
Duration	0.3727***	0.3800***	0.0355***	0.0353***
	(0.0397)	(0.0379)	(0.0107)	(0.0108)
Issue FE	✓	✓	✓	✓
Observations	80,435	80,435	196,909	196,909
R^2	0.78479	0.78496	0.89139	0.89140

Table A.9 Contemporaneous credit spread forecasts and initial rating from Moody's and S&P

Initial ratings are made by Moody's and S&P on the same day. Issue fixed effects are included. Standard errors are clustered at the issuer level and are shown below the parameter estimates in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: $Rating_{i,t}^{MR} - Rating_{i,t}^{SPR}$		
	(1)	(2)	(3)
$\left(\mathbb{E}_t^{MR} - \mathbb{E}_t^{SPR}\right)(Aaa_{t+1Q})$	-0.2323***		
	(0.0530)		
$\left(\mathbb{E}_t^{MR} - \mathbb{E}_t^{SPR}\right)(y_{t+1Q}^{(10)})$		0.0850	
		(0.0735)	
$\left(\mathbb{E}_t^{MR} - \mathbb{E}_t^{SPR}\right)(CS_{t+1Q}^{Aaa})$			-0.4184***
			(0.0577)
Issuer FE	✓	✓	✓
Observations	20,859	21,661	20,859
R^2	0.74997	0.73942	0.75494

Table A.10 CRA Forecast Deviations and Firms' Bank Debt Issuance Decisions

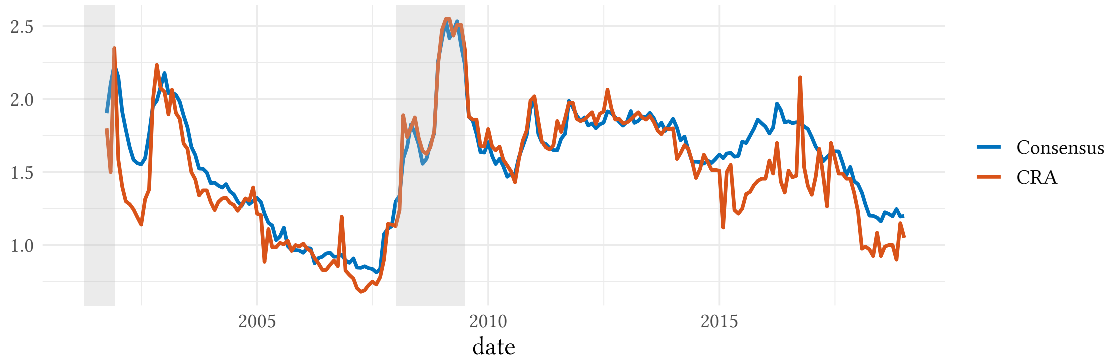
This table contains results testing whether CRA forecast deviations affect firms' bank debt issuance decisions. Robust standard errors double clustered by firm and quarter are shown below the parameter estimates in parenthesis *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Bank Debt	
	(1)	(2)
$AaaDev$	0.182	0.075
	(0.366)	(0.250)
$AaaCon$	0.379*	0.298*
	(0.221)	(0.169)
Rated		0.180
		(0.405)
AaaDev × Rated		0.530
		(0.517)
AaaCon × Rated		0.338
		(0.237)
Profitability	-0.067***	-0.064***
	(0.006)	(0.006)
Tangibility	0.104	0.105
	(0.100)	(0.100)
Sales	0.692***	0.659***
	(0.042)	(0.041)
Market-to-Book	-0.000***	-0.000***
	(0.000)	(0.000)
Firm FE	✓	✓
Observations	303564	303564
R^2	0.063	0.068

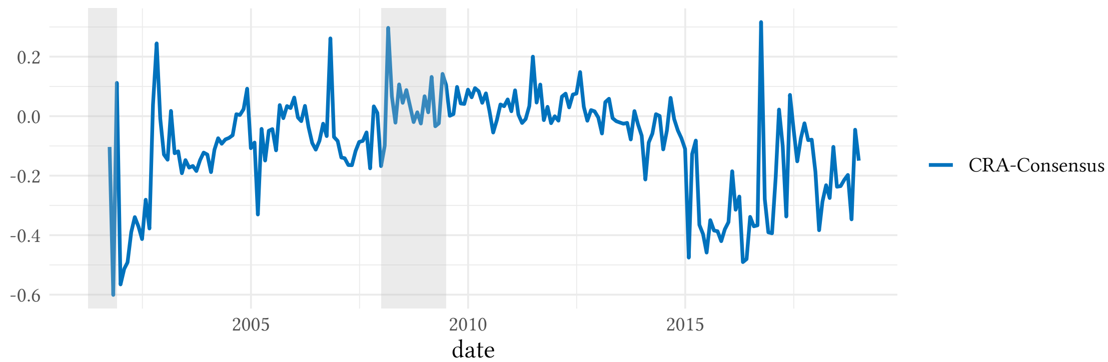
Table A.11 Blue Chip Financial Forecasts participants, grouped by institution types

Firms' commonly used names are reported, which may slightly differ from their legal names. We 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, we 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



A. Consensus and CRA Forecasts



B. Consensus-CRA

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

US Quarterly Forecasts
October 2019

	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.2 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.