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

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Abstract

We analyze the impact of rating agencies' beliefs on credit markets. We measure their beliefs as the difference between their forecasts of aggregate credit spreads and the consensus. When rating agencies become more optimistic, they issue higher ratings even though their forecasts do not predict future credit spreads. This optimism leads to lower initial bond yields and subsequent negative excess returns. Firms respond by increasing their leverage and investment. Finally, rating agencies become more optimistic as their head economists' property values increase. Our analysis shows how subjective beliefs drive aggregate financing and investment through mispricing in credit markets.

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1 Introduction

How do people's beliefs affect credit market conditions and aggregate economic activity? This question dates back to Minsky's (1977) financial instability hypothesis, whereby debt levels build up over time as agents become more optimistic.[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 address these issues by analyzing the relationship between beliefs and credit market conditions in the context of credit rating agencies. Rating agencies are central players in credit markets as firms use rating agencies to rate their debt securities and investors rely on credit ratings to price them. We create a measure of rating agencies' beliefs based on their forecasts of future aggregate corporate bond credit spreads and find that their beliefs deviate from rationality. We then isolate the subjective component of these beliefs by comparing rating agency forecasts to a consensus of other financial institutions. First, rating agencies act on their subjective beliefs through the credit ratings they issue even though these subjective beliefs do not contain any information regarding future aggregate credit spreads. Second, rating agencies' subjective beliefs induce mispricing in newly issued bonds. Third, firms respond to inflated ratings and mispricing in credit markets by increasing their leverage and investment. Finally, we show that rating agencies' beliefs are strongly related to their head economists' 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 data from the Blue Chip Financial Forecasts. In the survey, Moody's, S&P, and other financial institutions report monthly forecasts of various corporate bond and treasury yields. This data allows us to compare the rating agencies' beliefs to those of other major financial institutions such as large banks and asset managers (i.e., the "consensus"). We create a measure of rating agency beliefs based on the average one-quarter ahead forecast of Aaa credit spreads averaged across Moody's and S&P.

We start by testing whether rating agencies deviate from rationality in their forecasts using the methodology developed in Coibion and Gorodnichenko (2015), which analyzes the predictability of forecast errors. We show that when updating their forecasts of future credit spreads, rating

[1] Recent papers that formalize the connection between beliefs and credit cycles include Geanakoplos (2010), Gennaioli, Shleifer, and Vishny (2012) and Bordalo, Gennaioli, and Shleifer (2018).

[2] See Cochrane (2011) and Brunnermeier et al. (2021) for a review of this challenge.

agencies significantly overreact to the new information, suggesting that their forecasts deviate from rationality.[3] In contrast, the consensus forecast exhibits no apparent deviation from rationality.

After establishing a departure from rationality in rating agencies' forecasts of credit spreads, we attempt to isolate the subjective component of rating agencies' beliefs. To do so, we construct a variable *AaaDev* which equals the difference between the average rating agency forecast and the consensus forecast of Aaa credit spreads.[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 rating agencies' forecasts contain no additional information regarding future realized credit spreads.

In order for *AaaDev* to meaningfully reflect the subjective component of rating agency beliefs, it is critical that rating agencies act on these stated beliefs. We thus test whether rating agencies' forecasts affect their bond-level credit ratings. Consistent with rating agencies incorporating their beliefs regarding future aggregate credit spreads into their bond ratings, we find that bond ratings are higher when rating agencies are relatively more optimistic, i.e., when *AaaDev* is lower. Hence, rating agency beliefs about aggregate credit spreads have a material impact on their actions in the form of their credit assessments.[5]

These tests suggest we have identified a component of credit ratings related to the beliefs of rating agencies 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 rating agencies' subjective beliefs from private information about credit quality. If the latter were true, we would expect rating agency 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 rating agency pessimism leads to higher initial yields and subsequent negative excess returns among newly issued bonds.

Next, we explore whether rating agency beliefs affect firms' financing and investment behavior. If managers have a more accurate assessment of their own creditworthiness than financial markets, they can take advantage of their higher ratings and lower bond yields by issuing more debt and increasing their leverage. Consistent with this hypothesis, we find that when rating agencies are relatively more optimistic, firms respond by increasing their debt and leverage levels. Moreover,

[3]This overreaction in credit market expectations is consistent with the findings from Bordalo et al. (2020).

[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 rating agencies' formal guidance to incorporate aggregate economic forecasts into their individual credit ratings.

this effect is concentrated among rated firms and is entirely absent in firms' bank debt issuance decisions. This evidence suggests that rating agency 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 rating agency beliefs affect the asset side of the balance sheet through firms' investment decisions. Specifically, we show that firms increase their investment when rating agencies are more optimistic than the consensus. Hence, the subjectivity in rating agency beliefs also affects the real side of the economy through firms' investment decisions.

The effects we identify are large. When the rating agencies are 17bps more optimistic than the consensus regarding future credit spreads (one standard deviation), this leads to a 1.2pp (3.8%) increase in firm leverage and a 2.6% increase in total assets. Hence, around two-thirds of the proceeds raised through the firms' increase in leverage are invested in new assets.

A potential concern with our findings is that our measure of rating agency beliefs may simply correlate with aggregate sentiment in credit markets (e.g., Greenwood and Hanson, 2013, López-Salido, Stein, and Zakrajšek, 2017, Gulen, Ion, and Rossi, 2021 and Sørensen, 2021). First, our measure is based on the *difference* between rating agencies and the consensus of other financial institutions. Hence, we are differencing out any market-wide sentiment that affects the rating agencies and other financial institutions equally. Second, 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 rating agencies provide. Finally, our main results are robust to controlling for the main sentiment measures established in the existing literature.

It may seem puzzling that rating agencies' forecasts affect credit ratings and initial bond pricing but do not predict future aggregate realized spreads. First, as we discuss in further detail below, new bonds are not immediately added to the bond index and make up a very small portion of the index. Second, with relatively limited information about a bond at issuance, credit ratings are likely to be more salient to investors (Bordalo, Gennaioli, and Shleifer, 2012). Finally, in contrast to secondary market trading, during origination there are often many unsophisticated, buy and hold investors who rely heavily on credit ratings in their allocation decisions. Therefore, we argue that it is natural that the mispricing is specifically concentrated in new bonds.

Taken together, our results are consistent with rating agency beliefs inducing mispricing in bond markets, which firms respond to through their issuance, leverage, and investment decisions. This story fits the rational managers and irrational investors framework (e.g., Baker, Stein, and Wurgler, 2003, Shleifer and Vishny, 2003 and Stein, 2005), in which firms take advantage of mispricing in financial markets. However, we cannot fully determine whether firms act irrationally. For instance, managers may misinterpret their higher ratings, and consequently lower financing costs, induced by rating agency optimism a positive signal about the profitability of their investment opportunities, thereby inducing more investment. Nonetheless, 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 rating agencies' deviation from the consensus forecast? One explanation is that conflicts of interest cause rating agencies to choose forecasts that are intentionally biased to maximize their expected profits (e.g., Griffin and Tang, 2011 and Baghai and Becker, 2018). An alternative explanation is that these forecasts stem from biases from the subjective beliefs of the individual forecasters employed by the rating agencies. Inconsistent with the first channel, we find no relationship between measures of rating agency performance and their forecasts. However, we do find that the individual economists, i.e., economist fixed effects, explain a substantial portion of rating agency subjective beliefs.

To further explore this link between economists' idiosyncratic beliefs and their forecast deviation from the consensus, we use hand-collected data on property ownership to construct a proxy for returns to each economist's financial wealth using their experienced local housing market returns. If these economists are prone to behavioral biases, such as extrapolating past returns and overweighting personal experiences when forming beliefs about aggregate outcomes, we would expect a positive relationship between their experienced housing returns and their forecasts of future credit market conditions. Consistent with this hypothesis, we find that economists who have experienced higher (or lower) housing returns tend to make more optimistic (or pessimistic) forecasts about future aggregate credit spreads. Moreover, these returns explain a large portion of rating agencies' deviation from the consensus forecast. These results suggest that economists' idiosyncratic subjective beliefs, shaped by their personal experiences of realized returns, play a crucial role in influencing how rating agencies affect credit markets and real economic activity.

Related literature Our paper makes several contributions to the behavioral finance and economics literature that studies agents' beliefs and their effect on financial and macroeconomic outcomes.

First, we establish a strong link between the stated beliefs of rating agencies and their credit rating decisions. A common critique against using measured beliefs from survey data is that agents may not truthfully report their beliefs nor act on those beliefs (Cochrane, 2011 and Brunnermeier et al., 2021). Hence, this paper joins a growing literature that links agents' beliefs and economic decisions in contexts such as firms (Ben-David, Graham, and Harvey, 2013, Gennaioli, Ma, and Shleifer, 2016 and Ma et al., 2020), financial institutions (Kempf and Tsoutsoura, 2021, Wang, 2021, Ma, Paligorova, and Peydro, 2021, Andonov and Rauh, 2021 and Dahlquist and Ibert, 2022), households (Carroll, 2003, Malmendier and Nagel, 2016, Das, Kuhnen, and Nagel, 2019) and individual investors (Malmendier and Nagel, 2011, Giglio et al., 2021, Meeuwis et al., 2022 and Weber et al., 2021). 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 rating agency beliefs does not predict future credit spreads and that these beliefs are related to the forecasters' experienced housing returns, we can arguably distinguish biased beliefs from differences in private information. 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 those agents' actual decisions.

Second, by exploring the beliefs of rating agencies, we shed light on an important question raised by Brunnermeier et al. (2021): whose beliefs matter for asset prices? Just because agents act on their beliefs does not mean these agents are driving asset prices. Since rating agencies decide credit ratings themselves, their beliefs are clearly relevant to the credit market and firm-level outcomes, which we confirm in our analysis. Hence, our paper i) identifies certain agents whose beliefs matter for asset prices and ii) shows that the idiosyncratic, subjective component of these beliefs exerts a large impact on credit market conditions and real activity.

Third, our paper shows how personal experiences, specifically rating agencies' economists' personal housing returns, affect belief formation in credit markets. Hence our paper relates to the literature on experience effects in belief formation (e.g., Vissing-Jorgensen, 2003, Greenwood and Nagel, 2009, Malmendier, Tate, and Yan, 2011, Malmendier and Nagel, 2011, 2016, Chernenko, Hanson, and Sunderam, 2016, Bernile, Bhagwat, and Rau, 2017, Bailey et al., 2018, Adelino, Schoar, and Severino, 2018, Kuchler and Zafar, 2019, Malmendier, Nagel, and Yan, 2021 and Duchin, Simutin, and Sosyura, 2021).[6] To our knowledge, this is the first paper showing how beliefs arising from personal experiences affect aggregate market conditions. For this reason, our paper also contributes to the literature exploring the behavioral drivers of credit cycles, such as Gennaioli, Shleifer, and Vishny (2012); Greenwood and Hanson (2013); Gennaioli, Shleifer, and Vishny (2015); Bordalo, Gennaioli, and Shleifer (2018); Greenwood, Hanson, and Jin (2021).

Our paper also relates to the literature analyzing personal experiences of housing prices (e.g., Cheng, Raina, and Xiong, 2014, Kuchler and Zafar, 2019, Carvalho, Gao, and Ma, 2023 and Gargano, Giacoletti, and Jarnecic, 2023). Kuchler and Zafar (2019) show that individuals extrapolate from personal housing experiences when forming forecasts of aggregate economic outcomes.[7] Another related paper is Carvalho, Gao, and Ma (2023), who show that loan officers' experienced housing returns affect the credit spreads on loans they grant. Our paper distinguishes itself from

[6]See Malmendier (2021) for an excellent synthesis of the literature.

[7]In contrast to their analysis, we find that personal housing experiences affect forecasts of non-housing aggregate market outcomes. One key advantage of our data is that they construct housing returns based on the location of the respondent, rather than the actual ownership of the forecaster. In contrast, we directly observe the houses the forecasters own, which often include houses outside their immediate area. Ownership appears to be an important component of the belief formation process (Hartzmark, Hirshman, and Imas, 2021).

these papers in two critical ways: i) we are able to isolate the subjective component of beliefs, and ii) we show how these beliefs affect market-wide credit market conditions, which in turn influence firms' leverage and investment decisions.

Our paper also contributes to a broader literature analyzing the effects of ratings on firm financing and investment decisions.[8] Relatedly, we also contribute to the literature that analyzes the subjectivity in credit ratings (e.g., Griffin and Tang, 2012, Fracassi, Petry, and Tate, 2016, Cornaggia, Cornaggia, and Xia, 2016, Kempf and Tsoutsoura, 2021, Fracassi and Weitzner, 2020) and how rating agency standards evolve over time (e.g., Ashcraft, 2010, Becker and Milbourn, 2011, Jiang, Stanford, and Xie, 2012, Bar-Isaac and Shapiro, 2013, Alp, 2013 and Baghai, Servaes, and Tamayo, 2014).[9] For example, Kempf and Tsoutsoura (2021) show that credit rating analysts' partisan perception affects their credit ratings. To identify the effects of rating agency 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 differences in beliefs, it limits the ability to analyze how these beliefs affect bond and firm-level outcomes. In contrast, we compare the aggregate beliefs of rating agencies to a market consensus, allowing us to test how these beliefs affect bond and firm-level outcomes. Also, by analyzing the personal experiences of rating agency economists, we uncover a direct source of these subjective beliefs which we then connect to rating agencies' decisions and broader market outcomes.[10] Finally, a few papers show that rating quality is countercyclical (e.g., Ashcraft, 2010, Griffin and Tang (2012) and Bar-Isaac and Shapiro (2013)); however, to our knowledge, we are the first to show how this quality changes based on the *aggregate beliefs* of credit rating agencies, which in turn influence firms' financing and investment decisions by inducing mispricing in credit markets.

2 Data

In this section, we describe the various datasets used to construct our sample and how we measure the beliefs of rating agencies and other financial institutions.

[8]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).

[9]We also contribute 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, Griffin, Nickerson, and Tang, 2013 and Goldstein and Huang, 2020), by showing that the subjective beliefs of rating agencies can cause credit ratings to be either inflated or deflated.

[10]Our paper also 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 rating agencies' subjective beliefs.

Survey expectation data. The main dataset we use to study rating agency beliefs is survey data from the Blue Chip Financial Forecasts (BCFF). BCFF is a monthly survey that collects forecasts from an extensive panel of professional economists. It is closely monitored by key market participants and policymakers, including members of the Federal Open Markets Committee (FOMC).[11]

Each month, the BCFF survey collects forecasts from a panel of, on average, over 40 economists from leading financial institutions and economic consulting firms. They are asked to provide forecasts of future financial and macroeconomic variables at horizons from the current quarter ("nowcast") to five quarters ahead. These forecasts include various interest rate variables such as the Aaa and Baa corporate bond yields, as well as Treasury yields of different maturities.[12] 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.

The BCFF survey also contains the identity of each forecaster, i.e., the names of the economist and his/her affiliated institution.[13] Over the sample period we analyze (2002 to 2018), BCFF contains 100 unique forecasters. In Online Appendix Table OA.1 we include a list of the most frequent forecasters, which we define as those who made more than 60 monthly forecasts over the sample (Buraschi, Piatti, and Whelan, 2022). Among these forecasters, 26 are banks, 21 are economic consulting firms, 15 are broker-dealers, and 2 are the rating agencies we focus on (Moody's Investor Service and S&P Global Ratings).

In order to study the impact of beliefs on credit markets, we focus on the forecasts of aggregate corporate credit spreads. Credit spreads are ideally suited for this purpose because they imply changes in the economic outlook as well as stress in the financial system (e.g., Philippon, 2009, Gilchrist and Zakrajšek, 2012, and Nozawa, 2017). Specifically, we follow the BCFF methodology and construct forecasts of the credit spread as the difference between forecasts of the Aaa corporate bond index and forecasts of the 10-year constant maturity Treasury yield.[14] All interest rate forecasts are daily averages within a given quarter. Between January 2002 and October 2016, the underlying Aaa corporate bond index was Moody's Seasoned Aaa Corporate Bond Index, published in the

[11] Cieslak (2018) reveals that BCFF forecasts are frequently discussed during FOMC meetings; from 1994 and 2010, Blue Chip forecasts are mentioned 174 times in FOMC meeting transcripts.

[12] A sample BCFF survey questionnaire is displayed in Online Appendix Table OA.1.

[13] Following the procedure in Wang (2021), we manually adjust for changes in firm names caused by corporate restructuring events such as mergers and acquisitions. We do so by manually checking the name changes of the forecasters using the information provided by the Federal Financial Institutions Examinations Council (FFIEC) and combining the observations that belong to the same entity.

[14] We use forecasts of Aaa yields rather than Baa yields because there are more forecasts available. However, the Aaa and Baa credit spreads have a high correlation over the sample (0.87) and we obtain similar results using the Baa credit spreads. We find similar results when we use the all-in yield rather than the credit spread; however, the main effects come from the difference in the all-in yield and the treasury yield, not the treasury yield itself. These results are available upon request.

Federal Reserve's H.15 Table of Selected Interest Rates. After the Fed ceased publishing Moody's Aaa index in October 2016, forecasters were instructed by BCFF to instead predict the Bank of America-Merrill Lynch 15+ Year AAA-AA Corporate Bond Yield Index. We obtain realizations of Moody's Aaa index from FRED and realizations of the subsequent Bank of America-Merrill Lynch Index from BCFF. The correlation between these two indices is 0.99 over the portion of the sample both are available. We explain in further detail how these two indices are constructed in Appendix A.

To harmonize the data frequency across all our datasets, we convert the monthly forecasts into quarterly frequency by taking the first monthly forecast in each quarter. Because we focus on how beliefs affect credit market conditions and firm behavior, we use the one-quarter ahead forecast rather than the current quarter forecast (i.e., nowcast). This approach ensures that the uncertainty is not fully resolved over the period in which market and corporate outcome variables are measured.[15] We denote the current quarter t forecast of the one-quarter ahead credit spread as $\mathbb{E}_t(Aaa_{t+1})$. For example, for $t = 2015Q4$ we would use the forecast published on October 1 for the period of January 1 to March 31 (2016Q1). This notation is standard for papers using the BCFF data (e.g., see Bauer and Chernov, 2021).

We calculate a consensus forecast by averaging the forecasts from all BCFF forecasters, excluding Moody's and S&P, which we define as $AaaCon_t$. In order to study the aggregate effects of rating agency beliefs, we define $AaaCRA_t$ as the average one-quarter ahead quarter forecast of credit spreads across Moody's and S&P. In our analysis, we will often compare the differences in beliefs between the rating agencies and the consensus. Hence, we define $AaaDev_t$ as the difference between the average forecast of the rating agencies and that of the consensus:

$$AaaDev_t \equiv AaaCRA_t - AaaCon_t. \tag{1}$$

In our main analysis, we examine the impact of $AaaDev$ on various bond-level and firm-level outcomes. Additionally, we also analyze S&P and Moody's credit spread forecasts individually where we index the specific rating agency by j. We report all interest rate and return variables in percentage points. Since forecasts of Aaa and 10-year Treasury yields from both Moody's and S&P are available from 2002 onward, our final sample period runs from 2002:Q1 to 2018:Q4.[16]

A critical question is how informative the survey forecasts are about the forecasters' actual beliefs. First, the BCFF survey publicly discloses the forecasters' names and affiliations. Given the

[15]This is especially important given the forecast is an average over the quarter as uncertainty about the quarterly average diminishes as the quarter progresses. Several other papers analyzing the link between forecasts and economic decisions also use one or more quarter ahead forecasts rather than the nowcast (e.g., Giglio et al., 2021, Andonov and Rauh, 2021, Ma, Paligorova, and Peydro, 2021).

[16]There are 9 quarters in which we do not have S&P forecasts of the Aaa yields. In these quarters we simply use Moody's forecasts for the average.

survey's wide dissemination among financial market participants and policymakers, forecasters are incentivized by potential reputational and career impacts to provide accurate predictions. Moreover, there are regular awards given to the most accurate forecasters in the survey.[17] Second, Wang (2021) shows that, for the subset of BCFF forecasters that report their holdings through the Call Reports, their allocations to Treasurys of a given maturity vary significantly and positively with their forecasts of bond returns for the same maturity, suggesting that forecasters treat the surveys seriously enough to back their forecasts with their portfolio decisions.

Another concern is that the credit analysts within the rating agencies, who are responsible for issuing credit ratings, may not rely on the forecasts provided by their in-house macroeconomics teams. However, rating agencies 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:[18]

> "*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.*" (Moody's Investors Service, 2010)

We later confirm empirically that rating agencies' ratings are systematically higher (lower) when these forecasts are more optimistic (pessimistic).

Firm and bond data. We obtain data on corporate bond ratings and characteristics from the Mergent Fixed Income Securities Database (FISD). We also 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, which are in descending order, ranging from Aaa (28) to C (4).[19] We gather firms' quarterly financial information from Compustat Fundamentals Quarterly.

We collect 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 Enhanced datasets. Since our analysis is at the quarterly level, we convert monthly bond returns into quarterly returns. We apply standard filters in the bond literature, i.e., we exclude bonds that are convertible, do not have fixed coupons, asset-backed securities, Yankee bonds, junior bonds, and bonds denominated in foreign currencies. Additionally, we exclude foreign and financial firms from our sample.

[17]For example, the Lawrence R. Klein Award is presented annually by ASU to recognize consistency and accuracy in economic forecasting in Blue Chip forecasts. See https://wpcarey.asu.edu/alumni/klein-award

[18]A similar statement can be found at S&P Global's website: "S&P Global Ratings' team of economists, led by Chief Economist Dr. Paul Gruenwald, is responsible for developing the macroeconomic forecasts and risk scenarios used by S&P Global Ratings' analysts during the rating process, as well as leading key cross-sector and cross-divisional research projects" (Global Economic Outlook Q1 2023).

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

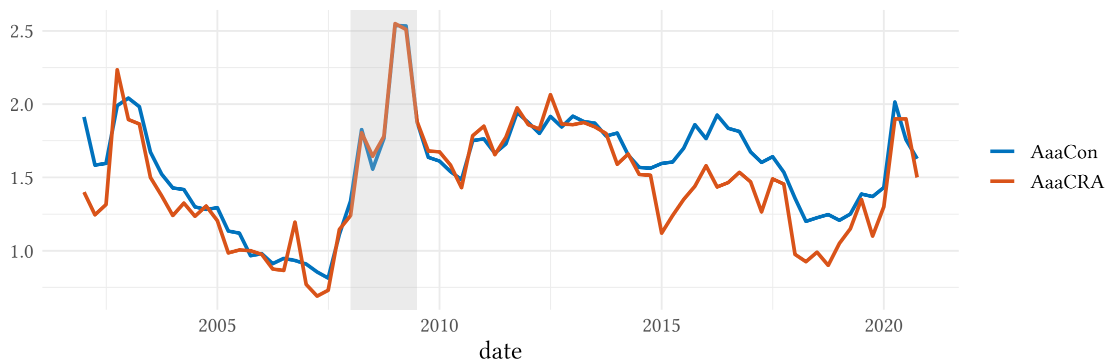
Table 1 Summary Statistics

This table contains summary statistics for one-quarter-ahead forecasts (Panels A), bond-level (Panel B), and firm-level characteristics (Panel C). Interest rates, credit spreads, coupon rates, and returns are reported in percentage points. Duration and maturity are measured in years.

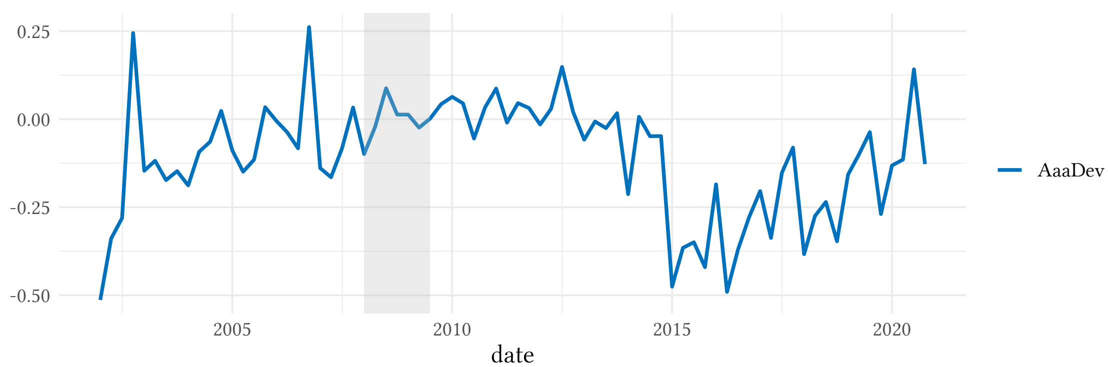
	N	Mean	Median	SD	P5	P95
Panel A: Forecasts						
$AaaCon$	68	1.58	1.62	0.37	0.92	1.99
$AaaCRA$	68	1.47	1.47	0.40	0.87	2.03
$AaaDev$	68	-0.11	-0.07	0.17	-0.41	0.09
Aaa^{MR}	68	1.53	1.58	0.42	0.76	2.05
Aaa^{SPR}	59	1.44	1.42	0.45	0.77	2.05
Panel B: Bond-Level Characteristics						
Next Quarter Return	261813	1.53	1.15	4.95	-5.13	8.80
S&P Rating	314488	18.74	19.00	3.76	12.00	24.00
Moody's Rating	306580	18.75	19.00	3.73	12.00	24.00
Average Rating	303632	18.58	19.00	3.89	11.00	24.00
Maturity	314119	10.05	6.46	10.61	0.68	28.49
Bid-Ask Spread	294219	0.01	0.00	0.01	0.00	0.02
Coupon	314488	6.27	6.38	2.06	2.70	9.75
Duration	312198	6.10	5.05	4.25	0.65	14.42
Credit Spread at Issuance	9794	2.70	1.77	2.42	0.45	7.61
Panel C: Firm-Level Characteristics						
Profitability	292264	-0.15	0.01	0.72	-0.61	0.06
Tangibility	295012	0.24	0.14	0.25	0.00	0.79
Market to Book	295012	8.87	1.41	40.91	0.50	19.21
Sales ($mm)	293598	602.71	36.00	3178.05	0.00	2286.12
Assets ($mm)	295012	3091.57	172.99	17906.11	0.53	11777.00
PPE ($mm)	295012	1014.08	22.26	5849.65	0.00	3715.00
Book Leverage	295012	0.30	0.21	0.32	0.00	1.00
Rated	295012	0.23	0.00	0.42	0.00	1.00
IG	295012	0.09	0.00	0.29	0.00	1.00
Junk	295012	0.14	0.00	0.35	0.00	1.00
S&P Rating	65587	16.92	17.00	3.34	12.00	22.00
Moody's Rating	44897	16.03	15.00	3.63	11.00	22.00

Rating agency and economist data. We collect stock prices, earnings, and earnings forecasts of publicly traded rating agencies or their parent companies from CRSP, Compustat, and I/B/E/S, respectively. For S&P, 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, we use stock information from Moody's Corporation, which is its sole parent company.

We also manually collect property transactions from the deeds records of the rating agencies' head economists from the LexisNexis Public Records Database in order to study the effect of economists' housing returns on their forecasts. To proxy for their housing returns, we compute economists' experienced local housing returns using the Zillow Home Value Index (ZHVI) for



A. Consensus and Rating Agency Forecasts



B. CRA-Consensus

Figure 1 This figure plots the time series of the consensus ($AaaCon$), rating agency ($AaaCRA$) and the difference between rating agency and consensus forecast ($AaaDev$) of Aaa credit spreads at the quarterly frequency. The shaded area corresponds to the period of recession identified by NBER.

single-family homes at the zip code level, described in more detail below.

Summary statistics. Table 1 displays summary statistics of the main variables used in this paper. Panel A reports rating agency and consensus forecasts of Aaa credit spreads as well as the individual S&P and Moody's forecasts. Rating agencies' credit spread forecast is on average, 11 basis points (bps) lower than the consensus (147bps versus 158bps), suggesting rating agencies are almost 8% more aggressive in their forecasts.

Figure 1 displays the time series of the credit spread forecasts of rating agencies, the consensus, and their difference. In Panel A, the credit spread forecasts from the rating agencies and the consensus generally align closely and both increase during the 2008/2009 recession. However, in Panel B, the difference in credit spread forecasts between the rating agencies and the consensus shows no large change in 2008/2009. Rather, the difference between the rating agencies and consensus fluctuates around zero, exhibiting a dip around 2015 before subsequently reverting.[20]

Panels B and C of Table 1 summarize bond-level characteristics and firm-level financials, respectively.

3 Rating Agency Beliefs

In this section, we test whether rating agencies' forecasts are rational and whether they contain information regarding future credit spreads beyond the consensus.

3.1 Rationality of Rating Agency Beliefs

We start by testing whether the forecasts from the rating agencies and the consensus are consistent with rational expectations. To do so, we apply the methodology developed by Coibion and Gorodnichenko (2015, CG), which examines the predictability of future forecast errors from current forecast revisions.[21]

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

$$\underbrace{Aaa_{t+1} - \mathbb{E}_t(Aaa_{t+1})}_{\text{Forecast Error}} = \alpha + \beta \underbrace{\left[\mathbb{E}_t(Aaa_{t+1}) - \mathbb{E}_{t-1}(Aaa_{t+1})\right]}_{\text{Forecast Revision}} + u_{t+1}, \tag{2}$$

where Aaa_{t+1} is the average Aaa credit spread realized in quarter $t+1$ and $\mathbb{E}_{t-1}(Aaa_{t+1})$ is the forecast about Aaa_{t+1} made in quarter $t-1$. We then separately estimate the time-series CG regression using the average forecasts of the rating agencies and the consensus forecasts.

The coefficient of interest is β, which represents the degree of predictability of the forecaster's forecast error. A positive coefficient suggests that the forecaster underreacts to new information concerning the credit spread, potentially attributable to information frictions such as rational inattention (e.g., Sims, 2003) or sticky information (e.g., Mankiw and Reis, 2002). However, a negative coefficient implies an overreaction and, importantly, a departure from rational expectations. For more details regarding these distinctions, see Bordalo et al. (2020).

The results of this regression are presented in Table 2. In column (1), we report the estimated coefficient for the rating agencies (CRA). The coefficient is negative and statistically significant at

[20]While in principle, the mispricing mechanism does not require large deviations between the CRAs and the consensus in their forecasts of aggregate credit spreads, in the Online Appendix we show that our main results hold if we remove the periods of the largest deviations (2002 to 2003 and 2015 to 2016).

[21]As discussed by Coibion and Gorodnichenko (2015), a key advantage of this error-on-revision test is its ability to infer forecasters' responses to news from their forecast revisions, eliminating the need for direct observation or measurement of the forecasters' information set.

Table 2 Coibion and Gorodnichenko (2015) Regressions for Rating Agency and Consensus Forecasts

This table reports the results of the Coibion and Gorodnichenko (2015) time series regression, which regresses one-quarter-ahead forecast errors of the Aaa credit spread on the corresponding forecast revisions. Columns (1) and (2) use forecasts from the rating agencies and the consensus, respectively. The data are quarterly and cover the period between 2002Q1 and 2018Q4. Appendix B includes detailed definitions of all variables. Newey-West standard errors with 4 lags are reported in parenthesis. *, **, and *** indicate statistical significance at 10, 5, and 1% levels, respectively.

	Forecast Error: $Aaa_{t+1} - \mathbb{E}_t(Aaa_{t+1})$	
	CRA (1)	Consensus (2)
Constant	-0.048	-0.173***
	(0.0644)	(0.051)
$\mathbb{E}_t(Aaa_{t+1}) - \mathbb{E}_{t-1}(Aaa_{t+1})$	-0.446***	-0.183
	(0.117)	(0.186)
Observations	68	68
R^2	0.096	0.014

the 1% level, implying that rating agencies overreact to information about aggregate credit spreads, consistent with a departure from rational expectations in rating agency forecasts.

In contrast, the β coefficient for the consensus, shown in column (2), is marginally negative but not significantly different from zero. These results suggest that rating agencies' credit spread forecasts deviate from rational expectations, while the consensus forecasts do not.[22]

3.2 Rating Agency Beliefs and Future Realized Credit Spreads

Despite deviating from rationality, rating agencies' forecasts may still be informative about future credit spreads beyond what is contained in the consensus if rating agencies have private information stemming from their expertise in forecasting credit market conditions. To test this hypothesis, we estimate the following time-series regression:

$$Aaa_{t+1} = \alpha + \beta_0 AaaCon_t + \beta_1 AaaDev_t + u_{t+1}, \tag{3}$$

where Aaa_{t+1} is the average realized Aaa credit spread in quarter $t+1$. If the estimated coefficient β_1 is statistically different from zero, this would suggest that rating agencies' forecasts add additional predictive content beyond the consensus. The results are displayed in Table 3, where we estimate Newey-West standard errors using four lags. In column (1), we only include the difference between the rating agencies and the consensus ($AaaDev$) and the estimated coefficient is close to zero and

[22]These results are also consistent with Bordalo et al. (2020) who apply CG regressions to consensus and individual forecasts for Aaa all-in yields. They find insignificant coefficient for the consensus forecasts and negative and significant coefficient for the individual forecasts. Our main innovation, as shown below, is to show how rating agency forecasts specifically affect credit markets.

Table 3 Rating Agency Forecast Deviations and Future Aggregate Credit Spreads

This table tests whether rating agencies' credit spread forecast deviations predict future realized credit spreads. The dependent variable is the one-quarter-ahead realized Aaa credit spread Aaa_{t+1}, measured as the average daily credit spread within the quarter in percentage points. The independent variables include rating agencies' credit spread forecast deviations $AaaDev_t$ and consensus credit spread forecast $AaaCon_t$, all measured in percentage points. Appendix B includes detailed definitions of all variables. Newey-West standard errors with four lags are shown below the parameter estimates in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Aaa_{t+1}		
	(1)	(2)	(3)
$AaaDev_t$	-0.132		-0.131
	(0.390)		(0.223)
$AaaCon_t$		0.694***	0.694***
		(0.171)	(0.167)
Constant	1.390***	0.308	0.294
	(0.113)	(0.270)	(0.269)
Observations	68	68	68
R^2	0.004	0.475	0.479
F-stat	0.24	60.64	30.76
p-value	0.623	0.000	0.000

statistically insignificant. Moreover, the R-squared is effectively zero. This suggests that rating agency credit spread forecast deviations do not contain information regarding future realized credit spreads.

In column (2), we estimate (3), but only include the consensus forecast $AaaCon$. The point estimate is 0.694 and statistically significant. Moreover, the R-squared is 0.475. This result suggests that the consensus forecast contains substantial information regarding future realized credit spreads. Finally, in column (3), we include both $AaaCon$ and $AaaDev$. Similar to column (1), the estimated coefficient for $AaaDev$ is close to zero and statistically insignificant, and the coefficient for $AaaCon$ does not change at all from column (2). These results suggest that the consensus forecast contains substantial information regarding future credit spreads, while rating agency deviations from the consensus do not.

4 Rating Agency Beliefs and Credit Ratings

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

As discussed in Section 2, the guidelines at major rating agencies require that the forecasts made by their macroeconomists be explicitly incorporated in the credit analysts rating decisions. We formally test whether rating agencies act on their forecasts through their credit rating decisions by estimating the following bond/rating agency level regression:

$$Rating^j_{b,t} = \beta \times \left[\mathbb{E}^j_t(Aaa_{t+1}) - \mathbb{E}^{Con}_t(Aaa_{t+1})\right] + \Gamma Z_b + \delta_b + u^j_{b,t}, \tag{4}$$

where $Rating^j_{b,t}$ is the credit rating, in its converted numerical value, of bond b by rating agency j in quarter t, $\mathbb{E}^j_t(Aaa_{t+1}) - \mathbb{E}^{Con}_t(Aaa_{t+1})$ is the difference between rating agency j's forecast of the Aaa credit spread and the consensus at time t, Z_b is a vector of bond-level controls and δ_b are bond fixed effects. We double-cluster our standard errors by bond and quarter.

The main coefficient of interest is β, representing how an increase in an individual rating agency forecast relative to the consensus affects that rating agency's bond rating. The results are displayed in column (1) of Table 4. The point estimate is -0.19 and statistically significant at the 1% level, suggesting that a 1 percentage point (pp) increase in an agency's forecast deviation from the consensus results in a 0.19 notch reduction in bond-level rating. In column (2), we also include the consensus forecast of credit spread $AaaCon$ to see if rating decisions are affected by the consensus forecast of future credit spreads. We find that the coefficient for $AaaDev$ only marginally changes from column (1) and remains highly significant, while the coefficient of $AaaCon$ is not significant. This result suggests that ratings are influenced by rating agencies' subjective beliefs, but do not seem to be impacted by the market-wide sentiment regarding credit spreads. In columns (3) and (4), we also include rating agency fixed effects and find qualitatively similar results.

Because most of our analysis below focuses on the bond and firm-level effects of aggregate rating agency beliefs, we also estimate the following bond-level regression where we predict the average credit rating using the average rating agency forecast deviation ($AaaDev$) as the main independent variable:

$$AverageRating_{b,t} = \beta AaaDev_t + \Gamma Z_b + \delta_b + u_{b,t}, \tag{5}$$

where $AverageRating_{b,t}$ is calculated by averaging the numerical ratings from Moody's and S&P for bond b in quarter t. The estimates, which are displayed in columns (5) and (6) of Table 4, show that when rating agencies are more optimistic than the consensus, bonds have on average higher ratings. The estimated coefficients suggest that a 1 percentage point (pp) increase in an agency's forecast deviation from the consensus results in a 0.34 notch reduction in bond-level rating.

It is important to mention that the rating agencies have access to the consensus forecast at the time ratings are measured in our regression. Hence, had they run the same analysis as we have done here, they would realize that it is best to simply use the consensus rather than putting extra weight on their own forecasts. Nevertheless, our results suggest that this is not the case: rating

Table 4 Rating Agency Forecast Deviations and Credit Ratings

This table tests whether rating agencies' credit spread forecast deviations affect their bond-level credit ratings. In columns (1) to (4), the dependent variable is the rating for bond b issued by agency j and the main independent variable is the differences in credit spread forecasts between rating agency j and the consensus. In columns (5) and (6), the dependent variable is the average rating for bond b from Moody's and S&P and the main independent variable is the differences in the average rating agency credit spread forecast and the consensus ($AaaDev$). Appendix B includes detailed definitions of all variables. 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.

	$Rating^j,\ j \in \{MR, SPR\}$				$AverageRating$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}_t^j(Aaa_{t+1}) - \mathbb{E}_t^{Con}(Aaa_{t+1})$	-0.193***	-0.191***	-0.092*	-0.089*		
	(0.059)	(0.059)	(0.053)	(0.053)		
$AaaDev$					-0.338***	-0.343***
					(0.117)	(0.116)
$AaaCon$		-0.016		-0.031		0.019
		(0.041)		(0.040)		(0.040)
Maturity	-0.038***	-0.038***	-0.040***	-0.041***	-0.029***	-0.029***
	(0.009)	(0.010)	(0.019)	(0.010)	(0.010)	(0.0100)
Bid-Ask Spread	-4.055***	-4.009***	-4.059***	-3.97***	-4.130***	-4.186***
	(0.953)	(0.894)	(0.957)	(0.888)	(0.944)	(0.919)
Duration	0.1915***	0.192***	0.190***	0.190***	0.174***	0.174***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)
Bond FE	✓	✓	✓	✓	✓	✓
CRA FE			✓	✓		
Observations	610,045	610,045	610,045	610,045	292,452	292,452
R^2	0.913	0.913	0.913	0.913	0.922	0.922

agencies seem to rely excessively on their own forecasts of aggregate conditions when determining firm-level ratings.

One possible concern is that changes in market-wide sentiment are driving these results. However, our measure captures the difference in beliefs between rating agencies and the consensus. Consequently, any market-wide sentiment should be accounted for by the consensus forecast. Additionally, we show in the Online Appendix that our results are robust to controlling for standard sentiment measures in the literature. Finally, in Figure 2, we perform a placebo test by randomly sampling forecasts from two random economists each quarter and reestimate (5) 1000 times. We find that the estimated coefficients follow a bell curve centered around zero and that the coefficient using the rating agencies is larger in magnitude than all placebo estimates. This result suggests that it is the rating agencies' forecasts themselves that are driving their credit ratings.

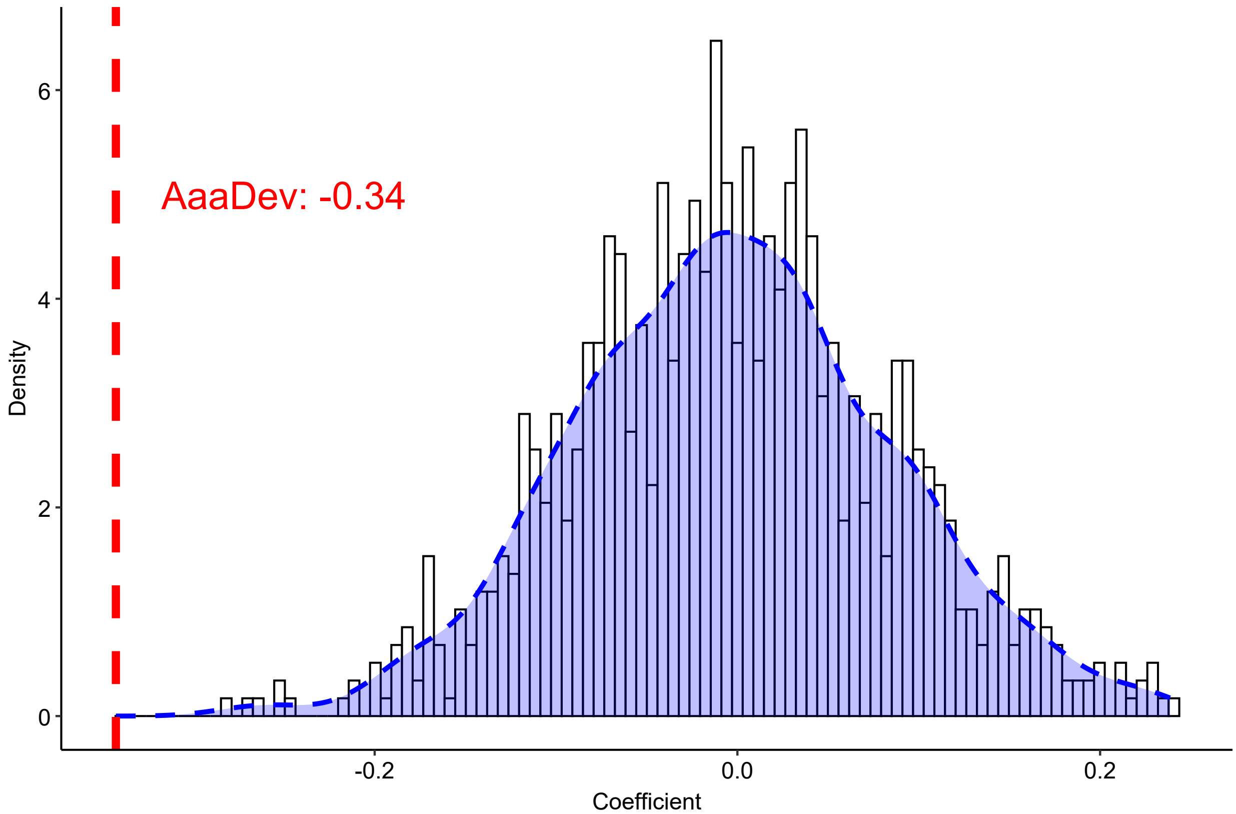


Figure 2 This figure shows the distribution of regression coefficients from equation (5), substituting $AaaDev$ with the difference between consensus and randomly sampled forecasts. We create a time series by averaging two randomly sampled forecasts from the cross-section of economists (excluding credit rating agencies) each quarter. Regression equation (5) is estimated using the difference between consensus forecasts and these averages. This process is repeated 1,000 times, and the density of the coefficients is plotted. The red dashed line indicates the $AaaDev$ coefficient from the original regression.

5 Rating Agency Beliefs and Bond Pricing

Thus far, we have shown that rating agencies' forecast deviations affect their bond-level credit ratings but do not seem to contain any additional information regarding future aggregate credit spreads. We now examine the impact of these subjective beliefs on the corporate bond market by investigating whether rating agency forecasts ultimately affect the initial prices of newly issued bonds.

If investors are rational and realize that rating agencies' forecasts do not predict future aggregate credit spreads beyond the consensus, we would expect no relationship between $AaaDev$ and bond prices. However, if investors cannot disentangle the component of rating agencies' beliefs that affects ratings and is unrelated to fundamentals, they may price bonds more favorably when rating agencies are more optimistic. To test this hypothesis, we create a sample of all newly issued bonds

Table 5 Rating Agency Forecast Deviations and Initial Bond Pricing

This table tests whether rating agency credit spread forecast deviations ($AaaDev$) affect bond credit spreads at issuance. The dependent variable is the corporate bond credit spread at issuance, measured in percentage points. Appendix B includes detailed definitions of all variables. 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.

	Credit Spread at Issuance		
	(1)	(2)	(3)
$AaaDev$	1.290***	1.000***	1.026***
	(0.353)	(0.226)	(0.226)
$AaaCon$		1.373***	1.384***
		(0.274)	(0.273)
Maturity			0.054
			(0.041)
Size			0.064*
			(0.038)
Covenants			-0.148**
			(0.071)
Firm FE	✓	✓	✓
Observations	9,794	9,794	9,794
R^2	0.798	0.821	0.822

and estimate the following regression:

$$CS_{b,t} = \beta_0 AaaCon_t + \beta_1 AaaDev_t + \Gamma Z_{b,t} + \alpha_i + u_{b,t}, \tag{6}$$

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

If rating agency optimism drives initial yields higher, we would also expect higher optimism to lead to a subsequent underperformance of recently issued bonds, as this initial optimism proves to be unwarranted over time.[23] To test this, we construct a panel of all bonds at the quarterly level and estimate the following regression:

$$\begin{aligned} Return_{b,t+1} = {} & \beta_0 AaaCon_t + \beta_1(AaaCon_t \times New_{b,t}) \\ & + \beta_2 AaaDev_t + \beta_3(AaaDev_t \times New_{b,t}) + \Gamma Z_b + \alpha_i + u_{b,t+1}, \end{aligned} \tag{7}$$

Where $Return_{b,t+1}$ 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 in either quarter t or quarter $t-1$. We double-cluster our standard errors by firm 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 terms in columns (3) and (4) we find that the coefficient for new bonds is highly significant and positive across both specifications. Specifically, a 17bp (one standard deviation) increase (decrease) in rating agency forecast deviation leads to around 49bps outperformance (underperformance) over the quarter. At first glance, this result might seem large; however, we have shown that credit spreads are on average 17bps higher at issuance when the rating agencies are 17bps more optimistic than the consensus. If we use the average duration of bonds in our sample (6.1 years), we would expect a total underperformance of 102bps if the rating agencies' initial optimism is entirely unwarranted. Hence, we view this point estimate as reasonable for one quarter of underperformance. Overall these results suggest that new bonds begin overpriced and subsequently underperform when rating agencies are more optimistic.

Why are the asset pricing effects concentrated in new bonds? First, with limited existing information regarding the bond, investors are more reliant on credit ratings to assess the credit risk when they purchase new bonds. Second, in contrast to secondary markets, there are more passive investors, such as pension funds, insurance companies and bond ETFs, participating in new issues. These investors are likely to be less sophisticated on average compared to investors who actively trade in the secondary market.[24] Credit ratings may also be more salient to these less sophisticated investors (Bordalo, Gennaioli, and Shleifer, 2012). In contrast, sophisticated investors are likely better able to disentangle the true credit risk of the bond from distortions in its rating.

Finally, the pattern that new bonds appear to be initially overpriced but experience negative subsequent returns following rating agency optimism is consistent with the result that rating agency

[23] It is unwarranted because, as shown earlier, rating agency optimism does not lead to lower aggregate credit spreads.
[24] See Choi, Cremers, and Riley (2021) for evidence that active bond funds earn positive alphas.

Table 6 Rating Agency Forecast Deviations and Subsequent Bond Returns

This table tests whether rating agency 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. Appendix B includes detailed definitions of all variables. 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)
$AaaDev$	2.006	1.403		
	(1.694)	(1.578)		
$AaaDev \times$ New			4.248***	2.870**
			(1.520)	(1.422)
$AaaDev \times$ Old			1.822	1.292
			(1.733)	(1.616)
$AaaCon$		2.281***		2.267***
		(0.838)		(0.844)
Maturity		-0.044**		-0.045**
		(0.018)		(0.018)
Bid-Ask Spread		-21.310*		-21.440*
		(11.960)		(11.960)
Coupon		0.209***		0.207***
		(0.046)		(0.045)
Duration		0.179***		0.180***
		(0.067)		(0.067)
Firm FE	✓	✓	✓	✓
Observations	261,813	253,880	261,813	253,880
R^2	0.049	0.082	0.050	0.082

optimism does not predict lower future *aggregate*-level credit spreads.[25]

6 Firm-Level Analysis

We have established that rating agencies' 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 rating agency 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 rating agency forecast deviations affect firms' financing and investment decisions. To do so, we estimate

[25]The underperformance by new bonds should not materially affect the aggregate index for two reasons. First, newly issued bonds only enter the index after at least one month. Second, given the large number of existing bonds outstanding, these newly added bonds can only make up a very small portion of the overall index.

the following regression

$$y_{i,t} = \beta_0 AaaCon_t + \beta_1 AaaDev_t + \Gamma X_{i,t} + \alpha_i + u_{i,t}, \tag{8}$$

where $y_{i,t}$ is a firm-level outcome variable, $X_{i,t}$ is a vector of firm characteristics which include sales (in logs), leverage ratio (total debt to capital), profitability ratio (EBITDA to net sales), and tangibility ratio (tangible assets to total assets)[26] and α_i are firm fixed effects. All firm-level variables are measured at the end of quarter t.[27] In all regressions in this section, we double-cluster our standard errors by firm and date.

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

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

where $Rated_{i,t}$ is a dummy variable that equals one if the firm is rated by either Moody's or S&P at the issuer level at time t. If rating agency forecasts affect firm behavior through the ratings they provide, we would expect β_2 to be statistically significant.

6.1 Rating Agency Beliefs and Firms' Capital Structure

We begin by testing whether rating agency forecast deviations predict firms' debt and leverage decisions. To do so, we first estimate (8) 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 -0.60. This estimate suggests that a 1pp increase in rating agencies' credit spread forecast deviation results in firms using 0.60pp less debt. In column (2), we estimate (9) 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 rating agency deviations than unrated firms. In columns (3) and (4), we estimate the same regressions but with leverage, defined as debt/capital as the dependent variable. The estimated coefficients are also negative and statistically significant, suggesting that the lower debt levels following rating agency pessimism lead to lower leverage ratios, especially among rated firms. A one standard deviation increase in $AaaDev$ (17bp) leads to a 2.0pp (3.8%) decrease in leverage among rated firms.[28] Note that we still find a smaller effect among unrated firms for both

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

[27] For example, we would see whether the forecast of the credit spread made at the beginning of January for the period from April to June predicts firms' outcomes variables measured at the end of March.

[28] Rated firms have an average book leverage of 51.3% in our sample.

Table 7 Rating Agency Forecast Deviations and Firms' Debt and Leverage Decisions

This table reports results testing whether rating agency 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)). Appendix B includes detailed definitions of all variables. 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)
$AaaDev$	-0.601***	-0.468***	-0.068***	-0.045***
	(0.120)	(0.101)	(0.014)	(0.011)
$AaaCon$	0.105***	0.065**	0.018***	0.010***
	(0.036)	(0.030)	(0.004)	(0.004)
Rated		1.375***		0.109***
		(0.093)		(0.013)
$AaaDev$ × Rated		-0.299***		-0.072***
		(0.083)		(0.014)
$AaaCon$ × Rated		0.138***		0.028***
		(0.046)		(0.006)
Profitability	-0.054***	-0.045***	0.032***	0.033***
	(0.006)	(0.006)	(0.002)	(0.002)
Tangibility	0.689***	0.687***	0.200***	0.200***
	(0.064)	(0.060)	(0.015)	(0.015)
Sales	0.734***	0.653***	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	291,871	291,871	291,872	291,872
R^2	0.149	0.206	0.033	0.050

debt levels and leverage. This result could be explained by the fact that some firms may have rated securities, which means they are affected by rating agency forecast deviations but not to the same extent as firms rated at the firm/issuer level. Furthermore, investors may form price inferences on unrated securities based on comparable rated firms (i.e., rated firms with similar characteristics). These unrated firms also have the possibility of becoming rated later on. Indeed, as shown below, firms become more likely to be rated when rating agencies become more optimistic.

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 also 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

Table 8 Rating Agency Forecast Deviations and Firms' Issuance Decisions

This table reports results testing whether rating agency 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)). Appendix B includes detailed definitions of all variables. 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)
$AaaDev$	-0.284***	-0.188***	0.075	0.015
	(0.073)	(0.055)	(0.083)	(0.057)
$AaaCon$	0.008	-0.023	-0.197***	-0.148***
	(0.027)	(0.019)	(0.032)	(0.023)
Rated		0.325***		0.401***
		(0.096)		(0.085)
$AaaDev$ × Rated		-0.313***		0.248*
		(0.112)		(0.125)
$AaaCon$ × Rated		0.119**		-0.212***
		(0.049)		(0.052)
Profitability	-0.030***	-0.027***	0.030***	0.030***
	(0.003)	(0.003)	(0.004)	(0.004)
Tangibility	0.091*	0.091**	-0.359***	-0.361***
	(0.046)	(0.045)	(0.035)	(0.035)
Sales	0.328***	0.300***	0.060***	0.059***
	(0.017)	(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	291,872	291,872	290,374	290,374
R^2	0.017	0.021	0.010	0.012

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 rating agencies are more pessimistic in their forecasts.

In Online Appendix Table OA.10, we also show that the increase in debt issuance is not driven by bank debt issuance. This result is natural given that bank debt is often unrated and is far less likely to be affected by the beliefs of credit rating agencies.[29]

6.2 Rating Agency Beliefs and Firms' Investment Decisions

After having established that rating agencies forecasts affect firms' leverage and issuance decisions, we now test whether they affect firms' investment decisions by once again estimating (8) and (10)

[29]If a bank loan is rated it usually occurs after the loan has already been granted in contrast to bonds where the rating is determined at issuance. Moreover, banks are less likely to base their lending decisions on public ratings given their access to private information (Weitzner, Beyhaghi, and Howes, 2022).

Table 9 Rating Agency Forecast Deviations and Firms' Investment Decisions

This table reports results testing whether rating agency 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)), both in logs. Appendix B includes detailed definitions of all variables. 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)
$AaaDev$	-0.152***	-0.099*	-0.172***	-0.136***
	(0.056)	(0.052)	(0.034)	(0.024)
$AaaCon$	-0.013	-0.045*	0.054***	0.039***
	(0.021)	(0.022)	(0.014)	(0.011)
Rated		0.105***		0.249***
		(0.038)		(0.037)
$AaaDev$ × Rated		-0.168***		-0.097*
		(0.045)		(0.049)
$AaaCon$ × Rated		0.127***		0.058***
		(0.023)		(0.018)
Profitability	0.464***	0.466***	0.012**	0.014***
	(0.014)	(0.014)	(0.005)	(0.005)
Tangibility	0.149**	0.149**	2.337***	2.337***
	(0.063)	(0.063)	(0.058)	(0.057)
Sales	0.733***	0.717***	0.614***	0.597***
	(0.019)	(0.018)	(0.014)	(0.013)
Market-to-Book	-0.008***	-0.008***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm FE	✓	✓	✓	✓
Observations	291,867	291,867	291,872	291,872
R^2	0.536	0.541	0.513	0.523

with different investment outcome variables. 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 (both in logs). Across the different specifications, we find a negative relationship between $AaaDev$ and investment which is also concentrated among rated firms. This result implies that the beliefs of rating agencies have real effects on firm behavior and that firms do not only adjust their capital structures in response to rating agency forecast deviations.

The economic magnitude of these effects is large. When the rating agencies are more optimistic than the consensus by one standard deviation (17bps) regarding future credit spreads, this optimism leads to a 3.8% (1.2pp) increase in firm leverage and a 2.6% increase in total assets. Therefore, about two thirds of the proceeds raised through the increase in leverage are invested in new assets rather than returned to shareholders.

To provide further support for the mispricing channel, we test whether the effects we find regarding firms' financing and investment decisions are stronger for investment grade firms. Investors in

Table 10 Rating Agency Forecast Deviations and Firm-Level Outcomes: Investment Grade versus Junk Firms

This table contains results testing whether the effects of rating agency forecast deviations on firm-level outcomes are stronger for investment-grade firms. Appendix B includes detailed definitions of all variables. Robust standard errors double clustered by firm and date are shown below the parameter estimates in parenthesis *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Debt	Leverage	LT Debt Issuance	Equity Issuance	Share Repurchase	Assets	PPE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$AaaDev \times$ IG	-0.446***	-0.053***	-0.009	0.402***	0.238	-0.205**	-0.134*
	(0.166)	(0.017)	(0.159)	(0.137)	(0.232)	(0.093)	(0.067)
$AaaCon \times$ IG	0.092	0.004	0.203	-0.053	-0.534***	0.058*	0.024
	(0.067)	(0.009)	(0.124)	(0.067)	(0.108)	(0.034)	(0.025)
$AaaDev$	-0.503***	-0.086***	-0.415***	0.156	-0.479***	-0.177***	-0.162***
	(0.077)	(0.018)	(0.141)	(0.141)	(0.159)	(0.031)	(0.030)
$AaaCon$	0.114***	0.040***	-0.016	-0.278***	-0.110**	0.017	0.043***
	(0.034)	(0.007)	(0.072)	(0.057)	(0.054)	(0.013)	(0.013)
IG	-0.150	-0.087***	-0.236	0.254**	1.585***	0.034	0.086*
	(0.116)	(0.018)	(0.214)	(0.124)	(0.190)	(0.059)	(0.047)
Profitability	-2.551**	-0.373**	-2.106*	0.316	1.409**	-1.343*	-1.391*
	(1.121)	(0.142)	(1.184)	(0.208)	(0.623)	(0.773)	(0.756)
Tangibility	-0.091	0.042	-0.221	-0.745***	-0.688***	-0.285**	2.716***
	(0.183)	(0.039)	(0.285)	(0.206)	(0.245)	(0.125)	(0.118)
Sales	0.796***	0.005	0.634***	0.078*	0.541***	0.731***	0.719***
	(0.039)	(0.006)	(0.050)	(0.040)	(0.049)	(0.032)	(0.030)
Market-to-Book	-0.104***	0.017***	-0.055	0.255***	0.246***	-0.126***	-0.100***
	(0.034)	(0.005)	(0.038)	(0.032)	(0.040)	(0.015)	(0.014)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Observations	67,150	67,150	67,150	66,429	66,868	67,150	67,150
R^2	0.228	0.054	0.015	0.028	0.057	0.574	0.562

investment grade bonds tend to be less sophisticated (e.g., pension funds, insurance companies) as opposed to the more sophisticated hedge funds and mutual funds that invest in junk bonds. Hence, we would expect bigger firm responses for investment grade as the investors in their bonds are more likely to rely on credit ratings to price the debt. In Table 10 we restrict the sample to firms that are rated and compare the effects across junk and investment grade firm by estimating the coefficient $AaaDev \times IG$. Across all specifications, the estimated point estimate is consistent with larger effects for investment grade firms, and $Debt$, $Leverage$, $EquityIssuance$, $Assets$, and PPE are all statistically significant. For each of these variables, the effects are about twice as large among the investment grade firms as compared to the junk ones.

Our evidence on firm responses to the mispricing induced by rating agencies' forecasts fits well in the rational managers and irrational investors framework (e.g., Baker, Stein, and Wurgler, 2003, Shleifer and Vishny, 2003, and Stein, 2005), where firms often capitalize on market mispricing. However, we cannot fully rule out the possibility that firms might also act irrationally. For instance, managers may misinterpret their favorable ratings (and consequently lower financing costs) induced by rating agency optimism as positive signals about the profitability of their investment opportunities, thereby over-investing. Nonetheless, 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.[30]

6.3 Rating Agency Beliefs and Firms' Likelihood of Being Rated

If rating agencies issue 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

$$Rated_{i,t} = \beta_0 AaaCon_t + \beta_1 AaaDev_t + \Gamma X_{i,t} + \alpha_i + u_{i,t}, \tag{10}$$

where the dependent variable, $Rated_{i,t}$, is a dummy that equals one if the firm is rated at quarter t. The results are displayed in Table 11. In column (1), the estimated coefficient of β is negative and statistically significant, indicating that firms are more likely to pursue a firm-level rating when the rating agencies are more optimistic relative to the consensus. In terms of economic magnitudes, a one standard deviation increase in rating agency optimism (17bp) leads to a 2.7% 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 firm 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 Rating Agency Beliefs

Given the large impact of rating agencies' subjective beliefs on credit markets and firm behavior, it is natural to ask what factors are actually driving these beliefs. In this section, we analyze the determinants of rating agencies' subjective beliefs. While in our main analysis, we focus on the average of rating agencies' forecasts, here we analyze differences across individual rating agency estimates to hone in on the factors that drive these forecasts.

Rating agencies could be more optimistic or pessimistic in their forecast of credit spreads because of their business incentives. For example, if a rating agency is performing poorly, it may find it advantageous to be more optimistic to attract more business from clients.

[30] An alternative, non-mutually exclusive, explanation could be that the rating agencies' forecasts may either tighten or relax rating-based covenants, thereby affecting firms' investment decisions (Fracassi and Weitzner, 2020). Goldstein and Huang (2020) show how ratings can raise investment even if they are inflated. However, in their model investors are fully aware of this inflation and therefore on average bonds are priced correctly. Our evidence on bond pricing and returns is inconsistent with rational investors.

Table 11 Rating Agency Forecast Deviations and the Likelihood of Firms' Being Rated

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

	Rated
	(1)
$AaaDev$	-0.036***
	(0.008)
$AaaCon$	0.005*
	(0.003)
Profitability	-0.006***
	(0.001)
Tangibility	0.002
	(0.010)
Sales	0.050***
	(0.003)
Market-to-Book	-0.000***
	(0.000)
Firm FE	✓
Observations	291,872
R^2	0.030

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., $\mathbb{E}_t^j(Aaa_{t+1}) - \mathbb{E}_t^{Con}(Aaa_{t+1})$ on various lagged measures of rating agency performance such as earnings surprises and stock returns. The results are displayed in Table 12. Interestingly, none of the performance measures have a statistically significant effect on the rating agencies' forecast deviations from the consensus. Moreover, the F-statistics range from 0.84 to 1.25 (p-values of 0.30 to 0.48) across the models, indicating that we cannot reject the null hypothesis that rating agency performance does not affect their forecast deviations from the consensus.

The subjectivity of rating agencies' beliefs could also stem from the behavioral biases of the individual economists who are responsible for these forecasts. To test this possibility, we collapse the forecast data to the economist level. 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.[31] In Table 13, 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 dummies to determine how much variation of the deviation could be explained by economist fixed effects. As

[31] David Blitzer and David Wyss were co-head economists for S&P from 2004Q3 to 2007Q1; hence we include two observations in these quarters. Our results are very similar if we use one observation and randomly assume one economist was the only head during this period.

Table 12 Rating Agency Performance and Forecast Deviations

This table contains results testing whether rating agency forecast deviations are affected by the performance of the individual 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: $\mathbb{E}_t^j(Aaa_{t+1}) - \mathbb{E}_t^{Con}(Aaa_{t+1})$. Appendix B includes detailed definitions of all variables. Robust standard errors clustered by date are shown below the parameter estimates in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	$\mathbb{E}_t^j(Aaa_{t+1}) - \mathbb{E}_t^{Con}(Aaa_{t+1})$		
	(1)	(2)	(3)
Earnings Surprise	0.024	-0.004	-0.017
	(0.019)	(0.030)	(0.028)
Quarterly Stock Return	0.248	0.603	0.586
	(0.171)	(0.525)	(0.514)
Annual Stock Return	-0.132	-0.276	-0.383
	(0.082)	(0.256)	(0.259)
Year-Quarter FE		✓	✓
CRA FE			✓
Observations	122	114	114
R^2	0.027	0.477	0.539
F-stat	1.07	0.84	1.25
p-value	0.370	0.480	0.301

references, in columns (1) - (3), we include year-quarter fixed effects, rating agency 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.[32] In both specifications, the F-statistic is above 5, allowing us to clearly reject the null hypothesis that economist fixed effects do not explain rating agencies' forecast deviations. In terms of R-squared, economist fixed effects alone explain around 16% of the variation in forecast deviations (column (4)) and they add an additional 11% to the explanatory power of the year-quarter fixed effects (column (5) compared to column (1)), suggesting that idiosyncratic characteristics of the individual economists indeed account for a sizable portion of rating agencies' forecast deviations.

Many studies, discussed in the related literature above, show that people tend to extrapolate from past returns when forming their beliefs about the future. Moreover, a growing literature shows that people's personal experiences shape their beliefs. Motivated by these two observations, we investigate whether economists' forecasts are affected by their experienced financial returns through their property ownership. We consider the financial returns of their houses because these houses likely represent a sizable portion of the economists' financial wealth, which can be identified empirically.

Following Cheng, Raina, and Xiong (2014), we use the LexisNexis Public Records Database to manually collect data on all properties owned and sold by economists from deeds records. To

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

Table 13 Individual Economists and Rating Agency Forecasts This table contains results testing whether rating agency forecasts are affected by their head economists. The dependent variable is the difference between rating agency j's forecast of the 10-year Aaa credit spread and the consensus forecast: $\mathbb{E}_t^j(Aaa_{t+1}) - \mathbb{E}_t^{Con}(Aaa_{t+1})$. John Lonski has been Moody's forecasting economist for our entire sample. S&P economists include David Blitzer from the beginning of our sample until 2004Q2, David Blitzer and David Wyss as co-heads from 2004Q3 to 2007Q1, David Wyss from 2007Q2 until 2011Q1 and Beth Ann Bovino from 2011Q2 to the end of our sample. We include two observations in the quarters in which there were two S&P co-head economists. Appendix B includes detailed definitions of all variables.

	$\mathbb{E}_t^j(Aaa_{t+1}) - \mathbb{E}_t^{Con}(Aaa_{t+1})$				
	(1)	(2)	(3)	(4)	(5)
Year-Quarter FE	✓		✓		✓
CRA FE		✓	✓		
Economist FE				✓	✓
Observations	130	139	130	139	130
R^2	0.488	0.032	0.536	0.162	0.602
F-stat	.	.	.	5.04	5.57
p-value	.	.	.	0.003	0.002

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 return as the one-year change in the zip-code level Zillow Home Value Index (ZHVI) for single-family homes. We then calculate economist f's experienced housing return, $\Delta ZHVI_t^f$, by calculating an equal-weighted average housing return over the year up to the date of the forecast across all the properties economist f owns.[33]

We then regress economist f's forecast deviation on her recently experienced housing return, while controlling for year-quarter and rating agency fixed effects. It is important to note that year-quarter fixed effects absorb any aggregate conditions driving nationwide housing prices.

The results are reported in Table 14. The recently experienced housing returns exhibit a negative and significant relationship with deviation in economists' forecasts from the consensus, suggesting that higher personal housing returns correspond to more optimistic forecasts for future aggregate credit markets. We find that a one standard deviation increase in experienced housing return (8.24pp) implies that Economist f's forecast will be approximately 18 bps lower than the consensus, which is slightly larger than one standard deviation of $AaaDev$. These results indicate that individual economists extrapolate based on their personal housing returns when forming beliefs about aggregate outcomes.[34] The impact of experienced housing returns on forecast deviations is

[33]For example, we would see whether the one-year housing return ending in December predicts the forecast of the credit spread made at the beginning of January. Our results are robust to measuring housing returns with lags. The number of observations in these regressions is slightly lower than that of Table 13 because housing returns are not available for all economists over the entire sample.

[34]They also could be consistent with the word of mouth and/or network effects influencing beliefs (e.g., Hong, Kubik, and Stein, 2005 and Bailey et al., 2018).

Table 14 Rating Agency Subjective Beliefs and Economists' Experienced Housing Price Changes

This table reports the relationship between rating agency economists' subjective beliefs and their experienced local housing market returns. In columns (1)-(4), the dependent variable is the difference in Aaa credit spread forecasts made by economist f and the consensus, $\mathbb{E}_t^f(Aaa_{t+1}) - \mathbb{E}_t^{Con}(Aaa_{t+1})$; The independent variable, $\Delta ZHVI_t^f$, is economist f's recently experienced housing market returns, calculated as the one-year change in the Zillow Home Value Index (ZHVI) for single-family homes, averaged across all zip codes where economist f owns a property. In column (5), the dependent variable is $AaaDev$, and the independent variable is the average experienced housing market return, $\overline{\Delta ZHVI_t}$, across all properties owned by Moody's and S&P economists. Appendix B includes detailed definitions of all variables. *, ** and *** indicate statistical significance at 10, 5, and 1% levels, respectively.

	$\mathbb{E}_t^f(Aaa_{t+1}) - \mathbb{E}_t^{Con}(Aaa_{t+1})$				$AaaDev_t$
	(1)	(2)	(3)	(4)	(5)
$\Delta ZHVI_t^f$		-0.022**		-0.020**	
		(0.005)		(0.005)	
$\overline{\Delta ZHVI_t}$					-0.006**
					(0.003)
Constant					-0.076**
					(0.035)
Year-Quarter FE	✓	✓	✓	✓	
CRA FE			✓	✓	
Standard-Errors	Clustered by Economist and Date				Newey-West, L=4
R^2	0.496	0.611	0.537	0.615	0.073
Observations	122	122	122	122	68
F-stat	.	15.79	.	10.54	5.25
p-value	.	0.000	.	0.002	0.025

economically large: a one standard deviation increase in $\Delta ZHVI_t$ leads to a one standard deviation increase in $AaaDev$ (17bps).

Since we have adjusted for time-varying macroeconomic conditions using year-quarter fixed effects, the 12% increase in R^2 (from column (1) to (2)) is due to the difference in housing returns between the economists. However, by including year-quarter fixed effects, we cannot directly see how individual economists' beliefs affect the aggregate rating agency deviation from the consensus $AaaDev$. To evaluate if the economist-level relationship can aggregate to the market level, in column (5) we regress the difference between the average rating agency credit spread forecast and the consensus, $AaaDev$, on the average economist housing return, $\overline{\Delta ZHVI_t}$. The coefficient of -0.006 is statistically significant at the 5% level, though smaller than the point estimates in columns (2) and (4). The smaller magnitude is natural given that both our independent and dependent variables are averaged across economists. Nonetheless, our evidence suggests that if the two rating agency economists happen to experience abnormally positive housing returns, this would lead to rating agencies becoming relatively more optimistic than the consensus.

Finally, one may wonder how plausible it is for these individuals to have such large effects on financial markets. However, the economists at Moody's and S&P are high-profile individuals in the financial industry. For instance, John Lonski, the long-time chief economist at Moody's Investors Service, is frequently cited and interviewed in the media for his insights into the credit market and the macroeconomy.[35] Given our evidence, we believe it's plausible that if John Lonski were to suddenly become much more optimistic, aggregate credit market conditions would heat up.

8 Conclusion

In this paper, we show that subjective beliefs have a substantial impact on credit market conditions and firm behavior. We analyze the beliefs of key players in credit markets, rating agencies, by comparing their forecasts of future aggregate credit spreads to a consensus of other financial institutions. When rating agencies 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 of newly issued bonds. This occurs even though rating agency forecasts do not contain information about future aggregate realized credit spreads. Firms take advantage of this mispricing by issuing more debt and increasing their leverage and investment. We also find a strong link between rating agency forecasts and the idiosyncratic beliefs of the individual economists the rating agencies employ. Moreover, these idiosyncratic beliefs are driven by the economists' personal housing returns, consistent with extrapolative belief formation based on personal experiences. Importantly, our paper shows how these idiosyncratic beliefs can have a substantial impact on broader credit market conditions.

In order to identify subjective beliefs, our analysis focuses on rating agencies beliefs about aggregate credit conditions. Hence, we are not able to identify the subjectivity of beliefs at the individual firm level. However, given the large effects we observe, we expect that rating agencies', and potentially other agents', subjective beliefs regarding individual firms would also have a large impact on those firms' credit and investment decisions.

[35]For a recent interview, see GDP Growth Will Limp Along for the Next 10 Years, Says Moody's Economist.

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Appendix A. Aaa Index Definitions

In this section, we describe in detail how we measure the Aaa credit spread forecast and realization in our sample. From 2002 (the beginning of our sample) and October 2016, Blue Chip Financial Forecasts (BCFF) forecasters were tasked with predicting the yield of the Moody's Seasoned Aaa Corporate Bond Index. This index was discontinued in October 2016 in the Federal Reserve H.15 Table so BCFF participants were thereafter asked to forecast the Bank of America-Merrill Lynch AAA-AA Corporate Bond Yield Index. BCFF refers to each of these as the Corporate Aaa Bond Yield. Below we describe how each of these indices is constructed.

Moody's Seasoned Aaa Corporate Bond Yield Index From 2002 to October 2016, forecasters were asked to predict the Moody's Seasoned Aaa Corporate Bond Yield Index. This index contains all seasoned bonds with a Moody's rating of Aaa and a maturity of 20 years or higher.[36] Bonds are excluded from the index if the remaining maturity falls below 20 years, if the bond is susceptible to redemption, or if the rating drops below Aaa. We obtain realizations of the index from FRED.

Bank of America-Merrill Lynch AAA-AA Corporate Bond Yield Index Following October 2016, the underlying index was switched to the Bank of America-Merrill Lynch 15+ Year AAA-AA US Corporate Index, later rebranded as the "ICE BofA 15+ Year AAA-AA US Corporate Index." The index contains seasoned bonds with a maturity of over 15 years (Bond Index Methodologies). As part of the index methodology, composite ratings of the index constituents are updated once a month during the rebalancing process.[37] In contrast to the Moody's Seasoned Aaa Corporate Bond Yield Index, this index includes both Aaa and Aa composite (across Moody's S&P and Fitch) rated bonds. To calculate the composite rating, the numeric equivalent average for each rating agency is rounded to the nearest integer and then converted back to an equivalent composite rating. We obtain realizations of the index from the BCFF reports.

The correlation between these indices is extremely high—0.99 over the portion of the sample for which we have data on both (2016:11–2018:12).

Treasury Yields To construct credit spreads, we would ideally match the maturity of the corporate bond index and treasuries as closely as possible. However, treasury yield forecasts with maturities exceeding 10 years are sporadic in BCFF. Hence, we use the 10-year treasury because it is closest in maturity to both of these indices and because it is available every quarter in our sample. This also follows the approach of BCFF as they refer to corporate bond spreads as the difference between the Aaa yield forecast and the 10-year treasury yield forecast.

[36] 89% of bonds with Aaa ratings from Moody's also receive AAA ratings from S&P.

[37] New issues must settle on or before the following calendar month-end rebalancing date in order to qualify for the coming month.

Appendix B. Variable Definitions

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

$\underline{AaaCRA}$: 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), in percentage points, from Blue Chip Financial Forecasts.

$\underline{AaaDev}$: 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, i.e., $AaaCRA - AaaCon$, in percentage points, from Blue Chip Financial Forecasts.

$\underline{Aaa}$: The realized Aaa credit spread, calculated as the difference between the effective yield of an Aaa corporate bond index and the 10-year Treasury yield, in percentage points. Until October 2016, the Aaa corporate bond index used for this calculation is Moody's Seasoned Aaa Corporate Bond Index. After October 2016, the BofA Merrill Lynch 15+ Year AAA-AA US Corporate Index, later rebranded as the "ICE BofA 15+ Year AAA-AA US Corporate Index", is used instead. Moody's index and Treasury yields are from FRED (Federal Reserve Bank of St. Louis). The realized values of the BofA index are obtained from BCFF.

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: Bid-ask spread of the bond, from TRACE.

Credit Spread at Issuance: Credit spread of the bond at issuance, calculated as the difference between the bond yield at issuance and the Treasury with the same maturity. Bond yields are from TRACE and Treasury yields are from the Federal Reserve Board.

Covenants: An indicator that equals one if the bond contains covenants, from Mergent FISD.

Duration: Modified duration of the bond, from FISD.

Earnings Surprise: Earnings surprises for the stock of Moody's or S&P based on the seasonal random walk model of earnings: eps-$\text{eps}_{(t-4)}$/std(past 8 eps-$\text{eps}_{(t-4)}$), from IBES.

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

IG: Dummy variable that equals one if the firm is rated investment grade, ratings data is collected from Thomson Eikon, Compustat and Capital IQ.

Leverage: short-term debt[dlcq] +long-term debt[dlttq] / short-term debt[dlcq] +long-term debt[dlttq] + stockholders equity[seqq], 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: Log of time-to-maturity of the bond (measured in years), from FISD.

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

Next Quarter Return: A bond's next quarter return, in percentage points, from WRDS Bond Returns using TRACE.

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, in percentage points, 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.

Size: log of the total amount issued (in thousands of dollars), from FISD.

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

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

$\Delta ZHVI^f$: economist f's recently experienced housing market returns, calculated as the equal-weighted average one-year change in the Zillow Home Value Index (ZHVI) for single-family homes, across all zip codes where economist f owns a property, in percentage points, from Zillow and LexisNexis.

$\overline{\Delta ZHVI}$: economists' average recently experienced housing market returns, calculated as the equal-weighted average of $\Delta ZHVI^f$ across all economists in a given quarter, in percentage points, from Zillow and LexisNexis.

Appendix for Online Publication

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 OA.1 Blue Chip Financial Forecasts sample survey questionnaire

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

Table OA.1 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. For parsimony, 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

Table OA.2 Rating Agency Subjective Beliefs and Credit Market Sentiment Measures

This table reports correlations between rating agency subjective beliefs ($AaaDev$) and other commonly used credit market sentiment measures. $AaaDev$ is the difference in Aaa credit spread forecasts between the average rating agency forecast, $AaaCRA$ 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 the 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						
$AaaCon$	-0.12	1.00					
HYS	-0.10	-0.06	1.00				
Credit Growth	0.21*	0.07	-0.06	1.00			
Easy Credit	0.06	0.53***	-0.09	-0.04	1.00		
$-EBP$	-0.07	-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 OA.3 Rating Agency Forecast Deviations and Credit Ratings (Controlling for Sentiment Measures)

This table tests whether rating agency credit spread forecast deviations affect their bond-level credit ratings, controlling for different measures of aggregate sentiment. 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 the Baker and Wurgler (2006) composite investor sentiment measure. Appendix B includes detailed definitions of all variables. 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.

	$Rating^j,\ j \in \{MR, SPR\}$				$AverageRating$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}_t^j(Aaa_{t+1}) - \mathbb{E}_t^{Con}(Aaa_{t+1})$	-0.166**	-0.172**	-0.098*	-0.104**		
	(0.073)	(0.069)	(0.055)	(0.052)		
$AaaDev$					-0.380***	-0.403***
					(0.129)	(0.120)
$AaaCon$		0.128*		0.111		0.155**
		(0.069)		(0.067)		(0.068)
Maturity	-0.045***	-0.040***	-0.045***	-0.041***	-0.036***	-0.030**
	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)	(0.012)
Bid-Ask Spread	-3.629***	-3.650***	-3.627***	-3.644***	-3.909***	-3.933***
	(0.832)	(0.830)	(0.831)	(0.829)	(0.904)	(0.903)
Duration	0.204***	0.202***	0.204***	0.202***	0.206***	0.204***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)
HYS	-0.150	-0.195	-0.209	-0.247	-0.013	-0.061
	(0.155)	(0.157)	(0.162)	(0.163)	(0.148)	(0.151)
Credit Growth	-1.715	-3.027*	-1.582	-2.719	-0.470	-1.917
	(1.662)	(1.732)	(1.722)	(1.745)	(1.483)	(1.550)
Easy Credit	-0.002*	-0.003***	-0.002*	-0.003**	-0.002*	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$-EBP$	-0.035	-0.016	-0.028	-0.012	-0.059**	-0.037
	(0.023)	(0.023)	(0.024)	(0.024)	(0.023)	(0.023)
BW Sentiment	0.051	0.111*	0.049	0.101	-0.038	0.037
	(0.057)	(0.063)	(0.055)	(0.062)	(0.055)	(0.059)
Bond FE	✓	✓	✓	✓	✓	✓
CRA FE			✓	✓		
Observations	510,095	510,095	510,095	510,095	232,655	232,655
R^2	0.917	0.917	0.917	0.917	0.925	0.925

Table OA.4 Rating Agency Forecast Deviations and Subsequent Bond Returns (Controlling for Sentiment Measures)

This table tests whether rating agency credit spread forecast deviations ($AaaDev$) forecast subsequent bond returns, controlling for different measures of aggregate sentiment. The dependent variable is one-quarter-ahead corporate bond returns. New bonds are defined as bonds issued during the most recent two quarters. Appendix B includes detailed definitions of all variables. 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 the Baker and Wurgler (2006) composite investor sentiment measure. 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)
$AaaDev$	3.068*	2.987*		
	(1.757)	(1.707)		
$AaaDev$ × New			4.584**	3.712*
			(1.825)	(1.893)
$AaaDev$ × Old			2.908	2.912
			(1.798)	(1.766)
$AaaCon$		1.934		1.916
		(1.266)		(1.290)
Maturity		-0.055***		-0.055***
		(0.017)		(0.017)
Bid-Ask Spread		-17.614**		-17.626**
		(7.308)		(7.315)
Coupon		0.106***		0.105***
		(0.038)		(0.038)
Duration		0.240***		0.240***
		(0.068)		(0.068)
HYS	-7.886**	-8.701***	-7.828**	-8.666***
	(3.146)	(3.031)	(3.122)	(3.008)
Credit Growth	40.566	12.288	40.946	12.718
	(31.272)	(32.562)	(31.409)	(32.939)
Easy Credit	0.063***	0.061***	0.062***	0.060***
	(0.019)	(0.020)	(0.019)	(0.020)
$-EBP$	1.690***	1.919***	1.696***	1.919***
	(0.554)	(0.488)	(0.551)	(0.486)
BW Sentiment	-0.617	0.469	-0.650	0.443
	(1.174)	(1.208)	(1.169)	(1.220)
Firm FE	✓	✓	✓	✓
R^2	0.10682	0.12505	0.10699	0.12509
Observations	205,679	198,708	205,679	198,708

Table OA.5 Rating Agency Forecast Deviations and Firms' Debt and Leverage Decisions (Controlling for Sentiment Measures)

This table reports results testing whether rating agency credit spread forecast deviations ($AaaDev$) affect firms' debt and leverage decisions, controlling for different measures of aggregate sentiment. 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 the Baker and Wurgler (2006) composite investor sentiment measure. Appendix B includes detailed definitions of all variables. 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)
$AaaDev$	-0.409***	-0.322***	-0.053***	-0.035***
	(0.090)	(0.074)	(0.012)	(0.009)
$AaaCon$	0.154***	0.098***	0.016***	0.007
	(0.040)	(0.035)	(0.005)	(0.005)
Rated		1.408***		0.109***
		(0.093)		(0.013)
$AaaDev \times$ Rated		-0.157*		-0.054***
		(0.083)		(0.013)
$AaaCon \times$ Rated		0.138***		0.029***
		(0.044)		(0.006)
Profitability	-0.033***	-0.025***	0.033***	0.034***
	(0.005)	(0.005)	(0.002)	(0.002)
Tangibility	0.759***	0.756***	0.206***	0.206***
	(0.061)	(0.059)	(0.015)	(0.015)
Sales	0.629***	0.558***	0.026***	0.020***
	(0.021)	(0.019)	(0.003)	(0.003)
Market-to-Book	-0.001***	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
HYS	0.177	0.156	0.021	0.018
	(0.134)	(0.121)	(0.014)	(0.013)
Credit Growth	4.208***	3.999***	0.239	0.216
	(1.339)	(1.183)	(0.158)	(0.144)
Easy Credit	-0.006***	-0.005***	-0.000***	-0.000***
	(0.001)	(0.001)	(0.000)	(0.000)
$-EBP$	0.057***	0.058***	0.009***	0.009***
	(0.018)	(0.017)	(0.002)	(0.002)
BW Sentiment	-0.084**	-0.079**	-0.012**	-0.011***
	(0.041)	(0.036)	(0.005)	(0.004)
Firm FE	✓	✓	✓	✓
Observations	256,007	256,007	256,008	256,008
R^2	0.131	0.188	0.031	0.046

Table OA.6 Rating Agency Forecast Deviations and Firms' Investment Decisions (Controlling for Sentiment Measures)

This table reports results testing whether rating agency credit spread forecast deviations ($AaaDev$) affect firms' investment decisions, controlling for different measures of sentiment. 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 the Baker and Wurgler (2006) composite investor sentiment measure. Appendix B includes detailed definitions of all variables. 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)
$AaaDev$	-0.062	-0.032	-0.099***	-0.086***
	(0.046)	(0.046)	(0.031)	(0.027)
$AaaCon$	0.023	-0.011	0.078***	0.059***
	(0.026)	(0.026)	(0.019)	(0.018)
Rated		0.103***		0.245***
		(0.035)		(0.035)
$AaaDev \times$ Rated		-0.085**		-0.010
		(0.041)		(0.054)
$AaaCon \times$ Rated		0.125***		0.060***
		(0.020)		(0.015)
Profitability	0.459***	0.461***	0.021***	0.023***
	(0.015)	(0.015)	(0.004)	(0.004)
Tangibility	0.194***	0.194***	2.293***	2.292***
	(0.064)	(0.064)	(0.057)	(0.057)
Sales	0.693***	0.680***	0.576***	0.562***
	(0.017)	(0.017)	(0.013)	(0.013)
Market-to-Book	-0.009***	-0.009***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
HYS	0.078	0.073	0.038	0.034
	(0.072)	(0.070)	(0.059)	(0.056)
Credit Growth	3.829***	3.775***	2.612***	2.564***
	(0.827)	(0.803)	(0.622)	(0.593)
Easy Credit	-0.003***	-0.003***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.000)	(0.000)
$-EBP$	0.020*	0.021*	0.012	0.013
	(0.011)	(0.011)	(0.009)	(0.008)
BW Sentiment	-0.010	-0.008	-0.005	-0.004
	(0.027)	(0.026)	(0.019)	(0.018)
Firm FE	✓	✓	✓	✓
Observations	256,003	256,003	256,008	256,008
R^2	0.533	0.537	0.504	0.513

Table OA.7 Rating Agency Forecast Deviations and Credit Ratings (Excluding High Deviation Periods)

This table tests whether rating agencies' credit spread forecast deviations affect their bond-level credit ratings, excluding periods in which the rating agencies deviate the most from the consensus (2002-2003 and 2015-2016). In columns (1) to (4), the dependent variable is the rating for bond b issued by agency j and the main independent variable is the differences in credit spread forecasts between rating agency j and the consensus. In columns (5) and (6), the dependent variable is the average rating for bond b from Moody's and S&P and the main independent variable is the differences in the average rating agency credit spread forecast and the consensus ($AaaDev$). Appendix B includes detailed definitions of all variables. 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.

	$Rating^j,\ j \in \{MR, SPR\}$				$AverageRating$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}_t^j(Aaa_{t+1}) - \mathbb{E}_t^{Con}(Aaa_{t+1})$	-0.158***	-0.133**	-0.092**	-0.058		
	(0.051)	(0.051)	(0.045)	(0.043)		
$AaaDev$					-0.320***	-0.268***
					(0.078)	(0.079)
$AaaCon$		-0.081**		-0.101***		-0.049
		(0.032)		(0.030)		(0.032)
Maturity	-0.045***	-0.048***	-0.048***	-0.051***	-0.041***	-0.043***
	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.010)
Bid-Ask Spread	-5.645***	-5.356***	-5.677***	-5.317***	-5.155***	-4.974***
	(1.240)	(1.161)	(1.247)	(1.150)	(0.993)	(0.950)
Duration	0.190***	0.189***	0.189***	0.188***	0.177***	0.176***
	(0.016)	(0.015)	(0.016)	(0.015)	(0.018)	(0.018)
Bond FE	✓	✓	✓	✓	✓	✓
CRA FE			✓	✓		
Observations	470,912	470,912	470,912	470,912	224,141	224,141
R^2	0.916	0.916	0.917	0.917	0.926	0.926

Table OA.8 Rating Agency Forecast Deviations and Firms' Debt and Leverage Decisions (Excluding High Deviation Periods)

This table reports results testing whether rating agency credit spread forecast deviations ($AaaDev$) affect firms' debt and leverage decisions, excluding periods in which the rating agencies deviate the most from the consensus (2002-2003 and 2015-2016). Appendix B includes detailed definitions of all variables. 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)
$AaaDev$	-0.922***	-0.746***	-0.097***	-0.069***
	(0.248)	(0.220)	(0.027)	(0.022)
$AaaCon$	0.158***	0.114***	0.021***	0.014***
	(0.043)	(0.036)	(0.005)	(0.005)
Rated		1.395***		0.116***
		(0.107)		(0.014)
$AaaDev \times$ Rated		-0.403***		-0.084***
		(0.115)		(0.021)
$AaaCon \times$ Rated		0.139**		0.023***
		(0.056)		(0.007)
Profitability	-0.053***	-0.046***	0.029***	0.029***
	(0.007)	(0.006)	(0.002)	(0.002)
Tangibility	0.766***	0.758***	0.213***	0.212***
	(0.067)	(0.063)	(0.016)	(0.016)
Sales	0.701***	0.624***	0.034***	0.026***
	(0.030)	(0.026)	(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	218,267	218,267	218,268	218,268
R^2	0.137	0.192	0.033	0.048

Table OA.9 Rating Agency Forecast Deviations and Firms' Investment Decisions (Excluding High Deviation Periods)

This table reports results testing whether rating agency credit spread forecast deviations ($AaaDev$) affect firms' investment decisions, excluding periods in which the rating agencies deviate the most from the consensus (2002-2003 and 2015-2016). 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)
$AaaDev$	-0.277**	-0.206**	-0.263***	-0.203***
	(0.105)	(0.097)	(0.082)	(0.067)
$AaaCon$	0.039*	0.009	0.079***	0.058***
	(0.021)	(0.019)	(0.017)	(0.013)
Rated		0.131***		0.203***
		(0.039)		(0.039)
$AaaDev$ × Rated		-0.225***		-0.181***
		(0.056)		(0.061)
$AaaCon$ × Rated		0.116***		0.077***
		(0.023)		(0.022)
Profitability	0.446***	0.448***	0.009*	0.011**
	(0.015)	(0.015)	(0.005)	(0.005)
Tangibility	0.222***	0.221***	2.365***	2.364***
	(0.066)	(0.065)	(0.066)	(0.066)
Sales	0.680***	0.665***	0.586***	0.570***
	(0.022)	(0.021)	(0.017)	(0.016)
Market-to-Book	-0.008***	-0.008***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm FE	✓	✓	✓	✓
Observations	218,263	218,263	218,268	218,268
R^2	0.520	0.525	0.504	0.513

Table OA.10 Rating Agency Forecast Deviations and Firms' Bank Debt Issuance Decisions

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

	Bank Debt	
	(1)	(2)
$AaaDev$	0.013	-0.053
	(0.413)	(0.284)
$AaaCon$	0.382	0.303*
	(0.230)	(0.176)
Rated		0.193
		(0.413)
$AaaDev$ × Rated		0.372
		(0.551)
$AaaCon$ × Rated		0.324
		(0.242)
Profitability	-0.064***	-0.061***
	(0.007)	(0.006)
Tangibility	0.132	0.134
	(0.105)	(0.104)
Sales	0.700***	0.668***
	(0.042)	(0.041)
Market-to-Book	-0.000***	-0.000***
	(0.000)	(0.000)
Firm FE	✓	✓
Observations	291,872	291,872
R^2	0.063	0.068