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Conflicts of interest in subscriber-paid credit ratings☆

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ABSTRACT

We provide the first evidence of systematic bias among an emerging type of credit rating agency that relies on subscriptions from institutional clients as its primary source of revenue. Using data from Egan-Jones Ratings Company (EJR), a representative subscriber-paid rating agency, we show that EJR issues more optimistically biased credit ratings, less timely downgrades, and less accurate ratings for firms held by more EJR clients. Our evidence is consistent with EJR optimistically biasing its ratings to bolster subscriber revenue, which allows institutional clients to invest in riskier bonds with higher expected returns. Taken together, our findings suggest that the emergence of subscriber-paid rating agencies as an alternative to more traditional issuer-paid agencies is unlikely to resolve problems arising from conflicts of interest but rather alter the nature of these conflicts in the ratings process.

1. Introduction

Information intermediaries play a central role in modern capital markets by influencing the allocation of scarce capital. Recognition of this role has given rise to a substantial literature exploring biases in these intermediaries' outputs and the implications for capital market outcomes. A central inference from this literature is that pervasive incentive misalignment problems exist between intermediaries and some of the constituencies they serve, often resulting in inferior trading decisions and distortions in market prices.

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In this study, we focus on credit rating agencies, which serve as information intermediaries in debt markets through a variety of actions including certifying assets as investment worthy, disseminating information, and monitoring firms' credit risk. The ratings industry has evolved in recent years, in part due to evidence that the traditional issuer-paid agencies face pressure to bias credit ratings in order to garner and retain issuing firms as clients.[1] Consequently, both Congress and the SEC have considered and continue to consider reforming the compensation model of rating agencies to reduce agencies' reliance on debt issuers for revenue (GAO, 2010; GAO, 2012; Jiang et al., 2012; Podkul, 2020).

A prominent alternative to the issuer-pay model is the subscriber-pay (or investor-pay) model, in which subscribers compensate credit rating agencies by paying for access to the ratings. Subscriber-paid rating agencies have grown in prominence in recent years with several receiving the Nationally Recognized Statistical Rating Organization (NRSRO) designation. Proponents of subscriber-paid agencies argue that this compensation structure combats incentive alignment problems by removing the rating agencies' reliance on revenues from the issuing firms whose bonds the agencies cover.[2] Although the subscriber-pay model likely makes agencies less beholden to issuing firms, the agencies' reliance on subscribers may introduce an alternative conflict of interest affecting ratings quality (SEC, 2011; Coffee, 2011; SEC, 2012; Neumann, 2013). Specifically, subscriber-paid agencies may face pressure to provide ratings that benefit their clients in exchange for greater subscription fees. In this context, the conflict of interest lies between bond investors and fund managers who subscribe to the rating agency as a means to access inflated ratings which allow them to justify holding riskier bonds. When providing inflated credit ratings, a subscriber-paid credit rating agency potentially harms bond fund investors by exposing them to higher levels of risk than they realize or desire.

In this study, we provide novel evidence that a prominent subscriber-paid rating agency caters to the preferences of its subscribers at the expense of ratings accuracy. Our central hypothesis is that subscriber-paid rating agencies cater to their subscribers by providing optimistically biased ratings for the securities in their subscribers' portfolios. Our hypothesis is motivated by the fact that institutional investors commonly face internal and regulatory restrictions to hold securities above a particular ratings threshold (Cantor et al., 2007; Bongaerts et al., 2012; Cornaggia and Cornaggia, 2013; Chen et al., 2014).[3] Thus, optimistically-biased ratings allow subscribing institutional investors to satisfy restrictions to comply with minimum ratings thresholds, while also holding riskier assets and likely earning higher yields (Cornaggia and Cornaggia, 2013; Opp et al., 2013; Becker and Ivashina, 2015).

The ability of institutional investors to earn higher expected returns—even if accompanied by greater risk—is important because prior research shows that the flow of investment into mutual funds more closely tracks recent total returns as opposed to risk-adjusted returns (e.g., Sensoy, 2009). Further, this incentive to 'window dress' fund performance is particularly strong in contexts where mutual funds are judged on a relative basis and when investors rely on past returns to judge fund manager skills (e.g., DeLong et al., 1990). Inflated ratings, therefore, likely allow investment managers to generate higher expected returns and earn larger management fees (Becker and Ivashina, 2015).

Our main tests examine the actions of a representative subscriber-paid rating agency, Egan-Jones Ratings Company (EJR), which earns the majority of its revenues from institutional investors that subscribe to its data feed. We focus on EJR because of its position as perhaps the most prominent subscriber-paid rating agency and due to the availability of its historical ratings data. Consistent with our main hypotheses, we predict that EJR caters to its subscribers by issuing more optimistic ratings, less timely downgrades, and less accurate ratings for bonds more extensively held by institutional investors that subscribe to EJR.

Subscriber-paid rating agencies, including EJR, do not publish their client lists. To overcome this challenge, we identify EJR's clients using a proprietary database of institutional trades from Ancerno Ltd. using the same approach as in Bhattacharya et al. (2019). Ancerno is a dataset that tracks the institutional trading activity of a large number of institutional investors. Our main tests identify EJR subscribers as those institutions that engage in abnormal equity trades in response to EJR ratings changes relative to Moody's rating changes. Because only subscribers can observe EJR ratings in real time, identifying institutions that trade in a timely fashion in response to rating changes indicates which institutions are likely subscribers. After identifying EJR clients, we obtain the stock holdings of each institutional client using Thomson Reuters Institutional (13f) Holdings. In doing so, our main dataset captures the likely clients of EJR and their stock holdings in each quarter.

We measure bias and timeliness by comparing EJR credit ratings to two different benchmarks: (i) concurrent ratings issued by Moody's (an issuer-paid rating agency), and (ii) the predicted credit rating from the model in Baghai et al. (2014) (hereafter "model-implied rating"). Comparing EJR ratings to these benchmarks allows us to focus on within-firm variation in ratings at the same point in time across agencies. Thus, our approach mitigates concerns that our results are driven by differences in the characteristics of firms that are more heavily weighted in EJR subscribers' portfolios compared to those that are not.

[1] See, for example, He et al. (2012), Jiang et al. (2012), Kedia et al. (2014), Efing and Hau (2015), Kraft (2015), Baghai and Becker (2018), and Beatty et al. (2019).

[2] For example, Laing (2007) argues that "[a]gencies must be encouraged to make their money from investor subscriptions rather than fees from issuers, to ensure more impartial ratings." Sean Egan, President of Egan-Jones Ratings Company (EJR), echoes this by suggesting that the NRSRO designation be tied to a requirement that credit rating agencies derive a certain level of revenue from investors (U.S. House of Representatives, 2008).

[3] Although the SEC removed references to certified (NRSRO) rating agencies following the Dodd-Frank Act of 2010, the Dodd-Frank Act did not alter the role of credit ratings in both state-level and international regulations (Cornaggia and Cornaggia, 2013; Becker and Ivashina, 2015). Additionally, credit ratings continue to play a critical role in internal mandates and portfolio governance for unregulated institutions (Cantor et al., 2007; Bongaerts et al., 2012; Chen et al., 2014).

Our first main result is that EJR provides more optimistic ratings for those firms with greater EJR client ownership. Specifically, greater EJR client ownership in a firm's stock significantly predicts the likelihood that EJR provides a more optimistic rating in the following quarter relative to Moody's. Economically, a one standard deviation increase in EJR client ownership represents a 34 percent increase in EJR optimism relative to the unconditional mean. We find similar results after comparing the EJR rating to the model-implied rating from Baghai et al. (2014), which mitigates concerns that our results are sensitive to the use of Moody's as a benchmark for identifying bias. Moreover, we find that these effects are more pronounced around the investment-grade threshold.

A key piece of evidence in our paper is the asymmetry in the bias of EJR ratings. Specifically, greater EJR client ownership predicts EJR optimism, but does not predict pessimism relative to Moody's or our ratings model. This predictable asymmetry toward an optimistic bias in EJR ratings, rather than a pessimistic bias, mitigates common alternative explanations for our findings. For example, the asymmetry mitigates concerns that our findings could reflect EJR clients' preference for investing in firms with greater potential for ratings disagreement, such as firms with greater information asymmetry or uncertainty (Morgan, 2002; Bonsall and Miller, 2017; Akins, 2018). An alternative explanation based on ratings disagreement or uncertainty may predict more divergent ratings, but not a divergence that asymmetrically manifests as EJR optimism rather than pessimism.

Our main results concentrate predictably in issuing firms held by larger institutional investors with greater assets under management. This evidence is consistent with the fact that EJR charges a subscription fee that varies based on investor size (Bruno et al., 2016). Thus, our evidence is consistent with EJR catering ratings toward the interests of larger institutional investors that represent a greater fraction of its revenue stream.

We also show that our findings are stronger among EJR clients that serve regulated entities (e.g., retirement plans, insurance companies, and banks) compared to unregulated entities. These results are consistent with EJR catering more to regulated entities that are more likely to face mandates to invest only in investment-grade securities or other similar ratings-based restrictions.

EJR ratings are also less predictive of future defaults when EJR client ownership is greater, which is predictably driven by instances where EJR is optimistic relative to Moody's. Similarly, EJR ratings are worse predictors of future market-based expectations of bankruptcy risk and bond returns for firms with greater EJR client ownership.

To bolster credibility that our main tests correctly identify EJR clients, we analyze funds' stated reliance on bond ratings textually using a subsample of Form 497K prospectuses. The funds we identify as EJR clients are less likely to mention a reliance on Moody's, S&P, or Fitch, but more likely to use vague language that refers to reliance on a “major” or “independent” credit rating agency. These results are consistent with EJR clients using EJR ratings to satisfy minimum requirements but obfuscating their reliance from investors. We also show that our results are robust to several alternative means of identifying EJR clients. Finally, drawing on recent advances in the statistics literature and following Oster (2019), we provide evidence that our findings are unlikely to be explained by unmodeled selection effects driving both EJR ratings and client holdings (i.e., bias due to endogenous matching).

A central contribution of our paper is in providing the first large sample evidence consistent with a subscriber-paid rating agency catering to its institutional clients to maximize subscriber revenues. In doing so, we extend the evidence in Tang et al. (2020) from an experimental setting related to conflicts of interest among subscriber-paid rating agencies. Further, our study calibrates the magnitude of the effects on ratings quality.

The scarcity of prior evidence on conflicts of interest among subscriber-paid agencies is noteworthy given their growing prominence among practitioners and regulators. A likely reason for this scarcity is that studying these conflicts of interest has posed several challenges, most notably of identifying the holdings of EJR subscribers. We overcome these challenges using an opportune time period when we are able to simultaneously observe three key datasets: the identity of institutions executing stock trades (to identify subscribers), the stock holdings of these institutions, and EJR ratings changes. The intersection of these three data sources spans 1999 through 2010, which make up the main sample in our study.

Collectively, our findings illustrate that the subscriber-paid model is not a panacea for conflicts of interest, despite their ratings being more informative and timely on average (e.g., Strobl and Xia, 2011; Cornaggia and Cornaggia, 2013; Bonsall et al., 2017). Our findings extend prior studies by demonstrating that the accuracy and timeliness of EJR ratings are predictably weaker in settings where the firm is held by a large number of EJR subscribers and the firm is close to the investment-grade boundary. As a result, our findings are also important for researchers who use EJR ratings as a benchmark for identifying bias among other ratings agencies. To the extent that researchers’ key sorting variable (e.g., disclosure quality) is correlated with EJR client ownership, inferences about the relation between the sorting variable and ratings bias are likely confounded by the conflict of interest that our study highlights.

Additionally, our results suggest that market prices rationally discount EJR ratings in cases when conflicts of interest are likely to be more severe. Nonetheless, a lack of transparency surrounding investment funds’ reliance on subscriber-paid ratings, such as EJR, may place less sophisticated investors at a disadvantage by obscuring the risk-return profile of investment funds. Such investors might benefit from enhanced disclosure about reliance on subscriber-paid ratings when deciding whether and to what extent to invest.

Our paper extends research examining conflicts of interest in the credit rating industry. Prior studies have focused almost exclusively on the issuer-pay model and how this compensation structure affects ratings accuracy (e.g., He et al., 2012; Jiang et al., 2012; Bonsall, 2014; Efing and Hau, 2015; Kraft, 2015; Baghai and Becker, 2018; Beatty et al., 2019). Our study highlights a novel form of conflicts of interest within the subscriber-pay revenue model, which is driven by incentives among subscribing institutional investors to invest in higher yield bonds while complying with internal and/or regulatory ratings requirements.

This study also relates to the literature examining the attributes of subscriber-paid credit rating agencies. The evidence in Beaver et al. (2006) and Bruno et al. (2016) indicates that EJR tends to provide more timely ratings than Moody's on average, which is driven by the use of Moody's ratings by regulators and in debt contracting, as well as the differences across the agencies' incentives structures. We add to this prior work by examining conflicts of interest among subscriber-paid rating agencies and the predictable biases they elicit.

Our study also relates to research showing that analysts face conflicts of interest driven by the desire for investment banking business (e.g., Kothari et al., 2016). A unifying feature of these studies is that they show analysts offer optimistically-biased recommendations, which are contrary to the interests of uninformed equity investors who rely on the ratings. In contrast, our study highlights a conflict of interest where some fund managers appear to rely on these ratings due to their optimism, even at the expense of ratings accuracy.

Taken together, our results are consistent with a wide range of testable predictions about the nature, concentration, and implications of conflicts of interests among a prominent subscriber-paid rating agency. Our findings, therefore, imply that changing the compensation structure of credit ratings to a subscriber-pay model will not necessarily eliminate conflicts of interest, but rather alter the nature of these conflicts in the ratings process.

2. Background

Egan-Jones Ratings Company (EJR) was founded in 1995 by Sean Egan and Bruce Jones. In contrast to the Big Three issuer-paid rating agencies (S&P, Moody's, and Fitch), EJR is compensated for its ratings by subscribers. Subscribers pay an annual subscription fee to access current and historical ratings, and these ratings are only available in real time to subscribers (Xia, 2014; Bruno et al., 2016). Specifically, EJR charges a variable subscription fee that ranges from $12,750 to $150,000 per year, depending on client size (Xia, 2014; Bruno et al., 2016). EJR's clientele includes “both regulated and non-regulated institutional investors, hedge funds, pension funds, banks, and fiduciaries but has never included retail investors” (Bruno et al., 2016, p.1579). In 2002, EJR established a proxy research service for voting recommendations to institutional clients.

EJR covers a broad range of asset classes. Compared to Moody's and S&P that rate approximately 95 percent of all corporate bonds (Bongaerts et al., 2012), EJR covers 80 percent of all firm assets in a given industry, relative to S&P (Xia, 2014). We report similar statistics in Fig. 1.

Subscriber-paid rating agencies, particularly EJR, rose to prominence as traditional issuer-paid rating agencies (e.g., S&P, Moody's) were criticized in the years following their perceived failure to predict the bankruptcies of Enron and WorldCom in the early 2000s, and once again during the recent financial crisis for their ratings of structured financial products. These perceived failures of the issuer-pay model led to calls for credit rating reform. Numerous academics, journalists, and practitioners have suggested that credit rating reform should include some form of adoption of the subscriber-pay model, arguing that this model leads to greater independence of the rating agency. For instance, in his Congressional testimony, John Coffee suggests that the subscriber-pay model is one that “issuers and underwriters may fear (because such a more independent rating agency may be more critical of issuers)” (U.S. Senate, 2008).[4]

Prior research provides evidence that subscriber-paid credit ratings outperform issuer-paid ratings and that the conflicts of interest inherent to the issuer-pay revenue model are responsible for less accurate, timely, and informative ratings (Beaver et al., 2006; Cornaggia and Cornaggia, 2013; Bonsall et al., 2017).[5] What remains unclear is whether subscriber-paid rating agencies, such as EJR, are affected by conflicts of interest that are inherent to the *subscriber-pay* model. The SEC has continued to highlight this concern and emphasized the need for evidence on conflicts of interest within this alternative ratings revenue model (SEC, 2011; SEC, 2012; SEC, 2020). In 2013, the SEC sanctioned EJR for falsely declaring that rating analysts were unaware of their clients' holdings. In its report, the SEC asserted that there was evidence that EJR's ratings analysts were aware of their clients' holdings in several instances, including the founder and primary analyst, Sean Egan.

Despite the SEC's sanction, there is no archival evidence to demonstrate whether EJR, or other subscriber-paid rating agencies, indeed provide biased ratings for their subscribers' holdings—a circumstance noted in SEC (2012).[6] Subscriber-paid rating agencies, including EJR, do not publish their lists of institutional clients. Consequently, archival studies have been unable to examine whether subscriber-paid rating agencies suffer from conflicts of interest because it is challenging to identify subscribers. We contribute to the literature by empirically identifying plausible EJR subscribers and using this identification to test whether the properties of EJR's ratings vary with the concentration of their subscribers' holdings.

[4] Consistently, many media articles have espoused the benefits of the subscriber-pay model, while heavily criticizing the issuer-pay model (Greenberg, 2002; Morgenson, 2002; Lucchetti, 2008; Worden, 2008; Bernard and Neumann, 2012; Eisinger, 2012; Temple-West, 2020).

[5] The view that issuer-paid credit rating agencies face conflicts of interest not faced by subscriber-paid credit rating agencies is pervasive in the literature. Beyond the studies already discussed, Bai (2010), Milidonis (2013), Xia (2014), Berwart et al. (2019), Bhattacharya et al. (2019), and Lee et al. (2021) emphasize this notion.

[6] The only related evidence is from Tang et al. (2020) using an experimental design with Masters of Accounting students that approximates the subscriber-pay model. The study finds evidence that the subscriber-paid rating agency is likely to assign credit ratings that are biased in favor of its clients' positions.

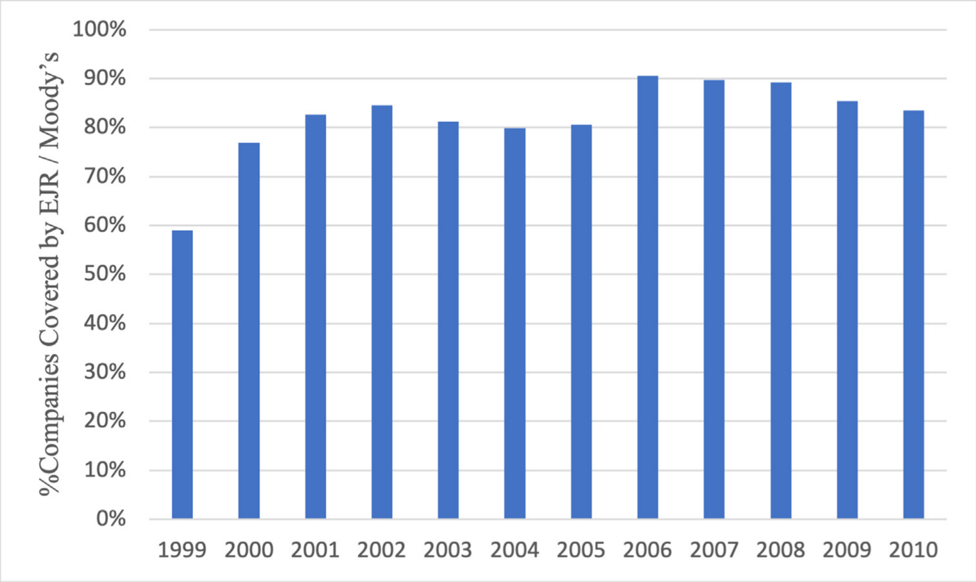


Fig. 1. EJR coverage over the sample period. This figure depicts EJR coverage over the sample period (1999–2010). For each year in the sample (x-axis), the blue bars show the percentage of all companies that are covered by Egan-Jones Ratings Company (EJR) relative to Moody's (y-axis). Specifically, the y-axis measures the market value of equity of all companies that receive an EJR rating in a given year, scaled by the market value of equity of all companies that receive a Moody's rating in the same year. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

3. Data and sample selection

3.1. Identifying EJR clients

We obtain EJR credit ratings data directly from EJR and from the historical ratings made available on its website and aggregated by Data.world. Our sample includes EJR ratings from July 14, 1999 through December 29, 2017.

We empirically identify the institutions that subscribe to EJR by observing those institutions that trade on EJR rating days using data from Ancerno Ltd. Ancerno is a dataset that tracks the institutional trading activity of a large number of institutional investors. Specifically, Ancerno provides detailed equity trade data from 1997 to 2010 and bond trade data from 2004 to 2010. We end our sample period in 2010 because Ancerno masks the names of the institutions executing trades after December 2010.

Prior studies demonstrate that the institutions in the Ancerno database are on average larger than other 13f institutions, but similar with respect to their stock holdings, return characteristics, and trading behavior (e.g., Puckett and Yan, 2011; Anand et al., 2012; Hu et al., 2018; Bhattacharya et al., 2019). Although we cannot observe all trades by all institutions on EJR rating days, we can cleanly identify the trading activity of those institutions covered in the Ancerno database.

We identify the institutions that trade on EJR rating announcements using the manager code name, which aggregates the trading activity of individual funds within one fund family. The benefit of performing the analysis on EJR rating days is that only subscribers have access to real-time dissemination of EJR ratings changes (e.g., Bruno et al., 2016). Therefore, our empirical identification relies on the idea that only those institutions that subscribe to EJR will trade in response to the EJR rating change.

Following Bhattacharya et al. (2019), we identify EJR subscribers as the institutions that have abnormal equity purchases around EJR upgrades and abnormal equity sales around EJR downgrades for the majority of firms in a given quarter. We measure abnormal equity trading activity by comparing each institution's equity trades around EJR rating changes to Moody's rating changes. If an institutional investor trades more in response to rating changes from Moody's compared to EJR, then we exclude this investor from the list of EJR clients.[7]

[7] For each institutional investor, we sum the volume traded on each EJR rating date by firm and scale by monthly lagged market value. We perform the same calculation for Moody's ratings dates. Thus, for each investor-firm pair, we have the total trading volume on EJR rating dates and on Moody's rating dates for each quarter. If the total volume traded on Moody's rating dates exceeds EJR for at least 50 percent of all firms in the investor's portfolio, then we exclude the investor from the list of EJR clients in that quarter.

We use equity trades rather than bond trades to identify EJR subscribers because equity markets are significantly more liquid than the corporate bond market. The availability of daily equity trading data is advantageous given that we identify subscribers using an event-study approach (Bhattacharya et al., 2019). The underlying assumption, however, is that the bonds and stock will generally respond to a given rating change in the same direction, an assumption that is supported by prior literature (e.g., Hand et al., 1992). To further support the validity of this identification method, we find similar results when we identify EJR subscribers using bond trades in Ancerno, as discussed in Section 5.2.

3.2. Identifying EJR client holdings

After identifying the institutions that are likely EJR subscribers in each quarter, we obtain the historical stock holdings of each subscriber on a quarterly basis using Thomson Reuters Institutional (13f) Holdings data. We merge the list of institutions in Ancerno Ltd. to Thomson Reuters by fund manager name and retain firms rated by both EJR and Moody's. We obtain a final sample of 15,986 firm-quarters from 1999 to 2010. Appendix C describes the sample selection process in further detail.

Given that we use equity trades to identify subscribers, we identify the equity holdings of each institution for consistency. In doing so, our analysis assumes that EJR subscribers invest in both the bonds and the stock of the same firm. Collectively, our empirical strategy uses equity trade and equity holdings data to identify those institutions that are likely EJR subscribers and likely invested in the firm's bonds. In Section 5.2, we verify that our results hold using bond trades in Ancerno and bond holdings data in Thomson Reuters eMaxx. Our results are similar.

Our main hypothesis is that EJR is incentivized to provide optimistic ratings when more EJR clients are invested in the firm. To capture this variation in EJR's incentives, we create the variable, *% EJR Clients*, which is equal to the number of EJR clients invested in the firm's stock, scaled by the total number of EJR clients. Thus, *% EJR Clients* captures variation in the relative importance of a given firm to EJR's total client base. We predict that higher values of *% EJR Clients* signal EJR's incentives to cater its ratings and therefore positively predict EJR ratings optimism.

3.3. EJR optimism

We estimate EJR optimism by comparing the EJR rating to two different benchmarks: (1) the concurrent Moody's rating, and (2) the model-implied rating following Baghai et al. (2014).[8] By comparing the EJR rating to a benchmark rating for the same firm in the same quarter, our measure of optimism is a relative measure. Using a benchmark rating from the same firm-quarter helps to alleviate the concern that economic differences across firms drive our results. For example, differences in the economic characteristics of firms with high versus low EJR client holdings are likely to drive differences in ratings levels. Consequently, without a benchmark rating, it is difficult to disentangle ratings bias from more favorable ratings justified by economic fundamentals. By comparing the EJR rating to a benchmark rating for the same firm in the same quarter, we can control for changes in the economic characteristics of each firm over time. Consequently, our measure of ratings bias (or optimism) is unlikely to be explained by confounding effects from changes in firm-specific credit risk, industry trends, or macroeconomic conditions.

3.4. Other data sources

We obtain Moody's ratings from Mergent FISD. Following Bruno et al. (2016), we compare the Moody's ratings on the senior unsecured bonds to the firm-level ratings from EJR within the same firm-quarter. To estimate the model-implied rating (and control variables), we obtain accounting information from Compustat and stock return data from CRSP. We winsorize continuous control variables at the top and bottom one percent sample values. For the additional analyses that incorporate bond returns, we obtain daily bond data from TRACE Enhanced and monthly bond data from WRDS Bond Returns.[9]

3.5. Descriptive statistics

Fig. 1 describes EJR ratings coverage over the sample period. For each year of the sample, Fig. 1 depicts the percentage of companies with public debt that receive an EJR rating in a given year, relative to Moody's. Specifically, the y-axis measures the market value of equity of all companies covered by EJR in a given year, scaled by the market value of equity of all companies covered by Moody's in the same year. From 1999 to 2010, EJR covers 82 percent of the market value of firms that receive a Moody's rating, on average.[10] The findings in Fig. 1 provide evidence that EJR plays an important role in capital markets by providing ratings for the majority of firms with public debt.

[8] Prior literature documents that Moody's is a good substitute for other issuer-paid rating agencies (Beaver et al., 2006; Cornaggia and Cornaggia, 2013; Bruno et al., 2016).

[9] We clean the data in TRACE Enhanced following the algorithm proposed by Dick-Nielsen (2014). This algorithm deletes errors and duplicate agency transactions that are likely to bias common measures of liquidity (Dick-Nielsen, 2009; Asquith et al., 2013; Lewis and Schwert, 2018).

[10] Our findings are similar to the statistics reported in Xia (2014), who finds that, relative to S&P, EJR covers 80 percent of all firm assets in a given industry.

Table 1
Descriptive statistics.

	N	Mean	p25	Median	p75	S.D.
Main Variables						
% EJR Clients	15,986	0.305	0.200	0.286	0.388	0.151
EJR Optimistic	15,986	0.454	0	0	1.000	0.498
Control Variables						
Firm Size	15,986	0.016	0.002	0.005	0.014	0.035
Leverage	15,986	1.234	0.418	0.754	1.359	2.592
MTB	15,986	2.959	1.333	2.090	3.485	4.013
Operating Margin	15,986	0.207	0.104	0.175	0.282	0.177
Std. Dev. Ret.	15,986	0.024	0.014	0.020	0.029	0.016

This table presents the descriptive statistics for the main sample of 15,986 firm-quarter observations. *% EJR Clients* is the number of EJR clients invested in the firm, scaled by the total number of EJR clients. *EJR Optimistic* is an indicator variable equal to one if the EJR rating is higher than the concurrent Moody's rating, and zero otherwise. The definitions of the control variables are provided in Appendix A.

Table 1 describes the main sample of 15,986 firm-quarters from 1999 to 2010. The mean of *% EJR Clients* is 0.305, indicating that 31 percent of all EJR clients are invested in a given firm, on average. *EJR Optimistic* is an indicator variable equal to one if the EJR rating is above the concurrent benchmark rating, and zero otherwise. In Table 1, *EJR Optimistic* is defined using the concurrent Moody's rating as the benchmark, and EJR provides an optimistic rating relative to Moody's in 45.4 percent of the observations.

4. Main results

4.1. EJR optimism

4.1.1. EJR optimism in the ratings distribution

Our main hypothesis is that EJR provides more optimistic ratings for those firms with greater EJR client ownership. Higher ratings allow subscribers to comply with internal and regulatory ratings-based restrictions. The most prominent ratings-based restriction faced by institutional investors is the mandate to invest only in assets that are investment-grade.[11] Thus, we also predict that the pressure to provide an optimistic rating is likely heightened over the investment-grade boundary.

We begin by examining whether EJR provides higher ratings relative to Moody's when more EJR clients are invested in the firm using the following regression specification:

$$EJR\ Optimistic_{iq+1} = \beta_0 + \beta_1\%\ EJR\ Clients_{iq} + \beta_2 IG\ Cutoff_{iq} + \beta_3\%\ EJR\ Clients_{iq} \times IG\ Cutoff_{iq} + \beta'\ X_k + \alpha_i + \theta_q + \varepsilon. \quad (1)$$

The dependent variable, *EJR Optimistic*, is an indicator variable equal to one if the EJR rating is higher than the Moody's rating in the same firm-quarter, and zero otherwise. The independent variable of interest, *% EJR Clients*, is the number of EJR clients invested in the firm's stock, scaled by the total number of EJR clients in that quarter. An indicator variable for the investment-grade boundary, *IG Cutoff*, equals one if the Moody's rating for the firm centers around the investment-grade cutoff, and zero otherwise. We define credit ratings equal to BB or BBB (e.g., between BB- and BBB+) as those near the investment-grade boundary.[12] Eqn. (1) includes control variables following Kedia et al. (2014), in addition to both firm (α_i) and year-quarter (θ_q) fixed effects.

Notably, in Eqn. (1), we estimate *EJR Optimistic* in quarter $q+1$, while we estimate *% EJR Clients* in quarter q. In other words, we estimate the likelihood that EJR provides an optimistic rating in the subsequent quarter ($q+1$) based on the number of EJR clients invested in firm i as of the end of quarter q. In doing so, our analysis tests whether we can predict EJR optimism in the future based on current client holdings. If EJR provides optimistic ratings when more of their clients are invested in the firm, then β_1 will be positive. In addition, if such behavior is more pronounced around the investment-grade threshold, then β_2 will also be positive.

Table 2 presents our first main result. In column (1), we estimate the likelihood that EJR provides a higher rating relative to Moody's. Consistent with our prediction, the coefficient on *% EJR Clients* is positive and significant (coef. = 1.023, t = 9.406). EJR is more likely to provide a higher rating than Moody's when more EJR clients are invested in the firm. Economically, a one

[11] See, for example, Cantor et al. (2007), Kisgen and Strahan (2010), Bongaerts et al. (2012), Cornaggia and Cornaggia (2013), Chen et al. (2014), and Bruno et al. (2016).

[12] Kisgen (2006) and Kisgen and Strahan (2010) use a similar measure.

standard deviation increase in *% EJR Clients* represents a 34 percent increase in *EJR Optimistic* relative to the unconditional mean.[13]

In column (3), we estimate Eqn. (1), which includes the interaction between *IG Cutoff* and *% EJR Clients*. The coefficient on *% EJR Clients* remains positive and significant (coef. = 0.785, $t = 5.44$). Additionally, the coefficient on the interaction term, *% EJR Clients × IG Cutoff*, is positive and significant (coef. = 0.368, $t = 2.11$). These results suggest that EJR is more likely to cater to their subscribers' demands when client ownership is greater and that this catering behavior is amplified around the investment-grade threshold.

The results in Table 2 are consistent with the hypothesis that EJR inflates ratings to beat the investment-grade cutoff. We further investigate the distribution of EJR ratings around the investment-grade boundary to corroborate these findings. Specifically, we expect that there is a difference in the distribution of EJR ratings for firms with high *% EJR Clients* versus low *% EJR Clients* around the investment-grade cutoff.

Consistent with our expectations, Fig. 2 shows that EJR is more likely to give investment-grade ratings to firms with more EJR clients. In Panel (a), the distribution of ratings just above the investment-grade boundary is larger for firms with high *% EJR Clients* than low *% EJR Clients* ($t = 13.80$).[14] Similarly, the distribution of ratings below the investment-grade boundary is smaller for firms with high *% EJR Clients* relative to low *% EJR Clients* ($t = -15.65$). In Panels (b) and (c) of Fig. 2, to account for mechanical correlations between *% EJR Clients* and ratings, we provide corroborating evidence that compares EJR ratings to that of Moody's and the implied model, respectively. In Panel (b), for example, the difference in the ratings distribution for firms with high *% EJR Clients* minus low *% EJR Clients* is greater for EJR than Moody's right above the threshold ($t = 7.81$) and smaller below the threshold ($t = -11.33$).[15] These results suggest that EJR is more likely to inflate ratings when optimism pushes the rating over the investment-grade threshold.[16]

Table 2
EJR optimism relative to Moody's.

	EJR Optimistic$_{iq+1}$	EJR Optimistic$_{iq+1}$	EJR Optimistic$_{iq+1}$
	(1)	(2)	(3)
% EJR Clients	1.023***	0.996***	0.785***
	(9.406)	(9.434)	(5.444)
IG Cutoff			−0.125**
			(−2.159)
% EJR Clients × IG Cutoff			0.368**
			(2.110)
Firm Size		−0.010	−0.006
		(−0.599)	(−0.378)
Leverage		−0.005	−0.004
		(−1.359)	(−1.317)
Operating Margin		0.126***	0.127***
		(3.354)	(3.404)
MTB		0.003	0.003
		(1.145)	(1.135)
Std. Dev. Ret.		−0.617	−0.744
		(−1.218)	(−1.467)
Time FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	15,986	15,986	15,986
R^2	0.470	0.471	0.472

This table describes the likelihood that Egan-Jones (EJR) provides a higher rating than Moody's based on the number of EJR clients invested in the firm. The sample is comprised of 15,986 firm-quarter observations. The dependent variable, *EJR Optimistic*, is an indicator variable equal to 1 if the EJR rating is higher than the Moody's rating in the same firm-quarter, and 0 otherwise. *% EJR Clients* is the number of EJR clients invested in the firm, scaled by the total number of EJR clients. *IG Cutoff* is an indicator variable equal to 1 if the firm's credit rating centers around the investment-grade cutoff, and 0 otherwise. The definitions of the control variables are provided in Appendix A. Each column includes year-quarter and firm fixed effects. T-statistics are presented in parentheses below the coefficient estimates and clustered by firm. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

[13] A one standard deviation increase in *% EJR Clients* is associated with an increase in the likelihood of EJR optimism by 15.3 percentage points, which corresponds to a 34 percent increase relative to the unconditional mean of *EJR Optimistic* of 45.4 percent. After considering the fixed effects that we employ in our model, a within fixed effects standard deviation change in *% EJR Clients* implies a 0.22 within fixed effects standard deviation change in *EJR Optimistic*. See Mummolo and Peterson (2018) and deHaan (2021).

[14] We calculate high and low *% EJR Clients* in Fig. 2 using the sample of firms with ratings around the investment-grade cutoff (i.e., BB- to BBB+). The results are similar using the whole sample to calculate high and low *% EJR Clients*.

[15] The differences between the rating distributions are statistically significant both above and below investment grade in all three panels.

[16] We perform a variety of additional regression analyses that confirm the results in Fig. 2. Specifically, EJR is more likely to assign investment-grade ratings when the firm has more EJR clients, relative to Moody's. Similarly, the likelihood that EJR provides an investment-grade rating while Moody's provides a below investment-grade rating increases when the firm has more EJR clients.

4.1.2. EJR optimism and client size

We next explore variation in the likelihood that EJR provides an optimistic rating based on the number and size of EJR clients invested in the firm. To facilitate comparison, we include the baseline model of *EJR Optimistic* as a function of *% EJR Clients* in column (1) of Table 3 with standardized coefficients. In column (2), we test whether our findings vary by client size because EJR charges a variable subscription fee that is increasing in client size (Xia, 2014; Bruno et al., 2016). Consequently, we expect the likelihood of EJR optimism to increase when the EJR clients invested in the firm are larger.

To test this prediction, we sort EJR clients into size terciles (large, medium, small) based on the total stock holdings of each client in a given quarter. Consistent with our prediction, EJR is more likely to provide an optimistic rating when the clients invested in the firm are larger. In column (2) of Table 3, the coefficients on all three measures of *% EJR Clients* are positive and significant. Importantly, the magnitude of the coefficients on *% EJR Clients* for the large and medium holdings groups are statistically larger than that for the small holdings group. These results support the intuition that optimism is correlated with the magnitude of the potential benefit, as EJR is more likely to provide optimistic ratings for those clients that pay higher fees.

4.1.3. EJR optimism relative to model-implied rating

Our second set of results defines EJR optimism relative to a ratings model. Specifically, we compare the EJR rating to the model-implied rating in the same firm-quarter using the credit rating prediction model from Baghai et al. (2014).[17] Correspondingly, we now define *EJR Optimistic* as an indicator variable equal to one if the EJR rating is more optimistic than the concurrent model-implied rating, and zero otherwise.

Table 4 reports results using the model-based ratings benchmark that are similar to those discussed above using Moody's ratings as the benchmark (in Table 3). In column (1) of Table 4, EJR is more likely to provide an optimistic rating (relative to the model-implied rating) when more EJR clients are invested in the firm (coef. $= 0.073$, $t = 4.93$). A standard deviation increase in *% EJR Clients* is associated with an increase in the likelihood of EJR optimism by 7.3 percentage points, which represents a 13 percent increase in *EJR Optimistic* relative to the unconditional mean.[18] In column (2), we augment the model to include the interaction term *% EJR Clients* $\times$ *IG Cutoff*. Similar to the findings in Table 2, we find that greater EJR client ownership is associated with optimistic EJR ratings, and incrementally so near the investment-grade boundary. In column (3), we re-estimate our client size tests and, similar to Table 3, find that greater EJR client ownership by larger clients has a larger effect than greater EJR client ownership by smaller clients. These results mitigate concerns that our results are driven by the choice of Moody's ratings as a comparison benchmark.

In columns (4) through (6) of Table 4, we perform a series of falsification tests using Moody's ratings. In these three columns, the dependent variable, *Moody's Optimistic*, is an indicator variable equal to one if the *Moody's* rating is more optimistic than the model-implied rating for the same firm-quarter, and zero otherwise. In these columns, we use Moody's ratings to estimate the model in Baghai et al. (2014). Overall, we do not find evidence that Moody's provides optimistic ratings for those firms with higher EJR client ownership.

4.1.4. Regulated vs. unregulated institutions

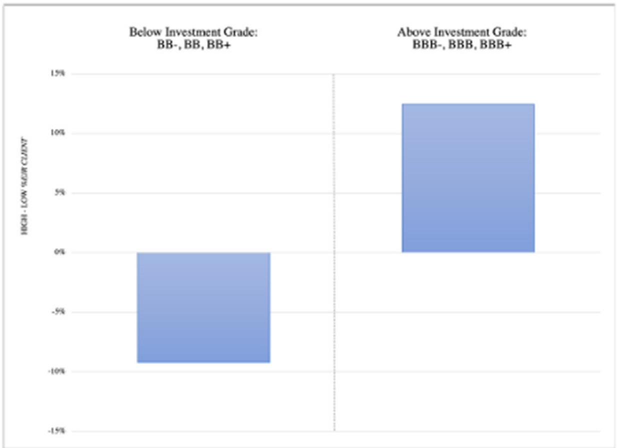
In cross-sectional analyses, we expect greater EJR client ownership by institutional investors that serve more regulated investors (e.g., pension funds, banks, insurance companies) to have a larger magnitude effect on EJR optimism than institutions that do not serve regulated investors. This prediction is based on the idea that the incentives for catering under the subscriber-pay model should be the strongest among funds that face more ratings-based investment mandates or capital requirements, which are more common for regulated institutions. Subscriber-paid ratings can facilitate regulatory arbitrage performed by their clients, whereby riskier, and hence higher yield, securities can be held by their clients but still satisfy regulatory requirements. Theoretical work by Opp et al. (2013) shows that issuer-paid rating agencies also face incentives to inflate ratings in the presence of rating-contingent regulation that favors highly rated securities.

To examine the potential differential effect of regulated versus unregulated investors, we begin by identifying whether EJR clients invest on behalf of any regulated institutions. We manually search each EJR client's website and read its description of the type of clients that it serves. If there was not any information available about its client base on the website, we search for client information in the fund's 10-K (if available). We classify EJR clients as regulated if their client description includes any of the following: (1) retirement plans (ERISA plans, defined benefit plans, defined contribution plans, pension funds, multi-employer benefit plans, Taft-Hartley plans, 401K plans); (2) insurance companies; and/or (3) financial institutions. In addition, if an EJR client itself is a financial institution (bank) then we classify it as regulated.[19] We use these classifications to break down our main variable *% EJR Clients* into the portion driven by regulated clients, denoted *% EJR Clients Regulated*, and the portion driven by unregulated clients, denoted *% EJR Clients Unregulated*.

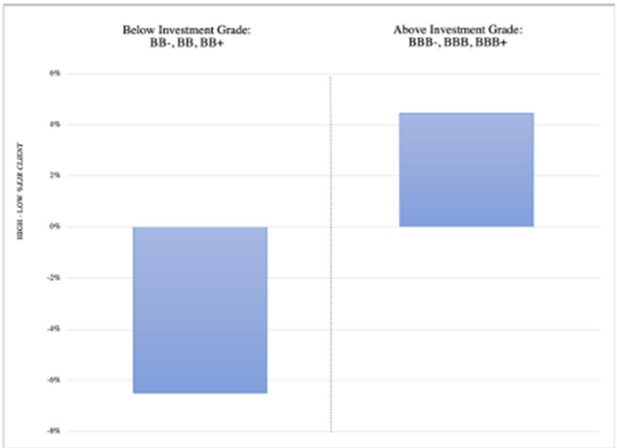
[17] We estimate the predicted EJR rating by estimating the model with industry fixed effects (model (3) in Baghai et al. (2014) Table III, Panel A) within our full sample of EJR ratings. In untabulated analyses, we find similar results using the model with firm fixed effects (model (6) of Table III, Panel A in Baghai et al. (2014)).

[18] The unconditional mean of *EJR Optimistic* as defined in Table 4 is 55.2% (*untabulated*). After considering the fixed effects that we employ in our model, a within fixed effects standard deviation change in *% EJR Clients* implies a 0.16 within fixed effects standard deviation change in *EJR Optimistic*.

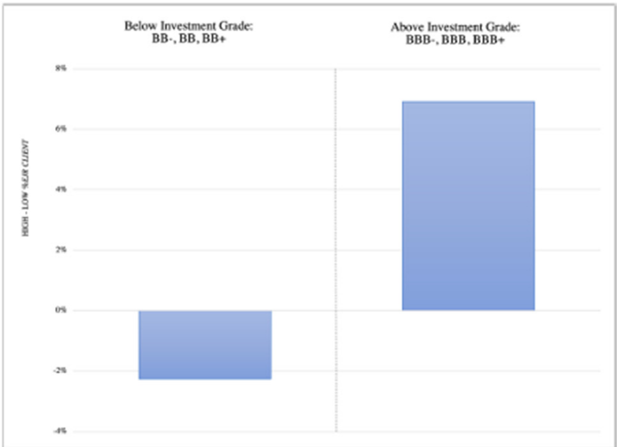
[19] To classify EJR clients as regulated versus unregulated, we rely on institutional investors' disclosure of their client base on their websites and/or 10-K forms. It is possible that some EJR clients serve regulated clients but do not disclose this information, which implies that some regulated EJR clients are incorrectly classified as unregulated. In this case, the estimates on *% EJR Clients Unregulated* in Table 5 may be overstated.



(a) EJR



(b) EJR relative to Moody's



(c) EJR relative to Implied Model

Fig. 2. EJR ratings around the investment-grade cutoff. These figures estimate the differences in the distributions of EJR ratings for firms with high *% EJR Clients* versus low *% EJR Clients* around the investment-grade cutoff. The distribution of EJR ratings is calculated as the percentage of all EJR ratings within each ratings category. To estimate the difference around the investment-grade cutoff, we subtract the distribution for high *% EJR Client* firms minus low *% EJR Client* firms. High (low) *% EJR Clients* is defined as firms above (below) the median in EJR client holdings. The x-axis groups ratings into below investment grade (BB-, BB, BB+) and above investment grade (BBB-, BBB, BBB+). The y-axis plots the difference in the EJR ratings distribution for high *% EJR Client* firms less low *% EJR Client* firms. Panel (a) provides the results for EJR ratings. Panels (b) and (c) compare EJR to Moody's and the implied model, respectively.

In column (1) of Table 5, we estimate an augmented version of column (1) in Table 2 with both *% EJR Clients Regulated* and *% EJR Clients Unregulated*. The results show that our main findings are stronger for regulated clients. Specifically, EJR optimism increases with both *% EJR Clients Regulated* and *% EJR Clients Unregulated*, but the former has a larger effect based on a formal test of the difference in these coefficients ($p = 0.01$). The fact that we also see a smaller but still significantly positive effect for *% EJR Clients Unregulated* is consistent with mutual funds still benefiting from ratings inflation because it allows them to potentially invest in higher yield assets. Additionally, prior research shows that investors are highly sensitive to fund yield rates, which creates an incentive for funds to invest in higher yield assets while relying on inflated ratings.

4.2. Timeliness of EJR downgrades

4.2.1. Persistence of EJR optimism

We next examine whether EJR provides less timely downgrades for firms with greater EJR client ownership. To do so, we plot the regression coefficients on *% EJR Clients* and their 95% confidence intervals for the 10 quarters subsequent to quarter *t* in Fig. 3. Overall, optimism gradually fades over time but remains statistically significant for approximately seven quarters.

Table 3
EJR optimism as a function of EJR client size.

	EJR Optimistic$_{iq+1}$	EJR Optimistic$_{iq+1}$
	(1)	(2)
% EJR Clients	0.153***	
	(9.434)	
% EJR Clients: Large		0.070***
		(4.821)
% EJR Clients: Medium		0.090***
		(6.179)
% EJR Clients: Small		0.024***
		(3.695)
Firm Size	−0.016	−0.002
	(-0.599)	(-0.091)
Leverage	−0.012	−0.012
	(-1.359)	(-1.411)
Operating Margin	0.023***	0.024***
	(3.354)	(3.500)
MTB	0.013	0.013
	(1.145)	(1.140)
Std. Dev. Ret.	−0.010	−0.011
	(-1.218)	(-1.354)
Prob > F: *%EJR (Large) > %EJR (Small)*		0.00***
Prob > F: *%EJR (Med) > %EJR (Small)*		0.00***
Prob > F: *%EJR (Large) > %EJR (Med)*		0.21
Time FE	Yes	Yes
Firm FE	Yes	Yes
R^2	0.471	0.473
Observations	15,986	15,986

This table describes the likelihood that Egan-Jones (EJR) provides an optimistic rating (relative to Moody's) based on the number and size of EJR clients invested in the firm. The sample is comprised of 15,986 firm-quarter observations. The dependent variable, *EJR Optimistic*, is an indicator variable equal to 1 if the EJR rating is higher than the Moody's rating in the same firm-quarter, and 0 otherwise. In column (1), *% EJR Clients* is the number of EJR clients invested in the firm, scaled by the total number of EJR clients. In column (2), *% EJR Clients* is broken into terciles by client size. Specifically, *% EJR Clients*: *Large (Medium, Small)* is defined as the number of large (medium, small) EJR clients invested in the firm, scaled by the total number of EJR clients. All of the continuous variables have been rescaled to a mean of zero and a standard deviation of one to facilitate comparison. The definitions of the control variables are provided in Appendix A. All columns include year-quarter and firm fixed effects. T-statistics are presented in parentheses below the coefficient estimates and clustered by firm. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

In Panel A of Table 6, we confirm that our baseline findings in column (1) of Table 2 hold for the sample of firms that survive until the reversal of the EJR optimism in quarter $q + 8$, indicating that the pattern in Fig. 3 is unlikely driven by sample attrition. We continue to find a significant positive association between *% EJR Clients* and *EJR Optimistic* within this subsample (coef. = 1.124, $t = 8.82$). In Panel B of Table 6, we provide evidence that the gradual decline in EJR optimism shown in Fig. 3 appears to be driven by EJR downgrades rather than by Moody's upgrades. The coefficient estimates for *EJR Optimistic* are positive and statistically significant for all eight quarters together (columns (1,4)), for the first four quarters (columns (2,5)), and last four quarters (columns (3,6)). These results suggest that EJR optimism at quarter q leads to an increase in the probability of an EJR downgrade in quarters $q + 1$ through $q + 8$. Overall, the findings in Table 6 regarding the persistence of EJR optimism imply that EJR downgrades are systematically less timely when EJR client ownership is greater.

4.2.2. Bond market reaction to EJR downgrades

We further test our prediction that EJR issues less timely downgrades for firms with greater EJR client ownership by examining the bond market reaction to rating downgrades. If EJR is slower to downgrade, then we expect the market reaction to EJR downgrades to be smaller in absolute value (i.e., the returns will be less negative). The intuition behind this event-study approach is that less timely rating changes are less informative to the market. As time passes, more negative information is impounded into bond prices from other sources, and this leads to a decline in the new information provided to market participants from the rating change.

Using a sample of bond market returns surrounding 4,501 EJR rating downgrades, we estimate the following linear regression model specified in Eqn. (2) below:

$$Bond\ Return_{it} = \beta_0 + \beta_1\%\ EJR\ Clients_{iq} + \beta_2 EJR\ Down_{it} + \beta_3\%\ EJR\ Clients_{iq} \times EJR\ Down_{it} + \beta' X_k + \alpha_i + \theta_q + \varepsilon. \quad (2)$$

The dependent variable, *Bond Return*, is the bond market response to a given rating change, calculated as the firm-level median bond market return from day $(t - 3)$ to day $(t + 3)$, centered on rating change date $(t = 0)$. *EJR Down* is an indicator variable equal to one when EJR issues a downgrade, and zero otherwise. The interaction term, *% EJR Clients* × *EJR Down*,

Table 4
EJR optimism using the model-implied rating as a benchmark.

	EJR Optimistic$_{iq+1}$	EJR Optimistic$_{iq+1}$	EJR Optimistic$_{iq+1}$	Moody's Optimistic$_{iq+1}$	Moody's Optimistic$_{iq+1}$	Moody's Optimistic$_{iq+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
% EJR Clients	0.073***	0.028		0.013	−0.009	
	(4.929)	(1.174)		(0.964)	(-0.449)	
IG Cutoff		0.041			0.063**	
		(1.392)			(2.270)	
% EJR Clients × IG Cutoff		0.070***			0.034	
		(2.720)			(1.534)	
% EJR Clients: Large			0.055***			−0.007
			(4.324)			(-0.613)
% EJR Clients: Medium			0.018			0.009
			(1.311)			(0.767)
% EJR Clients: Small			0.001			−0.002
			(0.144)			(-0.322)
Firm Size	0.146***	0.152***	0.155***	0.101***	0.106***	0.106***
	(5.503)	(5.961)	(5.780)	(4.089)	(4.383)	(4.275)
Leverage	−0.037***	−0.037***	−0.038***	−0.023***	−0.023***	−0.023***
	(-4.091)	(-4.074)	(-4.161)	(-2.977)	(-2.927)	(-2.990)
Operating Margin	0.013**	0.014**	0.014**	0.006	0.006	0.006
	(2.009)	(2.198)	(2.057)	(0.952)	(0.970)	(1.018)
MTB	0.021**	0.020**	0.023**	0.015*	0.014*	0.015*
	(2.444)	(2.338)	(2.556)	(1.873)	(1.783)	(1.896)
Std. Dev. Ret.	−0.034***	−0.034***	−0.034***	−0.029***	−0.029***	−0.029***
	(-4.299)	(-4.387)	(-4.432)	(-4.668)	(-4.680)	(-4.727)
Prob > F: *%EJR (Large) > %EJR (Small)*			0.00***			0.77
Prob > F: *%EJR (Large) > %EJR (Med)*			0.09*			0.50
Prob > F: *%EJR (Med) > %EJR (Small)*			0.10*			0.25
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.592	0.594	0.592	0.697	0.698	0.697
Observations	15,094	15,094	15,094	15,094	15,094	15,094

This table describes the likelihood that Egan-Jones (EJR) provides an optimistic rating (relative to the model-implied rating) based on the number and size of EJR clients invested in the firm. The sample is comprised of 15,094 firm-quarter observations. The dependent variable in columns (1)–(3), *EJR Optimistic*, is an indicator variable equal to one if the EJR rating is higher than the model-implied rating in the same firm-quarter, and zero otherwise. The model-implied rating is calculated using the credit risk model in Baghai et al. (2014). The dependent variable in columns (4)–(6), *Moody's Optimistic*, is an indicator variable equal to one if the Moody's rating is higher than the model-implied rating in the same firm-quarter, and zero otherwise. *% EJR Clients* is the number of EJR clients invested in the firm, scaled by the total number of EJR clients. *IG Cutoff* is an indicator variable equal to 1 if the firm's credit rating centers around the investment-grade cutoff, and 0 otherwise. In columns (3) and (6), *% EJR Clients* is broken into terciles by client size. Specifically, *% EJR Clients*: *Large (Medium, Small)* is defined as the number of large (medium, small) EJR clients invested in the firm, scaled by the total number of EJR clients. All continuous variables have been rescaled to a mean of zero and a standard deviation of one to facilitate comparison. The definitions of the control variables are provided in Appendix A. All columns include year-quarter and firm fixed effects. T-statistics are presented in parentheses below the coefficient estimates and clustered by firm. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

captures the moderation of the bond return to ratings downgrades for firms with higher levels of EJR client ownership. If EJR is slower to downgrade bonds with greater EJR client ownership, then the market reaction to downgrades for these firms will be less negative (i.e., smaller in absolute value), and β_3 will be positive.

Panel A of Table 7 presents the results. In column (1), the coefficient on *EJR Down* is negative (coef. $= -0.016$, $t = -3.70$), indicating that bond prices decline in response to EJR rating downgrades on average. Consistent with our prediction, the coefficient on *% EJR Clients* × *EJR Down* is positive and significant (coef. $= 0.026$, $t = 2.31$). Thus, these results are consistent with bond market investors seeing through the predictable bias in EJR ratings, which leads to a weaker response when the delayed downgrade of the inflated rating occurs.

In columns (2) and (3), we report results from estimating Eqn. (2) using samples where EJR was optimistic and where it was not, respectively. We find that the positive interaction effect between *% EJR Clients* and *EJR Down* is concentrated in cases when EJR ratings are optimistic relative to Moody's (column (2)). By contrast, we predictably find no significant interaction effect in cases when EJR is not optimistic relative to Moody's (column (3)).

Panel A of Table 7 also shows the results from a falsification test using EJR upgrades. Since EJR does not appear to engage in rating deflation, the information content of EJR upgrades should not vary systematically with the number of EJR clients. Consistent with this intuition, we find no significant interaction effect between *% EJR Clients* and *EJR Up* for EJR upgrades (column (4)).

In Panel B of Table 7, we examine whether the market response to Moody's rating changes is a function of the number of EJR clients invested in the firm. Because we expect market participants to rationally see through biases in EJR ratings, we expect the market reaction to Moody's rating changes to be independent of *% EJR Clients*. Accordingly, we fail to find evidence that the market response to Moody's rating changes varies with *% EJR Clients*.

Table 5
EJR optimism for regulated vs. unregulated clients.

	EJR Optimistic$_{iq+1}$	EJR Optimistic$_{iq+1}$
	(1)	(2)
% EJR Clients Regulated	0.098***	0.096***
	(6.293)	(6.292)
% EJR Clients Unregulated	0.066***	0.064***
	(4.724)	(4.504)
Firm Size		−0.015
		(-0.580)
Leverage		−0.012
		(-1.378)
Operating Margin		0.023***
		(3.351)
MTB		0.013
		(1.162)
Std. Dev. Ret.		−0.010
		(-1.217)
Prob > F: *%EJR Clients Reg. > Unreg.*	0.01***	0.00***
Time FE	Yes	Yes
Firm FE	Yes	Yes
R^2	0.470	0.471
Observations	15,986	15,986

This table examines the potential differential effect of regulated versus unregulated investors on EJR optimism. In this test, *% EJR Clients* is broken into the portion driven by regulated clients (*% EJR Clients Regulated*) and unregulated clients (*% EJR Clients Unregulated*). *EJR Optimistic* is an indicator variable equal to one if the EJR rating is higher than the Moody's rating in the same firm-quarter, and zero otherwise. All continuous variables have been rescaled to a mean of zero and a standard deviation of one to facilitate comparison. The definitions of the control variables are provided in Appendix A. All columns include year-quarter and firm fixed effects. T-statistics are presented in parentheses below the coefficient estimates and clustered by firm. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

4.3. *EJR ratings accuracy*

To corroborate our main inferences, we examine the accuracy of EJR ratings for firms with greater EJR client ownership. Thus far, we provide evidence that EJR issues more optimistic ratings and less timely downgrades for firms with greater EJR client ownership. These results imply that when EJR provides higher ratings for firms with greater EJR client ownership, these ratings are less accurate. We test this prediction more directly by examining whether the relation between EJR ratings levels and subsequent firm performance (or credit risk) is attenuated when EJR issues higher ratings for firms with greater EJR client ownership. To do so, we estimate the following linear regression model in Eqn. (3) below:

$$Firm\ Performance_{it+1} = \beta_0 + \beta_1 EJR\ Rating_{iq} + \beta_2 \%\ EJR\ Clients_{iq} + \beta_3 EJR\ Rating_{iq} \times \%\ EJR\ Clients_{iq} + \beta' X_k + \alpha_i + \theta_q + \varepsilon. \quad (3)$$

The dependent variable, *Firm Performance*, is one of three measures of future firm performance: (i) $Default_{iy+3}$, (ii) $Bond\ Return_{im+3}$, and (iii) $BSMProb_{iy+1}$. $Default_{iy+3}$ is an indicator variable equal to one if firm *i* defaults in the subsequent three years, and zero otherwise. $Bond\ Return_{m+3}$ is the firm-level average cumulative bond market return for firm *i* over the following three months.[20] $BSMProb_{iy+1}$ is the probability of bankruptcy implied by the Black-Scholes-Merton model in the following year.

The interaction term, *EJR Rating* × *% EJR Clients*, captures the moderation in the association between EJR ratings levels and subsequent firm performance when EJR issues higher ratings for firms with greater EJR client ownership. If the optimistic ratings issued by EJR for firms with higher EJR client ownership are less accurate, then these ratings will be positively associated with the likelihood of future default, future bond returns, and future bankruptcy risk ($\beta_3 > 0$).

We report the results from our analysis of ratings accuracy in Panels A through C of Table 8. In Panel A of Table 8, consistent with our predictions, the coefficient on the interaction term, *EJR Rating* × *% EJR Clients*, is positive in column (1) (coef. = 0.021, $t = 2.17$). Further, the coefficient on *EJR Rating* is negative (coef. = −0.009, $t = 2.21$). Importantly, when we use a subsample of observations for which EJR is optimistic relative to Moody's, we continue to find that the coefficient on *EJR Rating* × *% EJR Clients* is positive and statistically significant (column (2)). We, however, fail to find this result when EJR is not optimistic relative to Moody's (column (3)). Overall, the results in Panel A of Table 8 show that greater EJR client ownership leads to not only optimistic but also less accurate credit ratings from EJR.

[20] For the estimation of bond returns, we retain only those bonds with at least two months of bond return data available. Our results are similar using a variety of other similar data requirements.

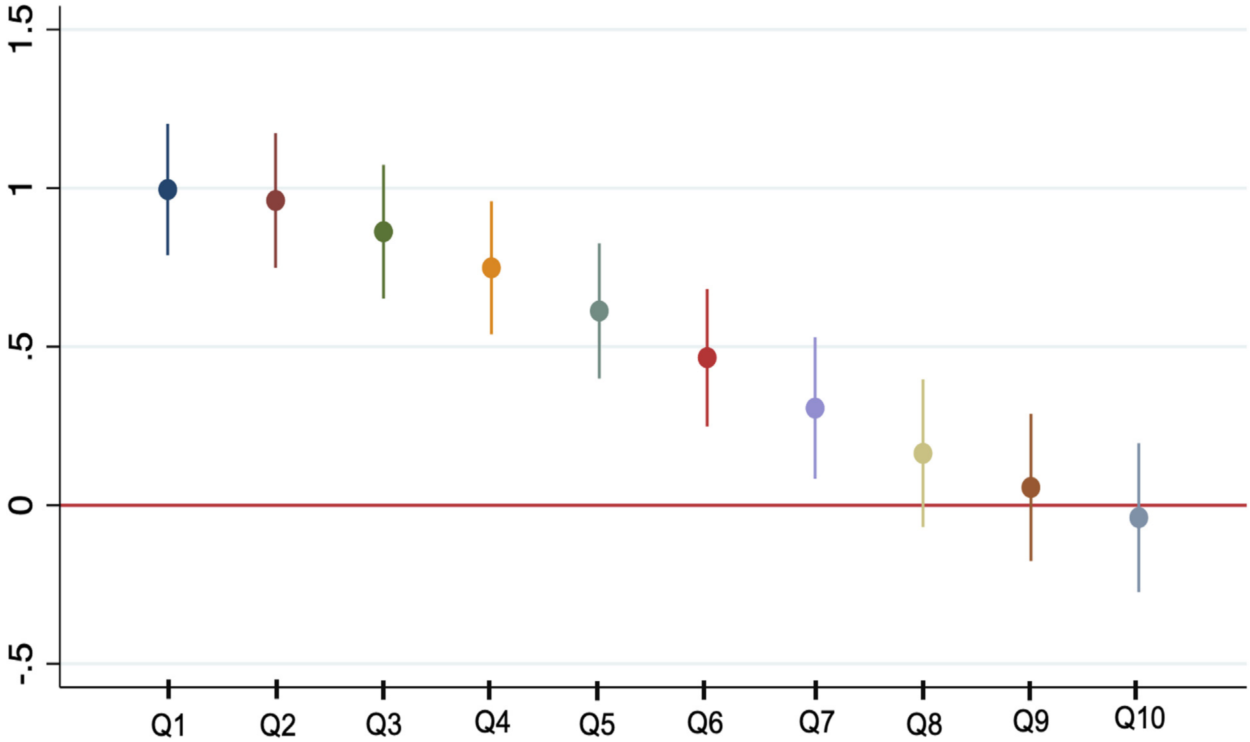


Fig. 3. EJR optimism over time. This figure depicts the persistence of EJR optimism over time. *EJR Optimism* is an indicator variable equal to 1 if the EJR rating is above the concurrent Moody's rating, and 0 otherwise. The x-axis provides the list of future quarters (Q1 - Q10). The dots (lines) are the estimated coefficients (95% confidence intervals) on *% EJR Clients* in the regression model shown in Table 2, column (2) for each subsequent quarter.

Panel B of Table 8 examines the link between EJR ratings and subsequent bond returns. The coefficient on the interaction term, *EJR Rating* × *% EJR Clients*, is positive in the full sample in column (1) and when restricted to observations for which EJR is optimistic relative to Moody's in column (2). This result is consistent with the notion that EJR's ratings optimism for firms with greater client ownership reduces their ability to predict future bond market performance. Finally, in Panel C of Table 8, we examine accuracy using ratings' ability to predict future bankruptcy risk as implied by the Black-Scholes-Merton model. Similar to Panel A, we find evidence that EJR ratings are negatively associated with future bankruptcy risk for the lower EJR client ownership firms, but this association is weaker for higher EJR client ownership firms.

5. Additional analyses

5.1. Correlated omitted unobservable variables

In this section, we examine the extent to which the main results reported in Table 2 (column (1)) could be driven by correlated omitted unobservable variables. Following Oster (2019), we calculate the δ statistic to examine the extent to which omitted variables could influence our estimates. This methodology has been recently adopted in the accounting literature (Cao et al., 2021; Ma et al., 2021; Scherf, 2021) and is based on the premise that the amount of selection between the treatment and the observed set of controls can be informative of the degree of selection on unobservables. Thus, this methodology provides a way to bound the magnitude of potential omitted variables bias in OLS estimates (Altonji et al., 2005).

In Table 9, we report the δ statistic, calculated as the ratio of the selection of unobservables to the selection of observables that would make our main result (the coefficient on *% EJR Clients* in column (1) of Table 2) equal to zero. A negative ratio of the selection of unobservables to the selection of observables (δ) indicates that the main coefficient of interest increases in magnitude when more controls are included in the regressions (e.g., Graham et al., 2017; Glewwe et al., 2018; Cao et al., 2021; Scherf, 2021). Our results are consistent with this expectation. We find a negative δ equal to −1.06 after running the regression without controls in Table 2, column (1), and a larger negative δ equal to −2.25 after adding controls in Table 2, column (1). Taken together, these negative statistics support the interpretation that our results are unlikely to be driven by omitted variables bias.

Table 6
The persistence of EJR optimism.

Panel A: Main Results within the Restricted Sample

	EJR $Optimistic_{iq+1}$	EJR $Optimistic_{iq+1}$
	(1)	(2)
% EJR Clients	1.124***	1.126***
	(8.820)	(9.118)
Firm Size		−0.021
		(−1.006)
Leverage		−0.005
		(−1.242)
Operating Margin		0.125***
		(2.940)
MTB		0.003
		(0.904)
Std. Dev. Ret.		−0.873
		(−1.533)
Time FE	Yes	Yes
Firm FE	Yes	Yes
R^2	0.497	0.498
Observations	11,564	11,564

Panel B: The Reversal of EJR Optimism

	Future EJR Downgrade (1)			Future EJR Downgrade (2)		
	Q1-Q8	Q1-Q4	Q5-Q8	Q1-Q8	Q1-Q4	Q5-Q8
	(1)	(2)	(3)	(4)	(5)	(6)
EJR Optimistic	0.131***	0.089***	0.067***	0.070***	0.010	0.057***
	(7.627)	(5.772)	(5.662)	(2.814)	(0.508)	(3.217)
Firm Size	0.121***	0.109***	0.071***	0.170***	0.145***	0.118***
	(6.323)	(6.529)	(6.166)	(5.611)	(6.032)	(6.314)
Leverage	−0.005	−0.003	−0.003	−0.010	−0.007	−0.010*
	(−1.128)	(−0.938)	(−1.044)	(−1.453)	(−1.188)	(−1.848)
Operating Margin	−0.033	−0.046	0.026	0.018	−0.065	0.117***
	(−0.730)	(−1.058)	(1.009)	(0.313)	(−1.182)	(3.106)
MTB	0.001	0.000	0.001	−0.000	−0.000	0.002
	(0.196)	(0.100)	(0.378)	(−0.047)	(−0.128)	(0.473)
Std. Dev. Ret.	−0.511	−0.043	−0.972***	−1.431*	−0.546	−1.623***
	(−0.960)	(−0.094)	(−2.648)	(−1.954)	(−0.876)	(−2.948)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.314	0.223	0.186	0.309	0.204	0.194
Observations	15,986	15,986	15,986	15,986	15,986	15,986

This table examines EJR optimism over time. Panel A examines whether the baseline results in Table 2 hold for the sample of firms that survive until the reversal of EJR optimism in quarter $q+8$. *EJR Optimistic* is an indicator variable equal to one if the EJR rating is higher than the Moody's rating in the same firm-quarter, and zero otherwise. Panel B examines whether the decline in EJR optimism shown in Fig. 3 is driven by EJR downgrades or Moody's upgrades. In columns (1)–(3), *Future EJR Downgrade (1)* is an indicator variable equal to 1 if there is an EJR downgrade during the period, and 0 otherwise. In columns (4)–(6), *Future EJR Downgrade (2)* is equal to 1 if there is an EJR downgrade during the period, equal to −1 if there is a Moody's upgrade during the period, and 0 otherwise (including affirmations). The definitions of the control variables are provided in Appendix A. All columns include year-quarter and firm fixed effects. T-statistics are presented in parentheses below the coefficient estimates and clustered by firm. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

5.2. *EJR client identification*

In this section, we examine the sensitivity of our results to our empirical estimation of EJR clients. In our main analysis, we identify EJR clients as institutional investors that execute equity trades on EJR rating change announcement dates following Bhattacharya et al. (2019). We adjust our main approach by identifying EJR clients using bond trades, rather than equity trades. Again using data from Ancerno Ltd., we define EJR clients as those institutional investors that trade in the rated firm's *bonds* on the date of an EJR rating change. After gathering the list of EJR subscribers, we obtain the historical bonds holdings of each institution on a quarterly basis from Thomson Reuters eMaxx. We replicate our main analysis from Table 2 and find similar results (*untabulated*), mitigating concerns that our findings are sensitive to how we identify EJR clients. These results support the validity of our main inferences and the assumption that funds tend to specialize in particular firms by holding both their equity and debt.

Table 7
Timeliness of EJR and Moody's downgrades.

Panel A: Timeliness of EJR Downgrades

	Full Sample	EJR Optimistic	EJR Not Optimistic	EJR Upgrade
	Bond Return$_{-3,+3}$	Bond Return$_{-3,+3}$	Bond Return$_{-3,+3}$	Bond Return$_{-3,+3}$
	(1)	(2)	(3)	(4)
% EJR Clients	−0.032***	−0.020	−0.048**	−0.012*
	(−2.647)	(−1.452)	(−2.396)	(−1.763)
EJR Down	−0.016***	−0.018***	−0.017**	
	(−3.697)	(−3.075)	(−2.102)	
% EJR Clients × EJR Down	0.026**	0.031**	0.025	
	(2.305)	(2.211)	(1.331)	
EJR Up				0.004
				(1.599)
% EJR Clients × EJR Up			−0.006	
				(−1.116)
Firm Size	0.006**	0.004	0.012**	0.001
	(1.970)	(1.079)	(2.082)	(0.737)
Leverage	0.000	−0.000	0.001	−0.000
	(1.006)	(−0.634)	(1.370)	(−0.044)
Operating Margin	0.015	0.035	−0.004	0.005
	(0.890)	(1.533)	(−0.126)	(0.606)
MTB	−0.000	0.000	−0.001	0.000
	(−0.669)	(1.377)	(−1.049)	(0.022)
Std. Dev. Ret.	−0.338***	−0.195**	−0.474**	−0.039
	(−2.672)	(−2.254)	(−2.279)	(−0.560)
Time FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
R^2	0.141	0.069	0.196	0.059
Observations	4,501	2,355	2,069	4,664

Panel B: Timeliness of Moody's Downgrades

	Moody's Downgrade	Moody's Upgrade
	Bond Return$_{-3,+3}$	Bond Return$_{-3,+3}$
	(1)	(2)
% EJR Clients	−0.022	0.008
	(−0.734)	(1.115)
MD Down	−0.010**	
	(−1.990)	
% EJR Clients × MD Down	0.013	
	(0.720)	
MD Up		0.003
		(1.582)
% EJR Clients × MD Up		0.006
		(1.140)
Firm Size	0.010	0.002
	(1.447)	(0.940)
Leverage	−0.000	0.000
	(−0.036)	(0.875)
Operating Margin	−0.052	0.002
	(−1.221)	(0.238)
MTB	−0.001	−0.000
	(−0.555)	(−1.283)
Std. Dev. Ret.	0.009	0.016
	(0.026)	(0.155)
Time FE	Yes	Yes
Firm FE	Yes	Yes
R^2	0.244	0.018
Observations	1,057	894

This table examines the timeliness of EJR and Moody's downgrades as a function of EJR client ownership. Panel A examines variation in the bond market reaction to EJR downgrades based on EJR client ownership. The sample is comprised of 4,501 EJR rating change observations. *Bond Return* is the firm-level median bond market return over days *[t-3, t+3]*, centered on rating date *t=0*. *% EJR Clients* is the number of EJR clients invested in the firm, scaled by the total number of EJR clients. *EJR Down* is an indicator variable equal to 1 if the rating change is an EJR downgrade, and 0 otherwise. Column (1) presents the results for the full sample. Column (2) presents the results for the sample of EJR ratings that are optimistic relative to Moody's, and column (3) presents the results for EJR ratings that are not optimistic. Column (4) presents the results for EJR upgrades. *EJR Up* is an indicator variable equal to 1 if the rating change is an EJR upgrade, and 0 otherwise. Panel B repeats the analysis for Moody's rating changes. *MD Down (Up)* is an indicator variable equal to 1 if the rating change is a Moody's downgrade (upgrade), and 0 otherwise. The definitions of the control variables are provided in Appendix A. All columns include year-quarter and firm fixed effects. T-statistics are presented in parentheses below the coefficient estimates and clustered by firm. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8
The accuracy of EJR ratings.

Panel A: Default

	Full Sample	EJR Optimistic	EJR Not Optimistic
	$Default_{iy+3}$	$Default_{iy+3}$	$Default_{iy+3}$
	(1)	(2)	(3)
EJR Rating	−0.009**	−0.018**	−0.004
	(−2.206)	(−2.180)	(−1.042)
% EJR Clients	−0.297**	−0.485**	−0.171
	(−2.320)	(−2.137)	(−1.375)
EJR Rating × % EJR Clients	0.021**	0.036**	0.012
	(2.172)	(2.076)	(1.251)
Firm Size	0.003	0.005*	0.002
	(0.997)	(1.765)	(0.512)
Leverage	−0.001	−0.001	−0.001
	(−1.223)	(−0.786)	(−1.279)
Operating Margin	−0.006	−0.002	0.005
	(−0.716)	(−0.292)	(1.210)
MTB	0.000	0.001	0.000
	(1.212)	(1.210)	(1.173)
Std. Dev. Ret.	0.138	0.015	0.322*
	(1.463)	(0.290)	(1.784)
Time FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
R^2	0.746	0.773	0.775
Observations	15,986	7,347	8,509

Panel B: Future Bond Returns

	Full Sample	EJR Optimistic	EJR Not Optimistic
	$Bond\ Return_{im+3}$	$Bond\ Return_{im+3}$	$Bond\ Return_{im+3}$
	(1)	(2)	(3)
EJR Rating	−0.008***	−0.010***	−0.005**
	(−5.631)	(−3.340)	(−2.394)
% EJR Clients	−0.184***	−0.154*	−0.116
	(−3.721)	(−1.752)	(−1.493)
EJR Rating × % EJR Clients	0.013***	0.013*	0.009
	(3.745)	(1.962)	(1.590)
Firm Size	0.001	−0.009	0.003
	(0.172)	(−0.944)	(0.271)
Leverage	−0.001	−0.000	−0.001
	(−0.798)	(−1.149)	(−0.827)
Operating Margin	−0.013	0.005	−0.032
	(−0.880)	(0.348)	(−1.177)
MTB	0.000	0.000*	0.001
	(0.807)	(1.717)	(0.671)
Std. Dev. Ret.	0.358**	0.333	0.373
	(2.003)	(1.599)	(1.313)
Time FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
R^2	0.314	0.233	0.333
Observations	5,973	2,987	2,913

Panel C: BSM Probability of Bankruptcy

	Full Sample	EJR Optimistic	EJR Not Optimistic
	BSM_{iy+1}	BSM_{iy+1}	BSM_{iy+1}
	(1)	(2)	(3)
EJR Rating	−0.005***	−0.004	−0.002
	(−3.073)	(−1.212)	(−0.726)
% EJR Clients	−0.129**	−0.226*	0.019
	(−1.970)	(−1.932)	(0.182)
EJR Rating × % EJR Clients	0.008*	0.016*	−0.003
	(1.779)	(1.901)	(−0.447)
Firm Size	0.017***	0.017***	0.015
	(3.545)	(2.910)	(1.557)
Leverage	−0.000	−0.001	−0.001
	(−0.163)	(−0.726)	(−0.525)

(continued on next page)

Table 8 (*continued*)

Panel C: BSM Probability of Bankruptcy

	Full Sample	EJR Optimistic	EJR Not Optimistic
	BSM_{iy+1}	BSM_{iy+1}	BSM_{iy+1}
	(1)	(2)	(3)
Operating Margin	−0.008	−0.049	0.008
	(−0.292)	(−1.205)	(0.148)
MTB	0.000	0.001	0.001
	(0.857)	(1.275)	(1.147)
Std. Dev. Ret.	−0.219	−0.644***	−0.353
	(−1.181)	(−3.044)	(−1.047)
Time FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
R^2	0.304	0.292	0.313
Observations	3,840	1,877	1,850

This table examines the subsequent performance of EJR ratings for firms with greater EJR client ownership. Panel A measures performance using the likelihood of future default. $Default_{iy+3}$ is an indicator variable equal to 1 if the firm defaults in the following three-year period, and 0 otherwise. Panel B examines future bond returns. $Bond\ Return_{im+3}$ is the firm-level average cumulative bond market return for firm *i* over the following three months. Panel C examines the probability of bankruptcy in the following year implied by the Black-Scholes-Merton model ($BSMProb_{iy+1}$), where higher values indicate a higher likelihood of bankruptcy. *EJR Rating* is the numerical equivalent of the EJR rating level, where higher values indicate higher credit quality (i.e., D = 1 and AAA = 21). *% EJR Clients* is the number of EJR clients invested in the firm, scaled by the total number of EJR clients. The interaction term, *EJR Rating* × *% EJR Clients*, captures moderation in the association between EJR ratings levels and subsequent firm performance when EJR issues higher ratings for firms with greater EJR client ownership. Across all three panels, column (1) presents the results for the full sample. Column (2) presents the results for the sample of EJR ratings that are optimistic relative to Moody's, and column (3) presents the results for EJR ratings that are not optimistic. The definitions of the control variables are provided in Appendix A. All columns include year-quarter and firm fixed effects. T-statistics are presented in parentheses below the coefficient estimates and clustered by firm. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

5.3. Changes in EJR client status over time

In this section, we address the concern that our findings could be driven by an unobservable firm characteristic that affects both the number of EJR clients and EJR ratings levels. We address this concern by exploiting changes in EJR client status over time. If an unobservable firm characteristic affects both EJR client holdings and EJR optimism, then we should observe EJR optimism in all periods, regardless of whether the EJR client is currently a subscriber or not. Alternatively, if EJR client status drives EJR optimism, then we should observe that EJR optimism appears *only* during those periods in which EJR clients actively subscribe to EJR.

We test these predictions by modifying the regression in Table 2 (column (2)) to include the following independent variables: *Pre-Subscription Holdings* and *Post-Subscription Holdings*. *Pre-Subscription Holdings* measures the number of EJR clients invested in the firm *prior* to subscription, scaled by the total number of EJR clients. *Post-Subscription Holdings* measures the number of EJR clients invested in the firm *after* subscription, scaled by the total number of EJR clients.

Fig. 4 plots the coefficients represented as dots, surrounded by 95 percent confidence intervals (lines). Similar to the main analysis in Table 2, the coefficient on *% EJR Clients* is positive and significant, indicating that the number of EJR clients that actively subscribe to EJR in the current quarter is positively associated with EJR optimism. To the left of *% EJR Clients*, the coefficient on *Pre-Subscription Holdings* is not significant. To the right of *% EJR Clients*, the coefficient on *Post-Subscription Holdings* is also not significant. These results imply that EJR optimism is not correlated with the number of EJR clients invested in the firm in the period before or after subscription.

Collectively, the findings in Fig. 4 use the timing of likely conflicts of interest to provide further evidence that it is the presence of these conflicts of interest that is the probable mechanism driving the positive association between EJR client holdings and EJR optimism. EJR optimism appears only in those periods in which EJR clients *actively* subscribe to EJR, alleviating the concern that our findings could be explained by an alternative static firm-level characteristic.

5.4. 497K forms

In this section, we examine our assumption that EJR clients can rely on EJR ratings in order to meet regulatory and internal ratings-based thresholds. One way to examine this assumption is to explore the language that EJR clients use when discussing credit ratings in their prospectuses. Correspondingly, we analyze a large sample of 497K forms available on EDGAR using textual analysis.

Form 497Ks are short, fund-specific summary prospectuses that are required to be filed on EDGAR as of January 1, 2010, pursuant to rule 497(k) of the Securities Act of 1933 (Baghai et al., 2021). Given that these forms are only available during the last year of our sample, we examine all 497K forms filed in 2010. We further reduce the sample to forms filed by funds with fixed-income securities that are identified as EJR clients using bond trades in Section 5.2 above.

To identify whether the fund that filed the 497K form is an EJR client, we first match each 497K form from EDGAR to WRDS SEC Analytics. WRDS SEC Analytics provides the filer name. We then match this list of 497K forms with filer names to the

Table 9
Bounding the effect of omitted variables using Oster (2019).

Dependent Variable =	EJR Optimistic	
Primary Variable =	% EJR Clients	
Model	Table 2, Column (1)	Table 2, Column (2)
Description	Controls Excluded	Controls Included
δ	(-1.06)	(-2.25)

This table provides the estimates of the relative degree of selection in unobservables that would make the coefficients on *% EJR Clients* in columns (1)–(2) of Table 2 equal to 0. Following Oster (2019), we assume that the inclusion of unobserved variables would produce a maximum R^2 of 1. We report the δ statistic for the model excluding controls in Table 2, column (1) and including controls in Table 2, column (2).

names of EJR clients by hand. The final sample is comprised of 379 497K forms filed in 2010 for all funds with fixed-income holdings. Further, the sample of 497K forms is divided into two groups: (1) 497K forms for EJR clients, and (2) 497K forms for non-EJR clients.

Using this sample, we explore variation in how these forms discuss credit ratings. We report the results in Appendix B. In column (1), we find that 497K forms for EJR clients are less likely to mention Moody's, S&P, or Fitch at all in the prospectus. In column (2), we find that EJR client forms are less likely to imply explicit reliance on Moody's, S&P, &/or Fitch (only) as ratings benchmarks. Finally, in column (3), EJR client forms are significantly more likely to describe reliance on credit ratings from an

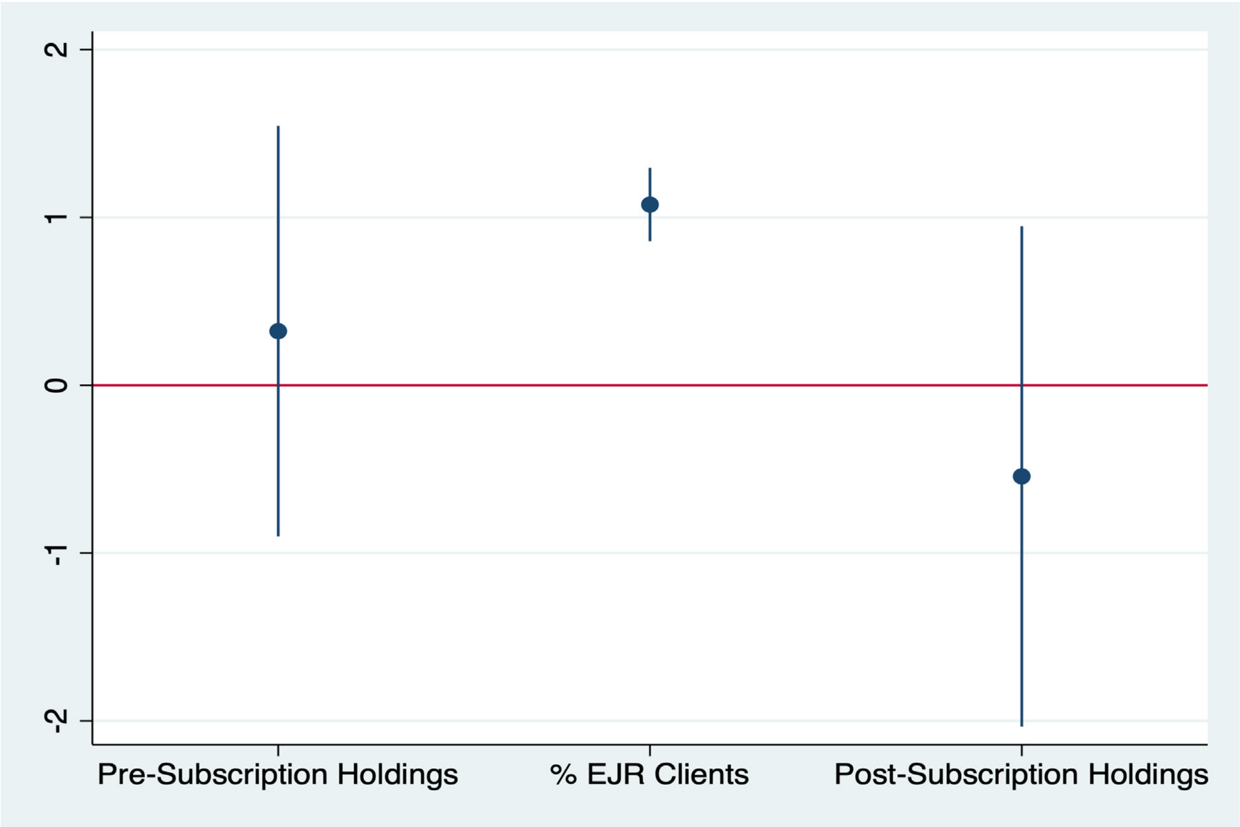


Fig. 4. Changes in EJR client status. This figure describes changes in EJR optimism based on changes in EJR client subscription status over time. The figure plots the coefficients (dots) and 95% confidence intervals (lines) for three main variables of interest in a regression similar to Table 2 (column (2)). The three main variables of interest are as follows: *% EJR Clients*, *Pre-Subscription Holdings*, and *Post-Subscription Holdings*. The dependent variable is *EJR Optimistic*, an indicator variable equal to 1 if the EJR rating is above the concurrent Moody's rating, and 0 otherwise. The regression model includes the same independent variables and fixed effects as Table 2 (column (2)), along with two new independent variables: *Pre-Subscription Holdings* and *Post-Subscription Holdings*. *Pre-Subscription Holdings* measures the number of EJR clients invested in the firm *prior* to subscription, scaled by the total number of EJR clients. *Post-Subscription Holdings* measures the number of EJR clients invested in the firm *after* subscription, scaled by the total number of EJR clients. *% EJR Clients* is calculated as the number of EJR clients invested in the firm, scaled by the total number of EJR clients.

"independent" or "major" credit rating agency. We report similar findings in columns (4)–(6) after including time (month) fixed effects.

Collectively, the findings in Appendix B suggest that EJR clients describe their reliance on credit ratings differently from non-EJR clients in their prospectuses. Importantly, EJR clients use language that less explicitly relies on Moody's, S&P, and Fitch. Instead, EJR clients are more likely to describe their use of credit ratings using broad or vague language that includes EJR as a viable ratings benchmark.

6. Conclusion

A central contribution of our paper is in providing the first large sample evidence consistent with a subscriber-paid rating agency catering to its institutional clients to maximize subscriber revenues. We triangulate our inferences using a variety tests, which show that Egan-Jones Ratings Company (EJR) issues more optimistically biased credit ratings, less timely downgrades, and less accurate ratings for firms held by more of their clients.

Our findings are important because they illustrate that the subscriber-pay model for rating agencies is not a panacea for conflicts of interest, despite subscriber-paid ratings being more informative on average. Instead, we show EJR ratings contain predictable biases that vary with ownership among their subscribers. Additionally, our results suggest that market prices appear to rationally discount EJR ratings in cases when conflicts of interest are likely to be more severe. These results suggest that policy debates should be focused on the potential impact of regulatory intervention on investors of funds who rely on EJR ratings, rather than market prices. Finally, our results suggest that a lack of transparency surrounding investment funds' reliance on subscriber-paid ratings may place less sophisticated investors at a disadvantage by obscuring the risk-return profile of investment funds, and that such investors may benefit from enhanced disclosure about reliance on subscriber-paid ratings when deciding whether and to what extent to invest.

Appendix A. Variable Definitions

Variable	Definition
# Bonds Held$_{fy}$	Average number of unique bonds held by each mutual fund within fund *f* 's fund family in year *y*.
% EJR Clients$_{iq}$	The number of EJR clients invested in firm *i* in quarter *q*, scaled by the total number of EJR clients in quarter *q*.
% EJR Clients: Large (Medium, Small)$_{iq}$	The number of large (medium, small) EJR clients invested in firm *i* in quarter *q*, scaled by the total number of EJR clients in quarter *q*.
% EJR Clients: Unregulated$_{iq}$	The number of unregulated EJR clients invested in firm *i* in quarter *q*, scaled by the total number of EJR clients in quarter *q*.
% EJR Clients: Regulated$_{iq}$	The number of regulated EJR clients invested in firm *i* in quarter *q*, scaled by the total number of EJR clients in quarter *q*.
# Words$_{ky}$	Natural log of the number of words in 497K form *k* in year *y*.
# Type Funds$_{fy}$	Natural log of the number of funds held in fund *f* 's fund family in year *y*.
Bond Return$_{-3,\ +3}$	The bond market reaction to the announcement of a credit rating change for firm *i*, calculated as the firm-level median bond return over the window *[t-3, t+3]*, where the rating announcement date is day $t = 0$. The bond market return is equal to the raw bond return less the return on a maturity-matched treasury bond over the same period.
Bond Return$_{im+3}$	The firm-level average cumulative bond market return for firm *i* over the three months following the rating change ($m+3$).
BSM$_{iy+1}$	The probability of bankruptcy for firm *i* in the year following the rating change ($y+1$). The probability of bankruptcy is calculated using the Black-Scholes-Merton model as described in Hillegeist et al. (2004), where larger values correspond to higher credit risk.
Default$_{iy+3}$	An indicator variable equal to 1 if firm *i* enters into default at any point in the following 3 years ($y+3$), and 0 otherwise.
EJR Client$_{ky}$	Indicator variable equal to 1 if 497K form *k* was filed by an EJR client in year *y*, and 0 otherwise.
EJR Down$_{it}$	Indicator variable equal to 1 if the rating change for firm *i* on day *t* is a downgrade issued by Egan-Jones Rating Company (EJR), and 0 otherwise.
EJR Optimistic$_{iq+1}$	Indicator variable equal to 1 if the EJR rating for firm *i* in quarter $q+1$ is above the given benchmark (i.e., either the concurrent Moody's rating or the model-implied rating following Baghai et al. (2014)). In this case, the model-implied rating is estimated using the distribution of EJR ratings in the sample. The rating level is defined as the existing rating level at the beginning of the quarter.
EJR Rating$_{iq}$	Numerical equivalent of the EJR rating level for firm *i* in quarter *q*, where higher values indicate higher credit quality (i.e., D = 1 and AAA = 21). The rating level is defined as the existing rating level at the beginning of the quarter.
EJR Up$_{it}$	Indicator variable equal to 1 if the rating change for firm *i* on day *t* is an upgrade issued by Egan-Jones Rating Company (EJR), and 0 otherwise.
Firm Size$_{iq}$	Market value of equity for firm *i* in quarter *q* (in millions).
Fund Size$_{fy}$	Natural log of the total amount of fixed-income assets under management for fund *f* 's fund family in year *y*.
Future EJR Downgrade (1)$_{iq+x}$	Indicator variable equal to 1 if there is an EJR downgrade for firm *i* in future quarters $q + x$, and 0 otherwise.

(*continued*)

Variable	Definition
Future EJR Downgrade (2)$_{iq+x}$	Variable equal to 1 if there is an EJR downgrade for firm *i* in future quarters $q+x$, equal to -1 if there is a Moody's upgrade for firm *i* in future quarters $q+x$, and 0 otherwise.
IG Cutoff$_{iq}$	Indicator variable equal to 1 if the credit rating for firm *i* in quarter *q* centers around the investment-grade cutoff, and 0 otherwise. Specifically, this variable is equal to 1 if the credit rating is BB or BBB (e.g., between BB- and BBB+), and 0 otherwise.
Indp. Maj.$_{ky}$	Indicator variable equal to 1 if 497K form *k* describes reliance on ratings from an “independent” or “major” rating agency in year *y*, and 0 otherwise.
Leverage$_{iq}$	Total leverage for firm *i* in quarter *q*, calculated as the sum of long-term and short-term liabilities scaled by stockholders' equity.
MD Down$_{it}$	Indicator variable equal to 1 if the rating change for firm *i* on day *t* is a downgrade issued by Moody's, and 0 otherwise.
MD Up$_{it}$	Indicator variable equal to 1 if the rating change for firm *i* on day *t* is an upgrade issued by Moody's, and 0 otherwise.
Moody's Optimistic$_{iq+1}$	Indicator variable equal to 1 if the Moody's rating for firm *i* in quarter *q+1* is above the model-implied rating following Baghai et al. (2014). In this case, the model-implied rating is estimated using the distribution of Moody's ratings in the sample. The rating level is defined as the existing rating level at the beginning of the quarter.
MTB$_{iq}$	Market-to-book ratio for firm *i* in quarter *q*, calculated as the market value of equity scaled by the book value of equity.
Operating Margin$_{iq}$	Operating margin of firm *i* in quarter *q*, calculated as operating income before depreciation scaled by total sales.
Pre-Subscription Holdings$_{iq}$	Number of EJR clients that held firm *i's* stock *before* subscribing to EJR in quarter *q*, scaled by the total number of EJR clients in quarter *q*.
Post-Subscription Holdings$_{iq}$	Number of EJR clients that held firm *i's* stock *after* subscribing to EJR in quarter *q*, scaled by the total number of EJR clients in quarter *q*.
SMF$_{ky}$	Indicator variable equal to 1 if 497K form *k* mentions S&P, Moody's, or Fitch in year *y*, and 0 otherwise.
State Rel.$_{ky}$	Indicator variable equal to 1 if 497K form *k* explicitly states reliance on S&P, Moody's, &/or Fitch as a ratings benchmark in year *y*, and 0 otherwise.
Std. Dev. Ret.$_{iq}$	Standard deviation of stock returns for firm *i* in quarter *q*.

Appendix B. 497K Forms

	SMF (1)	State Rel. (2)	Indp. Maj. (3)	SMF (4)	State Rel. (5)	Indp. Maj. (6)
EJR Client	−0.113*	−0.067**	0.244***	−0.147*	−0.106***	0.180***
	(-1.78)	(-2.02)	(4.53)	(-1.96)	(-2.61)	(2.96)
Fund Size	−0.025	−0.017*	−0.046***	−0.028	−0.020**	−0.047**
	(-1.45)	(-1.95)	(-3.20)	(-1.47)	(-2.04)	(-2.41)
# Words	0.113***	0.031***	0.060***	0.141***	0.033**	0.097***
	(4.89)	(2.60)	(3.05)	(6.98)	(2.45)	(6.21)
# Bonds Held	0.007**	0.002	0.007***	0.003	0.003*	0.003
	(2.38)	(1.61)	(2.98)	(1.06)	(1.68)	(1.29)
# Type Funds	0.088***	0.043***	0.083***	0.088***	0.044*	0.089***
	(2.95)	(2.74)	(3.26)	(2.71)	(1.95)	(2.87)
Observations	379	379	379	379	379	379
Adj.R^2	0.107	0.027	0.203	0.133	0.098	0.282
Time FE	No	No	No	Yes	Yes	Yes

The following table presents the results from textual analysis of 497K forms from 2010. The independent variable, *EJR Client*, is an indicator variable equal to 1 if the 497K form was filed by an EJR client, and 0 otherwise. In columns (1) and (4), the dependent variable, *SMF* (*S&P, Moody's, Fitch*), is an indicator variable equal to 1 if the 497K form mentions S&P, Moody's, or Fitch, and 0 otherwise. In columns (2) and (5), the dependent variable, *State Rel.* (*Stated Reliance*), is an indicator variable equal to 1 if the 497K form explicitly states that the fund relies on S&P, Moody's, &/or Fitch as a ratings benchmark, and 0 otherwise. In columns (3) and (6), the dependent variable, *Indp. Maj.* (*Independent rating or Major rating*), is an indicator variable equal to 1 if the 497K form describes reliance on ratings from an “independent” or “major” rating agency, and 0 otherwise. The definitions of the control variables are provided in Appendix A. Columns (4)–(6) include month fixed effects and robust standard errors. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix C. Sample Selection

Description	Obs.	Period
Institutional (13f) Holdings Data	28,706,853	1999Q1 - 2010Q4
(13f) Holdings Data with GVKEY	21,134,203	1999Q1 - 2010Q4
Keep firms with Moody's and EJR Ratings	6,264,656	1999Q1 - 2010Q4
Aggregate data by firm and quarter	18,443	1999Q1 - 2010Q4
Obs. with controls	15,986	1999Q1 - 2010Q4

Our sample selection begins with 28,706,853 stock holdings (institutional investor-stock pairs) available in Thomson Reuters Institutional (13f) Holdings data between the first quarter of 1999 and the fourth quarter of 2010. We eliminate observations with missing GVKEYs and fund management codes. We further retain 6,264,656 investor-firm pairs where the firm has both Moody's and EJR ratings. We aggregate the data by firm-quarter and remove observations with missing control variables, resulting in a final sample of 15,986 firm-quarters.

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