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 their primary source of revenue. Using data on Egan-Jones Ratings (EJR), a subscriber-paid rating agency, we show that EJR issues more optimistically biased bond ratings, less timely downgrades, and less accurate ratings for bonds held by more EJR clients. Our evidence is consistent with subscriber-paid agencies optimistically biasing their 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.

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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.

In this study, we focus on credit rating agencies, which serve as information intermediaries through a variety of actions including monitoring firms, disseminating information, and certifying assets as investment worthy. 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 reforming the compensation model of rating agencies to reduce agencies' reliance on debt issuers for revenue (GAO, 2010; 2012; Jiang et al., 2012).

One of the prominent alternatives to the issuer-pay model is the subscriber-pay model (or investor-pay model), where credit rating agencies are compensated by subscribers who pay for access to the ratings. 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] Likely as a result, subscriber-paid rating agencies have grown in both size and prominence in recent years.

[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, in his Congressional hearing, John Coffee Jr. advocates for "the entry of new competitors who are based on a subscription-funded system, not an issuer-funded system" (U.S. Senate, 2007). Similarly, Laing (2007) agues that "[a]gencies must be encouraged to make their money from investor subscriptions rather than fees from issuers, to ensure more impartial ratings." Egan (2002, 2008) echoes this by suggesting that the Nationally Recognized Statistical Rating Organization (NRSRO) designation be tied to a requirement that credit rating agencies derive a certain level of revenue from investors.

Although the subscriber-pay model is intuitively appealing, some question whether reliance on subscribers may also present certain conflicts of interest that affect ratings quality (SEC, 2011; Coffee, 2011; SEC, 2012). The SEC highlights this concern by noting that "subscribers have their own interest in credit ratings" and "in cases where the interests of a substantial number of subscribers are aligned, this potential conflict may be heightened" (SEC, 2012). Consequently, subscriber-paid agencies may face pressure to provide ratings that benefit their clients in exchange for higher subscription fees.

In this study, we provide novel evidence that a prominent subscriber-paid rating agency caters to the preferences of their 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

[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).

rely on past returns to judge fund manager skills (e.g., De Long et al., 1990).[4] Inflated ratings, therefore, likely allow investment managers to generate higher expected returns and earn larger management fees.

Our main tests examine the actions of a representative subscriber-paid rating agency, Egan-Jones Rating 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. Economically, a one standard deviation increase in the number of EJR clients corresponds to a 16.7 percent increase in EJR-optimism relative to the unconditional mean.

Subscriber-paid rating agencies, including EJR, do not publish their list of institutional clients. To overcome this challenge, we identify EJR's institutional clients using a proprietary database of institutional bond trades from Ancerno Ltd. Specifically, we identify EJR subscribers as those institutions that trade in a timely fashion in response to EJR ratings 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 the clients of EJR, we obtain the corporate bond holdings of each institutional client using Thomson Reuters eMaxx. In doing so, our main dataset captures likely clients of EJR and their bond holdings in each quarter. In subsequent tests described more below, we show that our results are remarkably robust to alternative approaches for identifying EJR clients.

We measure bias and timeliness by comparing EJR credit ratings to two different bench-

[4] Becker and Ivashina (2015) document that insurance companies "reach for yield" by investing in riskier bonds within each ratings class, consistent with the intuition that investment managers have incentives to increase risk relative to a given ratings benchmark.

marks: (i) concurrent ratings issued by Moody's (an issuer-paid rating agency), and (ii) the predicted credit rating from the ratings model in Baghai et al. (2014) (hereafter "model-implied rating").[5] This approach mitigates concerns that our results are driven by differences in the characteristics of those firms that are more heavily weighted in EJR subscribers' portfolios compared to those that are not.

Our first main result is that EJR provides more optimistic ratings for those firms with greater EJR client ownership, and this relationship is pronounced over the investment-grade boundary. Specifically, we find that EJR client ownership in a firm's bonds significantly increases the likelihood that EJR provides an investment-grade rating concurrent with Moody's providing a *below* investment-grade rating for the same firm in the same quarter. 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.

A key piece of evidence in testing our hypothesis is the asymmetry in the extent of bias in EJR ratings. Specifically, we find that greater EJR client ownership predicts EJR over-optimism, but also no evidence that predicts pessimism relative to Moody's nor our characteristic model. This asymmetry toward an optimistic bias in EJR ratings, rather than a pessimistic bias, mitigates concerns that our findings are being driven by EJR clients investing in firms with greater potential for disagreement.

Our main results predictably concentrate in issuing firms held by large 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 their revenue stream. As a falsification

[5]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).

test, we also show that the likelihood that Moody's provides an optimistic rating over the investment-grade boundary (relative to EJR or the model-implied rating) is not associated with EJR client ownership, regardless of institutional investor size.

We next provide evidence that EJR provides less timely downgrades relative to Moody's and our characteristic-model. On average, EJR optimism over the investment-grade boundary persists for two quarters. Using an event-study approach, we also show that bond prices decline by less in response to EJR downgrades, particularly for firms with high ownership by EJR clients. These results are consistent with EJR providing less timely downgrades when their subscribers hold more of the underlying bonds.

To corroborate our main inferences, we show that EJR ratings are also predictably less informative of firms' future performance when EJR client ownership is high. Specifically, EJR ratings are less predictive of future bond returns, future distress, and future firm performance, consistent with EJR ratings being less informative in cases of greater client ownership.

We perform two additional analyses that further support the interpretation of our results. First, we exploit changes in EJR client status over time and examine corresponding changes in EJR optimism. We find that EJR optimism is concentrated in those firms in which institutional investors *currently* subscribe to EJR, but that EJR optimism is *not* related to the holdings of *former* EJR clients. These tests help to alleviate the concern that EJR optimism is correlated with unobservable differences across firms that are similarly correlated with EJR client ownership. If this was true, then we should see that EJR optimism persists after institutional investors stop subscribing, which runs counter to our findings.

Finally, we perform a variety of robustness tests related to our identification of EJR clients. In our primary tests, we identify EJR clients based on institutional bond trades on EJR rating dates. We alter this identification strategy in two ways, and find similar results. First, we identify EJR clients using *abnormal* bond trading activity, which compares bond trades on EJR rating dates compared to Moody's and eliminates observations when trading around Moody's rating dates is higher relative to EJR. The results are similar. Second, we identify EJR clients using *stock* trading behavior in Ancerno Ltd. Our results are similar.

Our paper contributes to several streams of literature about the economics and functioning of the credit rating industry. Our study is the first to provide large sample evidence that subscriber-paid rating agencies' actions are consistent with catering to their institutional clients to maximize subscriber revenues. In doing so, we extend evidence from an experimental setting in Tang et al. (2020) of conflicts of interest among subscriber-paid rating agencies. Further, our study provides evidence on where this conflict of interest is more likely to manifest (e.g., over the investment-grade boundary) and the magnitude of the effects on ratings quality.

Our paper also extends research examining conflicts of interest in the credit rating industry. Prior studies have focused almost exclusively on the effects of the issuer-pay model. Both Jiang et al. (2012) and Bonsall (2014) provide evidence that adoption of the issuer-pay model in the 1970s led to more favorable ratings. Other studies have examined issuer-pay conflicts of interest by showing evidence of rating optimism for firms with rating-based performance pricing provisions (Kraft, 2015), in ABS markets for large issuers (He et al., 2012), when there is more securitization business (Efing and Hau, 2015), for firms paying for more non-rating services (Baghai and Becker, 2018), and in municipal debt markets (Beatty et al., 2019). Our study highlights a novel form of conflicts of interest within the subscriber-pay revenue model driven by pressure among subscribers to hold more highly rated bonds.

This study also relates to the literature examining the attributes of subscriber-paid credit rating agencies. Beaver et al. (2006) shows that on average EJR provides more timely ratings than Moody's and attributes the differences mainly to the use of Moody's ratings in debt contracting. Xia (2014) finds that EJR's initiation of rating coverage leads to improvements in the accuracy of Standard & Poor's ratings. Bruno et al. (2016) finds that the overall timeliness findings from Beaver et al. (2006) appear to persist even after EJR's registration as a NRSRO, suggesting that those differences are more of a consequence of compensation structure than contracting or regulatory incentives. We add to this prior work by directly examining subscriber-paid rating agencies in the context of their conflicts of interest.

Additionally, Strobl and Xia (2012), Cornaggia and Cornaggia (2013), and Bonsall et al. (2017) examine the accuracy of subscriber-paid rating agencies relative to subscriber-paid rating agencies. These studies document that, on average, the subscriber-pay model yields more accurate and more timely ratings. Our findings demonstrate that the accuracy and timeliness of EJR ratings are predictably weak in settings where the firm is held by a large number of EJR subscribers and the firm is close to the investment-grade boundary.

Overall, our study has important implications for the ongoing regulatory debate regarding the compensation structure of credit ratings and the effects on ratings quality. Our findings imply that changing the compensation structure of credit ratings to an subscriber-pay model will not necessarily eliminate conflicts of interest and result in higher quality ratings. Instead, changing the fee structure will amplify *different* conflicts of interest. The SEC has continued to emphasize the need for evidence on conflicts of interest within revenue models beyond the issuer-pay model (GAO, 2010; SEC, 2011; GAO, 2012; SEC, 2012; SEC, 2020). Our findings provide empirical evidence that the subscriber-pay model is susceptible to catering to subscribers' rating preferences. Our findings, therefore, have implications for the viability of the subscriber-pay model and suggest that monitoring such conflicts of interest among existing subscriber-paid rating agencies may be important going forward.

2. Background

Egan-Jones Rating Company (EJR) was founded in 1995 by Sean Egan and Bruce Jones. In contrast to the 'Big 3' issuer-paid rating agencies (e.g., 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 to subscribers in real time (Xia, 2014; Bruno et al., 2016).[6] 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 approximately 60 percent of all firms covered by S&P (Xia, 2014) as of 2011, including a wide range of firms and industries. In terms of total assets, EJR covers 80 percent of all firm assets in a given industry, relative to S&P (Xia, 2014).

Subscriber-paid rating agencies, particularly EJR, rose to prominence as traditional issuer-paid rating agencies (e.g., S&P, Moody's, and Fitch) 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 related to 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 the model leads to greater independence of the rating agency. For instance, Coffee (2008) 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)." Laing (2007) also suggests that part of the fix for the credit rating system is that "[a]gencies must be encouraged to make their money from investor subscriptions rather than fees from issuers, to ensure more impartial ratings." Egan (2002, 2008) echoes this by suggesting that the Nationally Recognized Statistical Rating Organization (NRSRO) designation be tied to a requirement that a credit rating agency derive a certain level of revenue from investors.

[6]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).

Ultimately, these calls for reform culminated in EJR receiving NRSRO status in 2007.

Consistent with the claims from proponents of the subscriber-pay model, prior research finds that EJR provides more timely and more accurate ratings relative to traditional issuer-paid ratings (Beaver et al., 2006; Xia, 2014; Bruno et al., 2016).[7] Additionally, EJR provides more frequent ratings changes relative to traditional issuer-paid rating agencies (Beaver et al., 2006; Bruno et al., 2016).[8]

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 this sanction, it is unknown whether the knowledge of client holdings materially affected EJR ratings or not.

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).[9] Subscriber-paid rating agencies, including EJR, do not publish their list 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

[7]Cornaggia and Cornaggia (2013) report similar results comparing Rapid Ratings (a subscriber-paid ratings service) to Moody's.

[8]Bruno et al. (2016) show that the properties of EJR's ratings changes and ratings levels (relative to Moody's) are similar both pre and post NRSRO status in 2007.

[9]The only related evidence is from Tang et al. (2020) using an experimental design with Master 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.

the properties of its ratings vary with the concentration of its subscribers' holdings.

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.[10] 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.[11,12] 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.

Using data on institutional trades from Ancerno Ltd., we define EJR subscribers as the institutions that execute at least one bond trade on the same day that EJR releases a credit rating change for the same firm.[13] Specifically, we identify the institutions that trade on EJR

[10]Data.world is a free, open-source website that scrapes public information sources, aggregates the data, and makes this information available in machine-readable form. For further information, please see https://www.law.ox.ac.uk/business-law-blog/blog/2018/03/making-credit-ratings-data-publicly-available.

[11]For a review of the Ancerno Ltd. data, please see Hu et al. (2018).

[12]We end our sample period in 2010 because Ancerno masks the names of the institutions executing trades after December 2010.

[13]We find similar results when we identify EJR subscribers using "abnormal" bond trading activity and equity trading activity, which we discuss further in Section 5.1 below.

rating announcements using the manager code name, which aggregates the trading activity of individual funds within one fund family. For each institutional investor, we identify EJR clients using the first quarter of EJR subscription and the last quarter of EJR subscription in the sample period. The benefit of performing the analysis on EJR rating days is that only subscribers have access to real-time dissemination of EJR rating changes (e.g., Bruno et al., 2016). Therefore, our empirical identification relies on the assumption that only those institutions that subscribe to EJR will trade in response to the rating change.

3.2. Identifying EJR Client Holdings

After identifying EJR subscribers in each quarter, we obtain the historical bond holdings of each institution on a quarterly basis from Thomson Reuters eMaxx. We merge the list of institutions in Ancerno to eMaxx by fund manager name and retain firms rated by both EJR and Moody's. We obtain a final sample of 10,716 firm-quarters from 2004 to 2010. Appendix B details the sample selection process in further detail.

Our main hypothesis is that EJR has greater incentives to provide optimistic ratings when more EJR clients are invested in the firm's bonds. 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 corporate bonds, 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. Our prediction is that higher values of *# EJR Clients* are positively correlated with EJR's incentives to cater their ratings, and therefore positively associated with EJR rating 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).[14] 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 largely free of confounding effects from changes in 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 Egan-Jones within the same firm-quarter. We obtain bond issue characteristics from Mergent FISD. 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.[15]

[14] 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).

[15] 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).

3.5. *Descriptive Statistics*

Table 1 describes the main sample of 10,716 firm-quarters from 2004 to 2010. The mean of *# EJR Clients* is 0.153, indicating that 15% of all EJR clients are invested in a given firm, on average. *EJR Optimistic* is an indicator variable equal to 1 if the EJR rating is just above the investment-grade cutoff and the concurrent benchmark rating is below investment-grade, and 0 otherwise. In Table 1, *EJR Optimistic* is defined using the concurrent Moody's rating as the benchmark. In 6.6 percent of the observations, EJR provides an optimistic rating relative to Moody's over the investment-grade cutoff.

4. Main Results

4.1. *EJR Optimism*

4.1.1. *EJR Optimism in the Ratings Distribution*

Our first hypothesis is that EJR provides more optimistic ratings for those firms with greater EJR client ownership, and this relationship is pronounced over the investment-grade boundary. Our hypothesis is that 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.[16] Consequently, the pressure to provide an optimistic rating is likely heightened over the investment-grade boundary.

We begin by examining whether Egan-Jones (EJR) provides higher ratings relative to Moody's when more EJR clients are invested in the firm's bonds: (i) around the investment-grade boundary, and (ii) throughout the rest of the ratings distribution. Using the sample of 10,716 firm-quarter observations described in Table 1, we test our hypothesis using the

[16]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).

linear model specified in Eqn. (1) below:

$$EJR > Moody\text{'}s_{iq+1} = \beta_0 + \beta_1 \#\ EJR\ Clients_{iq} + \beta_k' X_k + \alpha_i + \theta_q + \varepsilon_{iq}. \tag{1}$$

The dependent variable, *EJR > Moody's*, 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 bonds, scaled by the total number of EJR clients in that quarter. 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), *EJR > Moody's* is estimated in quarter q+1, while *# EJR Clients* is estimated in quarter q. 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 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's bonds, then β_1 will be positive.

Table 2 presents the results. In column (1), we estimate the likelihood that EJR provides a higher rating relative to Moody's around the investment-grade cutoff. Specifically, *EJR > Moody's* is an indicator variable equal to one if the EJR rating is just abov the investment-grade cutoff, and the concurrent Moody's rating is below the investment-grade cutoff, and zero otherwise. Consistent with our prediction, the coefficient on *# EJR Clients* is positive and significant (coef. = 0.052, s.e. = 0.015). EJR is more likely to provide a higher rating relative to Moody's when a greater number of EJR clients are invested in the firm's bonds, specifically over the investment-grade boundary.

In column (2), we estimate the same regression around other ratings cutoffs *excluding* the investment-grade boundary. The coefficient on *# EJR Clients* is positive but not significant. We conclude from this analysis that EJR is significantly more likely to cater to their subscribers' demands when the firm is close to the investment-grade boundary. Otherwise, we fail to find significant evidence of ratings catering in other areas of the ratings distribution. Consequently, the remainder of our analyses concentrate exclusively on the likelihood of providing optimistic ratings over the investment-grade cutoff.

4.1.2. EJR Optimism Relative to Moody's

Next, we explore the likelihood that EJR provides an optimistic rating over the investment-grade boundary based on the number and size of EJR clients invested in the firm's bonds. We report our results in Table 3 and first define EJR optimism relative to the concurrent Moody's rating. The dependent variable, *EJR Optimistic*, is an indicator variable equal to one if the EJR rating is just above the investment-grade cutoff and the concurrent Moody's rating is below the investment-grade cutoff, and zero otherwise. Column (1) of Table 3 replicates the result in column (1) of Table 2. Consistent with our prediction, EJR is more likely to provide an optimistic rating over the investment-grade boundary (relative to Moody's) when more EJR clients are invested in the firm's bonds. In terms of economic magnitude, a standard deviation increase in *# EJR Clients* is associated with an increase in the likelihood of EJR optimism by 1.1 percentage points. Given that the unconditional mean of *EJR Optimistic* is 6.6 percent, a one standard deviation increase in *# EJR Clients* represents a 16.7 percent increase in *EJR Optimistic* relative to the unconditional mean.

In column (2), we test whether our findings vary by client size. 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 bond holdings of each client in a given quarter. Consistent with our prediction, EJR is more likely to provide an optimistic rating over the investment-grade boundary when the clients invested in the firm are larger. In column (2), the coefficient on *# EJR Clients* is positive and significant for the two largest size terciles, but not significant for the smallest size tercile. 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.

We perform two falsification tests in columns (3) and (4) of Table 3. In these two columns, we estimate the likelihood that *Moody's* provides an investment-grade rating while EJR provides a below investment-grade rating in the concurrent quarter (*Moody's Optimistic*). In column (3), the number of EJR clients invested in the firm is not significantly related to the likelihood that Moody's provides an optimistic rating (relative to EJR). Similarly, Moody's optimism is not correlated with EJR client size in column (4). In summary, while EJR client holdings (particularly those of larger clients) predict EJR optimism, there is no evidence that these client holdings are associated with Moody's optimism. These results help to alleviate the concern that our findings are driven by an association between EJR client holdings and the potential for ratings disagreement. In contrast, our results are consistent with differences between the subscriber-pay model and the issuer-pay model and the corresponding differences in the incentives to cater credit ratings.

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). Correspondingly, we now define *EJR Optimistic* as an indicator variable equal to one if the EJR rating is just above the investment-grade cutoff and the concurrent model-implied rating is below the investment-grade cutoff, and zero otherwise.

Table 4 reports results using this model-based rating benchmark that are similar to those discussed previously that used a Moody's rating as the benchmark. In column (1) of Table 4, EJR is more likely to provide an optimistic rating (relative to the model-implied rating) over the investment-grade boundary when more EJR clients are invested in the firm's bonds (coef. = 0.075, s.e. = 0.013). A standard deviation increase in *# EJR Clients* is associated with an increase in the likelihood of EJR optimism by 1.6 percentage points, which represents a 24.2 percent increase in *EJR Optimistic* relative to the unconditional mean. In column (2), the likelihood of an optimistic rating increases with client size, similar to the findings in Table 3.

In columns (3) and (4) of Table 4, we perform a falsification test using Moody's ratings. In these two columns, *Moody's Optimistic* is an indicator variable if the *Moody's* rating is just above the investment-grade cutoff and the model-implied rating for the same firm-quarter is below the investment-grade cutoff, and zero otherwise. Similar to Table 3, we fail to find evidence that Moody's provides optimistic ratings for those firms with higher EJR client ownership. The coefficient on *# EJR Clients* is not significant in column (3). Similarly, the coefficients on *# EJR Clients: Large (Medium, Small)* are not significant in column (4).

To sum up, the results in Tables 3 and 4 suggest that EJR provides optimistic ratings for those firms with greater EJR client ownership, particularly when those clients are larger (and pay higher fees). We find similar results when measuring optimism using concurrent Moody's ratings and concurrent model-implied ratings, indicating that our results are not driven by the choice of ratings benchmark. We do not find similar results for Moody's, suggesting that our findings are linked to EJR ratings levels, and the incentives to cater to its subscribers, rather than some alternative economic factors that would similarly affect other rating agencies.

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. We begin by examining the persistence of EJR's optimism in Table 5. We find that optimistic ratings (relative to Moody's) over the investment-grade cutoff persist for two quarters, on average (columns (1) and (2)). However, these optimistic ratings dissipate in quarters q+3, q+4, and q+5 (columns (3)-(5)). The findings in Table 5 are suggestive evidence that EJR eventually downgrades rated firms after two quarters, which implies that EJR downgrades are systematically less timely when EJR client ownership is high.

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 using an event-study approach. Specifically, we examine 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 ratings 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 1,908 bond market returns surrounding EJR rating changes, we estimate the following linear regression model specified in Eqn. (2) below:

$$
\begin{aligned}
Bond\ Market\ Return_{it} = \beta_0 + \beta_1 \#\ EJR\ Clients_{iq} + \beta_2 EJR\ Down_{it} \\
+ \beta_3 EJR\ Down_{it} \times \#\ EJR\ Clients_{iq} + \beta_k' X_k + \alpha_i + \theta_q + \varepsilon_{it}.
\end{aligned}
\tag{2}
$$

The dependent variable, *Bond Market Return*, is the bond market response to a given rating change, calculated as the firm-level average 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 Down* $\times$ *# EJR Clients*, captures the incremental bond market reaction to ratings downgrades for firms with high 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.[17]

Table 6 presents the results. The coefficient on *EJR Down* is negative (coef. = -0.012, s.e. = 0.003), indicating that bond prices decline in response to EJR rating downgrades on average. Consistent with our prediction, the coefficient on *EJR Down* × *# EJR Clients* is positive and significant (coef. = 0.029, s.e. = 0.012). This result indicates that as EJR client ownership increases, the bond market reaction to EJR rating downgrades is less negative, suggesting that these downgrades are less timely.

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.

We estimate the following linear regression model in Eqn. (3) below:

$$\begin{aligned} Firm\ Performance_{iq+1} = {} & \beta_0 + \beta_1 \#\ EJR\ Clients_{iq} + \beta_2 EJR\ Rating\ Level_{iq} \\ & + \beta_3 \#\ EJR\ Clients_{iq} \times EJR\ Rating\ Level_{iq} + \beta_k' X_k \\ & + \alpha_i + \theta_q + \varepsilon_{iq}. \end{aligned} \tag{3}$$

The dependent variable, *Firm Performance*, is one of two measures of future firm perfor-

[17]In Eqn. (2), we estimate *Firm Size* using total assets instead of the market value of equity and find that the results are similar using the market value of equity instead of total assets.

mance: (i) *Bond Return*$_{iq+1}$, and (ii) *Bankruptcy Risk*$_{iq+1}$. *Bond Return*$_{q+1}$ is the firm-level average bond market return in the subsequent quarter $(q + 1)$. *Bankruptcy Risk*$_{iq+1}$ is the Black-Scholes-Merton (BSM) probability of bankruptcy in quarter $q+1$, where higher values indicate a higher probability of bankruptcy. The independent variable, *EJR Rating Level*, is the numerical equivalent of the EJR rating level, where higher values indicate higher credit quality (i.e., D = 1 and AAA = 21).

The interaction term, *# EJR Clients* × *EJR Rating Level*, captures the incremental difference 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 negatively associated with future bond returns ($\beta_3 < 0$) and positively associated with future bankruptcy risk ($\beta_3 > 0$).

We report the results from our analysis of rating accuracy in Table 7. Consistent with our predictions, the coefficient on the interaction term, *# EJR Clients* × *EJR Rating Level*, is negative in column (1) (coef. = -0.004, s.e. = 0.002). This result implies that bond market returns are lower following higher EJR ratings for firms with higher EJR client ownership, which implies that such ratings are less accurate predictors of future credit risk.[18] In column (2), the coefficient on *# EJR Clients* × *EJR Rating Level* is positive (coef. = 0.012, s.e. = 0.006).[19] This implies that higher EJR ratings for firms with greater EJR client ownership are positively associated with bankruptcy risk in subsequent periods. Collectively, the results in Table 7 imply that when EJR issues higher ratings for firms with greater EJR client ownership, the ratings are less predictive of future firm performance. These results are consistent with EJR providing less accurate ratings when client ownership is higher.

[18] In Table 7, column (1), we estimate *Firm Size* using total assets instead of the market value of equity and find that the results are similar using the market value of equity instead of total assets.

[19] We do not include the control variables in column (2) of Table 7 given that these variables are inputs into the estimation of the dependent variable, the BSM probability of bankruptcy. However, the results are similar after including the controls in the regression.

5. Additional Analyses

5.1. EJR Client Identification: Robustness

Finally, 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 bond trades on EJR rating change announcement dates. We replicate our analyses using two alternative methods of identifying EJR clients using trade data in Ancerno: (i) stock trades, and (ii) "*abnormal*" bond trades.

In our first robustness test, we identify EJR clients using stock trades, following Bhattacharya et al. (2019). Ancerno Ltd. provides stock trading data from 1999 to 2010. We define EJR clients as those institutional investors that trade in the rated firm's *stock* on the date of an EJR rating change. After gathering the list of EJR subscribers, we obtain the historical stock holdings of each institution on a quarterly basis from 13F filings available in Thomson Reuters. We merge the list of institutions in Ancerno to 13F filings by fund manager name. We replicate our main analysis in Table 8 (column (1)) and find similar results.

In our second robustness test, we identify EJR clients using "*abnormal*" bond trades. Bhattacharya et al. (2019) identify EJR clients using abnormal stock trades, and we follow a similar method for our primary measure of bond trades. The goal of this identification method is to benchmark institutional investors' trading volume on EJR rating days relative to Moody's rating days. If an institutional investor trades more in response to Moody's rating changes relative to EJR, then we do include this investor in the list of EJR clients. For each institutional investor in Ancerno, 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% of all firms in the investor's portfolio, then we do not include the investor in the list of EJR clients in that quarter.

After revising the list of EJR clients using "*abnormal*" bond trades, we replicate our main results in Table 8, column (2). The results are similar. Overall, our results hold using three different empirical strategies to identify EJR clients, including identification methods using both bond and equity securities.

5.2. Other Robustness Tests

We perform a battery of untabulated robustness tests that support the interpretation of our results. First, in our main analyses, we define EJR optimism using an indicator variable. The results are similar using a continuous measure of EJR optimism as the dependent variable, equal to the difference in the EJR rating level less the concurrent benchmark rating level. Second, in our main analyses, we define EJR optimism using the rating levels as of the beginning of the quarter. Our results are similar using the average rating levels within each quarter. Finally, our findings are similar using industry fixed effects instead of firm fixed effects.

6. Conclusion

Criticism of the issuer-pay revenue model employed by the leading credit rating agencies has been a central focus of academics and policy makers as they have reflected on perceived rating failures during the early 2000s, first following the historic collapse of Enron Corporation and later following the turmoil of the global financial crisis from 2007 to 2009. At the heart of the criticism levied against Moody's, S&P, and Fitch is the argument that by relying on revenues from issuers, these rating agencies face a strong incentive to cater to their issuers' interests, which results in both overly optimistic ratings and less informative rating actions.

Frequently, critics of the issuer-pay model have suggested that a viable alternative would be a subscriber-pay model in which credit rating agencies receive fees from institutional investors for access to their rating data. Proponents of the subscriber-pay model, including Sean Egan of Egan-Jones Ratings, the most well-known subscriber-pay rating agency, have suggested that the subscriber-pay model eliminates conflicts of interest in the rating process because rating agencies no longer have incentives to cater to issuers. However, this argument discounts the existence of conflicts of interest with respect to institutional investors. To the extent that institutional investor subscribers hold securities of firms covered by a subscriber-paid rating agency, they can have preferences for optimistic ratings to allow for portfolio governance arbitrage or delayed downgrades to allow time for the unwinding of long positions.

Using institutional investor trading data from Ancerno, which allow us to identify clients of Egan-Jones Ratings, over the period from 1999 to 2010, we test whether conflicts of interest manifest in subscriber-paid credit ratings when institutional investor subscribers hold larger equity positions in rated firms. We find evidence that Egan-Jones ratings are more optimistic relative to Moody's ratings for firms in which a greater proportion of EJR clients have bond holdings and that this relation is larger in magnitude for larger EJR clients. These results also hold when we use a predicted rating from a rating model as a benchmark. In addition, we find evidence that Egan-Jones rating downgrades are less timely than Moody's downgrades for firms whose bonds are held by a greater proportion of EJR clients using bond return evidence around EJR rating change announcement dates. Finally, we find evidence that Egan-Jones ratings are relatively less accurate for firms more widely held by Egan-Jones subscribers.

Taken together, our results offer the first archival evidence of how conflicts of interest manifest in the properties of subscriber-paid credit ratings. Our results build on the literature that has studied the conflicts of interest in the credit rating industry (Jiang et al., 2012; Bonsall, 2014; Xia, 2014; Bruno et al., 2016; Beatty et al., 2019) by extending the analysis from issuer-paid rating agencies to subscriber-paid rating agencies. Our study also builds on the prior work of Beaver et al. (2006), which first contrasted the properties of ratings issued by Egan-Jones and Moody's, by providing evidence that the investor clientele of subscriber-paid rating agencies can push for less timely and informative credit ratings. Finally, the results can offer policymakers some insights about the incentives of rating agency compensation as the debate over properly motivating credit rating agencies continues. Although the SEC has not yet mandated a particular revenue model for credit rating agencies, our study offers some evidence that the subscriber-pay model is not a panacea.

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Appendices

Variable	Definition
# EJR Clients$_{iq}$	The number of EJR clients invested in firm *i's* bonds in quarter q, scaled by the total number of EJR clients in quarter q. EJR clients are identified using bond trades in Ancerno Ltd. (see Section 3.1).
# EJR Clients: Large (Medium, Small)$_{iq}$	The number of large (medium, small) EJR clients invested in firm *i's* bonds in quarter q, scaled by the total number of EJR clients in quarter q. EJR clients are sorted into size terciles (large, medium, small) based on the total bond holdings of each EJR client in Thomson Reuters eMaxx in quarter q.
Bankruptcy Risk$_{iq+1}$	The Black-Scholes-Merton (BSM) probability of bankruptcy for firm i in quarter $q+1$, where higher values indicate a higher probability of bankruptcy. For further details on the computation of this measure, see Hillegeist et al. (2004).
Bond Market Reaction$_{it+1}$	The bond market reaction to the announcement of a credit rating change for firm i, calculated as the firm-level average 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$_{iq+1}$	The firm-level average cumulative bond market return for firm i in quarter $q+1$.
EJR > Moody's: Investment Grade Cutoff$_{iq+1}$	Indicator variable equal to 1 if the EJR rating for firm i in quarter $q+1$ is just above the investment-grade cutoff and the concurrent Moody's rating for firm i in quarter $q+1$ is below investment-grade, and 0 otherwise. The rating level is defined using the existing rating level at the beginning of the quarter.
EJR > Moody's: Other Cutoffs$_{iq+1}$	Indicator variable equal to 1 if the EJR rating for firm i in quarter $q+1$ is higher than the concurrent Moody's rating for firm i in quarter $q+1$, and 0 otherwise, *excluding* observations around the investment-grade cutoff. Specifically, if *EJR > Moody's: Investment-Grade Cutoff* = 1, then *EJR > Moody's: Other Cutoffs* = 0. The rating level is defined the existing rating level at the beginning of the quarter.

Variable	Definition
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 just above the investment-grade cutoff, and the rating from the given benchmark (i.e., either the concurrent Moody's rating or the model-implied rating following Baghai et al. (2014)) for firm i in quarter $q+1$ is below investment-grade, and 0 otherwise. The rating level is defined using the existing rating level at the beginning of the quarter.
EJR Rating Level$_{iq}$	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 using the existing rating level at the beginning of the quarter.
Firm Size$_{iq}$	Market value of equity for firm i in quarter q (in millions), except in Table 6 and Table 7 (column (1)), where *Firm Size* is estimated as the natural log of total assets for firm i in quarter q.
Leverage$_{iq}$	Total leverage for firm i in quarter q, calculated as the sum of long-term and short-term liabilities scaled by stockholder's equity.
Moody's Optimistic$_{iq+1}$	Indicator variable equal to 1 if the Moody's rating for firm i in quarter $q+1$ is just above the investment-grade cutoff, and the rating from the given benchmark (i.e., either the concurrent EJR rating or the model-implied rating following Baghai et al. (2014)) for firm i in quarter $q+1$ is below investment-grade, and 0 otherwise. The rating level is defined using 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.
Std. Dev. Ret.$_{iq}$	Standard deviation of stock returns for for firm i in quarter q.

Appendices

Description	Obs.	Period
Main Variables		
eMMAX Holding Data	30,393,020	1999Q1 - 2010Q4
eMMAX firms with GVKEY	12,753,536	1999Q1 - 2010Q4
eMMAX funds management code	12,485,198	1999Q1 - 2010Q4
Keep firms with Moody's and EJR Ratings	6,086,536	1999Q1 - 2010Q4
Aggregate data by firm and quarter	19,912	1999Q1 - 2010Q4
Match data with Ancerno Ltd.	12,855	2004Q3 - 2010Q4
Obs. with controls	10,716	2004Q3 - 2010Q4

Table 1. Descriptive Statistics

This table presents the descriptive statistics for the main sample of 10,716 firm-quarter observations. *EJR Optimistic* is an indicator variable equal to 1 if the EJR rating is just above the investment-grade cutoff and the concurrent Moody's rating is below investment-grade, and 0 otherwise. *# EJR Clients* is the number of EJR clients invested in the rated firm's bonds, scaled by the total number of EJR clients. The definitions of the control variables are provided in Appendix A.

	N	Mean	p25	Median	p75	S.D.
Main Variables						
# EJR Clients	10,716	0.153	0.000	0.077	0.250	0.209
EJR Optimistic	10,716	0.066	0.000	0.000	0.000	0.248
Control Variables						
Firm Size	10,716	0.016	0.002	0.006	0.016	0.033
Leverage	10,716	1.214	0.394	0.699	1.319	3.083
MTB	10,716	2.726	1.374	2.098	3.357	3.495
Operating Margin	10,716	0.211	0.106	0.177	0.287	0.185
Std. Dev. Ret.	10,716	0.023	0.013	0.019	0.027	0.017

Table 2. EJR Ratings Compared to Moody's Ratings

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's bonds. The sample is comprised of 10,716 firm-quarter observations. In column (1), the dependent variable, *EJR > Moody's: Investment-Grade Cutoff*, is an indicator variable equal to 1 if the EJR rating is just above the investment-grade cutoff and the concurrent Moody's rating is below investment-grade, and 0 otherwise. In column (2), the dependent variable, *EJR > Moody's: Other Cutoffs*, is an indicator variable equal to 1 if the EJR rating is higher than the concurrent Moody's rating, and 0 otherwise, *excluding* observations around the investment-grade cutoff. Specifically, if *EJR > Moody's: Investment-Grade Cutoff* = 1, then *EJR > Moody's: Other Cutoffs* = 0. The independent variable of interest, *# EJR Clients*, is the number of EJR clients invested in the rated firm's bonds scaled by the total number of EJR clients. The definitions of the control variables are provided in Appendix A. Both columns include year-quarter and firm fixed effects. Standard errors are presented in parentheses below the coefficient estimates and clustered by industry × year-quarter. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	EJR > Moody's: Investment-Grade Cutoff (1)	EJR > Moody's: Other Cutoffs (2)
# EJR Clients	0.052***	0.044
	(0.015)	(0.031)
Firm Size	0.013**	0.056***
	(0.006)	(0.012)
Leverage	-0.001	-0.008***
	(0.001)	(0.002)
Operating Margin	0.012	0.037
	(0.017)	(0.036)
MTB	-0.001	0.007***
	(0.001)	(0.002)
Std. Dev. Ret.	-0.189	0.123
	(0.181)	(0.396)
Constant	-0.049	0.018
	(0.051)	(0.109)
Observations	10,716	10,716
R^2	0.504	0.503
Time FE	Yes	Yes
Firm FE	Yes	Yes

Table 3. EJR Optimism relative to Moody's Ratings

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's bonds. The sample is comprised of 10,716 firm-quarter observations. The dependent variable in columns (1)-(2), *EJR Optimistic*, is an indicator variable equal to 1 if the EJR rating is just above the investment-grade cutoff and the concurrent Moody's rating is below the investment-grade cutoff, and 0 otherwise. The dependent variable in columns (3)-(4), *Moody's Optimistic*, is an indicator variable equal to 1 if the Moody's rating is just above the investment-grade cutoff and the EJR rating is below the investment-grade cutoff, and 0 otherwise. In columns (1) and (3), *# EJR Clients* is calculated as the number of EJR clients invested in the rated firm's bonds, scaled by the total number of EJR clients. In columns (2) and (4), *# 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 rated firm's bonds, scaled by the total number of EJR clients. The definitions of the control variables are provided in Appendix A. All columns include year-quarter and firm fixed effects. Standard errors are presented in parentheses below the coefficient estimates and clustered by industry × year-quarter. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	EJR Optimistic (1)	EJR Optimistic (2)	Moody's Optimistic (3)	Moody's Optimistic (4)
# EJR Clients	0.052***		-0.008	
	(0.015)		(0.012)	
# EJR Clients: Large		0.083***		-0.030
		(0.023)		(0.023)
# EJR Clients: Medium		0.062***		-0.005
		(0.023)		(0.020)
# EJR Clients: Small		-0.049		0.046
		(0.030)		(0.028)
Firm Size	0.013**	0.013**	0.007	0.007
	(0.006)	(0.006)	(0.004)	(0.004)
Leverage	-0.001	-0.001	0.001***	0.001***
	(0.001)	(0.001)	(0.000)	(0.000)
Operating Margin	0.012	0.013	-0.027**	-0.027**
	(0.017)	(0.017)	(0.013)	(0.013)
MTB	-0.001	-0.001	-0.001**	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
Std. Dev. Ret.	-0.189	-0.194	0.046	0.050
	(0.181)	(0.181)	(0.156)	(0.156)
Constant	-0.049	-0.053	-0.013	-0.010
	(0.051)	(0.050)	(0.037)	(0.037)
Observations	10,716	10,716	10,716	10,716
R^2	0.504	0.504	0.348	0.349
Time FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table 4. EJR Optimism relative to Model-Implied Ratings

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's bonds. The sample is comprised of 10,311 firm-quarter observations. The dependent variable in columns (1)-(2), *EJR Optimistic*, is an indicator variable equal to 1 if the EJR rating is just above the investment-grade cutoff and the predicted rating based on the credit risk model in Baghai et al. (2014) is below the investment-grade cutoff for a given firm, and 0 otherwise. The dependent variable in columns (3)-(4), *Moody's Optimistic*, is an indicator variable equal to 1 if the Moody's rating is just above the investment-grade cutoff and the predicted rating based on the credit risk model in Baghai et al. (2014) is below the investment-grade cutoff for a given firm, and 0 otherwise. In columns (1) and (3), *# EJR Clients* is calculated as the number of EJR clients invested in the rated firm's bonds, scaled by the total number of EJR clients. In columns (2) and (4), *# 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 rated firm's bonds, scaled by the total number of EJR clients. The definitions of the control variables are provided in Appendix A. All columns include year-quarter and firm fixed effects. Standard errors are presented in parentheses below the coefficient estimates and clustered by industry × year-quarter. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	EJR Optimistic (1)	EJR Optimistic (2)	Moody's Optimistic (3)	Moody's Optimistic (4)
# EJR Clients	0.075***		0.024	
	(0.013)		(0.017)	
# EJR Clients: Large		0.089***		0.023
		(0.019)		(0.032)
# EJR Clients: Medium		0.080***		0.007
		(0.021)		(0.025)
# EJR Clients: Small		0.019		0.068
		(0.034)		(0.043)
Firm Size	0.022***	0.023***	0.029***	0.029***
	(0.006)	(0.006)	(0.007)	(0.007)
Leverage	-0.003***	-0.003***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Operating Margin	0.034	0.034	0.028	0.027
	(0.027)	(0.027)	(0.023)	(0.023)
MTB	0.002	0.002	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Std. Dev. Ret.	0.593***	0.592***	1.038***	1.036***
	(0.213)	(0.213)	(0.272)	(0.272)
Constant	-0.178***	-0.181***	-0.160***	-0.160***
	(0.050)	(0.050)	(0.062)	(0.062)
Observations	10,311	10,311	10,311	10,311
R^2	0.380	0.380	0.526	0.526
Time FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table 5. Persistence of EJR Optimism

This table describes the persistence of EJR optimism (relative to Moody's) over time. The sample is comprised of 10,716 firm-quarter observations (column (1)). The dependent variable, *EJR Optimistic*, is an indicator variable equal to 1 if the EJR rating is just above the investment-grade cutoff and the concurrent Moody's rating is below the investment-grade cutoff, and 0 otherwise. In columns (1)-(5), *EJR Optimistic* is estimated in quarters q+1, q+2, q+3, q+4, and q+5, respectively. *# EJR Clients* is the number of EJR clients invested in the rated firm's bonds, scaled by the total number of EJR clients. The definitions of the control variables are provided in Appendix A. All columns include year-quarter and firm fixed effects. Standard errors are presented in parentheses below the coefficient estimates and clustered by industry × year-quarter. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	EJR Optimistic (q+1) (1)	EJR Optimistic (q+2) (2)	EJR Optimistic (q+3) (3)	EJR Optimistic (q+4) (4)	EJR Optimistic (q+5) (5)
# EJR Clients	0.052***	0.042***	0.024	-0.002	0.000
	(0.015)	(0.015)	(0.016)	(0.016)	(0.018)
Firm Size	0.013**	0.010*	0.007	0.001	-0.012
	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)
Leverage	-0.001	-0.000	0.001	0.003**	0.004**
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Operating Margin	0.012	-0.012	0.008	-0.012	0.010
	(0.017)	(0.016)	(0.017)	(0.018)	(0.019)
MTB	-0.001	-0.002	-0.003*	-0.004***	-0.005***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Std. Dev. Ret.	-0.189	-0.147	-0.086	-0.097	-0.217
	(0.181)	(0.180)	(0.183)	(0.186)	(0.178)
Constant	-0.049	-0.021	0.008	0.065	0.182***
	(0.051)	(0.054)	(0.057)	(0.062)	(0.067)
Observations	10,716	10,134	9,588	9,059	8,545
R^2	0.504	0.517	0.532	0.545	0.558
Time FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes

Table 6. Timeliness of EJR Downgrades

This table examines the bond market reaction to EJR downgrades based on EJR client ownership. The sample is comprised of 1,743 EJR rating change observations. *Bond Market Return* is the firm-level average 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 rated firm's bonds, scaled by the total number of EJR clients. *EJR Down* is an indicator variable equal to 1 if the rating change is a downgrade issued by EJR. The definitions of the control variables are provided in Appendix A. Both columns include year-quarter and firm fixed effects. Standard errors are presented in parentheses below the coefficient estimates and clustered by industry × year-quarter. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Bond Market Return (1)
# EJR Clients	-0.001
	(0.007)
EJR Down	-0.012***
	(0.003)
EJR Down × # EJR Clients	0.029**
	(0.012)
Firm Size	-0.008
	(0.005)
Leverage	0.000
	(0.001)
Operating Margin	-0.013
	(0.025)
MTB	-0.001
	(0.001)
Std. Dev. Ret.	-0.861***
	(0.281)
Constant	0.097*
	(0.051)
Observations	1,743
R^2	0.123
Time FE	Yes
Firm FE	Yes

Table 7. Subsequent Performance

This table examines the relation between EJR ratings and subsequent firm performance as a function of EJR client ownership. The sample is comprised of 9,717 firm-quarter-ratings level observations in column (1) and 2,474 firm-quarter-ratings level observations in column (2). In column (1), *Bond Return*$_{q+1}$, is the firm-level average cumulative bond market return in quarter q+1. In column (2), *Bankruptcy Risk*$_{q+1}$ is the Black–Scholes–Merton (BSM) probability of bankruptcy in quarter q+1, where higher values indicate a higher probability of bankruptcy. *# EJR Clients* is the number of EJR clients invested in the rated firm's bonds, scaled by the total number of EJR clients. *EJR Rating Level* is the numerical equivalent of the EJR rating level, where higher values indicate higher credit quality (i.e., D = 1 and AAA = 21). The definitions of the control variables are provided in Appendix A. All columns include year-quarter and firm fixed effects. Standard errors are presented in parentheses below the coefficient estimates and clustered by industry × year-quarter. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Bond Return$_{q+1}$ (1)	Bankruptcy Risk$_{q+1}$ (2)
# EJR Clients	0.071***	-0.147**
	(0.024)	(0.070)
EJR Rating Level	-0.000	-0.002
	(0.001)	(0.003)
# EJR Clients x EJR Rating Level	-0.004***	0.012**
	(0.002)	(0.006)
Constant	0.034	0.053
	(0.024)	(0.044)
Observations	9,717	2,474
R^2	0.258	0.322
Time FE	Yes	Yes
Firm FE	Yes	Yes
Controls	Yes	No
Period	Quarter	Annual

Table 8. Identifying EJR Clients: Robustness

This table describes the likelihood that Egan-Jones (EJR) provides an optimistic rating (relative to Moody's) based on the number of EJR clients, where EJR clients are identified using stock trades (column (1)) and abnormal bond trades (column (2)). The sample is comprised of 16,710 and 10,716 firm-quarter observations in columns (1) and (2), respectively. The dependent variable, *EJR Optimistic*, is an indicator variable equal to 1 if the EJR rating is just above the investment-grade cutoff and the concurrent Moody's rating is below the investment-grade cutoff, and 0 otherwise. *# EJR Clients* is the number of EJR clients invested in the rated firm's bonds, scaled by the total number of EJR clients. The definitions of the control variables are provided in Appendix A. All columns include year-quarter and firm fixed effects. Standard errors are presented in parentheses below the coefficient estimates and clustered by industry × year-quarter. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	EJR Optimistic: Stock Trades (1)	EJR Optimistic: Abnormal Bond Trades (2)
# EJR Clients	0.126***	0.054***
	(0.024)	(0.015)
Firm Size	0.011***	0.013**
	(0.004)	(0.006)
Leverage	-0.002**	-0.001
	(0.001)	(0.001)
Operating Margin	0.014	0.012
	(0.013)	(0.017)
MTB	0.000	-0.001
	(0.001)	(0.001)
Std. Dev. Ret.	-0.398***	-0.185
	(0.132)	(0.181)
Constant	-0.045	-0.049
	(0.031)	(0.051)
Observations	16,710	10,716
R^2	0.419	0.504
Time FE	Yes	Yes
Firm FE	Yes	Yes
Sample Period	1999-2010	2004-2010