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ARTICLE

Asymmetric trading responses to credit rating announcements from issuer- versus investor-paid rating agencies

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Abstract

The credit rating industry has traditionally followed the "issuer-pays" principle. Issuer-paid credit rating agencies (CRAs) have faced criticism regarding their untimely release of negative rating adjustments, which is attributed to a conflict of interests in their business model. An alternative model based on the "investor-pays" principle is arguably less subject to the conflict of interest problem. We examine how investors respond to changes in credit ratings issued by these two types of CRAs. We find that investors react asymmetrically: They abnormally sell equity stakes around rating downgrades by investor-paid CRAs, while abnormally buying around rating upgrades by issuer-paid CRAs. Our study suggests that, through their trades, investors capitalize on value-relevant information provided by both types of CRAs, and a dynamic trading strategy taking advantage of this information generates significant abnormal returns.

KEYWORDS
credit ratings, institutional investors, trading strategy

JEL CLASSIFICATION
G11, G24

1 INTRODUCTION

The credit rating sector has long been dominated by three major issuer-paid credit rating agencies (CRAs): Standard and Poor's (S&P), Moody's Investors Service (Moody's) and Fitch Ratings. These issuer-paid CRAs extract fees directly from bond issuers, which might lead to potential conflicts of interest when they provide rating services to those issuers. Issuer-paid CRAs tend to delay the release of negative ratings (Cornaggia & Cornaggia, 2013; J. He et al., 2012; Skreta & Veldkamp, 2009) while giving favorable ratings to stocks in their owners' portfolios (Kedia et al., 2017). Baghai and Becker (2018) find evidence that issuer-paid CRAs assign higher ratings even to those issuers who pay them for non-rating services. The lack of timeliness in negative rating adjustments in high-profile bankruptcies, such as Enron (2001), WorldCom (2002) and Lehman Brothers (2008), is often presented as evidence of such conflicts. For example, on September 10, 2008—the day Lehman Brothers announced its bankruptcy—S&P and Moody's had them rated at A2 and A, respectively, and only adjusted the credit ratings down after the bankruptcy announcement.

The entry of investor-paid CRAs (e.g., Egan-Jones Ratings [EJR] and Rapid Ratings) has changed the dynamics of the credit rating industry. These CRAs are paid by the end users of their ratings, such as institutional investors, and the conflict of interest problem is potentially alleviated. Extant literature documents significant evidence of high rating quality of investor-paid CRAs. Cornaggia and Cornaggia (2013) show that Rapid Ratings provides more timely downgrades for defaulting bonds than Moody's downgrades, which results in significant loss avoidance for investors. Xia (2014) considers the entry of EJR as a natural experiment to assess issuer-paid CRAs' reactions to potential competition from a new player. They find that due to reputational concerns, credit ratings issued by S&P tend to become more responsive and informative following the EJR entry. Beaver et al. (2006) and Bruno et al. (2016) report that EJR's credit ratings are more accurate and timely than Moody's, even after its successful registration as a nationally recognized statistical rating organization in December 2007. X. Hu et al. (2019) find corroborating evidence in a non-US setting. Using the introduction of China Bond Rating (CBR) in 2010, a CRA that combines a public utility model and an investor-paid model, the authors show that the CBR entry triggers a significant reduction in rating inflation and improvements in information quality of credit rating announcements by nine traditional issuer-paid CRAs in China.

Given the rise of investor-paid CRAs, the competition they bring about and the information content of their credit ratings relative to issuer-paid CRAs, it is crucial to understand whether and how financial market participants utilize credit ratings provided by both issuer- and investor-paid CRAs for their benefit. Xia (2014) and Berwart et al. (2019) find that stocks with downgrade announcements by EJR experience significantly more negative returns than following downgrades by issuer-paid CRAs, whereas EJR upgrades apparently do not trigger a positive response from investors. Investigating the reaction of institutional investors to EJR's rating changes, Bhattacharya et al. (2019) find that these investors are more responsive to its rating announcements than to other trading signals. They also show that institutional investors who follow EJR's credit rating announcements outperform those who ignore these signals. We contribute to this strand of literature and examine the value relevance of credit rating changes issued by both types of CRAs.

We argue that investor-paid CRAs cannot completely dominate traditional issuer-paid CRAs that have long-term positions in the credit rating sector. As argued in previous studies, issuer-paid CRAs only tend to delay negative credit rating announcements due to the potential conflict of interest (Cornaggia & Cornaggia, 2013; He et al., 2012; Skreta & Veldkamp, 2009). In contrast, issuer-paid CRAs are likely less conservative in issuing rating upgrades since it would be in their interest to cater positive ratings to their clients (e.g., Bolton et al., 2012; Griffin et al., 2013). Hence, it remains unclear whether investors show different trading patterns in responding to negative and positive credit rating adjustments from issuer- and investor-paid CRAs. The answer to this question is important as it provides a better understanding of the relevance and viability of different types of CRAs.

We use institutional investors and mutual funds' changes in stock holdings around rating announcements as a proxy for market reaction. We consider EJR as a representative of investor-paid CRAs, while the "Big Three" CRAs (S&P,

Moody's and Fitch) are representatives of issuer-paid CRAs. We find that institutional investors abnormally decrease their equity holdings surrounding investor-paid rating downgrades but do not respond to any issuer-paid rating downgrades. On the contrary, they significantly increase their equity holdings around issuer-paid rating upgrades but remain unresponsive to investor-paid rating upgrades. These results suggest that institutional investors and mutual funds consider investor-paid CRAs' rating downgrades as being timely and informative for their trading as opposed to issuer-paid CRAs' rating downgrades. Further, they regard issuer-paid rating upgrades as having more value-relevant information than investor-paid rating upgrades. In the main analysis, we use quarterly mutual fund (S12) holdings and quarterly institutional (13F) holdings provided by Thomson Reuters. We also use daily institutional trades provided by Abel Noser Corporation to measure institutional reactions to credit rating adjustments.[1]

We then examine whether investors can profit from trading decisions in response to rating changes. We construct and compare four trading strategies: (1) a "dynamic" strategy—selling following investor-paid negative signals and buying following issuer-paid positive signals, (2) a "naïve" strategy—selling following negative signals and buying following positive signals from any rating agency, (3) an "EJR-based" strategy—selling following negative signals and buying following positive signals announced by EJR and (4) an "issuer-paid CRA-based" strategy—selling following negative signals and buying following positive signals by any of the issuer-paid CRAs. Following Jagolinzer et al. (2011), we compute returns for each trading strategy adjusting for common risk factors using the Fama–French five-factor model. The trading strategy analysis is performed in two steps. First, we construct "notional" trading strategies to acknowledge the fact that any market player with access to credit ratings can potentially benefit from these strategies. These results also correspond to equally weighted returns of an investor who trades on every signal consistent with a given strategy. While all four strategies outperform the buy-and-hold strategy, we find that the dynamic strategy produces the highest returns, offering an average difference in annualized risk-adjusted returns of up to 5.02% over the other three strategies for a 1-month holding period. Second, using aggregate credit rating changes and institutional investors' quarterly stock holding changes from S12 and 13F data, we find that all four trading strategies earn substantially higher abnormal returns than the corresponding notional strategy returns and that the dynamic strategy consistently exhibits the highest abnormal returns. Finally, since Abel Noser Corporation provides daily trading data for institutional investors, we use them as an alternative dataset to identify trading strategies based on cumulative net buy around announcement dates. We thus explicitly acknowledge that an institution can dynamically switch between strategies and potentially follow multiple strategies at a time. Our results confirm the superiority of the dynamic trading strategy. More importantly, it outperforms the other three strategies by more than 10% per annum for a 1-month holding period and up to 7.26% per annum for a 9-month holding period. This outperformance is more than twice the notional strategies' corresponding outperformance; hence, they are consistent with the argument that institutional investors have advanced trading skills and knowledge (Puckett & Yan, 2011) to exploit the informative announcements in the financial markets.

Our study contributes to the literature in several important ways. First, we add to the knowledge of the relationship between the quality of credit ratings and market participants' behavior. The related literature finds that the high quality of investor-paid CRA ratings creates a reputational concern for issuer-paid CRAs, which motivates them to improve the overall quality of credit ratings (e.g., Berwart et al., 2019; Bruno et al., 2016; Ramsay, 2011; Xia, 2014). For example, Xia (2014) finds that following EJR's appearance, S&P ratings started to reflect credit risks more accurately. Similarly, Ramsay (2011) discovers that the entry of Rapid Ratings—another investor-paid CRA—motivates major issuer-paid CRAs to improve the quality of credit ratings. X. Hu et al. (2019) provide evidence of significant improvements in credit rating informativeness in the China bond market after the introduction of CBR, a combined public utility and investor-paid CRA. However, the impact of credit rating quality on investors' behavior remains underexamined. Our study fills this gap by examining the role of timeliness of credit rating adjustments—a proxy for credit rating quality—in driving institutional investors' behavior.

[1] We thank the editor and referee for this constructive suggestion.

Second, our findings enrich the understanding of how institutional investors, as professional players, analyze and react dynamically to negative and positive rating adjustments obtained from different sources over time. Baker and Mansi (2002) report interesting results regarding the view of institutional investors toward credit ratings. They find that a majority of institutional investors value credit ratings in their investment decisions and place significant importance on rating timeliness. Although they also generally agree on the accuracy of ratings in reflecting firms' creditworthiness, they believe that ratings could either overstate or understate credit risk. Therefore, institutional investors tend to also rely on their own internal analysis before responding to credit rating news. Cantor et al. (2007) find from their survey that investment managers in the United States and Europe share remarkably similar usage of credit ratings to conduct their investment activities. He (2021) finds that transient institutional investors tend to trade more intensively in low credit rating firms following their earnings announcements. Bhattacharya et al. (2019) find that institutional investors who follow EJR's rating announcements significantly focus on EJR rating news rather than important equity trading signals, such as analyst recommendations, earnings announcements and earnings forecast revisions. They also find that institutional investors who persistently follow EJR's credit rating announcements outperform those who do not embrace these signals. Our study extends their findings by providing new evidence that investors with access to rating announcements could dynamically exploit the value-relevant information of negative and positive rating signals provided by both investor-paid and issuer-paid CRAs in making their trading decisions. Our results show that while such trading behavior is generally profitable, institutional investors evidently earn the highest abnormal profits. Finally, the reported abnormal profits that continue to exist up to at least 6 months suggest that investors underreact to the information content of credit rating announcements, particularly to negative signals provided by investor-paid EJR and positive signals given by issuer-paid CRAs.

The remainder of the paper is organized as follows. Section 2 summarizes data collection, variable measurements and summary statistics. Section 3 presents the methodology and empirical results. Robustness checks are presented in Section 4. Section 5 concludes.

2 | SAMPLE SELECTION, VARIABLE MEASUREMENTS AND SUMMARY STATISTICS

2.1 | Sample selection

We consider two quarterly institutional holding databases to extract institutional investors' trading activities: mutual fund (S12) holdings and institutional (13F) holdings provided by Thomson Reuters. The S12 holdings database provides data on mutual fund holdings of US securities at the end of each quarter. The 13F holdings database provides a similar data structure at the institutional (i.e., investment company or fund family) level.[2] Our analysis includes all US equity mutual funds and institutional investors that have at least 65% of their assets in common stocks (e.g., Amihud & Goyenko, 2013; Cremers & Petajisto, 2009).[3] The final samples include 8566 mutual funds and 8656 institutional investors.

As mentioned above, we focus on two types of CRAs: investor- and issuer-paid CRAs. EJR is a representative of investor-paid CRAs, while the "Big Three" represent issuer-paid CRAs. Credit rating data are sourced from Egan-Jones Rating Company[4] and Bloomberg for the period from 1999 to 2017 to match with the S12 and 13F holding data. The credit rating databases include two types of rating information: rating warning announcements[5] and official rating

[2] Note that Form 13F is only required for institutional investment managers with more than $100 million in assets under management.

[3] We also consider alternative thresholds such as 50%, 60% and 70% as robustness checks. The results are consistent and available upon request.

[4] We wish to thank the Egan-Jones Rating Company for sharing its historical rating data.

[5] Based on the data availability, there are two types of rating warning announcements: outlook and developing signals. These signals are normally announced before official rating adjustments.

adjustments.[6] The databases also report the date of each credit rating adjustment. As we are interested in corporate credit ratings, sovereign credit and asset-backed securities ratings are excluded.

2.2 | Variable definitions

Since credit ratings are represented by different combinations of letters and numbers (e.g., AAA/Aaa, AA+/Aa1, AA/Aa2, AA-/Aa3), several prior studies follow Gande and Parsley (2005) to construct a unique "comprehensive credit rating" (CCR) scale to quantify alphabetic ratings (Alsakka & ap Gwilym, 2012; Chen et al., 2016; Dimitrov et al., 2015; Drago & Gallo, 2016). Based on the features of credit rating data availability, we follow Joe and Oh's (2018) rating conversion scale. The numeric score for letter rating and warning (single) signals are shown in Appendix A.[7] In addition, we also follow the literature (Chen et al., 2016; Vu et al., 2015) to measure the significance of the credit rating event for firm n at time t as the change in CCR, $\Delta CCR_{n,t}$:

$$\Delta CCR_{n,t} = CCR_{n,t} - CCR_{n,t-1}. \tag{1}$$

To match the frequency of fund holding data, we aggregate changes in credit rating adjustment on a quarterly basis. For instance, in the first quarter of 2010, S&P announces two credit rating adjustments for firm n, a single downgrade (i.e., −1 notch) on February 1, 2010, and a double downgrade (i.e., −2 notches) on March 2, 2010, and the aggregate credit rating change by S&P for firm n in the first quarter of 2010 is −3 notches.

We use abnormal mutual fund and institutional investors' trading as a proxy for investors' responses, measured by quarterly abnormal net buy, $NB_{i,n,q}$.

$$NB_{i,n,q} = nb_{i,n,q} - average\ nb_{i,n,q}, \tag{2}$$

where $nb_{i,n,q}$ is the quarterly net buy by mutual fund or institutional investor i on stock n measured as dollar stock holding in quarter q minus quarter $q-1$, normalized by the stock's total market value at the end of the quarter q.[8] $Average\ nb_{i,n,q}$ denotes the average value of $nb_{i,n,q}$ in the period from quarter $q-4$ to $q-1$ as follows:

$$average\ nb_{i,n,q} = \frac{\sum_{k=-1}^{-4} nb_{i,n,q+k}}{4}. \tag{3}$$

We follow Chemmanur et al. (2016) to convert $NB_{i,n,q}$ into basis points.

2.3 | Control variables

We also follow the related literature (Bernile et al., 2015; Bhattacharya et al., 2019; Henry et al., 2017) to control for a vector of firm characteristics related to institutional trading activities. The control variables include firm size, profitability, stock idiosyncratic volatility, Z-score, analyst coverage, interest coverage, firm age, leverage, high-tech

[6] Official rating adjustments are basically divided into two types: positive and negative signals. These signals can also include single and multiple events. In our study, a single event is either a one-notch upgrade or downgrade, and a multiple event is either a multiple-notch upgrade (downgrade) or a combined event of a rating warning announcement and an official rating adjustment.

[7] Gande and Parsley (2005) count positive and negative outlooks as one notch. In our study, to highlight the impacts of official upgrades (downgrades), positive and negative outlooks are counted as 0.5 notch and positive and negative developments as 0.25.

[8] This is to follow the merit of Chemmanur et al. (2009) who estimate institutional net buy based on shares traded and shares outstanding.

dummy and an S&P 500 index inclusion dummy. The descriptions of control variables and their sources are presented in Appendix B.

2.4 | Summary statistics

Table 1 presents summary statistics of mutual funds (S12) and institutional investors (13F). The number of mutual funds (institutional investors) has gradually increased from 3364 (1751) in 1999 to 4752 (4130) in 2017. The number of stocks held by mutual funds (institutional investors) has been relatively stable, ranging from 576 (562) in 1999 to 653 (692) in 2017. On average, each institutional investor holds 109 stocks in their portfolio in 1999. The number gradually increases to 162 in 2017. These figures are almost double those of mutual funds, which are at 52 stocks in 1999 and 99 stocks in 2017. Mutual funds' (institutional investors') stock holdings have sharply increased from $301 (267) billion in 1999 to $2573 (1168) billion in 2017. On average, each mutual fund holds $89 million worth of stocks in 1999, and the amount increases to $541 million in 2017. The figures for institutional investors are $153 million in 1999 and $283 million in 2017.

Table 2 displays summary statistics of credit rating events. The first row of panel A shows the number of unique firms that each CRA provides credit rating announcements over the sample period of 1999–2017. Despite being a relatively new player in the credit rating industry, EJR provides credit ratings for 1502 firms, which are only slightly fewer than S&P (1432 firms) but more than double the coverage by either Moody's (645) or Fitch (502). EJR is also the only CRA that provides developing signals, whereas the traditional issuer-paid CRAs do not provide such service during our sample period.[9] We split our rating announcements into negative and positive events and present them in panel A, sections 1 and 2. There are 2628 (2504), 1172 (546), 355 (172) and 200 (64) negative (positive) combined events[10] assigned by EJR, S&P, Moody's and Fitch, respectively. In addition, the sample comprises 2013 (1896), 1187 (1342), 370 (541) and 578 (549) solo downgrades (upgrades) and 415 (264), 428 (114), 187 (48) and 163 (70) multiple downgrades (upgrades) announced by EJR, S&P, Moody's and Fitch, respectively. Panel A also shows 1648 (1910), 1537 (730), 440 (299) and 278 (80) negative (positive) outlook signals by these CRAs, respectively.

Panel B of Table 2 presents the distribution of credit rating adjustments. Regarding the total number of rating events, EJR issues about 20% more rating changes than all issuer-paid CRAs' events combined. Within each CRA, EJR has more positive than negative rating announcements. This is opposite to the issuer-paid CRAs, which announce more negative rating adjustments than positive ones. Regarding the magnitude of rating adjustments, Fitch, on average, seems to provide the boldest adjustments, compared to the other CRAs. For example, the mean absolute value of negative rating adjustments is 1.174 for Fitch, while that is 1.041, 1.050 and 1.068 for EJR, S&P and Moody's, respectively. Negative rating adjustments are generally larger in absolute value than positive rating adjustments. The median column in panel B suggests that S&P is relatively more conservative in their negative rating adjustments: 50% of their negative rating events have a median value of 0.5 notch.

Table 3 presents the descriptive statistics of control variables computed around credit rating changes. Observations are divided into three groups: The first group includes firms rated by EJR and S&P, the second group is for firms rated by EJR and Moody's and the third group covers firms rated by EJR and Fitch. The N column shows the number of fund-firm-quarter observations. The first group has the largest number of observations in both S12 and 13F samples, followed by groups three and two. The third group includes, on average, larger and older firms. This appears to be

[9] EJR derives its "watch" assignments from the difference between the current and projected ratings. No difference between the two results in a "stable" watch, a higher projected rating results in a "positive" or "POS" watch and a lower projected rating results in a "negative" or "NEG" watch. The absence of a projected rating results in a "developing" or "DEV" watch or no watch being populated. The addition of a POS or NEG is at the discretion of the analyst or Rating Committee and usually results from the direction the rate is expected to move over time. See https://www.egan-jones.com/public/download/methodologies/20210510/EJR_Main_Methodologies_V15a.pdf

[10] A combined event is a multiple announcement when a CRA adjusts both credit rating score and outlook (or developing) signal.

TABLE 1 Mutual fund (S12) and institutional investor (13F) holdings statistics

	Mutual funds S12 (MFs)					Institutional investors 13F (IIs)				
Year	No. MFs	No. stocks	No. stocks per MF	Total stock value held by MFs (billions)	Total stock value held by each MF (billions)	No. IIs	No. stocks	No. stocks per II	Total stock value held by IIs (billions)	Total stock value held by each II (billions)
1999	3364	576	52	301	0.089	1751	562	109	267	0.153
2000	3726	608	61	381	0.102	1875	612	123	348	0.185
2001	3863	614	69	351	0.091	2012	611	128	314	0.156
2002	3984	618	75	348	0.087	2043	629	130	300	0.147
2003	4072	627	79	398	0.098	2046	637	139	347	0.170
2004	4003	644	82	525	0.131	2187	654	144	435	0.199
2005	4002	657	84	606	0.152	2401	669	141	494	0.206
2006	3923	653	86	718	0.183	2529	665	142	575	0.227
2007	4365	642	87	845	0.194	2780	665	142	681	0.245
2008	4694	628	91	719	0.153	2960	642	134	544	0.184
2009	4413	628	98	688	0.156	2923	642	135	459	0.157
2010	4113	638	98	857	0.208	2900	651	142	569	0.196
2011	4333	649	96	927	0.214	3070	671	148	634	0.207
2012	4328	657	99	1044	0.241	3182	676	152	722	0.227
2013	4254	673	100	1359	0.319	3340	691	159	863	0.259
2014	4454	680	98	1725	0.387	3593	699	165	1022	0.284
2015	4640	683	99	1793	0.387	3853	706	161	1008	0.262
2016	4836	673	100	2024	0.419	3989	696	159	1033	0.259
2017	4752	653	99	2573	0.541	4130	692	162	1168	0.283
Average	4217	642	87	957	0.219	2819	656	143	620	0.211

TABLE 2 Credit rating sample statistics

Panel A: Rating changes	Egan-Jones Ratings (EJR)	Standard and Poor (S&P)	Moody's Investors Service (Moody's)	Fitch Ratings (Fitch)
Number of firms rated	1502	1432	645	502
Section 1: Negative events				
Negative developing	186	–	–	–
Negative outlook	1648	1537	440	278
Negative combine event	2628	1172	355	200
Single downgrade	2013	1187	370	578
Multiple downgrade	415	428	187	163
Section 2: Positive events				
Positive developing	741	–	–	–
Positive outlook	1910	730	299	80
Positive combine event	2504	546	172	64
Single upgrade	1896	1342	541	549
Multiple upgrade	264	114	48	70

Panel B: The distribution of rating changes	*N*	Mean	Std. dev.	P1	P25	Median	P75	P99
EJR negative event	6885	1.041	0.758	0.250	0.500	1.000	1.250	4.000
EJR positive event	7315	0.909	0.740	0.250	0.500	0.750	1.000	3.750
S&P negative event	4325	1.050	0.933	0.500	0.500	0.500	1.000	5.000
S&P positive event	2730	1.024	0.961	0.500	0.500	1.000	1.000	5.500
Moody's negative event	1352	1.068	0.736	0.500	0.500	1.000	1.500	3.500
Moody's positive event	1060	0.884	0.423	0.500	0.500	1.000	1.000	2.500
Fitch negative event	1219	1.174	1.054	0.500	0.500	1.000	1.000	5.500
Fitch positive event	762	1.177	0.867	0.500	1.000	1.000	1.000	5.000

Note: The table presents credit rating events announced by EJR (investor-paid credit rating agency [CRA]) and S&P, Moody's and Fitch (issuer-paid CRAs). Panel A displays the number of firms rated and the number of rating events (negative and positive separately) announced by each CRA after being merged with COMPUSTAT, CRSP and S12/13F data. Panel B presents summary statistics for credit rating changes of each CRA, where the magnitude of a rating change is calculated as the total number of notches by which a rating agency changes a firm's credit rating.

consistent with EJR's and Fitch's policy of rating veteran firms. For instance, the mean market capitalization in the S12 (13F) sample in the third group is $36,874 ($44,837) million, while the number is $30,333 ($37,638) million for group one and $12,836 ($16,899) million for group two.

The mean Z-scores in the S12 (13F) sample are 2.12 (2.11), 1.72 (1.70) and 1.84 (1.86) for the first, second and third groups, respectively. These means are relatively close to the conventional threshold of 1.8 but above the risk level of a financially healthy firm. Leverage ratios are similar across all three groups. Finally, the median interest coverage ratio is slightly lower for firms in group two than for firms in groups one and three.

TABLE 3 Descriptive statistics for firms covered in S12 and 13F databases

Panel A: Mutual fund (S12) database									
	Firms rated by EJR and S&P			Firms rated by EJR and Moody's			Firms rated by EJR and Fitch		
	N	Mean	Median	*N*	Mean	Median	*N*	Mean	Median
Ln(MV)	2,808,671	10.32	9.37	1,079,231	9.46	8.59	1,716,964	10.51	9.65
ROA	2,808,671	0.04	0.04	1,079,231	0.03	0.04	1,716,964	0.04	0.04
IDIO_RISK	2,808,671	0.02	0.01	1,079,231	0.02	0.02	1,716,964	0.01	0.01
Z-SCORE	2,808,671	2.12	1.82	1,079,231	1.72	1.54	1,716,964	1.84	1.63
ANALYST_COVERAGE	2,808,671	7.15	6.78	1,079,231	6.33	5.84	1,716,964	7.38	7.00
Ln(AGE)	2,808,671	3.21	3.33	1,079,231	2.99	3.00	1,716,964	3.31	3.47
INTEREST_COVERAGE	2,808,671	15.65	9.26	1,079,231	11.78	7.15	1,716,964	14.39	8.59
LEVERAGE	2,808,671	0.33	0.27	1,079,231	0.33	0.31	1,716,964	0.37	0.28
S&P_500	2,808,671	0.65	1.00	1,079,231	0.48	0.00	1,716,964	0.76	1.00
HIGH_TECH	2,808,671	0.03	0.00	1,079,231	0.02	0.00	1,716,964	0.02	0.00
Panel B: Institutional investors (13F) database									
	Firms rated by EJR and S&P			Firms rated by EJR and Moody's			Firms rated by EJR and Fitch		
	N	Mean	Median	*N*	Mean	Median	*N*	Mean	Median
Ln(MV)	3,180,369	10.54	9.65	1,084,625	9.73	8.75	2,040,834	10.71	9.87
ROA	3,180,369	0.04	0.04	1,084,625	0.03	0.04	2,040,834	0.04	0.04
IDIO_RISK	3,180,369	0.01	0.01	1,084,625	0.02	0.02	2,040,834	0.01	0.01
Z-SCORE	3,180,369	2.11	1.86	1,084,625	1.70	1.51	2,040,834	1.86	1.66
ANALYST_COVERAGE	3,180,369	7.44	7.02	1,084,625	6.53	6.00	2,040,834	7.62	7.30
Ln(AGE)	3,180,369	3.32	3.40	1,084,625	3.05	3.04	2,040,834	3.44	3.56
INTEREST_COVERAGE	3,180,369	16.01	9.80	1,084,625	12.65	7.29	2,040,834	15.12	9.26
LEVERAGE	3,180,369	0.35	0.28	1,084,625	0.33	0.31	2,040,834	0.38	0.28
S&P_500	3,180,369	0.68	1.00	1,084,625	0.49	0.00	2,040,834	0.76	1.00
HIGH_TECH	3,180,369	0.03	0.00	1,084,625	0.02	0.00	2,040,834	0.02	0.00

Note: The table presents the summary statistics of control variables, which are defined in Appendix B. Statistics are computed around credit rating announcements.

3 | MAIN RESULTS

3.1 | Institutional responses to issuer- and investor-paid rating adjustments

We now examine institutional investors' responses to credit rating signals announced by issuer- and investor-paid CRAs. To ensure that reactions are comparable, we construct three paired samples, which include firms rated by EJR and each of the major issuer-paid CRAs: EJR and S&P, EJR and Moody's and EJR and Fitch. We estimate the following regression for each of the paired samples:

$$\begin{aligned} NB_{i,\,n,q} &= \alpha + \beta_1 NEG_{n,q} + \beta_2 POS_{n,q} + \beta_3 NEG_{n,q} * EJR_{n,q} + \beta_4 POS_{n,q} * EJR_{n,q} \\ &+ \beta_5 EJR_{(n,q)} + \textstyle\sum_1^k \gamma_k CONTROLS_{(n,q)} +_1^q \textstyle\sum_1^q \theta_q QuarterFE_q \\ &+ \sum_1^i \delta_i InvestorFE_i + \sum_1^n \varphi_n FirmFE_n + \varepsilon_{i,n,q} \end{aligned}, \tag{4}$$

where $NB_{i,n,q}$, defined in equation (2), denotes mutual fund (institutional investor) i's abnormal dollar net buy of firm n's stock for credit rating adjustments in quarter q. We sum all $\Delta CCRs$, as defined in equation (1), for each firm n in quarter q and denote it by $\sum \Delta CCR_{n,q}$.[11] We then define $NEG_{n,q}$ as $|\sum \Delta CCR_{n,q}|$ if $\sum \Delta CCR_{n,q} < 0$ and zero if $\sum \Delta CCR_{n,q} > 0$ and $POS_{n,q}$ as $\sum \Delta CCR_{n,q}$ if $\sum \Delta CCR_{n,q} > 0$ and zero if $\sum \Delta CCR_{n,q} < 0$. Therefore, an increase in $NEG_{n,q}$ ($POS_{n,q}$) represents an absolute increase in aggregate credit rating downgrade (upgrade) for firm n in quarter q. $CONTROLS_{n,q}$ represents a set of firm-level control variables as described in Table 3. $QuarterFE_q$ denotes quarter-specific dummy variables to control for differences in institutional trading behavior that can be induced by various economic conditions in different quarters. $InvestorFE_i$ ($FirmFE_n$) is used to control for investor- (firm-) characteristics that are not captured by $CONTROLS_{n,q}$. In this model, $NEG_{n,q}$ and $POS_{n,q}$ are interacted with $EJR_{n,q}$, a dummy variable that equals one for EJR's credit rating announcements and zero otherwise. $\varepsilon_{i,n,q}$ is a random error.

The results of equation (4) are presented in Table 4. We find significant asymmetries in the abnormal trading of institutional investors and mutual funds in relation to EJR's and issuer-paid CRAs' rating announcements. These results are robust to the inclusion of control variables and fixed effects. For example, for firms that are rated by EJR and S&P, columns 1 and 2 show significant increases in mutual funds' and institutional investors' net buy of stocks with an aggregate positive change in S&P's rating adjustments in a given quarter. The *POS* coefficient is positive and significant across the regression specifications. Its magnitude is also economically meaningful. For example, the 0.0571 basis point coefficient in column 2 of panel B is equivalent to an average increase of $215,824 in abnormal institutional net buy over the respective quarter with a one-notch upgrade.[12] Institutional investors, however, react significantly less to positive rating changes issued by EJR. The *EJR*POS* interaction coefficient is negative in almost every model. The *F*-test results for the overall impact of rating upgrades by EJR, that is, the sum of *POS* and *EJR*POS* coefficients, indicate that both mutual funds and institutional investors are unresponsive to EJR's positive rating changes.

Table 4 shows the opposite results for rating downgrades. Institutional investors and mutual funds apparently find EJR's negative rating adjustments more informative than S&P's announcements. While the *NEG* coefficient shows no clear pattern across specifications, the *EJR*NEG* is negative and statistically and economically significant across the models. For example, the −0.1368 coefficient of *EJR*NEG* in column 2 of panel B indicates that a firm receiving a one-notch rating downgrade by EJR experiences an average decrease of $517,077 in abnormal institutional net buy over the respective quarter, compared to a similar downgrade by S&P. The *F*-test results for the overall impact of rating downgrades by EJR, that is, the sum of *NEG* and *EJR*NEG* coefficients, indicate that the total effect of EJR downgrades is statistically and economically significant.

We find similar asymmetric responses by institutional investors to upgrades and downgrades for firms that are rated by EJR and Moody's. For example, a *POS* coefficient of 0.0931 in column 4 indicates that abnormal institutional net buy, on average, increases by $156,543 over the quarter in which a one-notch aggregate rating upgrade by Moody's takes place. The combined effect of *POS* + *EJR*POS* shows that institutional investors do not react to EJR's upgrades as opposed to Moody's. However, the results for rating downgrades support the notion that institutional investors respond to EJR's rather than Moody's downgrades. The *EJR*NEG* coefficient in column 4 of Panel B is −0.2707, indicating that EJR downgrades are associated with, on average, a decrease of $455,170 in abnormal institutional net buy, compared to Moody's downgrades. The significant *F*-test results for the sum of *NEG* and *EJR*NEG* in columns (3)

[11] In our analysis, we exclude firm-quarter observations that EJR and the paired issuer-paid CRA have different credit rating signals in a quarter.

[12] The increase is calculated by multiplying the *POS* coefficient of 0.0571 by the average market capitalization ($e^{10.54}$ = $37,798 million) of firms in the EJR and S&P group in panel B of Table 3 and dividing the result by 10,000 (since the net buy is in basis points).

TABLE 4 Abnormal trading responses to credit rating adjustments—S12 and 13F samples

Panel A: Mutual funds' abnormal holding changes	EJR versus S&P		EJR versus Moody's		EJR versus Fitch	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.1379***	−0.0856**	0.4049***	−0.3387***	0.1770***	−0.5467***
	(0.0183)	(0.0346)	(0.0445)	(0.0828)	(0.0234)	(0.0481)
NEG	0.0105*	−0.0013	−0.004	0.0234	0.0211**	0.0286**
	(0.0062)	(0.0073)	(0.024)	(0.0283)	(0.009)	(0.0122)
POS	0.0318***	0.0324***	0.0241**	0.0308**	0.0441***	0.0612***
	(0.0087)	(0.0108)	(0.0121)	(0.0123)	(0.0127)	(0.0179)
EJR×NEG	−0.0199***	−0.0103*	−0.0416*	−0.0512*	−0.0139	−0.0187
	(0.0074)	(0.0057)	(0.0253)	(0.0292)	(0.0102)	(0.0135)
EJR×POS	−0.0257***	−0.0262**	−0.0123	−0.0152	−0.0424***	−0.0587***
	(0.0097)	(0.012)	(0.0303)	(0.0337)	(0.0138)	(0.0191)
EJR	−0.2294***	−0.2410***	−0.5808***	−0.6357***	−0.2948***	−0.2884***
	(0.0084)	(0.0099)	(0.0267)	(0.030)	(0.0124)	(0.0165)
Control variables:	No	Yes	No	Yes	No	Yes
F-tests:						
NEG + EJR×NEG	−0.0094**	−0.0115**	−0.0456***	−0.0278***	0.0073	0.0100
	(0.0042)	(0.005)	(0.0084)	(0.0096)	(0.0051)	(0.0063)
POS + EJR×POS	0.0061	0.0062	0.0118	0.0156	0.0017	0.0025
	(0.0044)	(0.0056)	(0.0083)	(0.0095)	(0.0055)	(0.0072)
Fixed effects:						
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3,582,992	2,808,671	1,273,265	1,079,231	2,291,401	1,716,964
Adj. R^2	0.002	0.003	0.003	0.004	0.002	0.002
Panel B: Institutional investors' abnormal holding changes	**EJR versus S&P**		**EJR versus Moody's**		**EJR versus Fitch**	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.6663***	2.0098***	2.4527***	2.7954***	0.2020***	−1.3221***
	(0.0548)	(0.1136)	(0.1483)	(0.2731)	(0.0568)	(0.1378)
NEG	−0.0278	−0.0665***	0.0124	0.0511	−0.0383	0.0785**
	(0.0219)	(0.0257)	(0.0827)	(0.0959)	(0.0234)	(0.0346)
POS	0.0330*	0.0571**	0.1087***	0.0931***	0.0893**	0.1089**
	(0.0181)	(0.0285)	(0.0325)	(0.0224)	(0.0352)	(0.0531)
EJR×NEG	−0.1555***	−0.1368***	−0.2474***	−0.2707***	−0.0083	−0.0624
	(0.026)	(0.0305)	(0.0875)	(0.0992)	(0.0273)	(0.0387)

(Continues)

TABLE 4 (Continued)

Panel B: Institutional investors' abnormal holding changes	EJR versus S&P		EJR versus Moody's		EJR versus Fitch	
	(1)	(2)	(3)	(4)	(5)	(6)
EJR×POS	0.0071	−0.0288	−0.0956***	−0.0923***	−0.1045***	−0.1373**
	(0.035)	(0.0433)	(0.0276)	(0.027)	(0.039)	(0.0575)
EJR	−0.7735***	−1.0401***	−2.6222***	−2.6376***	−0.3948***	−0.3114***
	(0.0292)	(0.0342)	(0.0974)	(0.1075)	(0.0336)	(0.0466)
Control variables:	No	Yes	No	Yes	No	Yes
F-tests:						
NEG + *EJR×NEG*	−0.1833***	−0.2034***	−0.2350***	−0.2196***	−0.0467*	0.0162
	(0.0145)	(0.0174)	(0.0305)	(0.0334)	(0.0247)	(0.0189)
POS + *EJR×POS*	0.0401	0.0283	0.0131	0.0008	−0.0151	−0.0285
	(0.0265)	(0.0207)	(0.033)	(0.0361)	(0.0173)	(0.0238)
Fixed effects:						
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,088,703	3,180,369	1,281,861	1,084,625	2,729,378	2,040,834
Adj. R^2	0.001	0.001	0.002	0.002	0.001	0.001

Note: The table reports OLS regression results for mutual fund (S12) and institutional investor (13F) abnormal holding changes in response to credit rating adjustments announced by EJR and issuer-paid CRAs. The dependent variable, defined in equation (2), is a mutual fund's (institutional investor's) abnormal net buy of a stock during a quarter. Based on a firm's aggregate credit rating change in a quarter, we define *NEG* as the absolute value of a negative change and zero otherwise and *POS* as the value of a positive change and zero otherwise. Therefore, an increase in *NEG* (*POS*) represents an absolute increase in the firm's aggregate downgrade (upgrade) in that quarter. *EJR* is a dummy variable that equals one for EJR's credit rating announcements and zero otherwise. Detail descriptions of firm-level control variables are described in Appendix B. Standard errors in parentheses are adjusted for heteroskedisticity and clustering at the firm and quarter levels.
***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

and (4) indicate that the total effect of EJR downgrades is statistically and economically strong. The results for firms jointly rated by EJR and Fitch in columns 5 and 6 are less clear. While the *POS* coefficient is significant, indicating that investors react to Fitch's upgrades, *EJR***NEG* and *EJR* + *EJR***NEG* are mostly insignificant. We investigate this further in Section 3.5.

Overall, the results in Table 4 suggest that mutual funds and institutional investors find that credit rating upgrades are more informative; hence, they respond accordingly when issued by S&P or Moody's rather than by EJR. In contrast, they find that negative rating adjustments are more value-relevant when they are announced by EJR than by S&P or Moody's. These findings are consistent with the argument that institutional investors are well-equipped to assess the informativeness of credit rating announcements. Previous studies have shown that issuer-paid CRAs tend to delay rating downgrades due to conflict of interests (e.g., Cornaggia & Cornaggia, 2013) but still issue timely rating upgrades (e.g., Kedia et al., 2017). Brogaard et al. (2019) also find that upgrades issued by issuer-paid CRAs do convey new information. In contrast, investor-paid CRAs tend to be more timely in rating downgrade adjustments (e.g., Berwart et al., 2019; Johnson, 2004).

3.2 | Do CRAs behave the way we assume they do?

The findings in the previous section that institutional investors respond more to positive rating announcements by major issuer-paid CRAs and to negative rating announcements by the investor-paid EJR suggest a lead-lag in the timeliness of credit rating announcements between these two types of CRAs. We now empirically examine this.

As before, we separately consider three pairs: EJR and S&P, EJR and Moody's and EJR and Fitch. For each firm rated by each pair of CRAs, the credit rating score is adjusted multiple times by two paired CRAs throughout the sample period. We investigate the lead–lag relationship of each CRA pair for upgrades and downgrades separately. Based on the announcement timeline and the relative magnitude of consecutive rating adjustments, three scenarios are possible. First, when one CRA issues a rating adjustment that is relatively larger in magnitude than the subsequent adjustment announced by the other CRA, the leading CRA is classified as a "major leader." Second, when one CRA issues a rating adjustment relatively smaller in magnitude than the subsequent adjustment announced by the other CRA, the following CRA is classified as a "major confirmer." Third, if a rating adjustment by one CRA is followed by an adjustment of the same magnitude by the other CRA, we classify the leading CRA as an "equal magnitude leader." We then perform a binominal test with the null hypothesis that the relative frequencies that both CRAs in a pair hold for a specific role are equal.

In Table 5, section 1 reports the results for negative events, and section 2 shows the results for positive events. Panels A, B and C present the results for EJR and S&P, EJR and Moody's and EJR and Fitch, respectively. The results generally confirm our expectations that EJR issues relatively larger rating adjustments than the issuer-paid CRAs when these adjustments are downgrades. For example, EJR's downgrades are larger than S&P's subsequent downgrades 56.95% (= 422/(422 + 319)) of the time, which is statistically higher than 43.05% of the time when S&P plays the role of a major leader. The comparison is even higher for EJR than Moody's in Panel B, at 67.14% (= 141/(141 + 69)) versus 32.86%. When EJR follows S&P or Moody's after their respective negative rating adjustments, EJR tends to issue larger negative adjustments more frequently than when the other two CRAs follow EJR's downgrades with larger magnitudes. The major confirmer row for negative events confirms these differences statistically. There are no statistical differences between EJR and the other CRAs in the frequency of being an equal magnitude leader. However, we find no evidence of EJR's leading role, compared to Fitch in the issuance of negative signals. Fitch apparently issues larger negative adjustments more frequently than EJR, although these frequency differences are not statistically significant.

The results for positive events in Section 2 of Table 5 indicate that all three issuer-paid CRAs tend to issue larger rating upgrades more frequently than EJR. These frequency differences are statistically significant for both cases when these traditional CRAs are major leaders or major confirmers. There are no significant frequency differences in being an equal magnitude leader, except for the EJR and Fitch pair where EJR leads Fitch more often when they issue positive rating adjustments of the same magnitude.

Overall, the findings in this table support the results in Table 4 that EJR's negative rating announcements are apparently more timely and value-relevant to institutional investors than those rating downgrades by the other CRAs. However, the issuer-paid CRAs' positive rating announcements are valued more by institutional investors than EJR's rating upgrades.

3.3 | Profitability of asymmetric trading strategies

3.3.1 | Notional trading strategies

We now investigate whether a trading strategy based on credit rating signals with the highest information content can generate superior returns. Credit rating announcements are, in principle, available to all investors—not just

TABLE 5 The relative role of issuer- and investor-paid CRAs in negative and positive signals

	Panel A: EJR and S&P			Panel B: EJR and Moody's			Panel C: EJR and Fitch		
	EJR	S&P	*p*-value	EJR	Moody's	*p*-value	EJR	Fitch	*p*-value
Section 1: Negative events									
Major leader (*t*)	422 (56.95%)	319 (43.05%)	0.0002	141 (67.14%)	69 (32.86%)	< 0.0001	124 (46.62%)	142 (53.38%)	0.2697
Major confirmer (*t* + 1)	423 (55.88%)	334 (44.12%)	0.0012	129 (61.14%)	82 (38.84%)	0.0012	111 (44.94%)	136 (55.06%)	0.1117
Equal magnitude leader (*t*)	303 (52.15%)	278 (47.85%)	0.2997	72 (52.55%)	65 (47.45%)	0.5498	103 (49.05%)	107 (50.95%)	0.7825
Section 2: Positive events									
Major leader (*t*)	166(38.52%)	265 (61.48%)	< 0.0001	75 (41.44%)	106 (58.56%)	0.0212	42 (27.27%)	112 (72.73%)	< 0.0001
Major confirmer (*t* + 1)	172 (36.52%)	299 (63.48%)	< 0.0001	77 (43.75%)	99 (56.25%)	0.0973	30 (19.23%)	126 (80.77%)	< 0.0001
Equal magnitude leader (*t*)	237(50.21%)	235 (49.79%)	0.9267	103 (49.76%)	104 (50.24%)	0.9446	83 (58.04%)	60 (41.96%)	0.0544

Note: This table shows the relative role of issuer- and investor-paid CRAs in positive and negative credit rating announcements. Panels A, B and C are for announcements for firms rated by EJR and one of the "Big Three" CRAs (S&P, Moody's and Fitch). We consider three scenarios. First, when one CRA issues a rating adjustment that is relatively larger in magnitude than the subsequent adjustment announced by the other CRA, the leading CRA is classified as a "major leader." Second, when one CRA issues a rating adjustment that is relatively smaller in magnitude than the subsequent adjustment announced by the other CRA, the following CRA is classified as a "major confirmer." Third, if a rating adjustment by one CRA is followed by an adjustment of the same magnitude by the other CRA, we classify the leading CRA as an "equal magnitude leader." For each pair, we show the number of times and the relative frequency (in brackets) that a CRA holds a specific role. *p*-value is from a binomial test to compare the relative frequency of each CRA pair in a specific role.

institutions. Therefore, we begin by analyzing "notional" trading strategies available to a hypothetical investor with timely access to credit ratings.

The first strategy we consider is the "dynamic strategy"—selling following EJR's negative rating signals and buying following issuer-paid CRAs' positive rating signals. This trading strategy is our main interest. The second one is the 'naïve strategy'—selling following negative signals and buying following positive signals from any rating agency. The third strategy is the "EJR-based strategy"– selling following negative signals and buying following positive signals announced by EJR. The fourth strategy is the "issuer-paid CRA-based strategy"—selling following negative signals and buying following positive signals issued by any of the "Big Three" CRAs. We also add a passive strategy as an additional benchmark—investing in the S&P 500 index.

We measure the profitability for each trading strategy as follows. First, we examine various holding periods of k months (where $k = 1, 3, 6, 9$ and 12) starting from the rating announcement date t to day $t + 5$. We follow Jagolinzer et al. (2011) and estimate abnormal returns after adjusting for common risk factors. Specifically, for each day in the [0, 5] window, risk-adjusted return is the intercept (alpha) from the Fama and French (2015) five-factor model estimated over a holding period of k months:

$$(R_n - R_f) = \alpha + \beta_1 \left(R_{mkt} - R_f\right) + \beta_2 SMB + \beta_3 HML + \beta_4 RMW + \beta_5 CMA + e_i, \quad (5)$$

where R_n is the daily return of firm n; R_f is the daily risk-free rate; R_{mkt} is the CRSP (Center for Research in Security Prices) value-weighted market return; SMB, HML, RMW and CMA are size, book-to-market, operating profitability and investment factors, respectively.[13] For notional strategies, we assume that investors trade in accordance with a credit rating signal, that is, selling (buying) if the signal is negative (positive). Therefore, if the announcement is a rating downgrade, we multiply daily alphas in equation (5) by (−1) to represent risk-adjusted returns to investors' sales. This adjustment does not apply for investors' purchases following a rating upgrade. We calculate the risk-adjusted alpha for firm n's rating announcement t as the simple average of alphas over the [0, 5] window and denote it by $\alpha_{n,t}$. We use equal weightings to calculate the firm's mean alpha for each announcement event as with these hypothetical transactions we do not have data on investors' buy and sell values.

The event alphas, $\alpha_{n,t}$, are then grouped into appropriate trading strategies described above, and a t-test is performed across all rating announcements in a given strategy. We also test the mean difference in the value-weighted risk-adjusted returns (i.e., weighted by market capitalization) between strategies with a two-sample t-test and report the results in Table 6.[14] All returns are annualized. We find that all four strategies outperform the buy-and-hold of the S&P 500 index. In addition, consistent with our expectations, the dynamic strategy yields higher abnormal returns than all other strategies. Over the 1-month investment horizon, the dynamic strategy outperforms the other three strategies by an annualized risk-adjusted return ranging from 4.22% to 5.02%. Its outperformance is statistically significant for up to 6 months.

3.3.2 | Institutional trading strategies

We now examine trading strategies based on institutional transactions. The returns on notional strategies can be interpreted as equally weighted returns of an institution trading around every credit rating announcement consistent with a certain strategy. By explicitly considering institutional transactions, we acknowledge that institutions may

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[13] We thank Kenneth French for sharing data on the five risk factors in his website, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[14] We adjust firms' market capitalization for inflation following the merit of Acharya and Pedersen (2005). Specifically, we first calculate the ratio of CRSP total market value at the end of month m – 1 (relative to the credit event month) to CRSP total market value at the end of 1998 (just before our sample starts). We then divide a firm's market capitalization in month m by this ratio before using it as a weight in the t-test. Our (unreported) results are robust when unadjusted market capitalization is used.

TABLE 6 Notional trading strategy profitability

Holding periods	1 month	3 months	6 months	9 months	12 months
(1) Dynamic	0.0824***	0.0655***	0.0462***	0.0317***	0.0259
	(0.0104)	(0.0079)	(0.0061)	(0.0109)	(0.0248)
(2) Naïve	0.0356***	0.0349***	0.0203***	0.0141**	0.0035
	(0.0075)	(0.0046)	(0.0038)	(0.0068)	(0.0156)
(3) EJR-based	0.0322***	0.0327***	0.0344***	0.0147***	0.0156***
	(0.0086)	(0.0041)	(0.003)	(0.0023)	(0.0034)
(4) Issuer-paid CRA-based	0.0402***	0.0369***	0.019**	0.0132	−0.0068
	(0.0134)	(0.0093)	(0.008)	(0.016)	(0.0358)
(5) S&P 500 index	0.0011	0.0011	0.0011	0.0011	0.0011
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
(1)–(2)	0.0468***	0.0307***	0.0259***	0.0176	0.0224
	(0.0129)	(0.0092)	(0.0072)	(0.0129)	(0.0293)
(1)–(3)	0.0502***	0.0328***	0.0118*	0.017	0.0102
	(0.0135)	(0.0089)	(0.0068)	(0.0112)	(0.025)
(1)–(4)	0.0422**	0.0286**	0.0272***	0.0185	0.0327
	(0.0169)	(0.0122)	(0.0101)	(0.0194)	(0.0435)
(1)–(5)	0.0813***	0.0644***	0.0451***	0.0306***	0.0248
	(0.0105)	(0.008)	(0.0062)	(0.011)	(0.0248)
(2)–(5)	0.0345***	0.0337***	0.0192***	0.013*	0.0024
	(0.0076)	(0.0048)	(0.004)	(0.0069)	(0.0157)
(3)–(5)	0.0311***	0.0316***	0.0333***	0.0136***	0.0145***
	(0.0087)	(0.0043)	(0.0032)	(0.0026)	(0.0036)
(4)–(5)	0.0391***	0.0358***	0.0179**	0.0121	−0.0079
	(0.0134)	(0.0094)	(0.0081)	(0.016)	(0.0358)

Note: This table reports and compares annualized risk-adjusted returns on four notional trading strategies. "Dynamic" is a strategy that sells a stock when it receives an EJR's negative rating adjustment and buys the stock when its rating is upgraded by an issuer-paid CRA. The "naïve" strategy is simply to sell (buy) a stock following a negative (positive) signal from any rating agency. For the "EJR-based" strategy, an investor sells (buys) a stock when EJR announces a downgrade (upgrade) in the stock's credit rating. The "issuer-paid CRA-based" strategy involves selling (buying) a stock following a rating downgrade (upgrade) from an issuer-paid CRA. A buy-and-hold of the S&P 500 index is included as a benchmark strategy. We measure the profitability for each trading strategy as follows. For each day in the time window [0, 5] surrounding each rating announcement on a firm, risk-adjusted return is the intercept (or alpha) from the Fama–French five-factor model estimated over a holding period. The firm-event alpha is then calculated as a simple average of the estimated alphas in the assessment window. We multiply the firm-event alpha by (−1) to represent risk-adjusted returns to investors' sales following a rating downgrade. Based on the firm's rating change, we assign its event alpha to one of the trading strategies. Finally, we use firms' inflation-adjusted market capitalization as weights and assess the strategies' performance using one and two sample *t*-tests. Standard errors of the *t*-test for the mean and difference in means are in parentheses.
***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

follow multiple strategies at a time, switch in and out of strategies, and may not trade on every signal consistent with a given strategy. Since holding data in S12 and 13F forms are available on a quarterly basis, we assume that institutional holding adjustments (and aggregate credit rating changes) happen on the last day of each quarter.[15]

[15] In Section 4.2, we assume that trading occurs on the first day of each quarter. Our findings are robust.

We form trading strategies and estimate their returns in calendar time at the institutional investor level as follows. First, given firm n's aggregate rating change in quarter q, $\sum \Delta CCR_{n,q}$, and institutional investor i's dollar net buy of the firm's stock, $nb_{i,n,q}$, we classify this firm into a specific strategy. Since we assume that an institutional investor can concurrently follow multiple strategies, a firm can be assigned to more than one trading strategy. We multiply the stock's returns by (−1) if $\sum \Delta CCR_{n,q} < 0$ and $nb_{i,n,q} < 0$ to reflect stock returns to sales following a rating downgrade. Next, for each institutional investor i, we calculate portfolio returns for each strategy using the absolute values of stock net buy as weights.[16] These portfolio returns are computed for each day over an investment horizon of k months starting at the end of the quarter. We repeat this process for each quarter in our sample period. Finally, the risk-adjusted return for each strategy is obtained using a pooled cross-sectional time series regression of the Fama–French five-factor model. We use a two-sample t-test to examine the difference in mean risk-adjusted returns between strategies.

The strategy alphas are reported in Table 7. Generally, while all four trading strategies provide positive risk-adjusted profits for up to 12 months after credit rating announcements, the dynamic strategy that mimics the typical institutional response to credit rating adjustments yields the highest returns. For example, its 1-month annualized return is 17.54% and 16.73% for the mutual fund and institutional samples, respectively. While the return magnitude decreases with the holding period, it significantly outperforms all other strategies for the holding periods of at least 6 months. Among the other strategies, the strategy following issuer-paid CRAs' credit announcements, while still significantly outperforming the buy-and-hold, yields the lowest returns.

Overall, the results in Table 7 are consistent with our expectations that credit rating announcements have valuable information content and that the most value-relevant announcements are downgrades by the investor-paid EJR and upgrades by the issuer-paid CRAs. Our findings illustrate that institutional investors that dynamically change their trading behavior based on the advantages and disadvantages of credit rating information are likely to make abnormal profits beyond those of naïve trading strategies. Having said that, the prolonged abnormal profits are consistent with underreaction to credit rating information, especially to the information content of EJR's credit downgrades and the issuer-paid CRAs' credit upgrades.

3.4 | Alternative institutional trading data

In the preceding analysis of institutional trading, we rely on S12 and 13F quarterly data. In this section, we conduct the analysis using daily transaction-level data provided by the Abel Noser Corporation. G. Hu et al. (2018) describe several important features of Abel Noser's institutional trading data. The dataset covers at least 12% of the total CRSP trading volume, 233 million transactions with $37 trillion in traded volume. It also records equity transactions by a large number of institutions from January 1999 to September 2011.[17] Despite its limited availability, the data on institutional investors' daily trading activities enable us to better capture their trading responses to credit rating adjustments.[18] We winsorize institutional trading data at the 1st and 99th percentiles to minimize the effect of outliers. After matching with our credit rating samples, we find 1126, 1259, 509 and 420 firms rated by EJR, S&P, Moody's and Fitch, respectively.

[16] As a robustness check, we calculate each strategy's returns using stock returns and their associated institutional net buy values across all institutional investors in the quarter. Hence, we have one value-weighted return per strategy per day in a holding horizon. The unreported results are robust in both statistical significance and economic magnitude.

[17] While Abel Noser arguably provides "cleaner" transaction-level data, we rely on S12 and 13F data in the main analysis, as Abel Noser does not provide data for research purposes after 2011. We note that our results are robust to the choice of the dataset.

[18] Due to Abel Noser's high level of coverage, several prior studies have used these data to investigate institutional trading behavior. G. Hu et al. (2018) summarize 55 publications that use these data.

TABLE 7 Trading strategy profitability—S12 and 13F samples

Panel A: Mutual funds' trading strategy profitability					
Holding periods	**1 month**	**3 months**	**6 months**	**9 months**	**12 months**
(1) Dynamic	0.1754***	0.1421***	0.1242***	0.0791***	0.0608***
	(0.0003)	(0.0015)	(0.0009)	(0.001)	(0.001)
(2) Naïve	0.1398***	0.1114***	0.0974***	0.0766***	0.059***
	(0.0099)	(0.0034)	(0.001)	(0.001)	(0.001)
(3) EJR-based	0.1416***	0.1158***	0.1004***	0.0803***	0.0633***
	(0.0003)	(0.001)	(0.0003)	(0.0003)	(0.0003)
(4) Issuer-paid CRA-based	0.125***	0.0986***	0.086***	0.0322***	0.0384***
	(0.0114)	(0.0025)	(0.0018)	(0.0015)	(0.0023)
(5) S&P 500 index	0.033	0.033	0.033	0.033	0.033
	(0.0453)	(0.0453)	(0.0453)	(0.0453)	(0.0453)
(1)–(2)	0.0356***	0.0307***	0.0268***	0.0025**	0.0018
	(0.0099)	(0.0037)	(0.0011)	(0.0011)	(0.0011)
(1)—(3)	0.0338***	0.0263***	0.0238***	–0.0011	–0.0025
	(0.0004)	(0.0018)	(0.0007)	(0.0007)	(0.0111)
(1)–(4)	0.0504***	0.0436***	0.0382***	0.0469***	0.0224***
	(0.0114)	(0.0025)	(0.0018)	(0.0016)	(0.0023)
(1)–(5)	0.1424***	0.1091***	0.0912***	0.0461***	0.0278***
	(0.0045)	(0.0041)	(0.0025)	(0.0025)	(0.0025)
(2)–(5)	0.1068***	0.0784***	0.0643***	0.0436***	0.026***
	(0.0109)	(0.0051)	(0.0015)	(0.0015)	(0.0015)
(3)–(5)	0.1085***	0.0828***	0.0674***	0.0473***	0.0303***
	(0.0045)	(0.0039)	(0.0016)	(0.0015)	(0.0023)
(4)–(5)	0.092***	0.0656***	0.053***	–0.0008	0.0054
	(0.0172)	(0.0042)	(0.0034)	(0.0034)	(0.0034)
Panel B: Institutional investors' trading strategy profitability					
Holding periods	**1 month**	**3 months**	**6 months**	**9 months**	**12 months**
(1) Dynamic	0.1673***	0.1455***	0.1091***	0.0728***	0.0618***
	(0.0139)	(0.0015)	(0.0007)	(0.0004)	(0.0004)
(2) Naïve	0.1175***	0.1143***	0.0898***	0.0649***	0.0535***
	(0.0178)	(0.0046)	(0.0014)	(0.0014)	(0.0014)
(3) EJR-based	0.1236***	0.1191***	0.0953***	0.0727***	0.062***
	(0.0093)	(0.0009)	(0.0003)	(0.0002)	(0.0003)
(4) Issuer-paid CRA-based	0.1202***	0.0804***	0.0678***	0.0483***	0.0384***
	(0.0198)	(0.0062)	(0.0045)	(0.0038)	(0.0057)
(5) S&P 500 index	0.033	0.033	0.033	0.033	0.033
	(0.0453)	(0.0453)	(0.0453)	(0.0453)	(0.0453)
(1)–(2)	0.0498**	0.0312***	0.0194***	0.0078***	0.0084***
	(0.0226)	(0.0048)	(0.0014)	(0.0014)	(0.0014)

(Continues)

TABLE 7 (Continued)

Panel B: Institutional investors' trading strategy profitability					
Holding periods	**1 month**	**3 months**	**6 months**	**9 months**	**12 months**
(1)–(3)	0.0438***	0.0264***	0.0138***	0.0001	−0.0001
	(0.0168)	(0.0017)	(0.0005)	(0.0004)	(0.0005)
(1)–(4)	0.0471**	0.0651***	0.0414***	0.0245***	0.0235***
	(0.0204)	(0.0063)	(0.0045)	(0.0038)	(0.0057)
(1)–(5)	0.1343***	0.1125***	0.0761***	0.0397***	0.0288***
	(0.0147)	(0.004)	(0.0024)	(0.0023)	(0.0023)
(2)–(5)	0.0845***	0.0813***	0.0567***	0.0319***	0.0205***
	(0.0183)	(0.0059)	(0.0018)	(0.0018)	(0.0018)
(3)–(5)	0.0905***	0.0861***	0.0623***	0.0397***	0.0289***
	(0.0103)	(0.0039)	(0.0015)	(0.0015)	(0.0023)
(4)–(5)	0.0872***	0.0474***	0.0347***	0.0153**	0.0054
	(0.0298)	(0.0095)	(0.0077)	(0.0077)	(0.0077)

Note: This table reports and compares annualized risk-adjusted returns on four institutional trading strategies. "Dynamic" is a strategy that sells a stock when it receives an EJR's negative rating adjustment and buys the stock when its rating is upgraded by an issuer-paid CRA. The "naïve" strategy is simply to sell (buy) a stock following a negative (positive) signal from any rating agency. For the "EJR-based" strategy, an investor sells (buys) a stock when EJR announces a downgrade (upgrade) in the stock's credit rating. The "issuer-paid CRA-based" strategy involves selling (buying) a stock following a rating downgrade (upgrade) from an issuer-paid CRA. A buy-and-hold of the S&P 500 index is included as a benchmark strategy. We measure the profitability for each trading strategy as follows. First, based on a firm's aggregate rating change in a quarter and an institutional investor's net buy of the firm's stock, we classify it to a specific strategy. We multiply the stock's returns by (−1) if the quarterly rating change is negative and the investor exhibits a net sale of the stock to reflect stock returns to sales following a rating downgrade. Next, for each institutional investor, we calculate portfolio returns for each strategy using the absolute values of stock net buy as weights. These portfolio returns are computed for each day over an investment horizon starting at the end of the quarter. We repeat this process for each quarter in our sample period. Finally, the risk-adjusted return for each strategy is obtained using a pooled regression of the Fama–French five-factor model. We use a two-sample *t*-test to examine the difference in mean risk-adjusted returns between strategies. Robust standard errors are in parentheses.
***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

3.4.1 | Institutional trading response to credit rating announcements

We investigate abnormal institutional trading surrounding a stock's credit rating adjustments in the time window [0, 5].[19] Day 0 is the date of a credit rating event. We consider institutions' trading activities up to five days after the credit rating adjustment to account for investors' potential gradual reactions while also avoiding confounding effects that can appear in longer windows.

With detailed transaction data, we calculate institutional investor *i*'s abnormal net buy of stock *n* over the [0, 5] day window around a credit rating announcement, $AN\_NB_{i,n,w}$, as follows:

$$AN\_NB_{i,n,w} = \sum_{k=0}^{+5} (AN\_nb_{i,n,t+k} - average\ AN_{nb_{i,n,t}}), \tag{6}$$

[19] We also consider two different time windows [−2, 5] and [−2, 1] for robustness. The purpose is to account for institutional investors' pre-reactions because of potential information leakage (e.g., Bhattacharya et al., 2019). Our results are robust.

where $AN\_nb_{i,n,t}$ is the daily dollar volume bought minus daily dollar volume sold scaled by the stock's 1-month-lagged market capitalization as shown in equation (7). *average* $AN\_nb_{i,n,t}$ is the average value of $AN\_nb_{i,n,t}$ in the period from day $t-371$ to day $t-6$ prior to the announcement date t as shown in equation (8).

$$AN\_nb_{i,n,t} = \frac{BOUGHT_{i,n,t} - SOLD_{i,n,t}}{MARKET\_CAP_{i,n,m-1}}, \tag{7}$$

$$average\ AN\_nb_{i,n,t} = \frac{\sum_{k=-6}^{-371} AN\_nb_{i,n,t+k}}{365}. \tag{8}$$

We then estimate the following model, which is similar to equation (4), for each of the paired samples:

$$\begin{aligned} AN\_NB_{i,n,w} &= \alpha + \beta_1 NEG_{n,t} + \beta_2 POS_{n,t} + \beta_3 NEG_{n,t} * EJR_{n,t} + \beta_4 POS_{n,t} * EJR_{n,t} \\ &+ \beta_5 EJR_{n,t} + \sum_1^k \gamma_k CONTROLS_{n,t} + \sum_1^t \theta_t QuarterFE_t \\ &+ \sum_1^i \delta_i InvestorFE_i + \sum_1^n \varphi_n FirmFE_n + \varepsilon_{i,n,w} \end{aligned} . \tag{9}$$

Depending on the numeric change in the CCR scale, $\Delta CCR_{n,t}$, for firm n on the adjustment date t, we define $NEG_{n,t}$ as $|\Delta CCR_{n,t}|$ if $\Delta CCR_{n,t} < 0$ and zero if $\Delta CCR_{n,t} > 0$,and $POS_{n,t}$ as $\Delta CCR_{n,t}$ if $\Delta CCR_{n,t} > 0$,and zero if $\Delta CCR_{n,t} < 0$. Therefore, an increase in $NEG_{n,t}$ ($POS_{n,t}$) represents an absolute increase in credit rating downgrade (upgrade) for firm n at credit event t. Control variables and fixed effects are described in equation (4).

We present the results in Table 8. The results are qualitatively similar to those based on S12 and 13F data—institutional investors react asymmetrically to credit rating announcements made by EJR and issuer-paid CRAs.[20] Columns 1 and 2 show the results for firms jointly rated by EJR and S&P. Institutional investors' net buy increases significantly around S&P's positive rating adjustments. The *POS* coefficient is positive and significant across all specifications. The 0.1655 basis point coefficient in column 2 is equivalent to an average increase of $316,914 in abnormal net buy over [0, 5] days around the S&P's one-notch rating upgrade announcements. However, the insignificant *F*-test results for the overall impact of rating upgrades by EJR, that is, the sum of *POS* and *EJR*POS* coefficients, indicate that institutional investors are unresponsive to EJR's positive rating changes.

We document opposite results for rating downgrades. The *EJR*NEG* coefficient is negative and statistically and economically significant across all models. For example, the –0.1191 coefficient of *EJR*NEG* in column 2 shows that a one-notch downgrade announcement by EJR is equivalent to a decrease of $228,063 in abnormal institutional net buy over the [0, 5] day window compared to a similar announcement by S&P. The *F*-test for the overall impact of EJR downgrades, that is, the sum of *NEG* and *EJR*NEG* coefficients, indicates that the effect is strong statistically and economically.

We find similarly asymmetric responses for firms jointly rated by S&P and Moody's in columns 3 and 4. For example, the *POS* coefficient of 0.4078 in column 4 indicates that abnormal institutional net buy, on average, increases by $281,586 over the [0, 5] day window surrounding a credit rating upgrade by Moody's. The *F*-test results for the sum of *NEG* and *EJR*NEG* coefficients in column 4 indicate that EJR's downgrades, on average, are associated with a significant decrease of $111,378 in abnormal institutional net buy over the [0, 5] day window. The results in columns 5 and 6 do not exhibit any robust and significant difference in the response of institutional investors around credit rating changes for firms covered by both EJR and Fitch. All coefficients of interest are statistically insignificant. We further investigate investor reactions to Fitch ratings in Section 3.5.

[20] In order to assess the potential impact of changes in the sample period, we perform the analysis of S12 and 13F data on two sub-periods: 1999–2011 (to match Abel Noser data coverage) and 2012–2017. The results are presented in Tables A11 and A12 in the Online Appendix and are qualitatively similar across sub-periods.

TABLE 8 Abnormal trading responses to credit rating adjustments—Abel Noser sample

	EJR versus S&P		EJR versus Moody's		EJR versus Fitch	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.3095	−0.4884	−0.3379	−0.4840	0.8414	−0.4015
	(1.8238)	(2.1424)	(4.9528)	(4.7255)	(1.7814)	(2.0034)
NEG	0.0470*	0.0538	0.0966	0.0925	0.0285	0.0259
	(0.0266)	(0.0408)	(0.1154)	(0.1302)	(0.0233)	(0.0448)
POS	0.2450***	0.1655***	0.3324**	0.4078***	0.074**	0.0818
	(0.0300)	(0.0498)	(0.1319)	(0.1387)	(0.0353)	(0.0711)
EJR×NEG	−0.1014***	−0.1191**	−0.1984*	−0.2538*	−0.0295	−0.0636
	(0.0322)	(0.0478)	(0.1204)	(0.1342)	(0.0349)	(0.0568)
EJR×POS	−0.2125***	−0.1232**	−0.2723**	−0.4453***	0.0023	−0.0436
	(0.0360)	(0.0563)	(0.1387)	(0.1481)	(0.0443)	(0.0807)
EJR	0.1316***	0.1254**	0.2429**	0.4005***	0.0507	0.0744
	(0.0365)	(0.0493)	(0.1234)	(0.1282)	(0.0491)	(0.0738)
Control variables:	No	Yes	No	Yes	No	Yes
F-tests:						
NEG + *EJR×NEG*	−0.0544***	−0.0654**	−0.1018**	−0.1613***	−0.0011	−0.0377
	(0.0209)	(0.0273)	(0.0468)	(0.0487)	(0.0279)	(0.0369)
POS + *EJR×POS*	0.0325	0.0423	0.0601	−0.0375	0.0763***	0.0381
	(0.0216)	(0.0272)	(0.0496)	(0.0523)	(0.0285)	(0.0393)
Fixed effects:						
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No	Yes	No
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	429,268	304,731	114,354	93,867	207,587	133,788
Adj. R^2	0.010	0.004	0.016	0.010	0.006	0.008

Note: The table reports OLS regression results for institutional investors' abnormal trading around credit rating adjustments announced by EJR and issuer-paid CRAs. The dependent variable, defined in equation (6), is an institutional investor's abnormal net buy of a stock over the [0, 5] day window. We define *NEG* as the absolute value of a rating downgrade and zero otherwise and *POS* as the value of a rating upgrade and zero otherwise. Therefore, an increase in *NEG* (*POS*) represents an absolute increase in a firm's downgrade (upgrade). *EJR* is a dummy variable that equals one for EJR's credit rating announcements and zero otherwise. Detail descriptions of firm-level control variables are described in Appendix B. Standard errors in parentheses are adjusted for heteroskadisticity and clustering at the firm and quarter levels.
***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

3.4.2 | Institutional trading profits in response to credit rating announcements

We now turn to assess institutional trading strategy profitability based on Abel Noser data. First, we use the Fama–French five-factor model, as shown in equation (5), to estimate risk-adjusted returns, that is, alphas, for each day in the [0, 5] window around a credit rating announcement. We multiply a daily alpha by (−1) if an institutional investor's trades on that day represent a net sale. We calculate the average alpha over the assessment window using the institutional investor's absolute daily net trade values as weights. We then assign this firm-institution-event alpha to different trading strategies based on the institutional net buy over the assessment window and the credit rating signal. Finally, we assess the performance of these strategies using firms' market capitalization as weights in one and two-sample *t*-tests.

Strategy trading profits and their significance are presented in Table 9. The results are consistent with those based on S12 and 13F data. The dynamic strategy that follows EJR's negative signals and other CRAs' positive signals earns the highest returns, compared to the other strategies. For example, for the 1-month investment horizon, the dynamic strategy outperforms the other three strategies by an annualized value-weighted risk-adjusted return ranging from 10.17% to 10.95%. This outperformance is approximately twice as much as the corresponding outperformance of notional strategies. Although this outperformance decreases with the investment horizon, it is still statistically significant for up to 9 months. Among the other three active strategies, following EJR's signals alone apparently generates the best returns, whereas following issuer-paid CRAs' signals only yields the least profits. We also compare the four trading strategies to a passive strategy—a buy-and-hold annual return of the S&P 500 index. We observe that all trading strategies outperform the index for up to 6 months, except the strategy following issuer-paid CRAs' rating announcements.

3.5 | The case of Fitch ratings

We note that investor reactions around credit rating changes for firms jointly rated by EJR and Fitch are different from those covered by S&P and Moody's. In the S12 and 13F samples, we observe significant reactions to Fitch upgrades and no significant reactions to EJR downgrades. We document essentially no significant reactions in Able Noser data. This has prompted us to investigate this further.[21] Fitch has traditionally held a smaller market share relative to Moody's and S&P (Becker & Milbourn, 2011; Livingston & Zhou, 2016). This may have influenced both their rating behavior (Beatty et al., 2019; Hirth, 2014) and investor reaction.

Our empirical analysis suggests that Fitch differs in rating behavior from other issuer-paid CRAs. First, as reported in Table 5, not only does Fitch lead EJR in positive events (as expected) but is also the only issuer-paid CRA to lead EJR in negative announcements (although the difference is not statistically significant). Furthermore, our unreported analysis also shows that Fitch leads S&P and Moody's in both positive and negative announcements. We believe this is consistent with Fitch providing more timely rating announcements in order to increase their market share.

Second, we look at the information content of Fitch announcements by constructing two additional trading strategies: the "Fitch-based strategy"—buying on Fitch upgrades and selling on Fitch downgrades (for the sake of completeness, we also create "S&P-based strategy" and "Moody's-based strategy"), and the "modified dynamic strategy"—buying on credit upgrades by the "Big Three" and selling on Fitch downgrades. Our unreported results show that the Fitch-based strategy not only outperforms a simple buy-and-hold of the S&P 500 index but also produces better returns than the issuer-paid CRA-based strategy, particularly over longer time periods. This suggests that Fitch's announcements actually have higher information content than other issuer-paid CRAs. The modified dynamic strategy is the second-best performing strategy, suggesting that Fitch's negative announcements have substantial information content. However, the "dynamic strategy"—buying on positive issuer-paid CRA announcements and selling on EJR's negative announcements—yields the best returns, which is consistent with our main hypothesis.

Finally, we investigate institutional investors' reactions to Fitch's announcements in greater detail. In the main analysis, institutions do not appear to react significantly to either positive or negative announcements in the sample of firms jointly rated by Fitch and EJR, despite evidence that both CRAs' announcements have significant information content. We posit that as Fitch leads EJR in negative signals (although insignificantly), the lack of significant reaction to EJR's negative announcements may be due to the dilution of investors' reaction to both Fitch and EJR's announcements. Investors do not react to Fitch's announcements in a significant way (even though these announcements have significant informational content), and this still weakens investors' reactions to subsequent announcements by EJR.

[21] We thank an anonymous referee for this suggestion.

TABLE 9 Trading strategy profitability—Abel Noser sample

Holding periods	1 month	3 months	6 months	9 months	12 months
(1) Dynamic	0.1626***	0.1098***	0.0728***	0.0714**	0.0297
	(0.0223)	(0.0188)	(0.0224)	(0.033)	(0.0496)
(2) Naïve	0.0534*	0.0468*	0.0188	0.0078	0.0008
	(0.0317)	(0.0267)	(0.0129)	(0.0227)	(0.0451)
(3) EJR-based	0.0609***	0.047***	0.0476***	0.0129	0.0049
	(0.0113)	(0.0127)	(0.0114)	(0.0217)	(0.0909)
(4) Issuer-paid CRA-based	0.0531*	0.0395	−0.0213	−0.0012	0.0184
	(0.0297)	(0.0254)	(0.026)	(0.0265)	(0.0463)
(5) S&P 500 index	−0.0163	−0.0163	−0.0163	−0.0163	−0.0163
	(0.0621)	(0.0621)	(0.0621)	(0.0621)	(0.0621)
(1)–(2)	0.1092***	0.063*	0.054***	0.0635**	0.0289
	(0.0388)	(0.0327)	(0.0171)	(0.028)	(0.0515)
(1)–(3)	0.1017***	0.0628***	0.0253	0.0584*	0.0248
	(0.025)	(0.0227)	(0.0188)	(0.0309)	(0.1036)
(1)–(4)	0.1095***	0.0703***	0.0941***	0.0726**	0.0113
	(0.0306)	(0.0262)	(0.0275)	(0.0287)	(0.0525)
(1)–(5)	0.1789***	0.1261***	0.0891***	0.0877***	0.046
	(0.0232)	(0.0195)	(0.0226)	(0.0332)	(0.0497)
(2)–(5)	0.0697**	0.0631**	0.0351***	0.0241	0.0171
	(0.0323)	(0.0272)	(0.013)	(0.0227)	(0.0451)
(3)–(5)	0.0772***	0.0633***	0.0639***	0.0292	0.0212
	(0.0129)	(0.0137)	(0.0116)	(0.0218)	(0.091)
(4)–(5)	0.0694*	0.0558	−0.005	0.0151	0.0347
	(0.0376)	(0.0382)	(0.0434)	(0.053)	(0.0617)

Note: This table reports and compares annualized risk-adjusted returns on four institutional trading strategies. “Dynamic” is a strategy that sells a stock when it receives an EJR’s negative rating adjustment and buys the stock when its rating is upgraded by an issuer-paid CRA. The “naïve” strategy is simply to sell (buy) a stock following a negative (positive) signal from any rating agency. For the “EJR-based” strategy, an investor sells (buys) a stock when EJR announces a downgrade (upgrade) in the stock’s credit rating. The “issuer-paid CRA-based” strategy involves selling (buying) a stock following a rating downgrade (upgrade) from an issuer-paid CRA. A buy-and-hold of the S&P 500 index is included as a benchmark strategy. We measure the profitability for each trading strategy as follows. For each day in the time window [0, 5] surrounding each rating announcement on a firm, risk-adjusted return is the intercept (or alpha) from the Fama–French five-factor model estimated over a holding period. We multiply a daily alpha by (−1) if an institutional investor’s trades on that day represent a net sale. Next, we calculate the average alpha over the assessment window using the institutional investor’s absolute daily net trade values as weights. We then assign a stock’s event alpha to different trading strategies based on its institutional net buy over the assessment window and the credit rating signal. Finally, we use firms’ inflation-adjusted market capitalization as weights and assess the strategies’ performance using one and two sample *t*-tests. Standard errors of the *t*-test for the mean and difference in means are in parentheses.

***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

To investigate this, we remove negative announcements led by Fitch. Our unreported results are consistent with our expectations, that is, investors' reaction to EJR's negative announcements becomes negative and significant in three out of four specifications, which is consistent with the results reported in panels A and B of Table 4 for EJR and S&P and EJR and Moody's.

4 | ROBUSTNESS TESTS

4.1 | Hedge trading strategies

Although our findings on trading strategy profits suggest that investors generally underreact to the information content of credit rating signals, some investors may, in fact, overreact to rating events, which may result in subsequent profits for contrarian trading strategies (Ellul et al., 2011). Alternatively, CRAs could provide upward-biased credit ratings to some relationship firms (e.g., Baghai & Becker, 2018), and some institutional investors may be sophisticated enough to detect these overrated firms and respond in the opposite way around rating announcements, which subsequently earns them abnormal profits. We account for the effect of this potential contrarian trading strategy on the performance of our main strategies as follows. We follow the steps in Section 3.3.2 to construct portfolios that are opposite to our main strategies. For example, an institutional investor that increases its net holding of a stock with an aggregate downgrade by EJR and decreases its net holding of a stock with an aggregate upgrade by issuer-paid CRAs is considered to be a dynamic contrarian strategy. A dynamic hedge portfolio is then defined as longing the dynamic portfolio and shorting the dynamic contrarian portfolio. Finally, we estimate the four hedge portfolios' risk-adjusted returns using the Fama–French five-factor model and report the results in Table A1. The dynamic hedge portfolio remains the best performer, and its outperformance relative to the other hedge portfolios is qualitatively similar in magnitude and statistical significance to the results in Table 7.

4.2 | Alternative assumptions on the timing of trades

In the main analysis of quarterly S12 and 13F data, we assume that credit rating adjustments and fund-stock holding changes happen on the final day of each quarter. In this robustness check, we make an alternative assumption that these changes occur on the first day of each quarter. Trading strategy profitability is then re-estimated, and the results are presented in Table A2 in the Online Appendix. The results are consistent with those in the main analysis that the dynamic strategy significantly outperforms all other strategies considered.

We also consider alternative event windows in the analysis of daily Abel Noser data: [−2, 1] and [−2, 5] trading days. First, these time windows include the two days prior to credit rating adjustments to control for potential information leakage before official rating adjustments (Bhattacharya et al., 2019). Second, we also choose short time windows to control for any effect of clusters of rating signals (e.g., Alsakka & ap Gwilym, 2012; Gande & Parsley, 2005; Vu et al., 2015). In other words, shorter time windows enable us to avoid any information contamination problems caused by the appearance of other information in the financial market in longer time windows. The results for the two alternative event windows are presented in Table A3 in the Online Appendix and are consistent with the main findings. Institutional investors still exhibit asymmetric trading behavior to the issuer- and investor-paid credit rating signals, abnormally buying on issuer-paid CRAs' positive rating adjustments and abnormally selling on EJR's negative rating adjustments in both alternative time windows.

All four active trading strategies earn significant profits in similar patterns as in Table 4. They outperform the buy-and-hold return of the S&P 500 index for up to a 9-month horizon. Most importantly, the dynamic trading strategy is the best performer over all other strategies. The robust results of institutional trading strategies constructed surrounding alternative event windows of [−2, 1] and [−2, 5] days are reported in Table A4 in the Online Appendix. We also report the results for notional trading strategies for these alternative windows, and the results exhibit similar patterns as shown in Table A5 in the Online Appendix.

4.3 | Raw institutional trading

Our next robustness check analyzes "raw" reactions (i.e., unadjusted for the average of past trading activities) of institutional investors to credit rating announcements. We perform the analysis on both S12 and 13F quarterly data (Table A6) and in the [0, 5] day window on Abel Noser daily data (Table A7). The results are highly consistent with the main findings that institutional investors tend to abnormally sell stocks of firms with EJR's negative rating announcements but ignore positive ones; however, their net buy increases substantially surrounding issuer-paid CRAs' positive rating announcements.

4.4 | Combined issuer-paid CRA

In another robustness check, we treat all three issuer-paid CRAs as a combined issuer-paid CRA. We then investigate institutional investor's trading activities surrounding negative and positive rating signals by EJR and the combined issuer-paid CRA. The results are reported for the S12, 13F and Abel Noser Sample in Table A8 in the Online Appendix. The results are consistent: Institutional investors tend to abnormally sell stocks surrounding negative signals issued by EJR and abnormally buy stocks surrounding positive signals issued by the combined issuer-paid CRA.

4.5 | Excluding non-trading observations

In our main analysis, abnormal net buy is set at zero if institutional investors have no trading activities surrounding credit rating adjustments. In this final robustness check, we exclude these non-trading observations. We find robust results in Table A9 for S12 and 13F data and Table A10 for Abel Noser data in the Online Appendix. The results are robust. After excluding non-trading observations, institutional investors still have asymmetric responses, abnormally increasing (decreasing) stock holdings surrounding positive (negative) rating signals by issuer- (investor-) paid CRAs. Overall, these robustness tests confirm our main findings that institutional investors who have advanced trading skills selectively react to credit rating signals from different sources based on their relative informational values.

5 | CONCLUSION

This study investigates institutional investors' responses to credit rating adjustments announced by the investor-paid EJR and the "Big Three" issuer-paid CRAs. In recent years, traditional issuer-paid CRAs have faced criticism regarding lack of timeliness in negative signals in many infamous scandals such as Enron (2001), WorldCom (2002) and Lehman Brothers (2008). Meanwhile, investor-paid CRAs, particularly EJR, have built a good reputation regarding the timeliness of their negative rating adjustments. As a result, institutional investors with advanced trading skills and sophistication (Puckett & Yan, 2011) are likely to dynamically switch between following investor- and issuer-paid CRAs based on the timeliness of credit rating information.

We document considerable asymmetries in institutional investors' responses to issuer- and investor-paid CRA announcements. They react by abnormally selling following EJR's negative signals and abnormally buying following issuer-paid CRAs' positive signals. The results differentiate our paper from the existing literature. Several prior studies show that institutional investors simply tend to be more sensitive to negative rather than positive signals. Our study finds that institutional investors, as professional players, have their own responses to the lack of timeliness criticism by following investor-paid CRA's negative signals. They still maintain faith in positive issuer-paid rating announcements due to no evidence of their delays. The results are robust across different databases from which the institutional investors' trading activities are extracted.

We also document that a dynamic trading strategy based on selling following the investor-paid CRA' negative signals and buying following issuer-paid CRAs' positive signals produces superior returns. While any investor can take advantage of these strategies, institutional investors evidently achieve higher returns. Although we document the highly dynamic behavior of institutions in responding to important market signals, our results imply that market participants tend to underreact to positive signals by issuer-paid CRAs and negative signals by investor-paid CRA. Therefore, the information content of these signals is not fully reflected in prices at the announcement time, thus leading to opportunities to earn abnormal returns by trading following these signals. As further information in support of CRA creditworthiness predictions is released, abnormal returns are generally dissipated. Our results are consistent with this view—abnormal returns decrease as holding periods increase. The difference between dynamic strategy and naïve strategy returns becomes substantially smaller in the 12-month holding period.

Given that discrepancies in credit rating quality between issuer-paid CRAs and investor-paid CRAs are not limited only to the US bond market (e.g., X. Hu et al., 2019), we believe there are some interesting avenues for future research such as whether institutional investors also respond asymmetrically to credit rating announcements by issuer-paid and investor-paid CRAs in an international setting (e.g., China); if so, whether such asymmetric responses are conditional on some firm or market level shocks.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from third parties. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the authors with the permission of third parties.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX

APPENDIX A: NUMERIC TRANSFORMATION OF ALPHANUMERICAL RATING CODES

Investment grade		Speculative grade		Credit events[a]	
Rating	Score	Rating	Score		Score
AAA (Aaa)	22	BB+ (Ba1)	12	Single upgrade	1
AA+ (Aa1)	21	BB (Ba2)	11	Positive outlook	0.5
AA (Aa2)	20	BB– (Ba3)	10	Positive developing	0.25
AA- (Aa3)	19	B+ (B1)	9	Stable	0
A+ (A1)	18	B (B2)	8	Negative developing	–0.25
A (A2)	17	B– (B3)	7	Negative outlook	–0.5
A- (A3)	16	CCC+ (Caa1)	6	Single downgrade	–1
BBB+ (Baa1)	15	CCC (Caa2)	5		
BBB (Baa2)	14	CCC– (Caa3)	4		
BBB– (Baa3)	13	CC (Ca)	3		
		C	2		
		SD, D	1		

[a]Single upgrade (downgrade) is a credit rating announcement when a rating agency adjusts the firm's credit rating by one letter rating higher (lower; e.g., up from AA+ to AAA or down from AA+ to AA). A positive (negative) outlook is a credit rating review when a CRA adjusts its short-term expectations about the firm from being stable to positive (negative). A positive (negative) developing is a credit rating signal when a CRA adjusts its long-term expectations about the firm from being stable to positive (negative).

APPENDIX B: FIRM-LEVEL VARIABLE DEFINITIONS AND DATA SOURCES

Variable	Description	Data source
Ln(MV)	The natural log of total market capitalization in the quarter	CRSP
ROA	The ratio of operating income before depreciation to total assets in the quarter	COMPUSTAT
IDIO_RISK	The standard deviation of residual returns from the Fama–French three-factor model using daily stock returns from day $t - 31$ to day $t - 1$	Kenneth R. French & CRSP
Z-SCORE	Alman's Z-score that presents the probability that a firm will go into bankruptcy within 2 years	COMPUSTAT
ANALYST_COVERAGE	The average number of analysts covering a firm in the quarter	CRSP
Ln(AGE)	The natural log of number of years since a firm's first appearance on CRSP database	CRSP
INTEREST_COVERAGE	The ratio of earnings before interest, tax and depreciation and amortization to total interest expense in the quarter	COMPUSTAT
LEVERAGE	The ratio of sum of long-term debt and debt in current liabilities to total assets in the quarter	COMPUSTAT
S&P_500	A binary variable that equals one if a firm is included in the S&P 500 list	S&P 500 Index
HIGH_TECH	A binary variable that equals one if a firm's Standard Industry Classification (SIC) code is between 7370 and 7379 (Heron and Lie, 2009) and zero otherwise	CRSP