How do credit ratings affect corporate investment efficiency?

DOI 10.1002/ijfe.2920
ISSN 1076-9307
ESSN 1099-1158

Publisher: Wiley

Received: 28 October 2022 | Revised: 29 August 2023 | Accepted: 18 November 2023

DOI: 10.1002/ijfe.2920

RESEARCH ARTICLE

WILEY

How do credit ratings affect corporate investment efficiency?

Di Xiao[1] | **Xinyu Yu**[2]

[1]School of Economics, Finance and Accounting, Coventry University, Coventry, UK

[2]Surrey Business School, University of Surrey, Guildford, UK

Correspondence
Xinyu Yu, Surrey Business School, University of Surrey, Guildford, Surrey GU2 7XH, UK.
Email: xinyu.yu@surrey.ac.uk

Abstract

This study examines the impact of credit ratings on the efficiency of firms' investments. Using a large sample of US firms, we find a positive relationship between the existence of credit ratings and investment efficiency. The cross-sectional analyses show the positive relationship is more pronounced for firms with greater information asymmetry and weaker corporate governance. Our results are robust to different methods to address potential endogeneity concerns, alternative measures of key variables, and the inclusion of additional control variables. Overall, the findings support the notion that credit rating agencies enhance information transparency and external monitoring, thereby allowing rated firms to promote investment efficiency. The findings contribute to our understanding of the significant role played by credit rating agencies in shaping firms' investment behaviour and efficiency.

KEYWORDS

corporate governance, credit ratings, information asymmetry, investment efficiency

1 | INTRODUCTION

Credit rating agencies (CRAs) have a significant impact on the global financial markets by assessing the credit quality of companies and securities (Securities and Exchange Commision, 2003; Healy & Palepu, 2001; White, 2002). By assigning credit ratings, CRAs disclose and disseminate information to the market, alleviating the information asymmetry between firms and investors. This enables rated firms to access debt markets more readily. Prior literature extensively demonstrates the influence of having a credit rating on corporate capital structure (Faulkender & Petersen, 2006; Lemmon & Zender, 2010; Mittoo & Zhang, 2008). However, to the best of our knowledge, the effect of having a credit rating on firm investment quality remains unexplored. It is not clear whether and to what extent firms invest effectively as a result of having a credit rating.

This study aims to bridge this research gap by investigating whether and how credit ratings affect the efficiency of investment decisions. We hypothesize that the presence of credit ratings can improve investment efficiency through two primary channels. First, as information intermediaries, CRAs alleviate information asymmetry and help capital suppliers gain better insights into firms' operations and performance (An & Chan, 2008; Healy & Palepu, 2001). Second, CRAs serve as active monitors to firms, particularly during credit watch procedures, where they maintain regular interactions with firms and threaten firms with potential rating downgrades in response to adverse changes in firm characteristics and developments (Bannier & Hirsch, 2010; Boot et al., 2006). The increased information transparency and external monitoring facilitated by CRAs increase the likelihood of detecting firms' misbehaviours, thus deterring rated firms from adopting inefficient investments. The beneficial effect of CRAs is expected to be more pronounced in firms with asymmetric information and poor governance. Thus, we propose that there is a positive relationship between credit ratings and investment efficiency, and such a relationship varies with firm-level information asymmetry and corporate governance.

To empirically examine this, we use an unbalanced panel dataset of 72,946 observations from 9783 unique firms in the United States over the period of 1989–2017. Following Biddle et al. (2009) and Chen et al. (2011), we estimate a firm-specific investment model and measure investment efficiency based on the deviation from the expected optimal investment. The results show that firms with credit ratings exhibit higher investment efficiency than those without. Economically, on average, rated firms are associated with an increase of 5.04% in investment efficiency relative to the mean compared to unrated firms. Moreover, we find that the positive impact of rating existence on investment efficiency exists in the overinvestment subsample but is not significant in the underinvestment subsample after considering the effects of control variables. The results of the cross-sectional analysis indicate that the association between rating existence and investment efficiency is stronger for firms characterized by greater information asymmetry and weaker corporate governance. These findings confirm that the reduction of information asymmetry and improvement of external monitoring are two channels through which credit ratings improve investment efficiency. To address endogeneity concerns, we perform the Propensity Score Matching (PSM) method, the Instrumental Variable (IV) approach, and the Heckman two-step selection model. The results are consistent with our main findings.

We conduct several robustness tests and additional analyses. Our results remain the same using alternative measures of investment efficiency and credit ratings, as well as the inclusion of additional control variables. To gain further insights from the results, we decompose investment efficiency into different components and find that credit ratings significantly enhance the efficiency of capital expenditure and acquisitions, but not Research and Development (R&D). This aligns with the notion that evaluating and monitoring R&D expenditures can be challenging due to their relative opacity (Lara et al., 2016). Moreover, we find evidence that the effect of rating existence on investment efficiency is greater for firms with better financial reporting quality, suggesting that the functions of CRAs are influenced by the quality of corporate financial reporting (Alissa et al., 2013; Jung et al., 2013). Lastly, we analyse the impact of the Dodd–Frank Wall Street Reform and Consumer Protection Act (the Dodd–Frank Act, thereafter) on our results. Introduced in July 2010, the Dodd–Frank Act aimed to improve the accountability of CRAs and the quality of credit ratings (Dimitrov et al., 2015; Toscano, 2020). Our analysis reveals that credit ratings have a greater effect on investment efficiency following the Dodd–Frank Act, supporting that the regulatory reform has fostered the development of the credit rating industry and increased the real effects of CRAs (Toscano, 2020).

Our article contributes to the literature in several ways. First, it fits into the broad literature on corporate investment efficiency. Prior studies document that investment efficiency is determined by financial reporting quality (Biddle et al., 2009; Chen et al., 2011; Gomariz & Ballesta, 2014), internal corporate governance (Eisdorfer et al., 2013; Menshawy et al., 2021; Rajkovic, 2020), and corporate social responsibility (Benlemlih & Bitar, 2018; Cook et al., 2019). However, limited research has explored the role of external institutions.[i] Our study focuses on CRAs, an important external intermediary, and enriches the literature by demonstrating the importance of CRAs' informational and monitoring roles in increasing investment efficiency.

Our study also adds to the growing literature that examines the real effects of credit ratings on corporate financial decisions. Prior studies document that firms are concerned about their rating levels, especially potential downgrades, and adjust their policies to attain or maintain specific rating targets (Alissa et al., 2013; Graham & Harvey, 2001; Jung et al., 2013; Kisgen, 2006, 2009). However, the subprime mortgage crisis, characterized by significant downgrades and defaults, has raised doubts regarding the significance of CRAs in the financial markets and the conflicts of interest inherent in the issuer-pay model (Opp et al., 2013). Our findings emphasize the benefits provided by CRAs in lowering information asymmetry and exerting external monitoring. Moreover, our further analysis shows the effectiveness of the Dodd–Frank Act in increasing the accountability of CRAs. With increased regulatory oversight and growing reputation concerns in recent years, CRAs have improved their credit analysis, resulting in improved accuracy and timeliness of ratings (Cheng & Neamtiu, 2009; Gounopoulos & Pham, 2017).

Our study relates to Khieu and Pyles (2016), who find that firms prone to overinvest reduce their investment when dividends are cut and ratings are downgraded. This finding implies that managers, due to credit constraints, prioritize funding and select projects accordingly. Our study differs from Khieu and Pyles (2016) in several aspects. First, we identify and emphasize two channels through which credit ratings affect investment efficiency, highlighting the informational and monitoring roles of CRAs in shaping corporate decisions, which is neglected in Khieu and Pyles (2016). Second, Khieu and Pyles (2016) examine the combined impact of rating downgrades and dividend cuts on investments, while we focus explicitly on credit ratings and their association with investment efficiency. Finally, we measure investment efficiency based on the deviation from the optimal investment level (Biddle et al., 2009; Chen et al., 2011), capturing both overinvestment and underinvestment, while Khieu and Pyles (2016) focus solely on the investment decisions of downgraded firms which are likely to overinvest.

The remainder of the article is organized as follows. In the next section, we review the relevant literature and develop the hypotheses. Section 3 presents the data and methodology. Section 4 discusses the empirical results and Section 5 concludes the article.

2 | LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 | Determinants of investment efficiency

A fundamental question in the field of corporate finance is the factors that influence a firm's investment efficiency. According to the neo-classical paradigm, the investment opportunity is the sole driver of corporate investment (Modigliani & Miller, 1958). Firms maximize value by investing until the marginal benefit of investment equals the marginal cost. All positive Net-Present-Value (NPV) projects should be adopted in a perfect market. However, in practice, market frictions such as moral hazard and adverse selection introduce deviations from the optimal investment level, leading to overinvestment and underinvestment (Hubbard, 1998; Stein, 2003).

The moral hazard problem suggests that managers, driven by self-interest, may prioritize their personal objectives over shareholders' interest in the context of agency theory (Jensen, 1986; Jensen & Meckling, 1976; Stulz, 1990). In the absence of effective monitoring mechanisms, managers may engage in actions that deviate from the goal of maximizing firm value, such as empire-building, perquisite consumption, and management entrenchment. In addition, managerial behavioural traits, including career concerns, risk-taking preference, and hubris can also lead to negative NPV investments (Chen et al., 2017). The adverse selection problem arises when managers possess superior information about a firm's prospects and value, allowing them to time capital issuance and sell overpriced securities. Rational capital suppliers recognize this information asymmetry issue and are sceptical of such behaviours, leading them to undervalue newly issued securities. To avoid the high financing costs, managers may refuse to sell the securities. Without sufficient internal financing, financially constrained firms may give up profitable investment opportunities, leading to underinvestment (Fazzari et al., 1988; Myers & Majluf, 1984).

2.2 | Credit ratings and investment efficiency

We hypothesize that credit ratings can increase investment efficiency through two channels – reducing information asymmetry and increasing external monitoring.

2.2.1 | The informational intermediary view

Equipped with extensive financial expertise and sophisticated methodologies, CRAs specialize in collecting and processing financial information, analysing firms' business and financial risks, and assessing their overall creditworthiness and the capacity to satisfy financial obligations (Cornaggia et al., 2017; Kisgen, 2006, 2009). CRAs possess access to private information about firms' quality that managers are hesitant to disclose publicly, such as acquisition plans, business strategies, and multi-year forecasts (Healy & Palepu, 2001; Kisgen, 2006). Through the assignment of credit ratings, CRAs bridge the information gap between issuers and investors, thus improving the information environment.

The role of CRAs in disseminating information and reducing information asymmetry has been widely examined. For example, the changes in credit ratings, particularly downgrade, significantly affect stock and bond prices (Dichev & Piotroski, 2001; Hand et al., 1992; Holthausen & Leftwich, 1986; Steiner & Heinke, 2001). An and Chan (2008) examine the effect of credit ratings on initial public offering (IPO) pricing and find that rated firms are subject to less underpricing than unrated firms. Jory et al. (2016) find that, in mergers and acquisitions (M&As), bidders offer lower premiums to rated targets than unrated targets. These findings support the idea that credit ratings reduce information asymmetry and the uncertainty surrounding firm value in IPOs and M&As.

2.2.2 | The monitoring mechanism view

CRAs also perform the monitoring function, particularly through credit watch procedures (Bannier & Hirsch, 2010; Boot et al., 2006; Chung et al., 2012). CRAs maintain periodic communications with firms and establish implicit contracts with them. CRAs will place a firm's ratings "on watch" when they observe developments or decisions that could potentially impair the firm's credit quality. In such cases, firms are required to provide additional information and take necessary measures to address the concerns identified. If the recovery efforts succeed, the ratings may get reaffirmed. If not, costly downgrades will occur. Bannier and Hirsch (2010) and Chung et al. (2012) provide evidence that credit watches allow firms to rectify deficiencies such as poor operating performance, financial distress, and accounting and litigation problems.

Due to increased regulatory scrutiny and reputational concerns, CRAs now have greater motivations to monitor firms and provide timely and precise ratings.[ii] Gounopoulos and Pham (2017) investigate credit ratings and earnings management in the IPO process and find that rated firms are less likely to manipulate earnings, supporting both the informational and monitoring roles of CRAs. Based on the above discussions, we hypothesize that CRAs facilitate the information environment and external monitoring, thereby assisting rated firms in making efficient investments. Our main hypothesis is formulated as follows:

> **H1.** Rating existence is positively associated with investment efficiency.

As discussed above, firms are likely to make inefficient capital allocations due to moral hazards and adverse selection. If credit ratings mitigate firms' investment inefficiency through the channels of reducing information asymmetry and enhancing external monitoring, the beneficial effect of CRAs is expected to be more pronounced in firms with asymmetric information and poor governance. This leads to our next hypotheses:

> **H2.** The positive association between rating existence and investment efficiency is stronger for firms with greater information asymmetry.

> **H3.** The positive association between rating existence and investment efficiency is stronger for firms with weaker corporate governance.

3 | RESEARCH DESIGN

3.1 | Sample selection

We collect accounting and financial information from the Compustat and the Center for Research in Security Prices (CRSP) databases. Data on credit ratings are obtained from the Compustat S&P Rating database. In line with previous studies (Ashbaugh-Skaife et al., 2006; Karampatsas et al., 2014; Kisgen, 2006), credit ratings applied in this study refer to the Standard & Poor (S&P) long-term domestic issuer credit ratings. We adhere to standard procedures by excluding financial (SIC codes 6000-6999) and utility firms (SIC codes 4900-4999). We then delete observations with missing data. Our final unbalanced panel consists of 72,946 firm-year observations for 9,783 unique firms in the US market from 1989 to 2017.[iii]

3.2 | Model specification

Following previous studies (Benlemlih & Bitar, 2018; Biddle et al., 2009; Chen et al., 2011), we derive the optimal investment level using growth opportunities and measure investment efficiency based on the deviation from the expected optimal investment.

$$\text{Invest}_{i,t} = \alpha_0 + \alpha_1 \text{SG}_{i,t-1} + \alpha_2 \text{NEG}_{i,t-1} + \alpha_3 \text{NEG}_{i,t-1} \times \text{SG}_{i,t-1} + \varepsilon_{i,t.} \tag{1}$$

Invest is defined as the sum of capital expenditure, acquisition expenditure, and R&D less the cash received from selling property, plant, and equipment, scaled by lagged total assets. Growth opportunities are measured by the annual sales growth rate (SG). Since the changes in sales can affect the relationship between investment and sales growth, a dummy variable (NEG) and its interaction with sales growth (NEG × SG) are employed to distinguish between positive and negative sales growth (Chen et al., 2011; Gomariz & Ballesta, 2014). NEG equals one for negative sales growth, and zero otherwise. The model is estimated cross-sectionally for each industry-year, with a minimum requirement of 20 observations. Industries are categorized according to the Fama and French 48-industry classification.

The residual of the regression captures the deviation from the optimal investment, i.e., investment inefficiency. A smaller residual reflects higher investment efficiency, and a positive (negative) residual presents overinvestment (underinvestment). Following Gomariz and Ballesta (2014) and Rajkovic (2020), we define investment efficiency (InvEff) as the absolute value of the residual multiplied by minus one. Thus, a higher value of InvEff corresponds to greater investment efficiency.

We estimate the following regression model to test our main hypothesis (H1):

$$\text{InvEff}_{i,t} = \beta_0 + \beta_1 \text{Rating Existence}_{i,t} + \gamma \text{Controls}_{i,t} + \text{Year}_t + \text{Industry}_i + \varepsilon_{i,t,} \tag{2}$$

where the dependent variable is investment efficiency (InvEff). The main independent variable, Rating Existence, is a dummy variable that equals one for firms with a credit rating, and zero otherwise. In robustness tests, we further explore the effects of credit rating level and downgrade risk on investment efficiency. A significant and positive coefficient on Rating Existence is predicted by H1, that is, $\beta_1 > 0$.

Following prior studies (Biddle et al., 2009; Chen et al., 2011; Rajkovic, 2020), the control variables (Controls) include firm size (SIZE), firm age (AGE), tangibility (TANG), cash flow from operations (CFO), leverage (LEV), Altman (1968)'s Z-score (Z_SCORE), operating cycle (LNOC), Tobin's Q (TQ), the presence of loss (LOSS), the standard deviation of cash flow from operations (SDCFO), and the standard deviation of sales (SDSALE). Year and industry fixed effects are included to account for macroeconomic uncertainty and unobserved industry-specific heterogeneity. Detailed definitions of all variables are presented in Appendix A.

To test H2 and H3 and examine potential heterogeneity in the relation, we augment Equation (2) and perform the following model.

$$\begin{aligned}\text{InvEff}_{i,t} = {} & \beta_0 + \beta_1 \text{Rating Existence}_{i,t} \\ & + \beta_2 \text{Rating Existence}_{i,t} \times Z_{i,t} + \beta_3 Z_{i,t} \\ & + \gamma \text{Controls}_{i,t} + \text{Year}_t + \text{Industry}_i + \varepsilon_{i,t},\end{aligned} \tag{3}$$

where Z is a dummy variable for firms with high information asymmetry (High_IA) or weak corporate governance (Weak_CG). We employ three market-based measures for firm-level information asymmetry, including the probability of informed trade (PIN), the average of daily bid-ask spread over the year (Spread), and the standard deviation of daily stock returns over the year (Volatility) (Brown & Hillegeist, 2007; Lara et al., 2016).[iv] Firms with higher PIN, bid-ask spread and return volatility are prone to more asymmetric information. High_IA is a dummy variable equal to one if a firm's PIN, Spread or Volatility is higher than the sample median, and zero otherwise. In addition, we focus on three dimensions of corporate governance mechanisms: institutional ownership (InstOwn), CEO-chairman duality (Duality) and product market competition measured by the Herfindahl–Hirschman index (HHI) (Ashbaugh-Skaife et al., 2006; Shleifer & Vishny, 1986; Stoughton et al., 2017). Firms with more institutional ownership and product market competition (CEO-chairman duality) are subject to fewer (more) agency problems. Weak_CG is a dummy variable equal to one for firms with InstOwn below the sample median, Duality of one, or HHI above the sample median. H2 and H3 predict a positive and significant coefficient on the interaction term ($\beta_2 > 0$).

4 | EMPIRICAL RESULTS

4.1 | Descriptive statistics

In panel A of Table 1, we present the descriptive statistics of the main variables for the full sample. All continuous variables are winsorized at 1% at both tails to minimize the effect of outliers. The mean and median of investment efficiency (InvEff) are −0.119 and − 0.078, respectively. We further present and compare the descriptive statistics of investment efficiency in the subsamples of overinvestment (InvEff_Overinvest subsample) and underinvestment (InvEff_Underinvest subsample) based on the sign of residuals in Equation (1). Notably, 26,017 observations in our sample overinvest while 46,929 observations underinvest, consistent with prior studies (Gomariz & Ballesta, 2014; Rajkovic, 2020). Regarding our independent variable of interest, the mean of Rating Existence suggests that 16.9% of firms have credit ratings. The control variables are comparable with those in the previous studies (Biddle et al., 2009; Gomariz & Ballesta, 2014; Rajkovic, 2020).

In panel B of Table 1, we divide the sample into rated firms and unrated firms and compare the mean and median values of the variables in these two groups. Rated firms exhibit higher mean and median investment efficiency (−0.097 and − 0.062) compared to unrated firms (−0.123 and −0.082). These differences in mean and median are statistically significant at the 1% level. Within the overinvestment subsample, the mean and median investment efficiency values for rated firms (−0.139 and −0.059) are significantly higher than those for unrated firms (−0.172 and −0.087). Similar patterns can be found in the underinvestment subsample.

It is worth noting the time trends of investment efficiency for rated and unrated firms throughout the sample period. As depicted in Figure 1, rated firms consistently exhibit a higher median of investment efficiency than unrated firms over time. Overall, these preliminary findings align with our main hypothesis, suggesting that credit ratings are associated with higher investment efficiency, reducing both overinvestment and underinvestment.

4.2 | Credit ratings and investment efficiency

Table 2 presents the regression results of rating existence and investment efficiency from estimating Equation (2). In column 1, we initially regress investment efficiency (InvEff) on credit ratings (Rating Existence) for the full sample, while controlling for year and industry fixed effects. Consistent with our expectation, the coefficient on Rating Existence is positive and significant at the 1%

TABLE 1 Descriptive statistics.

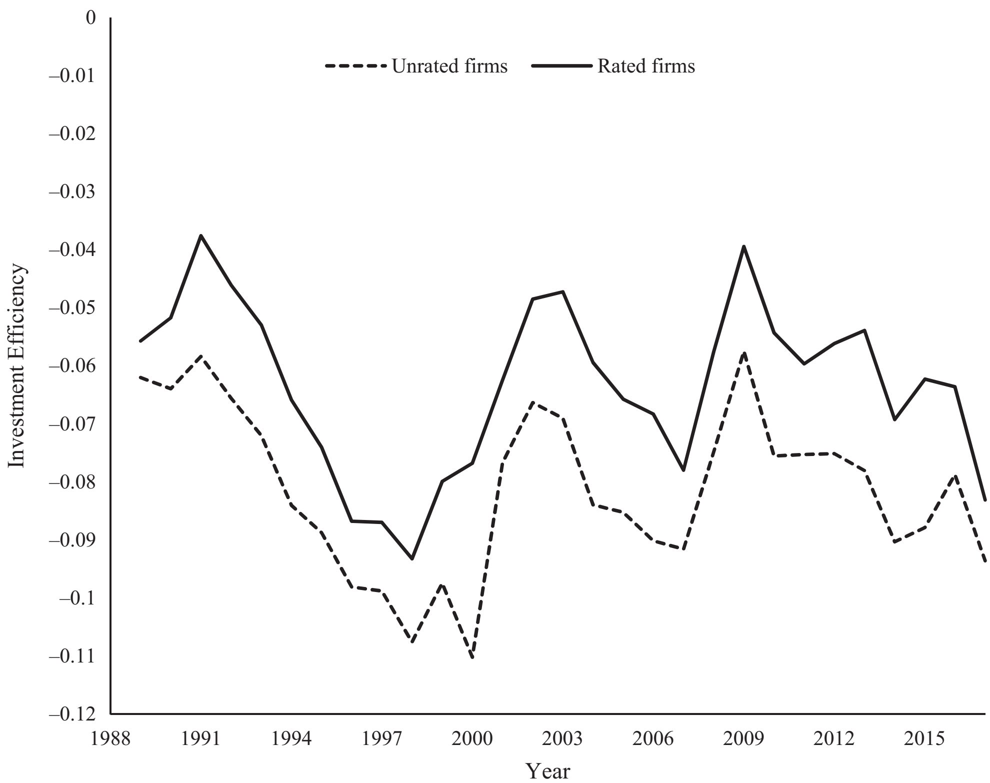
Panel A: Full sample						
Variable	*N*	Mean	p25	Median	p75	SD
InvEff	72,946	−0.119	−0.144	−0.078	−0.037	0.144
InvEff_Overinvest subsample	26,017	−0.167	−0.199	−0.082	−0.032	0.224
InvEff_Underinvest subsample	46,929	−0.093	−0.129	−0.077	−0.039	0.072
Rating Existence	72,946	0.169	0.000	0.000	0.000	0.375
SIZE	72,946	5.089	3.592	4.988	6.481	2.130
AGE	72,946	2.265	1.609	2.303	2.996	0.950
TANG	72,946	0.247	0.075	0.174	0.354	0.222
CFO	72,946	0.014	−0.016	0.066	0.128	0.226
LEV	72,946	0.156	0.000	0.059	0.243	0.209
Z_SCORE	72,946	4.110	1.609	3.278	5.722	8.394
LNOC	72,946	4.660	4.241	4.740	5.173	0.807
TQ	72,946	2.200	1.092	1.535	2.463	1.992
LOSS	72,946	0.380	0.000	0.000	1.000	0.485
SDCFO	72,946	0.090	0.026	0.051	0.100	0.125
SDSALE	72,946	0.187	0.055	0.113	0.227	0.222

Panel B: Subsamples of rated and unrated firms						
	Rated		Unrated			
Variable	Mean	Median	Mean	Median	*t*-value	Wilcoxon *z*-value
InvEff	−0.097	−0.062	−0.123	−0.082	18.54***	25.72***
InvEff_Overinvest subsample	−0.139	−0.059	−0.172	−0.087	8.54***	14.45***
InvEff_Underinvest subsample	−0.078	−0.063	−0.097	−0.08	21.21***	20.95***
SIZE	7.785	7.695	4.54	4.542	188.24***	147.71***
AGE	2.669	2.773	2.183	2.303	52.82***	50.75***
TANG	0.337	0.279	0.229	0.156	50.23***	52.89***
CFO	0.091	0.092	−0.001	0.058	42.07***	42.11***
LEV	0.298	0.245	0.127	0.026	86.87***	96.74***
Z_SCORE	2.987	2.571	4.339	3.512	−16.35***	−32.57***
LNOC	4.546	4.622	4.683	4.769	−17.27***	−21.87***
TQ	1.735	1.423	2.295	1.570	−28.63***	−16.59***
LOSS	0.239	0.000	0.405	0.000	−56.30***	−55.81***
SDCFO	0.037	0.027	0.101	0.058	−53.45***	−82.43***
SDSALE	0.117	0.072	0.201	0.124	−38.75***	−49.93***

Note: This table provides descriptive statistics of key variables for the full sample in panel A, and for rated and unrated firms in panel B. Definitions of all variables are in Appendix A. The *t*- and Wilcoxon *z*-tests are employed to compare the mean and median differences of each variable between rated and unrated firms in panel B. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.
Abbreviations: CFO, cash flow from operations; LEV, leverage; LNOC, operating cycle; LOSS, presence of loss; SDCFO, standard deviation of cash flow from operations; SDSALE, standard deviation of sales; SG, growth rate; TANG, tangibility; TQ, Tobin's Q.

level. To further confirm our result, we include the control variables in column 2. The coefficient on Rating Existence remains positive and significant at the 1% level. In economic terms, all else being equal, rated firms are associated with a 5.04% increase in investment efficiency relative to the mean than unrated firms.[v] To further explore the association, we examine two subsamples: overinvestment and underinvestment. The results are reported in columns 3–6 of Table 2. The coefficient on Rating Existence remains positive and highly significant

FIGURE 1 Median of Investment efficiency for rated and unrated firms, 1989–2017.



in the overinvestment subsample. Interestingly, the coefficient becomes insignificant in the underinvestment subsample when adding control variables. These findings indicate that having a credit rating reduces the overinvestment problem, but it does not necessarily mitigate the underinvestment issue.[vi] Overall, the findings confirm our first hypothesis that the rating existence has a positive effect on investment efficiency, with a more pronounced effect in the context of overinvestment than underinvestment.

The results related to the control variables are as expected in line with prior studies (Biddle et al., 2009; Chen et al., 2011; Rajkovic, 2020). Specifically, investment efficiency is positively associated with firm age, tangibility, and operating cycle; and is negatively related to firm size, leverage, growth opportunities, cash flow volatility, and sales volatility.

4.3 | Cross-sectional analysis

Next, we test our second and third hypotheses and explore the channels through which credit ratings affect investment efficiency. Specifically, we examine potential variations in the effect by considering different levels of information asymmetry and corporate governance based on Equation (3).

According to the informational intermediary view, CRAs reduce information asymmetry and, therefore, the enhanced information environment can reduce information risk and increase investment efficiency. If this channel holds, we expect that the effect of rating existence on investment efficiency increases with firm-level asymmetric information. Table 3 reports the estimation results, where information asymmetry is measured by PIN, bid-ask spread, and stock return volatility, respectively. The coefficient on Rating existence is still positive and statistically significant in all three columns. Importantly, the coefficient on the interaction term Rating existence × High_IA is positive and statistically significant, either at the 1% or 5% level, for the three indicators of information asymmetry. These results suggest that the positive association between rating existence and investment efficiency is stronger for firms with higher information asymmetry. The findings support the notion that CRAs fulfil an informational role that facilitates efficient investments, underscoring the importance of credit ratings in the presence of information asymmetry.

According to the monitoring mechanism view, CRAs engage in effective monitoring, discipline managerial behaviours, and reduce agency problems. Firms with weaker governance mechanisms would benefit more from this, leading to a stronger relationship between credit ratings and investment efficiency. Table 4 reports the results, where corporate governance is measured by institutional ownership, CEO-chairman duality, and product market competition, respectively. The coefficient on Rating existence becomes minimal and statistically insignificant, while the coefficient on the interaction term Rating existence × Weak_CG is positive and significant across all three

TABLE 2 Rating existence and investment efficiency.

	Full sample		Overinvest subsample		Underinvest subsample	
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Rating Existence	0.013***	0.006***	0.011**	0.010**	0.009***	−0.001
	(7.940)	(2.986)	(2.554)	(2.129)	(8.180)	(−0.847)
SIZE		−0.002***		−0.009***		0.003***
		(−4.604)		(−7.811)		(10.385)
AGE		0.011***		0.022***		−0.001***
		(13.764)		(12.550)		(−2.807)
TANG		0.008*		0.037***		0.032***
		(1.882)		(3.486)		(10.616)
CFO		0.008		−0.011		0.002
		(1.445)		(−1.001)		(0.654)
LEV		−0.055***		−0.166***		−0.029***
		(−16.707)		(−15.887)		(−14.693)
Z_SCORE		0.000		0.000		0.000*
		(1.026)		(1.110)		(1.900)
LNOC		0.003**		0.008***		−0.003***
		(2.360)		(2.813)		(−3.998)
TQ		−0.006***		−0.010***		0.002***
		(−8.039)		(−8.163)		(5.894)
LOSS		−0.001		−0.009**		0.001*
		(−0.550)		(−2.441)		(1.743)
SDCFO		−0.156***		−0.260***		−0.018***
		(−14.355)		(−13.515)		(−3.263)
SDSALE		−0.089***		−0.186***		−0.036***
		(−20.144)		(−18.834)		(−17.036)
Constant	−0.070***	−0.054***	−0.102***	−0.061***	−0.048***	−0.047***
	(−10.292)	(−5.581)	(−6.069)	(−2.715)	(−13.140)	(−8.447)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.11	0.18	0.08	0.21	0.27	0.31
Observations	72,946	72,946	26,017	26,017	46,929	46,929

Note: The table reports the regression results of rating existence and investment efficiency. The dependent variable is investment efficiency (InvEff) for the full sample in columns 1 and 2, for the overinvestment subsample in columns 3 and 4, and for the underinvestment subsample in columns 5 and 6. Definitions of all variables are in Appendix A. For all regressions, t-statistics (in parentheses) are based on robust standard errors clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.
Abbreviations: CFO, cash flow from operations; LEV, leverage; LNOC, operating cycle; LOSS, presence of loss; SDCFO, standard deviation of cash flow from operations; SDSALE, standard deviation of sales; SG, growth rate; TANG, tangibility; TQ, Tobin's Q.

columns. These results indicate that credit ratings enhance investment efficiency primarily in poorly governed firms, supporting the substitutive effect between credit ratings and governance mechanisms. The findings support the conjecture that CRAs play an effective monitoring role and reduce inefficient investment decisions, particularly in firms with inadequate governance mechanisms.

4.4 | Robustness tests

4.4.1 | Alternative measures of investment efficiency

We now conduct robustness checks utilizing three alternative measures of investment efficiency. First, we

TABLE 3 Rating existence, information asymmetry, and investment efficiency.

Variable	PIN (1)	Spread (2)	Volatility (3)
Rating Existence	0.007**	0.004**	0.004**
	(2.55)	(2.03)	(2.07)
Rating Existence × High_IA	0.010***	0.008**	0.007**
	(2.74)	(2.36)	(2.28)
High_IA	−0.002	0.005***	0.000
	(−1.12)	(3.16)	(0.08)
SIZE	−0.004***	−0.002***	−0.002***
	(−6.48)	(−3.12)	(−5.21)
AGE	0.013***	0.012***	0.012***
	(13.76)	(14.67)	(14.73)
TANG	0.015***	0.012***	0.011**
	(2.85)	(2.65)	(2.48)
CFO	−0.005	0.002	0.004
	(−0.75)	(0.41)	(0.75)
LEV	−0.068***	−0.064***	−0.060***
	(−15.86)	(−17.77)	(−17.29)
Z_SCORE	−0.000	−0.000	−0.000
	(−1.64)	(−0.63)	(−0.77)
LNOC	0.004***	0.003**	0.003***
	(2.63)	(2.26)	(2.59)
TQ	−0.004***	−0.003***	−0.004***
	(−4.88)	(−4.90)	(−5.64)
LOSS	−0.005***	−0.002	−0.002
	(−2.83)	(−1.46)	(−1.26)
SDCFO	−0.170***	−0.166***	−0.161***
	(−12.90)	(−14.08)	(−14.10)
SDSALE	−0.092***	−0.096***	−0.093***
	(−17.11)	(−19.96)	(−20.15)
Constant	−0.062***	−0.071***	−0.056***
	(−6.40)	(−5.48)	(−5.72)
Year effects	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Adj. R^2	0.16	0.17	0.17
Observations	47,478	66,389	69,086

Note: The table reports the regression results of rating existence, information asymmetry, and investment efficiency. The dependent variable is investment efficiency (InvEff). Definitions of all variables are in Appendix A. For all regressions, *t*-statistics (in parentheses) are based on robust standard errors clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Abbreviations: CFO, cash flow from operations; LEV, leverage; LNOC, operating cycle; LOSS, presence of loss; SDCFO, standard deviation of cash flow from operations; SDSALE, standard deviation of sales; SG, growth rate; TANG, tangibility; TQ, Tobin's Q.

estimate the reduced model of investment by Biddle et al. (2009), where the dummy variable for negative sales growth and its interaction with sales growth are excluded from Equation (1). Second, we focus on investment expenditure for new projects and employ an extended investment model of Richardson (2006) with additional

TABLE 4 Rating existence, corporate governance, and investment efficiency.

Variable	InstOwn (1)	Duality (2)	HHI (3)
Rating Existence	0.000	0.004	0.003
	(0.13)	(1.23)	(1.20)
Rating Existence × Weak_CG	0.014***	0.006*	0.006**
	(3.77)	(1.68)	(2.24)
Weak_CG	−0.003	−0.004*	−0.001
	(−1.06)	(−1.79)	(−0.30)
SIZE	−0.002***	−0.003***	−0.002***
	(−3.42)	(−2.99)	(−4.54)
AGE	0.011***	0.009***	0.011***
	(11.63)	(6.57)	(13.74)
TANG	0.011**	0.037***	0.008*
	(2.21)	(5.13)	(1.83)
CFO	0.009	0.029**	0.008
	(1.18)	(2.18)	(1.49)
LEV	−0.057***	−0.070***	−0.056***
	(−13.28)	(−9.99)	(−16.74)
Z_SCORE	0.000	0.001***	0.000
	(0.92)	(3.88)	(0.98)
LNOC	0.004**	0.001	0.003**
	(2.54)	(0.33)	(2.38)
TQ	−0.005***	−0.004***	−0.006***
	(−4.89)	(−4.22)	(−8.02)
LOSS	0.000	0.007**	−0.001
	(0.05)	(2.18)	(−0.55)
SDCFO	−0.167***	−0.043*	−0.156***
	(−11.21)	(−1.66)	(−14.37)
SDSALE	−0.095***	−0.151***	−0.089***
	(−15.96)	(−12.18)	(−20.13)
Constant	−0.053***	−0.052***	−0.053***
	(−4.09)	(−3.79)	(−5.49)
Year effects	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Adj. R^2	0.17	0.16	0.18
Observations	44,694	18,384	72,946

Note: The table reports the regression results of rating existence, corporate governance and investment efficiency. The dependent variable is investment efficiency (InvEff). Definitions of all variables are in Appendix A. For all regressions, *t*-statistics (in parentheses) are based on robust standard errors clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.
Abbreviations: CFO, cash flow from operations; LEV, leverage; LNOC, operating cycle; LOSS, presence of loss; SDCFO, standard deviation of cash flow from operations; SDSALE, standard deviation of sales; SG, growth rate; TANG, tangibility; TQ, Tobin's Q.

firm characteristics. We follow the standard procedures and construct investment efficiency (InvEff1 and InvEff2) based on the residuals from the models of Biddle et al. (2009) and Richardson (2006), respectively. Finally, we use the industry median investment as the proxy for the optimal investment (Guariglia & Yang, 2016) and

TABLE 5 Robustness tests.

Panel A: Alternative measures of investment efficiency			
Variable	**InvEff1 (1)**	**InvEff2 (2)**	**InvEff3 (3)**
Rating Existence	0.005***	0.004**	0.008***
	(2.69)	(1.98)	(3.55)
Controls	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Adj. R^2	0.18	0.15	0.17
Observations	72,946	59,742	72,946

Panel B: Credit rating level and downgrade risk				
Variable	**(1)**	**(2)**	**(3)**	**(4)**
Rating Level	0.002***			
	(4.47)			
Investment Grade		0.019***		
		(5.93)		
Broad_downgrade			0.002	
			(0.80)	
Micro_downgrade				0.007**
				(1.98)
Controls	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes
Adj. R^2	0.17	0.17	0.18	0.18
Observations	12,360	12,360	11,419	11,414

Panel C: Additional control variables				
Variable	**(1)**	**(2)**	**(3)**	**(4)**
Rating Existence	0.004**	0.004**	0.007***	0.006***
	(2.37)	(2.35)	(3.67)	(2.99)
FRQ1	0.278***			
	(24.04)			
FRQ2		0.090***		
		(4.57)		
STDebt			0.015***	
			(6.97)	
Dotcom				−0.046***
				(−7.04)
GFC				0.001
				(0.13)
Controls	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes
Adj. R^2	0.20	0.18	0.18	0.18
Observations	72,779	61,858	59,474	72,946

Note: The table reports the regression results of robustness tests, including alternative measures of investment efficiency in panel A, credit rating level and downgrade risk in panel B, and the inclusion of additional control variables in panel C. For all regressions, *t*-statistics (in parentheses) are based on robust standard errors clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.
Abbreviations: FRQ, financial reporting quality; GFC, global financial crisis.

measure investment efficiency (InvEff3) based on the deviation from the industry median investment. The results reported in panel A of Table 5 show that our results remain consistent after employing alternative measures of investment efficiency.

4.4.2 | Credit rating level and downgrade risk

The results reported thus far demonstrate that the existence of credit ratings increases investment efficiency. We now examine whether credit rating level and downgrade risk matter for investment efficiency. As discussed, rating downgrades come with substantial costs, prompting firms to make a concerted effort to avoid such downgrades. Higher credit ratings are associated with increased probabilities of rating migration, thus intensifying the pressure to prevent downgrades (Aktas et al., 2021; Cornaggia et al., 2017). In addition, firms with high credit ratings generally exhibit superior governance practices (Ashbaugh-Skaife et al., 2006), which further promote investment efficiency. Accordingly, we anticipate a positive association between investment efficiency and credit rating level, as well as downgrade risk.

We convert the categorical credit rating levels into numerical values and construct two rating level variables: Rating Level and Investment Grade (Cornaggia et al., 2017; Karampatsas et al., 2014). Rating Level is a continuous variable for rated firms which takes the value from 1 for D to 22 for AAA. Investment Grade is a dummy variable for the investment-grade ratings. In addition, we construct two proxies for downgrade risk at the broad and micro rating levels: Broad_downgrade and Micro_downgrade (Kang, 2022; Kisgen, 2006). Broad_downgrade is a dummy variable for firms with a minus credit rating. Micro_downgrade is a dummy variable for firms' credit scores within the low third of a credit rating level. The results reported in panel B of Table 5 demonstrate that firms with higher credit ratings (investment-grade rating) have greater investment efficiency. Both broad and micro downgrade risks have positive impacts on investment efficiency, although only micro downgrade risk is statistically significant. Overall, our findings suggest that rating level and downgrade risk improve investment efficiency.

4.4.3 | Additional control variables

To further evaluate the sensitivity of our main findings, we include additional controls in our model. Prior literature shows high-quality financial reporting reduces market frictions such as moral hazard and adverse selection, thus promoting efficient investment (Biddle et al., 2009; Chen et al., 2011; Gomariz & Ballesta, 2014). We employ two proxies for financial reporting quality (FRQ): FRQ1 represents Kothari et al.'s (2005) discretionary accruals measure and FRQ2 corresponds to the Dechow and Dichev (2002) measure estimated by Francis et al. (2005). We also consider the influence of debt maturity (STDebt) on investment efficiency, as short-term debt attenuates information asymmetry and agency costs between shareholders, creditors, and managers (Gomariz & Ballesta, 2014). Lastly, to account for turbulent crisis periods, we include dummy variables (Dotcom and global financial crisis) for the dot-com bubble and the global financial crisis (Gounopoulos & Pham, 2017). The results are reported in panel C of Table 5. Consistent with prior literature, investment efficiency is positively associated with financial reporting quality and short-term debt. Importantly, the positive impact of rating existence on investment efficiency continues to be robust.

4.5 | Endogeneity

While we have alleviated the concern of endogeneity by accounting for year and industry fixed effects, and by introducing additional control variables, the potential for self-selection and reverse causality may still lead to bias and inconsistency in our main results. It is also possible that CRAs offer ratings to firms that are already well-invested, rather than firms investing efficiently as a result of credit ratings. To address this and establish the causal link between credit ratings and investment efficiency, we employ three tests in this section.

4.5.1 | Propensity score matching

We employ propensity score matching to control for observable firm differences. To do this, we run a probit model regressing rating existence on all the control variables in Equation (2). The result is reported in panel A column 1 of Table 6. The propensity score of being rated is estimated, and each rated firm is matched to an unrated firm using the nearest neighbour technique. We employ two diagnostic checks. First, we re-estimate the probit model with the matched sample. The result reported in panel A column 2 shows that none of the coefficients are statistically significant. Additionally, the coefficients and the pseudo-R^2 in column 2 are much lower than those in column 1. Second, we examine the difference in mean values for each observable characteristic between the treated and control groups. The results in panel B show that none of the differences is significant. The two diagnostic tests collectively suggest that any remaining observable differences are effectively removed, and the two groups are indistinguishable. The result using the matched sample is reported in panel A column 3. The positive impact of rating existence on investment efficiency still holds.

4.5.2 | Instrumental variable approach

Next, an instrumental variable approach is performed to mitigate the concern of reverse causality. Prior literature documents that firms operating in well-established industries are more likely to have credit ratings and issue public bonds (An & Chan, 2008; Faulkender & Petersen, 2006). Furthermore, firms in industries where most firms possess credit ratings are more inclined to obtain credit ratings, as investors are already familiar with their competitors and industry conditions. Following Karampatsas et al. (2014) and Gounopoulos and Pham (2017), we use Industry Fraction as the instrumental variable, which represents the fraction of firms with credit ratings in the same industry.[vii] In the first stage of our analysis, we regress Rating Existence on Industry Fraction and all the control variables in Equation (2). The result is reported in column 1 of Table 7. As expected, the coefficient on Industry Fraction is positive and significant at the 1% level. The instrumental variable satisfies the relevant condition both theoretically and statistically. The validity tests of the instrumental variable, including of Kleibergen–Paaprk LM statistics for under-identification and the Cragg–Donald's F Wald statistics for weak identification, meet the standard criteria, indicating the validity and strength of our instrument. In the second stage, we estimate a model similar to Equation (2) but replace the original value of Rating Existence with its fitted value from the first stage. The result is reported in column

TABLE 6 Propensity score matching (PSM) results.

Panel A: Regression results using the PSM method			
	Pre-match sample	Post-match sample	
	Dep. Var: Rating Existence		Dep. Var: InvEff
Variable	(1)	(2)	(3)
Rating Existence			0.004*
			(1.68)
SIZE	0.692***	−0.014	0.002
	(104.72)	(−0.65)	(1.53)
AGE	0.150***	0.003	0.011***
	(16.42)	(0.11)	(7.58)
TANG	−0.694***	−0.013	0.025***
	(−13.68)	(−0.09)	(2.88)
CFO	0.591***	−0.057	0.047***
	(6.42)	(−0.27)	(2.90)
LEV	1.986***	−0.160	−0.033***
	(46.04)	(−1.47)	(−5.05)
Z_SCORE	−0.050***	−0.005	0.000
	(−21.25)	(−0.76)	(0.83)
LNOC	−0.156***	−0.019	−0.000
	(−10.68)	(−0.47)	(−0.05)
TQ	0.135***	−0.016	0.001
	(19.49)	(−0.92)	(0.75)
LOSS	0.039*	−0.032	0.009***
	(1.79)	(−0.83)	(2.61)
SDCFO	−1.291***	0.032	−0.067
	(−7.18)	(0.08)	(−1.38)
SDSALE	0.187***	0.098	−0.186***
	(3.29)	(0.87)	(−11.43)
Constant	−1.528***	−0.014	−0.102***
	(−30.50)	(−0.65)	(−4.35)
Year effects	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Pseudo/Adj. R^2	0.53	0.00	0.16
Observations	72,946	13,266	13,266

Panel B: Differences in firm characteristics				
Variable	Treated group ($N = 6{,}633$)	Control group ($N = 6{,}633$)	Difference	*t*-statistics
SIZE	7.055	7.076	−0.021	−0.91
AGE	2.444	2.440	0.004	0.25
TANG	0.325	0.326	−0.001	−0.19
CFO	0.087	0.087	0.000	−0.11
LEV	0.287	0.292	−0.005	−1.11
Z_SCORE	3.109	3.232	−0.122	−1.72
LNOC	4.545	4.560	−0.015	−1.16

(Continues)

TABLE 6 (Continued)

Panel B: Differences in firm characteristics				
TQ	1.778	1.818	−0.040	−1.69
LOSS	0.261	0.270	−0.009	−1.16
SDCFO	0.043	0.043	0.000	0.47
SDSALE	0.129	0.125	0.004	1.56

Note: The table reports the regression results using the PSM method. Panel A shows the result of pre-match propensity score regression in column 1, the post-match diagnostic regression in column 2, and the result of rating existence and investment efficiency using the matched sample in column 3. The dependent variable is rating existence (Rating Existence) in columns 1 and 2 and investment efficiency (InvEff) in column 3. Panel B reports the univariate comparisons of firm characteristics between firms with credit ratings and firms without. Definitions of all variables are in Appendix A. For all regressions, *t*-statistics (in parentheses) are based on robust standard errors clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Abbreviations: CFO, cash flow from operations; LEV, leverage; LNOC, operating cycle; LOSS, presence of loss; SDCFO, standard deviation of cash flow from operations; SDSALE, standard deviation of sales; SG, growth rate; TANG, tangibility; TQ, Tobin's Q.

2. Consistent with our earlier results, rating existence has a positive impact on investment efficiency.

4.5.3 | Heckman two-step model

Finally, we apply the Heckman two-step selection model to address the issue of self-selection. In the first step, we regress rating existence on a set of control variables using a probit model and estimate the inverse Mills ratio (Lambda). Following An and Chan (2008), the control variables include firm size (SIZE), age (AGE), tangibility (TANG), sales growth (SG), profitability (PROFIT), leverage (LEV), Z-score (Z_SCORE), and the fraction of rated firms in the industry (Industry Fraction). The first-step result is reported in column 3 of Table 7. In the second step, we incorporate the inverse Mills ratio as an additional independent variable in Equation (2). The second-step result is reported in column 4 of Table 7. We find the coefficient on Lambda is significant at the 10% level, indicating the existence of selection bias. Importantly, the result verifies our previous findings that rating existence helps increase investment efficiency.

Taken together, although it is difficult to completely rule out endogeneity, the results of three endogeneity tests all provide consistent evidence of a positive and causal effect of credit ratings on investment efficiency, consistent with our main hypothesis.[viii]

4.6 | Additional analyses

4.6.1 | Types of investment efficiency

Our main results examine the efficiency of total investment, encompassing capital expenditure, acquisitions, and R&D. It is natural to question whether the effect of credit ratings varies in different investment components. Compared to acquisitions, capital expenditures and R&D expenses are relatively more opaque and challenging to evaluate and monitor (Lara et al., 2016). Therefore, it is likely that credit ratings have varying effects on efficiency across capital expenditure, acquisitions, and R&D.

We break down total investment into capital expenditures, acquisitions, and R&D expenses, and re-estimate the model in Equation (1). Panel A of Table 8 displays the results, with the dependent variable reflecting the efficiency in capital expenditures, acquisitions, and R&D expenses in columns 1–3, respectively. The coefficient on Rating existence is positive and significant, suggesting that rated firms exhibit higher efficiency in capital expenditures and acquisitions. However, the coefficient on Rating existence is small and insignificant, suggesting rated and unrated firms have similar R&D efficiency. These findings demonstrate that credit ratings are valuable for enhancing efficiency in more transparent forms of investments, such as capital expenditures and acquisitions.

4.6.2 | The interaction effect of credit ratings and financial reporting quality

Prior literature highlights the influence of financial reporting quality on the efficiency of investment decisions (Biddle et al., 2009; Chen et al., 2011). An interesting question is the potential interaction effect of financial reporting quality and credit ratings. The effect of credit ratings on investment decisions may be mitigated by financial reporting quality, as the information and monitoring provided by credit ratings and financial reporting quality can be substitutes. In such a scenario, the effect of credit ratings on investment efficiency would likely be weaker for firms with better

TABLE 7 Instrumental variable and Heckman results.

Variable	IV First (1)	IV Second (2)	Heckman First (3)	Heckman Second (4)
Rating Existence		0.025**		0.006***
		(2.58)		(2.93)
SIZE	0.101***	−0.004***	0.622***	−0.004***
	(48.98)	(−3.64)	(38.89)	(−3.28)
AGE	0.037***	0.010***	0.176***	0.010***
	(11.20)	(11.84)	(10.52)	(12.30)
TANG	−0.090***	0.010**	−0.599***	0.009*
	(−5.35)	(2.22)	(−5.88)	(1.94)
CFO	−0.049***	0.005		0.005
	(−6.44)	(0.85)		(0.92)
LEV	0.269***	−0.060***	1.709***	−0.061***
	(17.16)	(−13.48)	(21.47)	(−12.60)
Z_SCORE	−0.004***	0.000	−0.040***	0.000*
	(−16.14)	(1.36)	(−5.71)	(1.65)
LNOC	−0.004	0.003**		0.003**
	(−1.26)	(2.45)		(2.47)
TQ	0.015***	−0.005***		−0.005***
	(16.64)	(−8.22)		(−8.09)
LOSS	0.022***	−0.002		−0.000
	(5.69)	(−1.43)		(−0.09)
SDCFO	0.062***	−0.143***		−0.152***
	(6.58)	(−13.81)		(−14.00)
SDSALE	0.045***	−0.090***		−0.088***
	(6.31)	(−20.35)		(−19.79)
Industry Fraction	0.509***		2.116***	
	(18.18)		(14.59)	
PROFIT			1.275***	
			(7.87)	
SG			0.007	
			(0.30)	
Lamda				−0.004*
				(−1.751)
Constant	−0.018	−0.102***	−6.565***	−0.035**
	(−1.35)	(−4.35)	(−27.29)	(−2.40)
Controls	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes
Pseudo/Adj. R^2	0.43	0.18	0.55	0.18
Observations	72,946	72,946	125,071	71,142

(Continues)

TABLE 7 (Continued)

Variable	IV First (1)	IV Second (2)	Heckman First (3)	Heckman Second (4)
Kleibergen–Paap rk LM statistic	230.16			
Cragg–Donald Wald F statistic	2,764.52			
Stock–Yogo weak ID 10% value	16.38			

Note: The table reports the regression results of the IV and Heckman models. Columns 1 and 2 show the results of the first and second stages of the IV regression. Columns 3 and 4 show the results of the first and second steps of Heckman regression. The dependent variable is rating existence (Rating Existence) in columns 1 and 3, and investment efficiency (InvEff) in columns 2 and 4. Definitions of all variables are in Appendix A. For all regressions, *t*-statistics (in parentheses) are based on robust standard errors clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.
Abbreviations: CFO, cash flow from operations; LEV, leverage; LNOC, operating cycle; LOSS, presence of loss; SDCFO, standard deviation of cash flow from operations; SDSALE, standard deviation of sales; SG, growth rate; TANG, tangibility; TQ, Tobin's Q.

financial reporting quality. In contrast, if the beneficial effects of credit ratings and financial reporting quality are complementary, the effect of credit ratings on investment efficiency may be stronger for those firms with better financial reporting quality. Therefore, the interaction effect of credit ratings and financial reporting quality on investment efficiency is an empirical question.

In addition to the previously used two proxies for financial reporting quality (FRQ1 and FRQ2), we further measure financial reporting readability (FRQ3) using the Bog index developed by Bonsall et al. (2017).[ix] We perform the model in Equation (3), where Z is each measure of financial reporting quality. If the substitutive (complimentary) effect dominates, then a negative (positive) coefficient on the interaction is predicted. The results reported in panel B of Table 8 show that the effect of credit ratings on investment efficiency increases with financial reporting quality, supporting the complementary effect. The role of CRAs becomes more significant when firms provide high-quality financial information. The results are consistent with the idea that the effectiveness of CRAs is affected by financial reporting quality and firms may manage earnings to move toward expected ratings (Alissa et al., 2013; Jung et al., 2013).

4.6.3 | The impact of the Dodd–Frank Act

CRAs have been widely criticized for their inherent conflict of interests under the issuer-pay model and their failure to accurately assess default risk before the global financial crisis (deHaan, 2017; Opp et al., 2013). In response to the crisis, the Dodd–Frank Wall Street Reform and Consumer Protection Act was introduced in July 2010. This Act increases CRAs' liability for biased ratings and imposes new penalties for material misstatements and misconduct (Dimitrov et al., 2015; Toscano, 2020). Due to the increased regulatory oversight and reputational concerns, CRAs have stronger incentives to diligently monitor issuers and promptly adjust their ratings. Toscano (2020) examines the difference between the issuer-paid and investor-paid models before and after the implementation of the Dodd–Frank Act. Her findings indicate that post the Act, issuer-paid ratings are lower, more accurate, and timelier relative to investor-paid ratings, thereby providing support to the effectiveness of the Dodd–Frank Act.

We investigate whether the impact of credit ratings on investment efficiency differs before and after the Dodd–Frank Act. In the post-Act period, it is anticipated that CRAs will intensify their monitoring of issuers and alleviate information symmetry. Consequently, we expect the positive association between rating existence and investment efficiency strengthen after the Act. We follow Toscano (2020) and focus on a subsample period from 2005 to 2014 to isolate the effect of the Sarbanes–Oxley Act. A dummy variable, Post-Act is defined as one over the period between July 2010 and December 2014, and zero otherwise. We perform the model in Equation (3), where Z is Post-Act. The results are reported in panel C of Table 8 without (with) year fixed effects in columns 1 and 3 (columns 2 and 4). To distinguish the effects of the Dodd–Frank Act from those of the global financial crisis, we exclude the financial crisis sample period in columns 3 and 4. As anticipated, the coefficient on the interaction term is consistently positive and significant across all four columns, suggesting that the positive effect of credit ratings on investment efficiency increases after the Act. These results suggest that the regulatory reform has promoted the development of the credit rating industry and strengthened the informational and monitoring roles of CRAs.

TABLE 8 Additional analyses.

Panel A: Investment efficiency by investment types			
Variable	**Capital expenditures (1)**	**Acquisitions (2)**	**R&D (3)**
Rating Existence	0.003***	0.004***	−0.000
	(3.33)	(2.67)	(−0.09)
Controls	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Adj. R^2	0.23	0.08	0.44
Observations	72,946	72,946	72,946

Panel B: The role of financial reporting quality			
Variable	**FRQ1 (1)**	**FRQ2 (2)**	**FRQ3 (3)**
Rating Existence	0.076***	0.016***	0.011***
	(4.19)	(6.38)	(3.85)
Rating Existence × FRQ	0.246***	0.177***	0.001***
	(5.13)	(2.67)	(3.73)
FRQ	0.247***	0.074***	0.000
	(21.42)	(3.68)	(1.03)
Controls	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Adj. R^2	0.19	0.20	0.18
Observations	51,937	72,779	61,858

Panel C: The impact of the Dodd–Frank Act				
	Inclusion of crisis period		**Exclusion crisis period**	
Variable	**(1)**	**(2)**	**(3)**	**(4)**
Rating Existence	−0.007**	−0.006	−0.008	−0.008
	(−1.97)	(−1.55)	(−1.53)	(−1.54)
Rating Existence × Post-Act	0.010**	0.010**	0.009*	0.009*
	(2.45)	(2.56)	(1.68)	(1.71)
Post-Act	−0.004*	−0.004	0.006**	−0.004
	(−2.02)	(−0.50)	(2.09)	(−0.51)
Controls	Yes	Yes	Yes	Yes
Year effects	No	Yes	No	Yes
Industry effects	Yes	Yes	Yes	Yes
Adj. R^2	0.19	0.20	0.20	0.21
Observations	23,760	23,760	16,465	16,465

Note: The table reports the regression results of additional analyses, including investment efficiency by investment types in panel A, the role of financial reporting quality in panel B, and the impact of the Dodd–Frank Act in panel C. The dependent variable is investment efficiency (InvEff). Definitions of all variables are in Appendix A. For all regressions, *t*-statistics (in parentheses) are based on robust standard errors clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.
Abbreviation: FRQ, financial reporting quality.

5 | CONCLUSIONS

Using a large panel sample of US firms, this study investigates the impact of credit ratings on investment efficiency. The findings consistently demonstrate that firms with credit ratings have greater investment efficiency than firms without ratings. We further explore the heterogeneity in this relationship and find that the positive impact of credit ratings on investment efficiency is stronger for firms characterized by greater information asymmetry and weaker corporate governance. This suggests that credit ratings enhance investment efficiency through two channels: improving information transparency and exerting external monitoring. We carefully address endogeneity concerns through the implementation of the PSM method, the IV approach and the Heckman analysis. The results remain robust with alternative measures of investment efficiency and credit ratings, as well as the inclusion of additional control variables.

Our findings provide valuable insights and have significant practical implications for investors, corporate directors and executives, and regulators. First, investors choosing capital investments and other stakeholders should recognize the important role that CRAs play in attenuating information asymmetry and monitoring managerial behaviour in the financial markets. Second, this study provides guidance to corporate directors and executives on enhancing governance practices and financial decisions. Credit ratings serve as an effective external governance mechanism and can improve firm value. Third, our study provides important evidence to regulators and contributes to ongoing debates over the regulatory oversight of CRAs. It would be helpful for policymakers to continue to promote the development of the credit rating industry and improve the quality of credit ratings to ensure a more efficient and transparent financial system.

This study is not free from limitations. First, our sample period ends in 2017, due to the unavailability of credit ratings in Compustat afterwards. We recognize that the accuracy of our conclusions may be affected due to such sample limitations, and it would be better to obtain a rich dataset from different countries. Second, we employ S&P long-term domestic issuer credit ratings. It would be worthwhile extending our analysis and using credit ratings assessed by other CRAs like Moody's and Fitch, comparing their implications for corporate decisions.

ACKNOWLEDGEMENTS

We appreciate the helpful comments and suggestions from the editors, the two anonymous reviewers and the participants at the Annual Conference 2022 of British Accounting and Finance Association.

CONFLICT OF INTEREST STATEMENT

There is no conflict of interest to declare.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

ORCID

Di Xiao https://orcid.org/0000-0003-1535-6176
Xinyu Yu https://orcid.org/0000-0002-3127-2709

ENDNOTES

[i] One exception is Chen et al. (2017), who find that external financial analysts and the quality of their forecasts influence investment efficiency.

[ii] Several regulatory reforms have been enacted to foster the development of the credit rating industry. For instance, in the United States, regulatory reforms such as the Credit Rating Agency Reform Act of 2006, and the Dodd–Frank Wall Street Reform and Consumer Protection Act of 2010 have been introduced.

[iii] Our sample period ends in 2017 due to the unavailability of S&P credit ratings in Compustat afterward.

[iv] PIN estimates the probability of a privately informed trade and captures information asymmetry in the secondary market. The data are available for the period 1993–2010, retrieved from Professor Stephen Brown's website (https://terpconnect.umd.edu/~stephenb/). We would like to thank Professor Stephen Brown for sharing the data.

[v] With an average investment efficiency of 0.119, the difference of 0.006 between rated and unrated firms corresponds to approximately 5.04% (= 0.006 / 0.119).

[vi] The presence of credit ratings enables firms to easily access public debt markets, potentially lowering financial constraints and mitigating underinvestment. However, the insignificant effect of credit ratings on investment efficiency in the underinvestment subsample challenges this mechanism. Our findings align with Karampatsas et al. (2014) and Lemmon and Zender (2010) that the mere existence of credit ratings does not necessarily lower financial constraints. Unrated firms with high growth opportunities and robust financial structures can still rely on internal and equity financing, which may explain why they are unlikely to underinvest compared to rated firms.

[vii] Karampatsas et al. (2014) and Gounopoulos and Pham (2017) consider industry profitability and industry risk as additional instrumental variables in their studies. However, we argue that industry profitability and risk may have a direct effect on firm-level investment efficiency, making them unsuitable due to the exclusion restriction. Nevertheless, our result remains the same when industry profitability and risk are included as additional instrumental variables.

[viii] Although a series of tests are conducted to address potential concerns on selection bias and reverse causality, we acknowledge that endogeneity may still exist. We thank the anonymous referee for pointing out the caveat.

[ix] The Bog index scores quantify the extent of plain and easily understandable language used in disclosures, retrieved from Professor Brian P. Miller's website (https://host.kelley.iu.edu/bpm/activities/bogindex.html). We would like to thank Professor Brian P. Miller for providing the data.

REFERENCES

Aktas, N., Petmezas, D., Servaes, H., & Karampatsas, N. (2021). Credit ratings and acquisitions. *Journal of Corporate Finance*, *69*, 101986.

Alissa, W., Bonsall, S. B., Koharki, K., & Penn, M. W. (2013). Firms' use of accounting discretion to influence their credit ratings. *Journal of Accounting and Economics*, *55*(2–3), 129–147.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance*, *23*(4), 589–609.

An, H., & Chan, K. C. (2008). Credit ratings and IPO pricing. *Journal of Corporate Finance*, *14*(5), 584–595. https://doi.org/10.1016/j.jcorpfin.2008.09.010

Ashbaugh-Skaife, H., Collins, D. W., & LaFond, R. (2006). The effects of corporate governance on firms' credit ratings. *Journal of Accounting and Economics*, *42*(1), 203–243. https://doi.org/10.1016/j.jacceco.2006.02.003

Bannier, C. E., & Hirsch, C. W. (2010). The economic function of credit rating agencies – What does the watchlist tell us? *Journal of Banking and Finance*, *34*(12), 3037–3049.

Benlemlih, M., & Bitar, M. (2018). Corporate social responsibility and investment efficiency. *Journal of Business Ethics*, *148*(3), 647–671.

Biddle, G. C., Hilary, G., & Verdi, R. S. (2009). How does financial reporting quality relate to investment efficiency? *Journal of Accounting and Economics*, *48*(2–3), 112–131.

Bonsall, S. B., Leone, A. J., Miller, B. P., & Rennekamp, K. (2017). A plain English measure of financial reporting readability. *Journal of Accounting and Economics*, *63*(2–3), 329–357.

Boot, A. W., Milbourn, T. T., & Schmeits, A. (2006). Credit ratings as coordination mechanisms. *Review of Financial Studies*, *19*(1), 81–118.

Brown, S., & Hillegeist, S. A. (2007). How disclosure quality affects the level of information asymmetry. *Review of Accounting Studies*, *12*(2), 443–477.

Chen, F., Hope, O.-K., Li, Q., & Wang, X. (2011). Financial reporting quality and investment efficiency of private firms in emerging markets. *Accounting Review*, *86*(4), 1255–1288.

Chen, T., Xie, L., & Zhang, Y. (2017). How does analysts' forecast quality relate to corporate investment efficiency? *Journal of Corporate Finance*, *43*, 217–240.

Cheng, M., & Neamtiu, M. (2009). An empirical analysis of changes in credit rating properties: Timeliness, accuracy and volatility. *Journal of Accounting and Economics*, *47*(1–2), 108–130.

Chung, K. H., Frost, C. A., & Kim, M. (2012). Characteristics and information value of credit watches. *Financial Management*, *41*(1), 119–158.

Cook, K. A., Romi, A. M., Sánchez, D., & Sanchez, J. M. (2019). The influence of corporate social responsibility on investment efficiency and innovation. *Journal of Business Finance & Accounting*, *46*(3–4), 494–537.

Cornaggia, J. N., Cornaggia, K. J., & Hund, J. E. (2017). Credit ratings across asset classes: A long-term perspective. *Review of Finance*, *21*(2), 465–509.

Dechow, P. M., & Dichev, I. D. (2002). The quality of accruals and earnings: The role of accrual estimation errors. *Accounting Review*, *77*(s-1), 35–59.

de Haan, E. (2017). The financial crisis and corporate credit ratings. *Accounting Review*, *92*(4), 161–189.

Dichev, I. D., & Piotroski, J. D. (2001). The long-run stock returns following bond ratings changes. *Journal of Finance*, *56*(1), 173–203.

Dimitrov, V., Palia, D., & Tang, L. (2015). Impact of the Dodd-Frank act on credit ratings. *Journal of Financial Economics*, *115*(3), 505–520.

Eisdorfer, A., Giaccotto, C., & White, R. (2013). Capital structure, executive compensation, and investment efficiency. *Journal of Banking and Finance*, *37*(2), 549–562.

Faulkender, M., & Petersen, M. A. (2006). Does the source of capital affect capital structure? *Review of Financial Studies*, *19*(1), 45–79.

Fazzari, S., Hubbard, R. G., & Petersen, B. (1988). Investment, financing decisions, and tax policy. *American Economic Review*, *78*(2), 200–205.

Francis, J., LaFond, R., Olsson, P., & Schipper, K. (2005). The market pricing of accruals quality. *Journal of Accounting and Economics*, *39*(2), 295–327.

Gomariz, M. F. C., & Ballesta, J. P. S. (2014). Financial reporting quality, debt maturity and investment efficiency. *Journal of Banking and Finance*, *40*, 494–506.

Gounopoulos, D., & Pham, H. (2017). Credit ratings and earnings management around IPOs. *Journal of Business Finance and Accounting*, *44*(1–2), 154–195.

Graham, J. R., & Harvey, C. R. (2001). The theory and practice of corporate finance: Evidence from the field. *Journal of Financial Economics*, *60*(2–3), 187–243.

Guariglia, A., & Yang, J. (2016). A balancing act: Managing financial constraints and agency costs to minimize investment inefficiency in the Chinese market. *Journal of Corporate Finance*, *36*, 111–130.

Hand, J. R., Holthausen, R. W., & Leftwich, R. W. (1992). The effect of bond rating agency announcements on bond and stock prices. *Journal of Finance*, *47*(2), 733–752.

Healy, P. M., & Palepu, K. G. (2001). Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics*, *31*(1–3), 405–440.

Holthausen, R. W., & Leftwich, R. W. (1986). The effect of bond rating changes on common stock prices. *Journal of Financial Economics*, *17*(1), 57–89.

Hubbard, R. (1998). Capital-market imperfections and investment. *Journal of Economic Literature*, *36*, 193–225.

Jensen, M. C. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *American Economic Review*, *76*(2), 323–329.

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, *3*(4), 305–360. https://doi.org/10.1016/0304-405X(76)90026-X

Jory, S. R., Ngo, T. N., & Wang, D. (2016). Credit ratings and the premiums paid in mergers and acquisitions. *Journal of Empirical Finance*, *39*, 93–104.

Jung, B., Soderstrom, N., & Yang, Y. S. (2013). Earnings smoothing activities of firms to manage credit ratings. *Contemporary Accounting Research*, *30*(2), 645–676.

Kang, M. (2022). Credit rating downgrade risk and acquisition decisions. *Journal of Business Finance and Accounting*, *49*(5–6), 1011–1073.

Karampatsas, N., Petmezas, D., & Travlos, N. G. (2014). Credit ratings and the choice of payment method in mergers and acquisitions. *Journal of Corporate Finance*, *25*, 474–493.

Khieu, H. D., & Pyles, M. K. (2016). The influence of a credit rating change on dividend and investment policy interactions. *Financial Review*, *51*(4), 579–611.

Kisgen, D. (2006). Credit ratings and capital structure. *Journal of Finance*, *61*(3), 1035–1072.

Kisgen, D. (2009). Do firms target credit ratings or leverage levels? *Journal of Financial Quantitative Analysis*, *44*(6), 1323–1344.

Kothari, S. P., Leone, A. J., & Wasley, C. E. (2005). Performance matched discretionary accrual measures. *Journal of Accounting and Economics*, *39*(1), 163–197.

Lara, J. M. G., Osma, B. G., & Penalva, F. (2016). Accounting conservatism and firm investment efficiency. *Journal of Accounting and Economics*, *61*(1), 221–238. https://doi.org/10.1016/j.jacceco.2015.07.003

Lemmon, M. L., & Zender, J. F. (2010). Debt capacity and tests of capital structure theories. *Journal of Financial Quantitative Analysis*, *45*(5), 1161–1187.

Menshawy, I. M., Basiruddin, R., Mohd-Zamil, N. A., & Hussainey, K. (2021). Strive towards investment efficiency among Egyptian companies: Do board characteristics and information asymmetry matter? *International Journal of Finance and Economics.*, *28*, 2382–2403.

Mittoo, U. R., & Zhang, Z. (2008). The capital structure of multinational corporations: Canadian versus US evidence. *Journal of Corporate Finance*, *14*(5), 706–720.

Modigliani, F., & Miller, M. H. (1958). The cost of capital, corporation finance and the theory of investment. *American Economic Review*, *48*(3), 261–297.

Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, *13*(2), 187–221.

Opp, C. C., Opp, M. M., & Harris, M. (2013). Rating agencies in the face of regulation. *Journal of Financial Economics*, *108*(1), 46–61.

Rajkovic, T. (2020). Lead independent directors and investment efficiency. *Journal of Corporate Finance*, *64*, 101690.

Richardson, S. (2006). Over-investment of free cash flow. *Review of Accounting Studies*, *11*(2), 159–189.

Securities and Exchange Commision. (2003). *Report on the role and function of credit rating agencies in the operation of the securities markets*. Retrieved from https://www.sec.gov/about/divisions-office/office-credit-ratings/reports-and-studies or more specifically https://www.sec.gov/news/studies/credratingreport0103.pdf

Shleifer, A., & Vishny, R. W. (1986). Large shareholders and corporate control. *Journal of Political Economy*, *94*(3, Part 1), 461–488.

Stein, J. C. (2003). Agency, information and corporate investment. *Handbook of the Economics of Finance*, *1*, 111–165.

Steiner, M., & Heinke, V. G. (2001). Event study concerning international bond price effects of credit rating actions. *International Journal of Finance and Economics*, *6*(2), 139–157.

Stoughton, N. M., Wong, K. P., & Yi, L. (2017). Investment efficiency and product market competition. *Journal of Financial Quantitative Analysis*, *52*(6), 2611–2642.

Stulz, R. (1990). Managerial discretion and optimal financing policies. *Journal of Financial Economics*, *26*(1), 3–27.

Toscano, F. (2020). Does the Dodd-Frank act reduce the conflict of interests of credit rating agencies? *Journal of Corporate Finance*, *62*, 101595.

White, L. J. (2002). The credit rating industry: An industrial organization analysis. In *Ratings, rating agencies and the global financial system* (pp. 41–63). Springer.

How to cite this article: Xiao, D., & Yu, X. (2023). How do credit ratings affect corporate investment efficiency? *International Journal of Finance & Economics*, 1–22. https://doi.org/10.1002/ijfe.2920

APPENDIX A: VARIABLE DEFINITIONS

Variable	Definition
Invest	Sum of capital expenditure, acquisition expenditure and R&D less cash receipts from the sale of property, plant, and equipment, all scaled by lagged total asset (Biddle et al., 2009)
SG	The annual rate of change in sales (Chen et al., 2011)
NEG	A dummy variable which takes the value of one for negative sales growth, and zero otherwise (Chen et al., 2011)
InvEff	The absolute value of the residual from the investment model, Equation (1), multiplied by minus one (Gomariz & Ballesta, 2014; Rajkovic, 2020)
Rating Existence	A dummy variable which takes the value of one if the firm has a credit rating, and zero otherwise (Karampatsas et al., 2014)
SIZE	The natural logarithm of total assets (Biddle et al., 2009)
AGE	The natural logarithm of the difference between the first year when the firm appears in CRSP and the current year plus one (Biddle et al., 2009)
TANG	The ratio of property, plant, and equipment to total assets (Biddle et al., 2009)
CFO	The ratio of cash flow from operations to total assets (Chen et al., 2011)
LEV	The ratio of long-term debt to the sum of long-term debt and the market value of equity (Biddle et al., 2009)
Z_SCORE	1.2 × (working capital/total assets) + 1.4 × (retained earnings/total assets) + 3.3 × (the earnings before interest and taxes/total assets) + 0.6 × (the market value equity/book value of total debt) + 0.999 × (sales/total assets) (Altman, 1968)
LNOC	The natural logarithm of account receivables to sales plus inventory to cost of goods multiplied by 360 (Biddle et al., 2009)
TQ	The ratio of the market value of assets to the book value of assets (Biddle et al., 2009)
LOSS	A dummy variable which takes the value of one if net income before extraordinary items is negative, and zero otherwise (Biddle et al., 2009)
SDCFO	The standard deviation of cash flow from operations divided by total assets from years $t-2$ to t (Chen et al., 2011)
SDSALE	The standard deviation of the sales divided by total assets from years $t-2$ to t (Chen et al., 2011)
High_IA	A dummy variable equal to one if a firm's PIN, spread, or volatility is higher than the sample median, and zero otherwise. PIN is the probability of a privately informed trade (Brown & Hillegeist, 2007). Spread is the average of daily bid-ask spread over the year and Volatility is the standard deviation of daily stock returns over the year (Lara et al., 2016).
Weak_CG	A dummy variable equal to one if a firms' InstOwn is below the sample median, a firm's Duality is one, or an industry's HHI is above the sample median, respectively. InstOwn is the percentage of ownership by institutional investors and Duality is a dummy variable equal to one if a firm's CEO also serves as the board chairperson (Ashbaugh-Skaife et al., 2006). HHI is the sum of the squares of the market shares of all firms in the same industry in a year (Stoughton et al., 2017).
Industry Fraction	The fraction of firms with credit ratings in the same industry group (Karampatsas et al., 2014)
PROFIT	The ratio of earnings before interest, taxes, depreciation, and amortization to total assets (An & Chan, 2008)
InvEff1	The absolute value of the residual from the reduced investment model by Biddle et al. (2009), multiplied by minus one
InvEff2	The absolute value of the residual from the extended investment model by Richardson (2006), multiplied by minus one
InvEff3	The difference between a firm's investment and industry median investment, multiplied by minus one (Guariglia & Yang, 2016)

(Continues)

Variable	Definition
Rating Level	Continuous variable for rated firms, which takes the value from 1 (D rating) to 22 (AAA rating) (Karampatsas et al., 2014)
Investment Grade	A dummy variable which takes the value of one for the investment grade (above BBB- threshold), and zero for the speculative grade (below BBB- threshold) (Karampatsas et al., 2014)
Broad_downgrade	A dummy variable equal to one if the firm has a minus credit rating, and zero otherwise (Kisgen, 2006)
Micro_downgrade	A dummy variable equal to one if the firm's credit score is within the low third of a credit rating level. The credit score is calculated by regressing credit level on firm size, debt-to-capitalization ratio and earnings before interest, taxes, depreciation, and amortization-to-assets ratio (Kisgen, 2006)
STDebt	The ratio of short-term debt to total debt (Gomariz & Ballesta, 2014)
FRQ1	The absolute value of discretionary accruals based on the model of Kothari et al. (2005) multiplied by minus one
FRQ2	The standard deviation of residuals over the prior 5 years based on the model of Dechow and Dichev (2002) and Francis et al. (2005) multiplied by minus one
FRQ3	Bog index developed by Bonsall et al. (2017) multiplied by minus one
Dotcom	A dummy variable equal to one for the period of 1999–2000, and zero otherwise (Gounopoulos & Pham, 2017)
GFC	A dummy variable equal to one for the period of 2007–2009, and zero otherwise (Gounopoulos & Pham, 2017)
Post-Act	A dummy variable equal to one over the period between July 2010 and December 2014, and zero otherwise (Toscano, 2020)

Abbreviations: FRQ, financial reporting quality; GFC, global financial crisis.