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Are credit rating agencies still relevant? Evidence on certification from Moody's credit watches

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ABSTRACT

We show that a rating agency can provide certification for corporate borrowers through the mechanism of a credit watch with direction downgrade. We find that firms with watch-preceded rating confirmations (firms for which original ratings are confirmed after a credit watch warning) experience an increase in their long-term debt financing and ramp up their investment activities following the credit watch period. These firms are able to maintain their profitability from before to after the watch period, while we find no such evidence for firms with watch-preceded rating downgrades. Among firms with confirmed ratings, those with less access to credit markets obtain more long-term debt financing at a lower cost of debt capital only in the post-watch period, indicating that rating agencies can help alleviate firm capital constraints. The certification effects persist after controlling for potential endogeneity bias.

1. Introduction

The recent financial crisis has triggered a debate on the credibility of credit rating agencies (CRAs) and their real economic functions in the financial system. CRAs have faced criticism mainly for being slow to revise ratings and for inflating ratings due to conflicts of interest and competition for issuers (Becker and Milbourn, 2011; Bolton et al., 2012). Despite these views, CRAs' certification services remain essential to many participants in financial markets. Ratings provide a useful risk measure for investors who lack the resources or skills to assess credit risk, have regulatory impact (Bongaerts et al., 2012; Opp et al., 2013), affect IPO pricing (An and Chan, 2008) and the choice of payment method in mergers and acquisitions (Karampatsas et al., 2014), and most importantly they facilitate firms' access to credit markets (Faulkender and Petersen, 2006; Sufi, 2009; Tang, 2009).[1] That is, CRAs' certification services have real effects on the economy.

The enormous gap between the reality of CRAs and the negative perception about their credibility motivates us to investigate the real effects of CRAs' certification from a novel perspective. We investigate whether a CRA affects firm financing, investment, and profitability outcomes through the mechanism of a credit watch with direction downgrade, under which mechanism the CRA announces that it is reviewing whether to downgrade the firm and institutes a monitoring regime. From a theoretical perspective, in their seminal paper Boot et al. (2006) show that a CRA's role is not limited to initial information dissemination, but includes the

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[1] See Cantor (2004) for a summary of the literature on the roles of CRAs.

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credit watch mechanism when market and/or firm developments threaten to affect the credit rating.[2] That is, in theory CRAs affect corporate decisions and provide certification for borrowers through the watch mechanism. Despite its relevance and potential implications, the watch mechanism remains relatively unexplored.

We develop our hypotheses in the spirit of the existing empirical literature (Faulkender and Petersen, 2006; Sufi, 2009; Tang, 2009), which argues that CRAs facilitate firm access to credit markets. To the extent that CRAs act as honest certification intermediaries, one would expect borrowers with confirmed ratings to be in a position to raise more long-term debt financing as they would have better access to debt capital from less informed investors. In turn, the availability of more long-term debt financing would allow these borrowers to ramp up their investment activities and to remain profitable. We hypothesize that firms that are not downgraded (hereafter, confirmed firms) obtain more long-term debt financing, ramp up their investment activities, and are able to avoid deterioration in their profitability following the watch period. These patterns are hypothesized to be the outcomes of CRA certification via the channel of alleviation of firm capital constraints.

The mechanism of a credit watch with direction downgrade offers a promising setup for testing the certification role of CRAs for two reasons. First, in theory such a credit watch is typically triggered by moral hazard situations, in which CRA monitoring and certification services are highly valuable (e.g., Boot et al., 2006). After receiving a bad signal on a firm's credit quality, a CRA could initiate a credit watch action with direction downgrade, in which case a monitoring regime is put in place. The monitoring regime is equivalent to an implicit contract under which the firm is asked to undertake specific turnaround effort to avoid a rating downgrade. After interacting with the firm and observing its turnaround effort, the CRA determines whether that effort is likely to be successful and then resolves the watch action. Assuming that the CRA acts as an honest certification intermediary, watch resolution decisions truthfully reveal firm effort outcomes. By confirming the initial rating, the CRA certifies that the firm has successfully put in appropriate turnaround effort. In contrast, a rating downgrade reveals that the firm has failed to take appropriate actions to address the concerns that led to the initial watch warning.

Second, anecdotal evidence suggests that CRAs could exert pressure on rated borrowers to put in turnaround effort and reward compliant borrowers by confirming their initial ratings. For example, on February 10, 2003, Moody's placed the senior unsecured rating (Caa2) of AMR Corp under watch for possible downgrade on concerns related to "[…] increasing demands on the company's limited financial resources, the limited potential for a near term recovery in the company's revenues and its continued high costs." In addition, Moody's stated that its review would primarily focus on "[…] the company's ability to achieve a meaningful reduction in its costs through operating changes […]." On June 09, 2003, Moody's confirmed AMR Corp's Caa2 rating, stating the company had "[…] reduced its costs by cutting salaries and wages and amending work rules for all employees." Moody's also stated that AMR Corp would "[…] need to access the capital markets to fund capital expenditures, debt maturities, pension obligations and cash losses."[3]

We obtain a sample of 2016 issuer-level watch assignments with direction downgrade reported by Moody's between 1992 and 2014, in which about 27% of watch actions were resolved with a rating confirmation. Fig. 1 depicts the time frame of our empirical analysis. For each watch observation in our sample, we identify the four quarters before and four quarters after the watch period. Our reason for excluding the watch period is to allow enough time for a firm to make a turnaround effort and subsequently to observe the implications of CRA certification of that effort for corporate outcomes. A typical watch period in our sample is one quarter.

We employ both one-way difference and difference-in-differences tests to analyze the dynamic pattern of firm outcomes from four quarters before to four quarters after the watch period. Consistent with our hypothesis, we document a substantial economic increase in the long-term debt financing and investment (total investment expenditures scaled by assets, Property, Plant, and Equipment (PPE) growth rate, and total assets growth rate) of confirmed firms in the four quarters following the watch period. These results hold true regardless of whether we compare the outcomes of confirmed firms before and after the watch period or when we benchmark them against firms with watch-preceded rating downgrades (hereafter, nonconfirmed firms). Additionally, confirmed firms are able to maintain the same levels of operating performance around the watch period, while we find no such evidence for nonconfirmed firms. Consistent with the expected effects of CRA certification, confirmed firms substantially outperform their nonconfirmed peers only in the post-watch period.

We present evidence that CRA certification effort via the mechanism of a credit watch can facilitate firms' access to credit markets. We find that confirmed firms with more financial constraints (measured by the WW-index of Whited and Wu (2006) or the cash flow-investment gap as in Rajan and Zingales (1998)) and higher information asymmetry (measured by idiosyncratic volatility or earnings forecast dispersion) behave differently from other confirmed firms only in the post-watch period. The former group experiences a greater increase in their long-term debt financing, which coincides with an economically meaningful reduction in their cost of debt capital. Collectively, these findings suggest that CRA certification through the watch mechanism can alleviate firms' capital constraints, giving them better access to credit markets.

We also consider—and rule out—two alternative explanations for the post-watch outperformance of confirmed firms. It is possible that this finding is due to reverse causality; that is, CRAs could have anticipated the future operating performance of firms placed under watch based on recent revisions in market expectations, and resolved credit watches accordingly without exerting any certification effort. We rule out this alternative explanation and present evidence that the effects of CRA certification

[2] Most of the existing empirical literature focuses on the first role of CRAs, i.e., the initial information dissemination (see, e.g., Hand et al., 1992; Holthausen and Leftwich, 1986).

[3] Moody's press releases are available at www.moodys.com.

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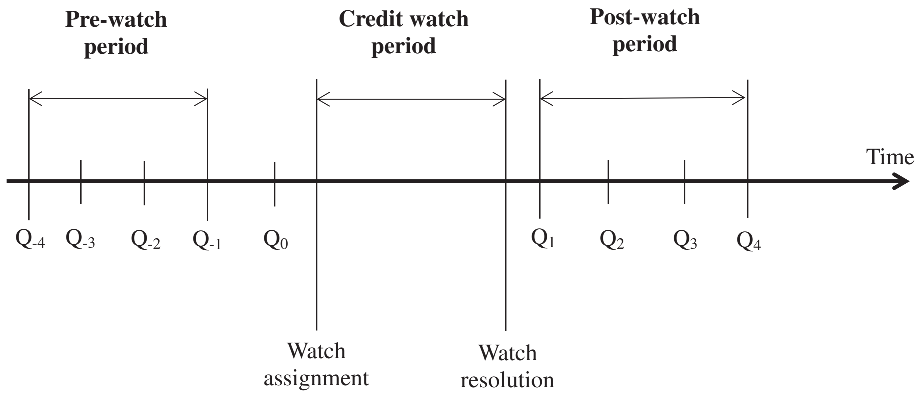

Fig. 1. The time frame of our empirical analysis. The credit watch period is the period from the watch assignment to the watch resolution announcement. The post-watch period is the period beginning in quarter one (Q_1) and lasting for four quarters, where Q_1 is the quarter ending immediately after the watch resolution announcement. The pre-watch period is the period lasting for four quarters and ending in quarter Q_{-1}. Q_0 is the quarter ending immediately prior to the watch assignment announcement.

on firm operating performance persist within groups of firms with similar ex ante market expectations (measured by changes in analyst consensus recommendations or the market reaction to watch announcements). Another possible explanation for the ability of confirmed firms to outperform their nonconfirmed peers is that these firms could be better governed. We provide evidence contrary to this alternative explanation and show that the post-watch outperformance of confirmed firms is unrelated to differences in the strength of corporate governance (measured by the G-index of Gompers et al. (2003) or the *E*-index of Bebchuk et al. (2009)) between confirmed and nonconfirmed firms.

Our major concern with the certification interpretation of our results is endogeneity. The firm that avoids a downgrade may have stronger financial condition and better ability to address potential deterioration in its credit quality. To investigate this concern, we match confirmed and nonconfirmed firms based on the characteristics that matter for firm ability to avoid a downgrade (e.g., size, Tobin's Q, asset tangibility, and credit quality). We find that confirmed firms increase their long-term debt financing, invest more capital, and achieve better operating performance when benchmarked against their matched nonconfirmed counterparts in the four quarters following the watch period. These findings indicate that our prior conclusions about the effects of CRA certification are robust to endogeneity concerns related to firm ability to avoid a downgrade. Additionally, we address these endogeneity concerns econometrically by estimating a switching regression model with endogenous switching and find consistent evidence.

Our paper contributes to the ongoing discussion on the economic roles of CRAs, and demonstrates that CRAs are effective certification intermediaries. It is also related to an emerging strand of literature examining the implications of CRAs' actions for firm financing and investment behavior. Previous researchers in this field include Sufi (2009), who showed that the introduction of syndicated bank loan ratings provides certification for borrowers and has real effects on their financial and investment policies, and Tang (2009), who conducted a natural experiment on credit rating refinement and demonstrated that CRAs can help alleviate information asymmetry in credit markets. Our paper extends this literature by providing new evidence that CRAs can affect firms' long-term debt financing, investment, and profitability outcomes through the mechanism of a credit watch with direction downgrade. Our findings suggest that CRAs play an economically meaningful role in the financial system and facilitate borrowers' access to credit markets.

The remainder of this paper is organized as follows. Section 2 briefly reviews the related literature. Section 3 describes the sample and presents descriptive statistics. Section 4 lays the foundations for our empirical tests. Section 5 presents our main results. Section 6 conducts robustness tests, and Section 7 concludes the paper.

2. Related literature

2.1. Existing literature on the credit watch mechanism

Our paper complements the work of Bannier and Hirsch (2010), who examined the equity market reaction to rating changes following the institutional implementation of the watch mechanism by Moody's on October 1, 1991. They found that the informational content of downgrades significantly increased after the watchlist introduction, and concluded that the CRAs' role had been extended from pure information certification towards active monitoring. In the current paper, our objective is to uncover the impact of CRA certification on firms' long-term debt financing, investment, and profitability, and thus we adopt a different empirical framework that analyzes changes in corporate outcomes around the watch period.

A second related paper is that by Bannier et al. (2012), who investigated whether CRAs affect firm investment decisions. They reported that firms reduce (increase) their investment around rating downgrades (upgrades), and interpret this result as being

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consistent with the monitoring role of CRAs. Our paper is different in three respects. First, our sample consists of watch actions with direction downgrade, while in their main analysis they employed direct rating changes. Second, we study firm long-term debt financing, investment, and profitability. In contrast, they focused on firm investment only. Third, we investigate the implications of CRA certification effort, which are absent from their study.

At a broader level, our paper is related to the literature on the timeliness (or lack thereof) of CRAs. While prior research (e.g., Beaver et al., 2006) showed that ratings actions from non-certified CRAs lead actions from certified CRAs, Berwart et al. (2014) provided evidence that issuer-paid CRAs have become more responsive over time due to regulatory changes and increased investor scrutiny. Our paper extends this literature by showing that the mechanism of a credit watch with direction downgrade can affect firms' long-term debt financing, investment, and profitability outcomes in a timely manner.

2.2. Existing literature on the effects of CRAs on corporate outcomes

Our paper also belongs to an emerging strand of literature relating to the real effects of CRAs' actions on firms' behavior. Empirical studies within this literature primarily focus on firms' capital structure and investment decisions. For example, Sufi (2009) showed that the introduction of syndicated bank loan ratings induced firms to use more debt and to increase their investment, indicating that CRA debt certification has real effects on firms' financial and investment policies. Tang (2009) investigated the effects of the introduction of Moody's 1982 credit rating refinement on rated firms. The paper demonstrates that firms with higher refined ratings (e.g., a rating refinement from A to A1 as opposed to A3) enjoy better access to credit markets and have more capital investment, indicating that CRAs can help alleviate firm capital constraints resulting from information asymmetries in credit markets. Faulkender and Petersen (2006) showed that firms with access to public bond markets, as measured by having a bond rating, choose higher levels of debt financing. Kisgen (2006) provided evidence that firms adjust their capital structure to maintain a particular bond rating, indicating that credit ratings can influence capital structure decisions. In a survey of chief financial officers, Graham and Harvey (2001) found that credit ratings are one of the most important factors in corporate financing decisions, indicating that firms are concerned about their credit ratings. We contribute to this literature and show that CRAs can provide certification and affect corporate outcomes through the mechanism of a credit watch with direction downgrade.

3. Data description and variable construction

Our sample of credit watch actions is from Moody's senior rating database, which contains *estimated senior unsecured ratings*. According to Moody's Investors Service (2009), "a company's estimated senior rating is set equal to its actual senior unsecured debt rating or, if there is none, by implying such a rating on the basis of rated subordinated or secured debt." We focus on issuer-level data to abstract from issue-level differences in seniority or security, so that we can better capture changes in issuers' fundamental credit quality. For each credit watch observation, Moody's data provide detailed information that includes the name of the issuer, credit rating placed under watch, watch initial direction, and watch announcement date. Once the credit watch is resolved, we observe the watch final direction, final rating, and watch resolution date.

We begin our sampling procedure by selecting credit watches with direction downgrade that are resolved with either a rating confirmation or downgrade on any date between 1992 and 2014.[4] The set of Moody's ratings consists of 21 letter ratings, which are formed based on generic rating categories (Aaa; Aa; A; Baa; Ba; B; Caa; Ca; and C) along with numerical modifiers (1; 2; and 3) appended to each generic classification from Aa through Caa. Consistent with prior papers, we translate these ratings into numerical scores on the following scale: Aaa = 1; Aa1 = 2; Aa2 = 3; Aa3 = 4; …; and C = 21.

Next, we merge credit watch observations with quarterly data from Compustat. We follow the literature on firm financing and investment decisions and exclude financial firms (Standard Industrial Classification (SIC) codes 6000–6999), then build a watch-quarter level dataset for firms for which accounting information is available from Compustat. Based on this information, we construct the following measures, which we use as outcome variables in our empirical analysis: long-term debt financing ratio (annual change in long-term debt (DLTTQ) scaled by average total assets (ATQ)); total investment ratio (the sum of (i) trailing-twelve-months capital expenditures (CAPXY) adjusted for fiscal quarter accumulation, (ii) trailing-twelve-months acquisitions expenditures (AQCY) adjusted for fiscal quarter accumulation (set to zero if missing), and (iii) trailing-twelve-months research and development expenditures (XRDQ, set to zero if missing), all scaled by average total assets (ATQ)); PPE growth rate (natural logarithm of PPE scaled by previous year's PPE (PPENTQ)); total assets growth rate (natural logarithm of total assets scaled by previous year's total assets (ATQ)); industry-adjusted operating income ratio (trailing-twelve-months operating income before depreciation (OIBDPQ) scaled by average total assets (ATQ), from which ratio we subtract the median operating income ratio of the corresponding SIC-based industry in the same quarter and industry-adjusted return on assets (trailing-twelve-months net income (NIQ) scaled by average total assets (ATQ), from which ratio we subtract the median return on assets of the corresponding SIC-based industry in the same quarter). We use the Fama–French 38 SIC classification. Additionally, we construct the following measures, which we use as control variables: assets (total assets (ATQ)); industry-adjusted Tobin's Q (total assets (ATQ) less common equity (CEQQ) less deferred taxes (TXDITCQ) plus common shares outstanding (CSHOQ) multiplied by end-of-quarter price per share (PRCCQ), all divided by total assets (ATQ), from which ratio we subtract the median Tobin's

[4] Although Moody's has been publishing credit watches since 1985, watches gained the status of formal credit actions only in 1991. Since there are few observations in 1991, we restrict our sample to start in 1992.

Q of the corresponding SIC-based industry in the same quarter); tangibility (PPE (PPENTQ) scaled by average total assets (ATQ)); sigma (idiosyncratic volatility, measured each calendar quarter as the root mean square error from a regression of daily stock returns on the Center for Research in Security Prices (CRSP) value-weighted index returns; we require at least 30 observations, otherwise idiosyncratic volatility is set to missing); institutional ownership (total institutional holdings of common shares from the Thomson Financial 13F database scaled by total number of common shares outstanding); fraction of independent directors (number of independent directors scaled by total number of directors on a board; data are from the Investor Responsibility Research Center (IRRC) database); and nonemployee blockholder dummy (an indicator variable for the presence of nonemployee blockholders on a board; a nonemployee blockholder is defined as any nonemployee director holding at least 1% of the total voting power; data are from the IRRC database). To mitigate the effects of outliers, we follow the literature and winsorize continuous variables each calendar quarter at the 1st and 99th percentile. The resulting baseline sample consists of 551 rating confirmations and 1465 rating downgrades, for a total of 2016 watch actions on 841 unique issuers and for a total of 18,144 watch-quarter panel observations.

Table 1 shows the distribution of credit watches by calendar year. Most watches are resolved with a rating downgrade rather than confirmation. Among 2016 credit watches, 72.7% watches are resolved with a rating downgrade, and only 27.3% watches are resolved with a rating confirmation. As expected, the incidence of credit watches and rating downgrades peaks in the years 2002 and 2009, which coincide with times of slow economic activity.

Table 2 reports the means of several watch characteristics (Panel A) and firm attributes (Panel B) as of the quarter ending immediately prior to the watch period, quarter 0, for both confirmed and nonconfirmed firms, along with their difference tests. Moody's takes on average 93 days to resolve a watch action with a rating downgrade, compared with 142 days to make a rating confirmation decision. A longer watch period for confirmed firms is suggestive of more interactions and longer discussions between Moody's and these firms. Among downgraded ratings, only about 28% are initially categorized as noninvestment grade ratings (rating of Ba or lower). By contrast, roughly 34% of confirmed ratings belong to the noninvestment grade category. There is no evidence that firms in financial distress (with an initial rating of Caa or lower) are more likely to receive a rating downgrade than confirmation. The average magnitude of a rating downgrade is equal to 1.5 notches, and about 15% of downgraded ratings are "fallen angels", firms which cross the investment grade boundary (a downgrade from Baa or higher to Ba or lower).

In Panel B of Table 2, we compare characteristics of confirmed and nonconfirmed firms. The two sets of firms exhibit no significant differences in terms of their long-term debt financing or total investment ratios immediately before being placed under watch. Relative to nonconfirmed firms, confirmed firms grow their PPE and total assets faster. Meanwhile, confirmed firms are more profitable, smaller, subject to higher information asymmetry as measured by sigma, less likely to have nonemployee blockholders, and have marginally better growth profiles based on industry-adjusted Tobin's Q. However, confirmed firms are comparable to nonconfirmed firms in terms of their asset tangibility, institutional ownership, and board independence structure.

Table 1
The distribution of credit watches, rating confirmations, and rating downgrades by calendar year. The baseline sample consists of 551 rating confirmations and 1465 rating downgrades, for a total of 2016 Moody's issuer-level watch actions between 1992 and 2014.

	Watches		Rating confirmations		Rating downgrades	
Year	*N*	%	*N*	%	*N*	%
1992	17	0.8%	3	17.6%	14	82.4%
1993	64	3.2%	27	42.2%	37	57.8%
1994	56	2.8%	23	41.1%	33	58.9%
1995	52	2.6%	22	42.3%	30	57.7%
1996	66	3.3%	25	37.9%	41	62.1%
1997	67	3.3%	26	38.8%	41	61.2%
1998	83	4.1%	35	42.2%	48	57.8%
1999	107	5.3%	40	37.4%	67	62.6%
2000	135	6.7%	45	33.3%	90	66.7%
2001	180	8.9%	39	21.7%	141	78.3%
2002	252	12.5%	34	13.5%	218	86.5%
2003	158	7.8%	25	15.8%	133	84.2%
2004	93	4.6%	31	33.3%	62	66.7%
2005	97	4.8%	21	21.6%	76	78.4%
2006	93	4.6%	26	28.0%	67	72.0%
2007	95	4.7%	28	29.5%	67	70.5%
2008	98	4.9%	24	24.5%	74	75.5%
2009	110	5.5%	16	14.5%	94	85.5%
2010	34	1.7%	11	32.4%	23	67.6%
2011	34	1.7%	8	23.5%	26	76.5%
2012	47	2.3%	12	25.5%	35	74.5%
2013	39	1.9%	17	43.6%	22	56.4%
2014	39	1.9%	13	33.3%	26	66.7%
Overall	2016	100.0%	551	27.3%	1465	72.7%

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Table 2
Summary statistics for credit watch characteristics (Panel A) and firm characteristics (Panel B) for the subsample of firms with rating confirmations (confirmed firms) and the subsample of firms with downgraded ratings (nonconfirmed firms). Variables are measured as of quarter 0, the quarter ending immediately prior to the watch period. The table also provides difference tests. All variables are as defined in the text. The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The baseline sample consists of 551 rating confirmations and 1465 rating downgrades, for a total of 2016 Moody's issuer-level watch actions between 1992 and 2014.

	Confirmed firms		Nonconfirmed firms		Confirmed - nonconfirmed	
	N	Mean	*N*	Mean	Mean	*p*-Value
Panel A: watch characteristics						
Watch days	551	141.6	1465	93.0	48.6%***	(<0.000)
Noninvestment grade dummy	551	33.9%	1465	27.7%	6.2%***	(0.007)
Financial distress dummy	551	2.9%	1465	2.9%	0.0%	(0.964)
Rating change	551	0.0	1465	1.5	–	–
Fallen angel dummy	551	0.0%	1465	15.3%	–	–
Panel B: firm characteristics						
Long-term debt financing ratio	496	2.3%	1338	2.5%	-0.2%	(0.728)
Total investment ratio	469	9.1%	1292	9.3%	-0.2%	(0.662)
PPE growth rate	494	6.6%	1346	4.4%	2.2%*	(0.088)
Total assets growth rate	498	7.9%	1352	4.2%	3.7%***	(0.001)
Operating income ratio (adjusted)	386	2.3%	1065	1.5%	0.8%	(0.124)
Return on assets (adjusted)	486	0.8%	1326	−0.7%	1.5%***	(0.002)
Assets	508	13,450.2	1370	15,514.7	−2064.5**	(0.027)
Tobin's Q (adjusted)	466	-0.05	1257	−0.15	0.10**	(0.010)
Tangibility	504	40.5%	1365	39.1%	1.4%	(0.233)
Sigma	546	2.0%	1451	2.4%	−0.4%***	(<0.000)
Institutional ownership	538	63.3%	1419	63.1%	0.2%	(0.885)
Fraction of independent directors	327	72.4%	1031	72.8%	−0.4%	(0.745)
Nonemployee blockholder dummy	327	15.9%	1031	22.1%	−6.2%**	(0.010)

4. Empirical design

To investigate the effects of CRA certification while controlling for the standard determinants of corporate policies, we analyze the dynamic pattern of corporate outcomes from four quarters before to four quarters after the watch period. Specifically, we employ a panel regression model of the following specification:

$$
\begin{aligned}
Y_{it} = {} & \alpha + \sum\nolimits_{q=1}^{4} \delta_q Before_{it}^{q} \times Confirmed_i + \sum\nolimits_{q=1}^{4} \mu_q After_{it}^{q} \times Confirmed_i \\
& + \sum\nolimits_{q=1}^{4} \varphi_q Before_{it}^{q} + \sum\nolimits_{q=1}^{4} \omega_q After_{it}^{q} + \theta Confirmed_i \\
& + \gamma X_{it} + Industry_i + CalendarQuarter_t + FiscalQuarter_{it} + \varepsilon_{it},
\end{aligned} \tag{1}
$$

where Y_{it} is a measure of corporate financing, investment, or profitability; X_{it} is a set of control variables (measures of firm attributes and credit characteristics); $Before_{it}^{q}$ is a dummy variable equal to 1 if the observation is q quarters prior to the watch period, where $q = 1, 2, 3$, or 4 quarters; $After_{it}^{q}$ is a dummy variable equal to 1 if the observation is q quarters after the watch period, where $q = 1, 2, 3$, or 4 quarters; $Confirmed_i$ is a dummy equal to 1 if the credit watch is resolved with a rating confirmation; i indexes firms; t indexes time measured in calendar quarters; $Industry_i$ are 38 SIC-based industry fixed effects; $CalendarQuarter_t$ are calendar quarter fixed effects; and $FiscalQuarter_{it}$ are fiscal quarter fixed effects. Comparable specifications to Eq. (1) have been used in prior literature to study firm behavior around corporate events (see, e.g., Bertrand and Mullianathan, 2003; Chemmanur et al., 2010; Schoar, 2002).

In the above specification, the group of interest consists of confirmed firms, and the control group consists of nonconfirmed firms. For the latter group of firms, the interaction variables $Before_{it}^{q} \times Confirmed_i$ and $After_{it}^{q} \times Confirmed_i$ are always equal to 0. We also note that the reference quarter, quarter 0, is the quarter ending immediately prior to the watch period. By construction, Eq. (1) is a difference-in-differences specification, and the coefficients δ_q and μ_q identify the residual changes in corporate outcomes around the watch period for confirmed firms relative to nonconfirmed firms. The industry fixed effects, $Industry_i$, control for differences across industries; the calendar quarter fixed effects, $CalendarQuarter_t$, are meant to account for changes in market conditions that may influence credit actions or affect corporate outcomes; and the fiscal quarter fixed effects, $FiscalQuarter_{it}$, are intended to account for seasonal patterns of corporate outcomes related to fiscal quarters. Following Petersen (2009) and Thompson (2011), we estimate standard errors clustered at the firm and calendar quarter levels to control for potential biases related to heteroskedasticity and serial correlation in the residuals.

5. The real effects of CRA certification

In this section, we present our main empirical results. First, we discuss the relations between watch resolution decisions and corporate outcomes. Second, we provide evidence that CRA certification helps alleviate firms' capital constraints and reduce their

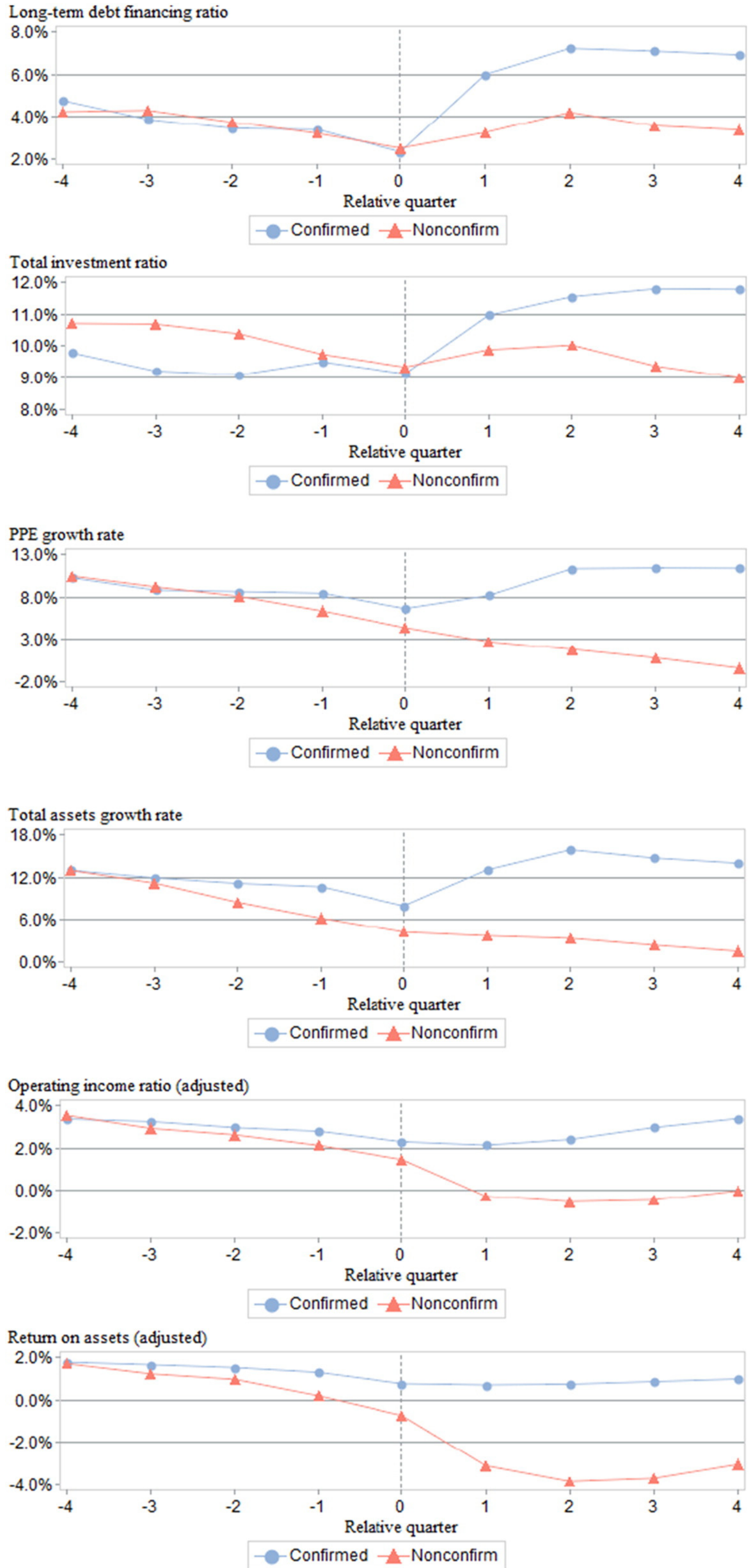

Fig. 2. Watch resolutions and firm outcomes. Patterns of long-term debt financing, total investment ratio, PPE growth rate, total assets growth rate, industry-adjusted operating income ratio, and industry-adjusted return on assets for firms with confirmed ratings (confirmed firms) and firms with downgraded ratings (nonconfirmed firms) from four quarters before to four quarters after the watch period. All variables are as defined in the text. Quarter 0 is the quarter ending immediately before the watch assignment announcement, and quarter 1 is the quarter ending immediately after the watch resolution announcement. The baseline sample consists of 551 rating confirmations and 1465 rating downgrades, for a total of 2016 Moody's issuer-level watch actions between 1992 and 2014.

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cost of debt capital, giving them better access to credit markets under more favorable terms. Third, we present evidence against two alternative explanations to CRA certification: changes in market expectations and differences in the strength of corporate governance.

5.1. Watch resolution decisions and firm outcomes

Our central hypothesis states that confirmed firms obtain more long-term debt financing, ramp up their investment activities, and are able to remain profitable following the watch period. Fig. 2 shows the patterns of the long-term debt financing ratio, total investment ratio, PPE growth rate, total assets growth rate, industry-adjusted operating income ratio, and industry-adjusted return on assets of confirmed and nonconfirmed firms from four quarters before to four quarters after the watch period. We ensure that each firm has nonmissing values for the measure of interest in every quarter within the event window. Quarter 0 is the quarter ending immediately prior to the watch period.

Fig. 2 provides evidence largely consistent with our hypothesis. Relative to nonconfirmed firms, confirmed firms increase their long-term debt financing, invest more capital, and achieve higher operating performance in the post-watch period. The long-term debt financing and total investment ratios exhibit similar patterns for both sets of firms in the pre-watch period. In the post-watch period, however, both ratios increase markedly for confirmed firms, while those of nonconfirmed firms remain little changed. Moreover, confirmed and nonconfirmed firms grow their PPE and total assets at a comparable rate prior to the watch period. However, confirmed firms appear to invest more capital than nonconfirmed firms in the post-watch period, as indicated by the sharp post-watch increase in the growth rates of their PPE and total assets. Further, confirmed firms outperform their nonconfirmed peers based on industry-adjusted operating income ratio or return on assets most notably in the four quarters following the watch period, although this is largely due to deterioration in the operating performance of nonconfirmed firms.

Table 3 complements Fig. 2 and reports differences in the outcomes of confirmed firms between quarter 0 and each of the four quarters following the watch period (quarter 1, 2, 3, and 4). It provides evidence that the post-watch increases in the long-term debt financing and investment metrics of confirmed firms are economically important and statistically significant, while any changes in their operating performance measures around the watch period are trivial. By the fourth quarter post-watch, confirmed firms have obtained 4.6% additional long-term debt financing and raised their total investment ratio by roughly 2.7%, the increases being highly significant. Additionally, confirmed firms grow their fixed and total assets at a higher rate in the quarters following the watch period. In particular, four quarters after their ratings were confirmed, these firms have been able to grow their PPE and total assets by an additional 4.7% and 6%, respectively. Moreover, confirmed firms do not experience a decline in their operating performance in the post-watch period, as indicated by the mostly insignificant differences in their industry-adjusted operating income ratio or return on assets between quarter 0 and each of the four quarters post-watch.

To investigate the effects of watch resolution decisions while controlling for other relevant factors, we run difference-in-differences panel regressions following the specification in Eq. (1). The dependent variable is a measure of long-term debt financing, investment, or operating performance, and the regressors of interest are the interaction dummy variables $Before^q \times Confirmed$ and $After^q \times Confirmed$, where $q = 1, 2, 3,$ or 4 quarters. As discussed in Section 4, the coefficients of these interaction variables identify the residual changes in the outcome variable of interest around the watch period for confirmed firms relative to nonconfirmed firms. Our control variables include the natural logarithm of one plus any rating change and dummy variables

Table 3

Univariate patterns of the outcomes of confirmed firms. Differences in the long-term debt financing ratio, total investment ratio, PPE growth rate, total assets growth rate, industry-adjusted operating income ratio, and industry-adjusted return on assets of firms with confirmed ratings (confirmed firms) between the quarter ending prior to the watch period (quarter 0) and each of the four quarters following the same period (quarter 1, 2, 3, or 4). All variables are as defined in the text. The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The baseline sample consists of 551 rating confirmations and 1465 rating downgrades, for a total of 2016 Moody's issuer-level watch actions between 1992 and 2014.

	Long-term debt financing ratio	Total investment ratio	PPE growth rate	Total assets growth rate	Operating income ratio (adjusted)	Return on assets (adjusted)
Quarters	Estimate (p-Value)	Estimate (p-VALUE)	Estimate (p-value)	Estimate (p-Value)	Estimate (p-Value)	Estimate (p-Value)
Q0	0.0231	0.0911	0.0662	0.0794	0.0229	0.0076
Q1	0.0599	0.1096	0.0816	0.1305	0.0213	0.0070
Q2	0.0722	0.1155	0.1132	0.1587	0.0240	0.0073
Q3	0.0709	0.1179	0.1140	0.1471	0.0296	0.0085
Q4	0.0691	0.1177	0.1137	0.1398	0.0338	0.0098
Q1 - Q0	0.0368***	0.0185***	0.0154	0.0511***	−0.0016	−0.0006
	(<.000)	(0.007)	(0.398)	(0.004)	(0.806)	(0.916)
Q2 - Q0	0.0490***	0.0243***	0.0470**	0.0793***	0.0010	−0.0002
	(<.000)	(0.000)	(0.016)	(<.000)	(0.877)	(0.964)
Q3 - Q0	0.0478***	0.0268***	0.0478**	0.0677***	0.0067	0.0009
	(<.000)	(0.000)	(0.014)	(0.000)	(0.327)	(0.868)
Q4 - Q0	0.0460***	0.0266***	0.0474**	0.0604***	0.0109*	0.0022
	(<.000)	(0.000)	(0.012)	(0.001)	(0.095)	(0.694)
Quarter-watch observations	2480	2345	2470	2490	1930	2430
Confirmed observations	496	469	494	498	386	486

indicating a fallen angel, a noninvestment grade, or financial distress. Since a multi-notch downgrade or a fallen angel signals potentially more severe deterioration in firm credit quality, we would expect to observe weaker outcomes for firms with stronger downgrades or firms whose ratings have crossed the investment grade boundary. The noninvestment grade and financial distress dummy variables are to control for the level of ratings and to abstract from situations of financial distress, respectively. Following Rajan and Zingales (1995), we also include a set of control variables that may reflect either variations in firm preferences for financing and investment, the supply of external financing, or future investment opportunities. These additional control variables are: firm size, industry-adjusted Tobin's Q, and asset tangibility. Size has been found to be positively correlated with financial leverage because larger firms are expected to have lower costs of financial distress (e.g., Graham et al., 1998; Hovakimian et al., 2001). Size could also be used as an inverse proxy for information asymmetry (e.g., Rajan and Zingales, 1995). We include

Table 4

Watch resolution decisions and firm outcomes. Dynamic pattern of firm long-term debt financing ratio, total investment ratio, total assets growth rate, industry-adjusted operating income ratio, and industry-adjusted return on assets from four quarters before to four quarters after the watch period. Results are for firms with confirmed ratings (confirmed firms) benchmarked against firms with downgraded ratings (nonconfirmed firms). The dynamic pattern is estimated based on the following regression specification:

$$Y_{it} = \alpha + \sum_{q=1}^{4} \delta_q Before_{it}^q \times Confirmed_i + \sum_{q=1}^{4} \mu_q After_{it}^q \times Confirmed_i + \sum_{q=1}^{4} \varphi_q Before_{it}^q + \sum_{q=1}^{4} \omega_q After_{it}^q + \theta Confirmed_i$$
$$+ \gamma X_{it} + Industry_i + CalendarQuarter_t + FiscalQuarter_{it} + \varepsilon_{it},$$

where Y_{it} is an outcome variable; X_{it} is a set of control variables, which are as defined in the text; $Before_{it}^q$ is a dummy variable equal to 1 if the observation is q quarters prior to the watch period, where $q = 1, 2, 3$, or 4 quarters; $After_{it}^q$ is a dummy variable equal to 1 if the observation is q quarters after the watch period, where $q = 1, 2, 3$, or 4 quarters; *Confirmed* is a dummy variable equal to 1 if the credit watch is resolved with a rating confirmation; i indexes firms; t indexes time measured in calendar quarters; $Industry_i$ are 38 SIC-based industry fixed effects; $CalendarQuarter_t$ are calendar quarter fixed effects; and $FiscalQuarter_{it}$ are fiscal quarter fixed effects. Standard errors are clustered at the firm and calendar quarter levels. The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The baseline sample consists of 551 rating confirmations and 1465 rating downgrades, for a total of 2016 Moody's issuer-level watch actions between 1992 and 2014.

	Long-term debt financing ratio		Total investment ratio		Total assets growth rate		Operating income ratio (adjusted)		Return on assets (adjusted)	
	[1]		[2]		[3]		[4]		[5]	
	Coefficient	*p*-Value	Coefficient	*p*-Value	Coefficient	*p*-Value	Coefficient	*p*-Value	Coefficient	*p*-Value
$Before^4 \times$ Confirmed	0.0133	(0.127)	−0.0031	(0.670)	−0.0144	(0.547)	−0.0020	(0.708)	−0.0022	(0.653)
$Before^3 \times$ Confirmed	0.0069	(0.492)	−0.0086	(0.247)	−0.0106	(0.647)	0.0026	(0.522)	0.0007	(0.876)
$Before^2 \times$ Confirmed	0.0054	(0.529)	−0.0076	(0.302)	0.0051	(0.762)	0.0036	(0.447)	0.0035	(0.571)
$Before^1 \times$ Confirmed	0.0089	(0.316)	0.0015	(0.837)	0.0176	(0.312)	0.0027	(0.484)	0.0041	(0.370)
$After^1 \times$ Confirmed	0.0217**	(0.035)	0.0103	(0.134)	0.0282	(0.186)	0.0113***	(0.004)	0.0109**	(0.034)
$After^2 \times$ Confirmed	0.0253**	(0.027)	0.0171**	(0.014)	0.0524**	(0.033)	0.0182***	(0.000)	0.0199***	(0.000)
$After^3 \times$ Confirmed	0.0305**	(0.033)	0.0259***	(0.000)	0.0516**	(0.035)	0.0230***	(0.000)	0.0191***	(0.006)
$After^4 \times$ Confirmed	0.0298**	(0.010)	0.0305***	(0.000)	0.0584**	(0.028)	0.0225***	(0.000)	0.0189***	(0.005)
Confirmed	−0.0055	(0.635)	0.0090	(0.273)	0.0151	(0.497)	−0.0124*	(0.055)	−0.0092	(0.158)
$Before^4$	0.0055	(0.368)	0.0080*	(0.071)	0.0536***	(0.000)	0.0096***	(0.000)	0.0092***	(0.008)
$Before^3$	0.0091	(0.111)	0.0089***	(0.009)	0.0437***	(0.002)	0.0062**	(0.010)	0.0066**	(0.040)
$Before^2$	0.0064	(0.125)	0.0071***	(0.003)	0.0226***	(0.003)	0.0039*	(0.050)	0.0053	(0.104)
$Before^1$	0.0030	(0.401)	0.0026	(0.493)	0.0072	(0.235)	0.0024	(0.146)	0.0011	(0.726)
$After^1$	0.0173***	(0.001)	0.0081***	(0.007)	0.0200**	(0.025)	−0.0088***	(0.000)	−0.0077**	(0.034)
$After^2$	0.0290***	(0.000)	0.0100**	(0.027)	0.0183	(0.149)	−0.0135***	(0.000)	−0.0190***	(0.000)
$After^3$	0.0226***	(0.006)	0.0034	(0.447)	0.0082	(0.552)	−0.0150***	(0.000)	−0.0208***	(0.000)
$After^4$	0.0209***	(0.004)	−0.0010	(0.823)	−0.0056	(0.738)	−0.0122***	(0.000)	−0.0183***	(0.001)
Ln(rating change + 1)	0.0129	(0.163)	0.0214**	(0.014)	0.0033	(0.877)	−0.0125**	(0.020)	−0.0121**	(0.043)
Fallen angel dummy	−0.0064	(0.285)	−0.0102**	(0.047)	−0.0310**	(0.028)	−0.0140***	(0.000)	−0.0127***	(0.000)
Noninvestment grade dummy	0.0180**	(0.015)	−0.0054	(0.316)	−0.0142	(0.329)	−0.0249***	(0.000)	−0.0273***	(0.000)
Financial distress dummy	−0.0046	(0.786)	−0.0051	(0.591)	−0.0483	(0.199)	−0.0042	(0.738)	−0.0103	(0.349)
Ln(assets)	0.0033	(0.108)	−0.0006	(0.772)	0.0143***	(0.009)	−0.0046***	(0.003)	−0.0026*	(0.099)
Tobin's Q (adjusted)	0.0121***	(0.000)	0.0270***	(0.000)	0.0143*	(0.094)	0.0480***	(0.000)	0.0310***	(0.000)
Tangibility	−0.0160	(0.408)	0.0590***	(0.001)	−0.1668***	(0.000)	0.0333***	(0.005)	−0.0117	(0.345)
Sigma	−0.8560***	(0.000)	−0.0929	(0.419)	−2.4040***	(0.000)	−0.8437***	(0.000)	−2.2663***	(0.000)
Institutional ownership	0.0443***	(0.006)	0.0156	(0.278)	0.0457	(0.222)	−0.0031	(0.794)	−0.0137	(0.285)
Fraction of independent directors	−0.0444**	(0.026)	−0.0309*	(0.065)	−0.1399***	(0.001)	0.0026	(0.863)	−0.0278*	(0.070)
Nonemployee blockholder dummy	0.0063	(0.307)	0.0011	(0.856)	0.0107	(0.617)	0.0002	(0.967)	−0.0156	(0.146)
Missing governance dummy	−0.0074	(0.637)	−0.0140	(0.280)	−0.0262	(0.486)	−0.0082	(0.579)	−0.0124	(0.353)
Total investment ratio (t − 1)							0.0567***	(0.000)	0.0239***	(0.000)
Intercept	−0.0031	(0.948)	0.0856**	(0.012)	−0.0183	(0.872)	0.1132***	(0.000)	0.1239***	(0.000)
Quarter-watch observations	14,805		14,220		14,841		11,295		13,878	
Confirmed observations	444		425		445		332		414	
Nonconfirmed observations	1201		1155		1204		923		1128	
Adjusted R^2	0.089		0.180		0.143		0.669		0.502	

industry-adjusted Tobin's Q as an additional control because it is a standard proxy for growth opportunities and is expected to be positively related to firm external financing and investment (e.g., Baker and Wurgler, 2002).

Tangible assets could be used as collateral and thus asset tangibility is expected to be positively correlated with financial leverage (e.g., Baker and Wurgler, 2002). We include sigma as a proxy for the degree of information asymmetry. To abstract from any effects of internal or external governance forces on firm outcomes, we also control for institutional ownership, fraction of independent directors, and presence of nonemployee blockholders on a board. All variables are as defined in Section 3. Given IRRC-related variables are missing for roughly 30% of our sample observations and to preserve our sample size, we set any missing values of the fraction of independent directors or nonemployee blockholder dummy to zero and control for those cases by including a missing governance dummy. Finally, in the operating performance regressions, we include the total investment ratio as of the previous quarter, as we suspect there is a positive relation between the level of a firm's investment in a given quarter and its operating performance in the following quarter.

Table 4 reports the results. Consistent with our hypothesis, confirmed firms increase their long-term debt financing only in the post-watch period when benchmarked against nonconfirmed firms. In Model [1], the coefficients of the interaction dummy variables $After^q \times Confirmed$ are positive, economically important, and statistically significant, indicating that confirmed firms obtain substantially more long-term debt financing following the watch period. The incremental long-term debt financing for confirmed firms amounts to more than 2% of their average assets in every quarter within the post-watch period. In particular, by four quarters post-watch confirmed firms have raised their long-term debt financing by roughly 3%. As reported in Table 2, the long-term debt financing ratio of confirmed firms as of the quarter ending immediately before the watch period (quarter 0) amounts to 2.3%. Accordingly, these firms have more than doubled (3%/2.3%) their long-term debt financing as of the fourth quarter post-watch.

Models [2] and [3] of Table 4 show that confirmed firms have a higher total investment ratio and grow their total assets faster than nonconfirmed firms only after the watch period. For example, in Model [2] the negative and insignificant coefficients of the interaction dummy variables $Before^q \times Confirmed$ suggest that confirmed and nonconfirmed firms have comparable levels of total investments as a percentage of their respective average assets before the watch period. In the post-watch period, however, we observe a monotonic increase in the total investment ratio of confirmed firms. By four quarters post-watch, these firms have raised their total investment ratio by about 3.1% of their average assets, which represents an approximately 34% (3.1%/9.1%) increase above their pre-watch level (see Table 2). We then refine the analysis and re-estimate specification [2] after replacing the total investment ratio by each of its three components (capital expenditures ratio, acquisitions expenditures ratio, and research and development expenditures ratio) as a dependent variable. In unreported results, we find that relative to nonconfirmed firms, confirmed firms have employed 1.3% additional capital expenditures and 1.7% additional acquisitions expenditures by the end of the fourth quarter post-watch, while any changes in research and development expenditures are both economically and statistically insignificant. Thus, the post-watch increase in the total investment ratio of confirmed firms is mainly due to additional capital and acquisition expenditures.

Models [4] and [5] of Table 4 provide evidence that confirmed firms substantially outperform their nonconfirmed counterparts, and most importantly the higher profitability attributed to confirmed firms is not part of a long-term trend. Rather, confirmed firms are more profitable only in the post-watch period. As noted above, this outperformance is due to the joint observation that confirmed firms are able to maintain their profitability while nonconfirmed firms experience a sharp deterioration in their profitability following the watch period. In Model [4], by the end of the fourth quarter post-watch, confirmed firms have achieved a 2.3% improvement in their industry-adjusted operating income ratio when benchmarked against their nonconfirmed peers. Relative to the pre-watch industry-adjusted operating income ratio of confirmed firms of 2.3% (see Table 2), the 2.3% increase represents a 100% (2.3%/2.3%) improvement in profitability. Finally, as expected, we find that the coefficient estimate on the lagged total investment ratio is both positive and significant, indicating that the improvement in operating performance in a given quarter is positively related to the additional investments made in the previous quarter.

To summarize, the watch resolution event represents a turning point for the patterns of long-term debt financing, investment, and operating performance. Relative to nonconfirmed firms, confirmed firms obtain more long-term debt financing, ramp up their investment activities, and are able to achieve better operating performance only subsequent to watch resolution decisions. These patterns are not part of long-term trends in firm outcomes, but instead are changes that occur only after the watch period. Underlying this interpretation is the parallel trends assumption necessary for the validity of the difference-in-differences framework. We formally test this assumption in Section 6.

5.2. CRA certification and alleviation of capital constraints

In this section, we investigate whether CRAs can facilitate firms' access to credit markets when they certify firm turnaround effort via the watch mechanism. To the extent that CRA certification helps alleviate firms' capital constraints, one would expect financially constrained firms to benefit more than their less constrained peers from better access to credit markets once their ratings are confirmed following the initial watch warning. As argued by Derrien and Kecskés (2013), financially constrained firms face impediments to long-term debt financing. However, one would expect these firms to obtain more long-term debt financing once they benefit from CRA certification and alleviation of their capital constraints. We hypothesize that confirmed firms with more financial constraints obtain more long-term debt financing relative to their less constrained counterparts in the post-watch period. To test this hypothesis, we condition upon firms' financial constraints and study the dynamic pattern of their long-term debt financing around the watch period.

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Table 5

Testing alleviation of capital constraints. Firms are sorted into more or less financially constrained groups based on the median value of the WW-index (Panel A) or cash flow-investment gap ratio (Panel B). The table presents for each of those groups the dynamic pattern of their long-term debt financing ratio from four quarters before to four quarters after the watch period. Results are for firms with confirmed ratings (confirmed firms) benchmarked against firms with downgraded ratings (nonconfirmed firms). The dynamic pattern is estimated for the more and less financially constrained firm groups separately (along with difference tests) based on specification [1] in Table 4; for brevity of presentation, only the coefficients on the variables of interest are reported here; all variables are as defined in the text. Standard errors are clustered at the firm and calendar quarter levels. The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable is long-term debt financing ratio						
	More constrained		Less constrained		More - less	
	Coefficient	*p*-Value	Coefficient	*p*-Value	Difference	*p*-Value
Panel A: classification is by the WW-index						
$Before^4 \times$ Confirmed	0.0258	(0.107)	−0.0006	(0.967)	0.0264	(0.114)
$Before^3 \times$ Confirmed	0.0126	(0.396)	−0.0006	(0.959)	0.0132	(0.512)
$Before^2 \times$ Confirmed	0.0082	(0.596)	0.0069	(0.579)	0.0013	(0.947)
$Before^1 \times$ Confirmed	0.0173	(0.237)	0.0054	(0.611)	0.0119	(0.555)
$After^1 \times$ Confirmed	0.0456**	(0.023)	0.0011	(0.936)	0.0445**	(0.029)
$After^2 \times$ Confirmed	0.0525**	(0.012)	−0.0047	(0.752)	0.0572***	(0.005)
$After^3 \times$ Confirmed	0.0513**	(0.017)	0.0084	(0.653)	0.0429**	(0.035)
$After^4 \times$ Confirmed	0.0456**	(0.013)	0.0078	(0.622)	0.0378*	(0.063)
Quarter-watch observations	5823		5832			
Confirmed observations	195		149			
Nonconfirmed observations	452		499			
Adjusted R^2	0.138		0.120			
Panel B: classification is by the cash flow investment gap ratio						
$Before^4 \times$ Confirmed	0.0206	(0.116)	0.0008	(0.941)	0.0198	(0.153)
$Before^3 \times$ Confirmed	0.0125	(0.547)	−0.0012	(0.913)	0.0137	(0.440)
$Before^2 \times$ Confirmed	0.0094	(0.531)	−0.0004	(0.965)	0.0098	(0.579)
$Before^1 \times$ Confirmed	0.0112	(0.538)	0.0096	(0.240)	0.0016	(0.929)
$After^1 \times$ Confirmed	0.0428**	(0.042)	0.0009	(0.934)	0.0419**	(0.019)
$After^2 \times$ Confirmed	0.0438**	(0.039)	0.0015	(0.899)	0.0423**	(0.018)
$After^3 \times$ Confirmed	0.0553**	(0.040)	0.0015	(0.905)	0.0538***	(0.002)
$After^4 \times$ Confirmed	0.0384**	(0.030)	0.0120	(0.347)	0.0264	(0.147)
Quarter-watch observations	6975		6975			
Confirmed observations	171		247			
Nonconfirmed observations	604		528			
Adjusted R^2	0.148		0.125			

As a first test, we use the WW-index of Whited and Wu (2006) to classify firms as more or less constrained. The index is a linear combination of the following six variables: cash flow to assets (with a negative loading); a dummy indicating whether a firm pays a dividend (negative); long-term debt to total assets (positive); size (negative); sales growth (negative); and industry sales growth (positive).[5] We divide our sample firms into two groups based on the median value of the WW-index as of quarter 0. Next, we estimate Eq. (1) following specification [1] in Table 4 for each group of firms using the long-term debt financing ratio as a dependent variable.

Panel A of Table 5 reports the results. For brevity, we only show the coefficients of the key variables ($Before^q \times Confirmed$ and $After^q \times Confirmed$) and their difference tests. Consistent with our hypothesis, we find that confirmed firms with more financial constraints experience a substantial increase in their long-term debt financing in the post-watch period. These firms obtain additional long-term debt financing corresponding to approximately 5% of their average assets in each quarter within the post-watch period, while we find no such evidence for the less constrained confirmed firms. Post-watch difference tests show that the incremental long-term debt financing of confirmed firms with more financial constraints is positive and significant in each quarter of the post-watch period, indicating that these firms take advantage of better access to credit markets post-certification to raise additional debt capital.

As an alternative test, we employ the cash-flow investment gap as in Rajan and Zingales (1998) to classify firms as more or less constrained. We measure the cash-flow investment gap as cash flow minus capital expenditures all divided by average assets (trailing-twelve-months income before extraordinary items (IBQ) plus trailing-twelve-months depreciation and amortization (DPQ) less trailing-twelve-months capital expenditures (CAPXY) adjusted for fiscal quarter accumulation, all scaled by average total assets (ATQ)). We divide our sample firms into two groups based on the median value of the cash-flow investment gap as of quarter 0. We then estimate Eq. (1) following specification [1] in Table 4 for each group of firms using the long-term debt financing ratio as a dependent variable.

The results in Panel B of Table 5 show that confirmed firms with more severe financial constraints obtain more long-term debt financing in the post-watch period. The additional long-term debt financing for these firms varies between roughly 4% and 6% of their average assets. In contrast, the positive post-watch increase in the long-term debt financing of confirmed firms with fewer

[5] We construct these variables following the definitions in Whited (1992) and Whited and Wu (2006) and then use the reported coefficient estimates in Whited and Wu (2006) to create index values for our sample firms. Higher index values indicate more financial constraints.

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financial constraints is of smaller magnitude and statistically insignificant. Post-watch difference tests indicate that the incremental long-term debt financing of confirmed firms with more financial constraints is positive and significant, although it loses significance in the fourth quarter post-watch.

We conduct three robustness tests using alternative measures of financial constraints. First, firms that pay no dividends are considered as more constrained than firms paying dividends. Second, noninvestment grade firms are regarded as more constrained than their investment grade peers. Third, we employ the Size-Age (SA) index (Hadlock and Pierce, 2010) as a proxy for financial constraints. The index is a combination of three factors: size (with a negative loading), the square of size (positive), and age (negative). Firms with index values above the median are considered as more constrained, and firms with index values below the median are classified as less constrained. While not reported, the robustness results provide qualitatively similar evidence as in Table 5. Generally speaking, the post-watch increase in long-term debt financing is economically and statistically more important for confirmed firms with more financial constraints than for confirmed firms with fewer constraints.[6]

Overall, these findings suggest that CRA certification through the watch mechanism helps alleviate firms' capital constraints and facilitate their access to credit markets. Insofar as CRA certification gives firms better access to debt capital from less informed investors, one would expect the positive relation between CRA certification and long-term debt financing to be stronger for firms with higher as opposed to lower information asymmetry. We investigate this prediction in the following section.

5.3. CRA certification and alleviation of information asymmetry

We argue that CRA certification via the watch mechanism can benefit firms with financial constraints due to information asymmetry by facilitating their access to less informed debt capital. We hypothesize that relative to confirmed firms with lower information asymmetry, confirmed firms with higher information asymmetry raise more long-term debt financing in the post-watch period, as they take advantage of CRA certification and alleviation of their capital constraints resulting from information asymmetry. To test this hypothesis, we condition upon the degree of firm information asymmetry and study the dynamic pattern of firm long-term debt financing around the watch period.[7] We employ two of the most widely used proxies for information asymmetry: idiosyncratic volatility (sigma, as defined in Section 3) and earnings forecast dispersion. We collect analyst forecasts from the Institutional Brokers' Estimate System (I/B/E/S). We estimate earnings forecast dispersion each calendar quarter as the standard deviation of analyst annual EPS forecasts (a minimum of three forecasts) submitted any time during a quarter, scaled by the stock price as of the end of this quarter. If an analyst makes more than one forecast during the quarter, only the last forecast is used in our calculations. We use the median value of sigma or earnings forecast dispersion as of quarter 0 to separate our sample firms into higher and lower information asymmetry firm groups. Next, we follow the empirical design as in Table 5 and estimate a panel regression model for each group of firms, where the dependent variable is the long-term debt financing ratio.

Panel A of Table 6 reports the results using sigma as a proxy for information asymmetry and provides evidence in support of our hypothesis. In the post-watch period, the financing behavior of confirmed firms with higher information asymmetry is different from that of confirmed firms with lower information asymmetry. The former secure additional long-term debt financing equivalent to roughly 5% of their average assets in each quarter post-watch, whereas the positive increase in the long-term debt financing of the latter is neither economically important nor statistically significant. The difference test results are in line with this observation. Confirmed firms subject to higher information asymmetry have positive and significant incremental long-term debt financing only in the post-watch period.

Panel B of Table 6 presents qualitatively consistent evidence using earnings forecast dispersion as an alternative proxy for information asymmetry. Confirmed firms with higher information asymmetry experience a monotonic increase in their long-term debt financing ratio, which becomes economically important and statistically significant in the last two quarters post-watch. By contrast, we find no evidence of higher long-term debt financing for confirmed firms with lower information asymmetry in any quarter of the post-watch period. Difference tests show that the two types of firms have different post-watch financing behavior, with confirmed firms subject to higher information asymmetry being able to obtain additional long-term debt financing of approximately 4% by the fourth quarter post-watch.

We conclude that CRA certification via the watch mechanism benefits confirmed firms subject to high information asymmetry by facilitating their access to debt capital from less-informed debt suppliers. A natural question that arises is whether a firm's better access to credit markets is accompanied by a reduction in its cost of debt capital. In the following section, we investigate whether CRA certification helps lower a firm's cost of debt capital.

5.4. CRA certification and the cost of debt capital

In this section, we investigate the dynamic pattern of a firm's cost of debt capital around CRA certification. Previously, we have established that confirmed firms with more financial constraints or those subject to higher information asymmetry enjoy better

[6] For the dividends test, differences in long-term debt financing are positive and significant in the last three quarters post-watch; for the rating test, they are positive and significant in each of the four quarters post-watch; and for the SA-index test, they are positive and significant only in the fourth quarter post-watch. The lack of significance of the SA-index results is not unexpected given that out-of-sample extrapolation of index coefficients may not be appropriate for our sample firms. The index is constructed for a combination of asset size and firm age with the assumption that financial constraints flatten beyond a $4.5 billion firm size (see, Hadlock and Pierce, 2010, pp. 1927–1929), which is lower than the size of the typical firm in our sample (see Table 2).

[7] We thank an anonymous referee for suggesting this test.

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Table 6
Testing alleviation of information asymmetry. Firms are sorted into higher or lower information asymmetry groups based on the median value of sigma (Panel A) or earnings forecast dispersion (Panel B). The table presents for each of those groups the dynamic pattern of their long-term debt financing ratio from four quarters before to four quarters after the watch period. Results are for firms with confirmed ratings (confirmed firms) benchmarked against firms with downgraded ratings (nonconfirmed firms). The dynamic pattern is estimated for the higher and lower information asymmetry firm groups separately (along with difference tests) based on specification [1] in Table 4; for brevity of presentation, only the coefficients on the variables of interest are reported here; all variables are as defined in the text. Standard errors are clustered at the firm and calendar quarter levels. The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable is long-term debt financing ratio	Higher information asymmetry		Lower information asymmetry		Higher - lower	
	Coefficient	*p*-Value	Coefficient	*p*-Value	Difference	*p*-Value
Panel A: classification is by sigma						
$\text{Before}^4 \times$ Confirmed	0.0231	(0.177)	0.0094	(0.343)	0.0137	(0.134)
$\text{Before}^3 \times$ Confirmed	0.0089	(0.651)	0.0078	(0.303)	0.0011	(0.958)
$\text{Before}^2 \times$ Confirmed	0.0126	(0.496)	0.0025	(0.666)	0.0101	(0.585)
$\text{Before}^1 \times$ Confirmed	0.0219	(0.248)	0.0023	(0.650)	0.0196	(0.274)
$\text{After}^1 \times$ Confirmed	0.0445**	(0.026)	0.0054	(0.559)	0.0391**	(0.027)
$\text{After}^2 \times$ Confirmed	0.0494**	(0.024)	0.0031	(0.776)	0.0463***	(0.008)
$\text{After}^3 \times$ Confirmed	0.0585**	(0.024)	0.0043	(0.731)	0.0542***	(0.002)
$\text{After}^4 \times$ Confirmed	0.0489***	(0.009)	0.0107	(0.365)	0.0382**	(0.029)
Quarter-watch observations	7398		7407			
Confirmed observations	179		265			
Nonconfirmed observations	643		558			
Adjusted R^2	0.127		0.126			
Panel B: classification is by earnings forecast dispersion						
$\text{Before}^4 \times$ Confirmed	0.0143	(0.378)	−0.0157	(0.196)	0.0300	(0.152)
$\text{Before}^3 \times$ Confirmed	−0.0036	(0.787)	−0.0100	(0.426)	0.0064	(0.767)
$\text{Before}^2 \times$ Confirmed	0.0061	(0.611)	−0.0046	(0.542)	0.0107	(0.610)
$\text{Before}^1 \times$ Confirmed	0.0103	(0.268)	0.0031	(0.686)	0.0072	(0.732)
$\text{After}^1 \times$ Confirmed	0.0107	(0.465)	0.0002	(0.984)	0.0105	(0.607)
$\text{After}^2 \times$ Confirmed	0.0191	(0.190)	−0.0102	(0.494)	0.0293	(0.161)
$\text{After}^3 \times$ Confirmed	0.0295**	(0.036)	−0.0062	(0.712)	0.0357*	(0.089)
$\text{After}^4 \times$ Confirmed	0.0400***	(0.003)	−0.0037	(0.797)	0.0437**	(0.039)
Quarter-watch observations	4716		4725			
Confirmed observations	114		143			
Nonconfirmed observations	410		382			
Adjusted R^2	0.103		0.151			

access to credit markets post-certification. We build on this finding and investigate whether these firms are able to raise additional debt capital under better terms, that is, whether their cost of debt capital decreases in an economically meaningful manner subsequent to CRA certification.[8] We hypothesize that CRA certification leads to a reduction in the cost of debt capital of confirmed firms, particularly for those with more financial constraints or higher information asymmetry. We collect corporate bond pricing data and construct monthly credit spreads at the issuer level (see Appendix A for details). We then match monthly credit spreads to our original credit watch data and retain the monthly credit spreads observed in the month ending immediately prior to the credit watch announcement (month 0) and those observed in each of the three months ending immediately after the watch resolution announcement (month 1, 2, and 3). Our objective is to analyze changes in the cost of debt capital of confirmed firms from one month before to three months after the watch period.

Panel A of Table 7 reports the results for the sample of confirmed firms for which the values of the WW-index (our proxy for financial constraints) are non-missing. As expected, we find that bond spreads of confirmed firms decrease by about 60 basis points following the watch period, and interestingly, the decrease in spreads is not only immediate but persists for at least three months post-certification. However, not all firms benefit equally from CRA certification. When we split our sample firms into two groups using the median value of the WW-index, we find that the decrease in spreads of confirmed firms is exclusively driven by those with more financial constraints, consistent with our prediction. By three months post-watch, these firms have enjoyed a substantial decrease in their bond spreads by roughly 145 basis points. By contrast, changes in bond spreads of confirmed firms with fewer financial constraints are positive and insignificant, indicating that these firms receive little real benefit from CRA certification. Difference tests show that the incremental decrease in bond spreads of confirmed firms with more financial constraints are statistically significant and economically important (roughly 150 basis points).

We conduct two robustness tests using alternative measures of financial constraints. First, categorizing non-dividend payers as constrained may not be appropriate because we have only 13 issuers that do not pay dividends out of 115 issuers with nonmissing spread data; instead, we use the median of the dividend ratio (dividends to assets) to classify firms as more or less constrained. Second, we use the noninvestment/investment grade classification to identify more or less constrained firms.

[8] We thank an anonymous referee for suggesting this test.

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Table 7

Certification and the cost of debt capital. The table presents changes in monthly credit spreads (measured in basis points) of confirmed firms from the month ending immediately prior to their credit watch announcement (month 0) to the three months ending immediately after their rating confirmation (month 1, 2, and 3). In Panel A, confirmed firms are sorted into more or less financially constrained groups based on the median value of the WW-index. In Panel B, confirmed firms are sorted into higher or lower information asymmetry groups based on the median value of sigma. Appendix A provides a detailed description of the process we use to construct credit spreads. Standard errors are clustered at the firm level. The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Changes in bond spreads of confirmed firms

Panel A: classification is by the WW-index

	Overall	More constrained	Less constrained	More - less
Month 0	304.1	439.7	174.5	
Month 1	248.4	303.5	195.6	
Month 1 - month 0	−55.7**	−136.2***	21.1	−157.3***
	(0.048)	(0.008)	(0.291)	(0.004)
Month 2	250.9	305.9	198.3	
Month 2 - month 0	−53.2*	−133.8**	23.8	−157.6***
	(0.071)	(0.013)	(0.251)	(0.006)
Month 3	237.6	294.4	183.2	
Month 3 - month 0	−66.5**	−145.3***	8.6	−153.9***
	(0.025)	(0.008)	(0.621)	(0.008)
Confirmed observations	90	45	45	

Panel B: classification is by sigma

	Overall	Higher information asymmetry	Lower information asymmetry	Higher - lower
Month 0	316.2	480.1	157.9	
Month 1	264.4	374.3	158.1	
Month 1 - month 0	−51.8**	−105.8**	0.1	−105.9**
	(0.044)	(0.038)	(0.976)	(0.042)
Month 2	272.8	382.9	166.5	
Month 2 - month 0	−43.4	−97.2*	8.5	−105.7*
	(0.119)	(0.079)	(0.297)	(0.061)
Month 3	260.2	361.1	162.7	
Month 3 - month 0	−56.0**	−119.0***	4.7	−123.7**
	(0.043)	(0.028)	(0.560)	(0.025)
Confirmed observations	116	58	58	

In unreported results, we find consistent evidence that only confirmed firms with more constraints experience an economically important and statistically significant decrease in their bond spreads subsequent to CRA certification.

Panel B of Table 7 reports qualitatively similar evidence using sigma as a proxy for information asymmetry. For the full sample, there is a 56 basis points decrease in bond spreads of confirmed firms from one month before to three months after the watch period. When we condition upon the extent of information asymmetry, however, the results reveal that reduction in the cost of debt capital of confirmed firms is fully driven by those with higher information asymmetry. Difference tests show that the incremental decrease in spreads of confirmed firms with higher information asymmetry relative to those subject to lower information asymmetry is persistent and amounts to around 100 basis points in each of the three months following CRA certification. In unreported results, we use earnings forecast dispersion as an alternative proxy for information asymmetry and find that confirmed firms with higher information asymmetry achieve a lower cost of debt capital post-certification, although these results are statistically insignificant, which is likely due to the smaller sample size (88 observations in total).[9]

These findings complement our evidence on long-term debt financing in Tables 5 and 6, and together allow for an interesting economic interpretation. Confirmed firms with severe financial constraints or those subject to high information asymmetry appear to take advantage of a significant decrease in their cost of debt capital post-certification to obtain a large amount of long-term debt financing at a reduced cost.

5.5. Certification vs. changes in market expectations

We have shown that, relative to nonconfirmed firms, confirmed firms achieve better operating performance in the post-watch period, and we have interpreted this finding as being consistent with the expected effects of CRA certification effort. However, this finding could also be consistent with a reverse causality explanation: CRAs could have simply anticipated the future operating performance of firms based on recent revisions in market expectations, and resolved credit watches accordingly without exerting any independent certification effort. If this is the case, then the credit watch mechanism serves only as a secondary channel for

[9] For completeness, we also investigate the change in spreads of nonconfirmed firms. As expected, we find that nonconfirmed firms experience an increase in their spreads by roughly 70 basis points immediately following their downgrade announcements.

Table 8
Certification vs. changes in market expectations. Firms are sorted into positive and negative ex ante changes in market expectations groups based on the direction of changes in equity analyst consensus recommendation (Panel A) or the direction of watch announcement abnormal returns (Panel B). The table presents for each of those groups the dynamic pattern of industry-adjusted operating income ratio from four quarters before to four quarters after the watch period. Results are for firms with confirmed ratings (confirmed firms) benchmarked against firms with downgraded ratings (nonconfirmed firms). The dynamic pattern is estimated for the positive and negative ex ante changes in market expectations for firm groups separately (along with difference tests) based on specification [4] in Table 4; for brevity of presentation, only the coefficients on the variables of interest are reported here; all variables are as defined in the text. Standard errors are clustered at the firm and calendar quarter levels. The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable is operating income ratio (adjusted)						
	Better market expectations		Worse market expectations		Better - worse	
	Coefficient	*p*-Value	Coefficient	*p*-Value	Difference	*p*-Value
Panel A: classification is by the direction of consensus recommendation revision						
$\text{Before}^4 \times$ Confirmed	−0.0065	(0.557)	−0.0011	(0.885)	−0.0054	(0.597)
$\text{Before}^3 \times$ Confirmed	0.0021	(0.813)	0.0009	(0.865)	0.0012	(0.910)
$\text{Before}^2 \times$ Confirmed	0.0047	(0.651)	0.0032	(0.542)	0.0015	(0.887)
$\text{Before}^1 \times$ Confirmed	0.0042	(0.581)	0.0022	(0.630)	0.0020	(0.847)
$\text{After}^1 \times$ Confirmed	0.0104	(0.233)	0.0133*	(0.051)	−0.0029	(0.775)
$\text{After}^2 \times$ Confirmed	0.0234**	(0.033)	0.0180***	(0.001)	0.0054	(0.610)
$\text{After}^3 \times$ Confirmed	0.0297***	(0.003)	0.0218***	(0.001)	0.0079	(0.448)
$\text{After}^4 \times$ Confirmed	0.0270**	(0.026)	0.0211***	(0.002)	0.0059	(0.575)
Quarter-watch observations	3483		6696			
Confirmed observations	125		164			
Nonconfirmed observations	262		580			
Adjusted R^2	0.723		0.679			
Panel B: classification is by the direction of watch announcement abnormal returns						
$\text{Before}^4 \times$ Confirmed	−0.0046	(0.634)	−0.0042	(0.546)	−0.0004	(0.966)
$\text{Before}^3 \times$ Confirmed	−0.0010	(0.888)	0.0025	(0.660)	−0.0035	(0.712)
$\text{Before}^2 \times$ Confirmed	−0.0007	(0.924)	0.0024	(0.646)	−0.0031	(0.745)
$\text{Before}^1 \times$ Confirmed	−0.0002	(0.975)	0.0016	(0.731)	−0.0018	(0.853)
$\text{After}^1 \times$ Confirmed	0.0122	(0.130)	0.0113*	(0.070)	0.0009	(0.930)
$\text{After}^2 \times$ Confirmed	0.0204**	(0.034)	0.0149***	(0.004)	0.0055	(0.583)
$\text{After}^3 \times$ Confirmed	0.0221***	(0.004)	0.0210***	(0.000)	0.0011	(0.917)
$\text{After}^4 \times$ Confirmed	0.0193**	(0.036)	0.0200***	(0.007)	−0.0006	(0.902)
Quarter-watch observations	4302		5904			
Confirmed observations	137		160			
Nonconfirmed observations	341		496			
Adjusted R^2	0.676		0.697			

the dissemination of prior market expectations rather than as an effective certification mechanism.[10] To investigate the empirical merits of this argument, we test whether the effects of CRA certification on firm operating performance persist once we hold ex ante changes in market expectations constant. We hypothesize that in the post-watch period, confirmed firms outperform their nonconfirmed peers even if they experienced similar ex ante changes in market expectations about their future profitability.

We employ equity analysts' opinions as a proxy for market expectations about the future profitability of firms placed under watch and compute their consensus recommendation revisions (equity analysts' average recommendation as of the end of a quarter ending immediately before watch resolution announcements minus average recommendation as of the beginning of that quarter (minimum of three recommendations); the recommendation data are from I/B/E/S). We divide our sample firms into two groups based on the direction of changes in analyst consensus recommendations, and then estimate Eq. (1) following specification [4] in Table 4 for each group of firms using the industry-adjusted operating income ratio as a dependent variable (using the industry-adjusted return on assets instead leads to qualitatively similar results).

Panel A of Table 8 reports the results and provides evidence against the reverse causality explanation.[11] For brevity, we only show the coefficients for the key variables $Before^q \times Confirmed$ and $After^q \times Confirmed$ as well as their difference tests. Regardless of whether equity analysts downgrade or upgrade firms immediately prior to watch resolution announcements, we observe post-watch improvements in the operating performance of confirmed firms relative to their nonconfirmed counterparts. By the fourth quarter post-watch, confirmed firms have achieved at least 2% higher industry-adjusted operating income as a proportion of their average assets, regardless of whether these firms experienced a positive or negative revision in their consensus recommendation. By matching confirmed firms to their nonconfirmed peers on the direction of changes in their consensus recommendation, we are able to establish that the positive effects of CRA certification effort on firm profitability are not subsumed by any impact of recent revisions in market expectations. The difference tests are also of interest, as they show that the post-watch outperformance of confirmed firms with positive ex ante changes in their consensus recommendation is statistically indistinguishable from that of confirmed firms with negative ex ante changes in their consensus recommendation. Recent revisions in market expectations

[10] Examples of papers on the lack of timeliness of credit ratings are Altman and Rijken (2004); Amato and Furfine (2004); Hull et al. (2004), and Norden and Weber (2004).

[11] In our regressions, we discard firms for which analysts do not revise their consensus recommendations immediately prior to watch resolution announcements.

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appear to play no role in explaining the cross-sectional variations in the post-watch outperformance of confirmed firms. Collectively, these findings indicate that the post-watch outperformance of confirmed firms is strongly related to CRA certification, but is independent of any ex ante changes in market expectations about the future profitability of confirmed firms.

It is also interesting to investigate whether equity investors have ability to predict watch resolution outcomes as well as to anticipate subsequent changes in firm operating performance. A full anticipation on the part of equity investors would undermine the role of CRAs as certification intermediaries. To test this, we first need to measure the equity market reaction to watch assignment announcements. For each firm placed under watch in our sample, we compute a cumulative abnormal return (CAR) from day 0 (watch announcement day) to day 2 using the return on a benchmark portfolio with comparable size, book-to-market, and momentum characteristics (Daniel et al., 1997).[12] In the full sample, we find that the average CAR is equal to −1.68% (p-value = 0.000), indicating that watch announcements are significant events as perceived by equity investors. The market still reacts negatively but with different percentages when we condition upon forthcoming watch resolution outcomes. Specifically, we find that the average CAR associated with the watches to be resolved with a rating downgrade is equal to −2.01% (p-value = 0.000) compared with −0.78% (p-value = 0.042) for the watches to be resolved with a rating confirmation, the difference being significant (p-value = 0.007). While this finding suggests that equity investors may have some ability to predict upcoming watch outcomes, it does not undermine the role of CRAs as valuable certifiers for several reasons. First, the evidence does not imply full anticipation because the market reaction to the announcements of those watches to be resolved with a rating confirmation is still negative and significant. If all equity investors were fully informed, they would not react at all to such events, which is contrary to what we found. Second, we cannot rule out the possibility that CRAs making watch announcements concurrently disclose additional information (e.g., in press releases) that would provide hints on the likely watch resolution decisions. To the extent that equity investors account for such information (which we cannot observe), the CAR results are actually supportive of a certification story in that certification begins to have an impact even before watch resolution decisions are made public. Third, the positive relation between CRA certification and firm operating performance persists even after controlling for the initial market reaction. As reported in Panel B of Table 8, the industry-adjusted operating income ratio of confirmed firms significantly improves in the post-watch period irrespective of whether equity investors reacted positively or negatively to the initial watch announcements. Additionally, the insignificant difference tests indicate that the initial market reaction has little power to predict the cross-sectional variations in the post-watch outperformance of confirmed firms. In unreported robustness results, we find similar evidence using the industry-adjusted return on assets as an alternative measure of operating performance.

5.6. Certification vs. differences in corporate governance

Prior research shows that firms with stronger governance are more profitable (e.g., Gompers et al., 2003).[13] A plausible, alternative explanation for the post-watch outperformance of confirmed firms relative to their nonconfirmed peers is that the former may have put in place adequate turnaround effort simply because they are better governed, independent of any CRA's actions. To explore the validity of this explanation, we test whether the effects of CRA certification on firm operating performance persist within groups of firms with comparable corporate governance. We hypothesize that in the post-watch period, confirmed firms outperform their nonconfirmed peers even if they have similarly strong corporate governance.

To test this hypothesis, we condition upon the strength of corporate governance and study the effects of CRA certification on firm operating performance. We measure the strength of corporate governance using two antitakeover provisions indices: the G-index (which is based on 24 provisions) of Gompers et al. (2003) and the *E*-index (which is based on 6 provisions) of Bebchuk et al. (2009). The G-index records the number of antitakeover provisions in a firm's charter as reported by the IRRC and varies from zero to 24, whereas the E-index records the incidence of six out of the 24 antitakeover provisions and varies from zero to 6. Given the provisions in these indices restrict shareholder rights, a higher index score is viewed as indicative of weaker governance.[14] Firms with index values below our sample median (10 for the G-index; 2 for the E-index) are classified as firms with stronger governance, and other firms are categorized as firms with weaker governance. For each group of firms, we run difference-in-differences panel regressions following specification [4] in Table 4 using the industry-adjusted operating income ratio as a dependent variable.

Panel A of Table 9 reports the results using the G-index, and Panel B of Table 9 presents the results using the E-index. Both sets of results provide evidence that the effects of CRA certification on firm operating performance are positive and generally significant within each group of firms, and interestingly these effects are statistically indistinguishable. For example, in Panel B by four quarters post-watch confirmed firms with stronger governance have achieved an incremental 2.51% industry-adjusted operating income ratio

[12] Using the CRSP value-weighted or equally-weighted index returns as a benchmark leads to virtually identical results.

[13] Additionally, prior research shows that board monitoring can affect debt financing terms. For example, Senbet and Tosun (2016) find a positive relation between board independence and debt maturity.

[14] We obtain the time series of the G-index from the Legacy IRRC Governance Database and the time series of the *E*-index from Bebchuk's data webpage (http://www.law.harvard.edu/faculty/bebchuk/data.shtml). Both indices are based on IRRC governance provisions, which are published in volumes every two to three years. We follow the forward-fill approach of Gompers et al. (2003) and Bebchuk et al. (2009). Specifically, we assume that the governance provisions remain unchanged during the period immediately following the publication of one IRRC volume until the publication of the subsequent IRRC volume. Finally, we do not use index data published after 2006 because changes were made in the data collection methods following the acquisition of IRRC by RiskMetrics. We fill forward the 2006 index data for two years until December 2007. Consequently, our test results are based on a subsample ending in December 2007.

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Table 9
Certification vs. differences in the strength of corporate governance. Firms are sorted into stronger and weaker corporate governance groups based on the median value of the G-index of Gompers et al. (2003) or the *E*-index of Bebchuk et al. (2009). The table presents for each of those groups the dynamic pattern of industry-adjusted operating income ratio from four quarters before to four quarters after the watch period. Results are for firms with confirmed ratings (confirmed firms) benchmarked against firms with downgraded ratings (nonconfirmed firms). The dynamic pattern is estimated for the stronger and weaker governance firm groups separately (along with difference tests) based on specification [4] in Table 4; for brevity of presentation, only the coefficients on the variables of interest are reported here; all variables are as defined in the text. Standard errors are clustered at the firm and calendar quarter levels. The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable is operating income ratio (adjusted)	Stronger governance		Weaker governance		Stronger - weaker	
	Coefficient	*p*-Value	Coefficient	*p*-Value	Difference	*p*-Value
Panel A: classification is by the G-index						
$Before^4 \times$ Confirmed	−0.0043	(0.669)	−0.0000	(0.990)	−0.0043	(0.738)
$Before^3 \times$ Confirmed	0.0052	(0.516)	0.0055	(0.414)	−0.0003	(0.969)
$Before^2 \times$ Confirmed	0.0058	(0.434)	0.0042	(0.465)	0.0016	(0.843)
$Before^1 \times$ Confirmed	0.0020	(0.660)	0.0072	(0.323)	−0.0052	(0.645)
$After^1 \times$ Confirmed	0.0229***	(0.003)	0.0087	(0.187)	0.0142	(0.190)
$After^2 \times$ Confirmed	0.0287***	(0.001)	0.0202***	(0.005)	0.0085	(0.423)
$After^3 \times$ Confirmed	0.0286***	(0.000)	0.0281***	(0.000)	0.0005	(0.942)
$After^4 \times$ Confirmed	0.0267***	(0.002)	0.0278***	(0.001)	−0.0011	(0.939)
Quarter-watch observations	3870		4581			
Confirmed observations	111		128			
Nonconfirmed observations	319		381			
Adjusted R^2	0.696		0.732			
Panel B: classification is by the E-index						
$Before^4 \times$ Confirmed	−0.0049	(0.580)	0.0021	(0.805)	−0.0070	(0.511)
$Before^3 \times$ Confirmed	0.0055	(0.443)	0.0044	(0.538)	0.0011	(0.907)
$Before^2 \times$ Confirmed	0.0038	(0.609)	0.0030	(0.700)	0.0008	(0.934)
$Before^1 \times$ Confirmed	0.0028	(0.622)	0.0046	(0.572)	−0.0018	(0.865)
$After^1 \times$ Confirmed	0.0149**	(0.022)	0.0139**	(0.043)	0.0010	(0.929)
$After^2 \times$ Confirmed	0.0210***	(0.007)	0.0233***	(0.003)	−0.0023	(0.829)
$After^3 \times$ Confirmed	0.0264***	(0.000)	0.0278***	(0.001)	−0.0014	(0.895)
$After^4 \times$ Confirmed	0.0251***	(0.002)	0.0249***	(0.006)	0.0002	(0.986)
Quarter-watch observations	4293		4158			
Confirmed observations	117		122			
Nonconfirmed observations	360		340			
Adjusted R^2	0.717		0.726			

compared with an additional 2.49% ratio for confirmed firms with weaker governance, the difference being economically small and statistically insignificant. To check the robustness of our findings, we repeat the same analysis using the industry-adjusted return on assets as a dependent variable and find qualitatively comparable results (unreported, for brevity). We conclude that the post-watch outperformance of confirmed firms is unrelated to differences in the strength of corporate governance between confirmed and nonconfirmed firms, and that the effects of differences in the strength of corporate governance on firm operating performance are trivial once we account for the impact of CRA certification.

6. Robustness tests

In this section, we conduct robustness tests on our main results. First, we formally test the parallel trends assumption underlying the difference-in-differences framework. Second, we address potential endogeneity in CRA watch resolution decisions using a propensity score matching framework and a switching regression with endogenous switching.

6.1. Testing the parallel trends assumption

A valid concern with our difference-in-differences results is that the positive post-watch differences in the long-term debt financing, investment, and operating performance measures between confirmed and nonconfirmed firms may be part of long-term trends. If this is the case, then we cannot attribute these differences to CRA certification effort, but rather to other unobservable factors that matter for the long-term trends of firm outcomes. To address this concern, we test the parallel trends assumption underlying the difference-in-differences framework (e.g., Roberts and Whited, 2012). This assumption implies that any pre-watch trends in the long-term debt financing, investment, and operating performance outcomes of confirmed and nonconfirmed firms should be statistically indistinguishable. To implement this test, we falsely assume that the onset of CRA certification occurs two years before it actually does, and then we re-estimate the difference-in-differences model in Eq. (1) following the specifications as in Table 4 based on this assumption.

Consistent with the parallel trends assumption, results (unreported) indicate that the evidence from our main analysis in Table 4 is not reproduced under the false certification test. The coefficients of the interaction dummy variables $After^q \times Confirmed$ are generally statistically insignificant. In those cases in which the coefficients are significant, they always take an unexpected sign. This test confirms the validity of our prior difference-in-differences results, that is, the previously documented positive post-watch differences in the long-term debt financing, investment, and operating performance measures between confirmed and nonconfirmed firms are not part of long-term trends.

6.2. Propensity score matching

Our primary concern with the certification interpretation of our results is endogeneity, specifically endogeneity with regard to potential omitted variables. Firms that have their ratings confirmed after a credit watch undertake different actions than those that have their ratings downgraded; this is due to their superior ability rather than to CRA certification. The firm that avoids a downgrade is perhaps stronger operationally, has better relationships with creditors, has better management, or has lower costs of financial distress. Any of these omitted factors could compromise the interpretation of our results.

To explore the robustness of our results with respect to these endogeneity concerns, we employ propensity score matching, which allows for direct matching between confirmed and nonconfirmed firms based on the characteristics that matter for firm ability to avoid a downgrade. In the first stage, we run a probit regression to estimate propensity scores. The dependent variable is a dummy equal to one for confirmed firms and zero for nonconfirmed firms. In our first set of matching variables, we consider firm size, industry-adjusted Tobin's Q, asset tangibility, long-term debt ratio (long-term debt to assets), cash ratio (cash to assets), age (number of years since a firm has a nonmissing stock price in Compustat), sigma, institutional ownership, fraction of independent directors, nonemployee blockholders, missing governance dummy, and the WW-index. For example, larger firms, firms with better growth prospects, or firms with more tangible assets are expected to have stronger financial conditions and better ability to avoid a downgrade. The second set consists of dummy variables indicating various initial rating categories (Aaa, Aa, Baa, Ba, and B), which are meant to match firms on their costs of financial distress. The third set contains dummy variables that indicate calendar years and 38 SIC-based industries, which are used to control for external events such as economic downturns and industry shocks, respectively. In our matching, we determine candidate nonconfirmed firms by allowing for an absolute difference between propensity scores of 2%. Then, we match each confirmed firm to two nonconfirmed firms chosen randomly with no replacement from the group of candidate nonconfirmed firms.[15] In our second stage, we conduct difference-in-differences comparisons for the 232 confirmed firms that could be matched to nonconfirmed firms based on nonmissing values for the matching variables.

Table 10 reports the results. As expected, confirmed firms increase their long-term debt financing, ramp up their investment activities, and are more profitable when benchmarked against their matched nonconfirmed counterparts in the four quarters following the watch period. For example, consider the difference tests between quarter 4 and 0. Confirmed firms increase their long-term debt financing by approximately 2% of their average assets, have a 2.2% higher total investment ratio, and achieve an incremental industry-adjusted return on assets of 3.1%. These results indicate that any differences in firms' ability to avoid a downgrade have little impact on our results, and our previous conclusions about CRA certification through the watch mechanism are robust to endogeneity concerns.

6.3. Switching regression with endogenous switching

The switching regression model with endogenous switching offers an alternative econometric framework to address endogeneity concerns. The model is discussed in Maddala (1983) and used by Fang (2005) to control for endogeneity in issuer–underwriter matching in her study of the effects of investment bank reputation on the price and quality of debt underwriting services. A distinctive feature of this model is the explicit modeling of endogeneity. Technically, unobserved or missing variables that could influence watch resolution decisions, such as firms' unobserved ability to avoid a downgrade, are allowed to affect firms' outcomes. Intuitively, the model makes it possible to hold firms' profiles fixed and to measure the net effects due to watch resolution decisions only. We estimate this model and compute the difference between actual and hypothetical changes in the long-term debt financing, investment, and operating performance measures of confirmed firms (see Appendix B for a formal description). The hypothetical change in a confirmed firm's measure is obtained by holding the firm's profile fixed and by computing the change in that measure as if the firm had its rating downgraded rather than confirmed.

Table 11 reports the means of the actual and hypothetical changes in a confirmed firm's long-term debt financing ratio, total investment ratio, total assets growth rate, industry-adjusted operating income ratio, and industry-adjusted return on assets, along with their difference tests (see Eq. (B.10) in Appendix B for details). The changes in those measures are computed between each of the four quarters post-watch (quarter 1, 2, 3, and 4) and the quarter ending immediately prior to the watch period (quarter 0). To illustrate, we focus on the changes from quarter 0 to 4. The actual change in the long-term debt financing ratio of confirmed firms is equal to roughly 5.7%, 3% higher than the 2.7% hypothetical change in the same ratio. By quarter 4, confirmed firms have experienced a 3.3% increase in their total investment ratio; if these firms had been downgraded instead, they would have achieved only a 1.6%

[15] Our results are robust to various matching assumptions. For example, we obtain qualitatively similar results if we choose one-to-one matching with a propensity score distance of 1% or one-to-three matching with a propensity score distance of 3%.

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Table 10
Propensity score matching. This table reports results based on a propensity score matching framework, which involves two stages. In the first stage, we run a probit regression to estimate propensity scores. The dependent variable is a dummy variable that equals one for firms with confirmed ratings (confirmed firms) and zero for firms with downgraded ratings (nonconfirmed firms). The independent variables are: firm size, industry-adjusted Tobin's Q, asset tangibility, long-term debt ratio, cash ratio, age, sigma, institutional ownership, fraction of independent directors, nonemployee blockholders, missing governance dummy, the WW-index, dummy variables indicating initial rating categories (Aaa, Aa, Baa, Ba, and B), 38 SIC-based industry dummy variables, and calendar quarter dummy variables. In the second stage, we randomly match each confirmed firm to two nonconfirmed firms with no replacement based on a 2% allowable absolute difference between propensity scores. The matching algorithm is optimized to maximize the number of propensity score matches. In this respect, the optimization algorithm retains the matches for confirmed firms with the fewest possible number of matches first. The table compares the means of the changes in the long-term debt financing ratio, total investment ratio, total assets growth rate, industry-adjusted operating income ratio, and industry-adjusted return on assets of matched confirmed and nonconfirmed firms and reports difference tests. Changes in firm outcomes are computed from the quarter ending immediately prior to the watch period (quarter 0) to each of the four quarters subsequent to the watch period. All variables are as defined in the text. The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Quarters	Matched confirmed firms ($N = 232$)	Matched nonconfirmed firms ($N = 464$)	Confirmed - nonconfirmed	*p*-Value
Long-term debt financing ratio	Q_1 - Q_0	0.0434	0.0246	0.0188**	(0.042)
	Q_2 - Q_0	0.0600	0.0426	0.0174*	(0.086)
	Q_3 - Q_0	0.0602	0.0384	0.0218*	(0.052)
	Q_4 - Q_0	0.0528	0.0332	0.0196*	(0.062)
Total investment ratio	Q_1 - Q_0	0.0230	0.0161	0.0069	(0.262)
	Q_2 - Q_0	0.0368	0.0244	0.0124*	(0.093)
	Q_3 - Q_0	0.0383	0.0183	0.0200***	(0.009)
	Q_4 - Q_0	0.0363	0.0144	0.0219***	(0.005)
Total assets growth rate	Q_1 - Q_0	0.0666	0.0072	0.0594***	(0.000)
	Q_2 - Q_0	0.1031	0.0253	0.0778***	(0.000)
	Q_3 - Q_0	0.0966	0.0212	0.0754***	(0.000)
	Q_4 - Q_0	0.0877	0.0200	0.0677***	(0.002)
Operating income ratio (adjusted)	Q_1 - Q_0	-0.0009	−0.0177	0.0168***	(<0.000)
	Q_2 - Q_0	0.0016	−0.0200	0.0216***	(<0.000)
	Q_3 - Q_0	0.0050	−0.0179	0.0229***	(<0.000)
	Q_4 - Q_0	0.0061	−0.0122	0.0183***	(<0.000)
Return on assets (adjusted)	Q_1 - Q_0	0.0014	−0.0209	0.0223***	(<0.000)
	Q_2 - Q_0	0.0059	−0.0270	0.0329***	(<0.000)
	Q_3 - Q_0	0.0096	−0.0270	0.0366***	(<0.000)
	Q_4 - Q_0	0.0086	−0.0223	0.0309***	(<0.000)

increase in the same ratio, the difference (1.7%) being significant at the 5% level. The actual change in the industry-adjusted operating income ratio of confirmed firms is equal to approximately 1%, which is 4.2% higher than the −3.2% hypothetical change in the same ratio. Overall, these results provide evidence that confirmed firms obtain more long-term debt financing, invest more, and are more profitable when benchmarked against their counterfactual counterparts in the post-watch period, a set of results that is consistent

Table 11
Switching regression with endogenous switching. This table compares the means of the actual and hypothetical changes in the long-term debt financing ratio, total investment ratio, total assets growth rate, industry-adjusted operating income ratio, and industry-adjusted return on assets of confirmed firms and reports the differences in means computed as in Eq. (B.10). Appendix B provides a formal description of the switching regression model along with its empirical estimation. The estimated hypothetical change in a firm's fundamentals measure reflects what the change would be if the firm's rating had been downgraded rather than confirmed. Changes in a firm's fundamentals measure are computed from the quarter ending prior to the watch period (quarter 0) to up to four quarters subsequent to the watch period. Variables are as defined in the text. The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Quarters	Actual change for confirmed firms ($N = 322$)	Hypothetical change for counterfactuals ($N = 322$)	Actual - hypothetical	*p*-Value
Long-term debt financing ratio	Q_1 - Q_0	0.0508	0.0234	0.0274***	(0.004)
	Q_2 - Q_0	0.0675	0.0453	0.0222**	(0.030)
	Q_3 - Q_0	0.0656	0.0412	0.0244**	(0.020)
	Q_4 - Q_0	0.0573	0.0266	0.0307***	(0.001)
Total investment ratio	Q_1 - Q_0	0.0200	0.0094	0.0106	(0.104)
	Q_2 - Q_0	0.0312	0.0169	0.0143*	(0.064)
	Q_3 - Q_0	0.0338	0.0213	0.0125*	(0.090)
	Q_4 - Q_0	0.0325	0.0160	0.0165**	(0.024)
Total assets growth rate	Q_1 - Q_0	0.0733	0.0427	0.0306*	(0.075)
	Q_2 - Q_0	0.1094	0.0554	0.0540***	(0.005)
	Q_3 - Q_0	0.0996	0.0610	0.0386**	(0.049)
	Q_4 - Q_0	0.0851	0.0574	0.0277	(0.158)
Operating income ratio (adjusted)	Q_1 - Q_0	-0.0005	−0.0274	0.0269***	(<0.000)
	Q_2 - Q_0	0.0028	−0.0271	0.0299***	(<0.000)
	Q_3 - Q_0	0.0077	−0.0269	0.0346***	(<0.000)
	Q_4 - Q_0	0.0097	−0.0321	0.0418***	(<0.000)
Return on assets (adjusted)	Q_1 - Q_0	0.0005	−0.0223	0.0228***	(<0.000)
	Q_2 - Q_0	0.0031	−0.0292	0.0323***	(<0.000)
	Q_3 - Q_0	0.0039	−0.0190	0.0229***	(<0.000)
	Q_4 - Q_0	0.0034	−0.0189	0.0223***	(<0.000)

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with our prior findings. We conclude that the post-watch differences in the outcomes of confirmed and nonconfirmed firms are unlikely to be due to unobservable factors which we may have failed to account for in our empirical analysis.

7. Conclusion

In this paper, we investigate whether CRAs certify firm turnaround effort through the mechanism of a credit watch with direction downgrade. We argue that if CRAs act as certification intermediaries, then confirmed firms should have better access to credit markets subsequent to the watch period. In turn, more long-term debt financing should allow these firms to invest more and achieve better profitability relative to nonconfirmed firms. To this end, we examine the relations between credit watch resolution decisions and subsequent changes in firm long-term debt financing, investment, and operating performance measures.

We find that confirmed firms obtain more long-term debt financing, ramp up their investment activities, and achieve better operating performance than nonconfirmed firms following the credit watch period. Further, confirmed firms with more financial constraints or higher information asymmetry experience an economically meaningful reduction in their cost of debt capital and substantially increase their long-term debt financing only in the post-watch period, indicating that CRA certification via the watch mechanism can facilitate firms' access to credit markets.

We present evidence against several alternative explanations of our findings. First, the post-watch differences in the outcomes of confirmed and nonconfirmed firms are not part of long-term trends. Second, our results are robust to potential endogeneity bias in watch resolution decisions; in particular, the effects of CRA certification on firms' outcomes persist after accounting for any differences in their ability to avoid a downgrade. Third, the post-watch outperformance of confirmed firms can be explained neither by positive ex ante changes in market expectations about their future profitability nor by the strength of their corporate governance.

Our results have important policy implications. It is clear that there is a crucial need for the certification services of CRAs, despite negative perceptions of their credibility. Without CRA certification, less-informed investors who lack the resources or skills to assess credit risk would likely abstain from participating, potentially threatening the existence of the bond market. Further, the certification services of CRAs have a real positive impact on the economy, as they facilitate firms' access to credit markets, which in turn can lead to better real outcomes. For regulators, it is important to ensure that any new regulations further strengthen CRAs' incentives to fulfill their certification function. The evidence we present in this paper could be developed further in future research exploring, for example, the impact of the 2010 Dodd-Frank Wall Street Reforms on CRAs' incentives to provide certification.

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Appendix A. Construction of bond spreads

To construct credit spreads, we use corporate pricing data from the Trade Reporting and Compliance Engine (TRACE) database and merge it with bond characteristics data from Fixed Income Securities Database (FISD). The National Association of Securities Dealers (NASD) introduced the TRACE database in July 2002 in an effort to increase price transparency in the U.S. corporate bond market. The system captures and disseminates consolidated information on secondary market transactions in publicly traded TRACE-eligible bonds representing all over-the-counter market activity in these bonds.

Following prior literature, we apply several filters to address likely erroneous data entries and reporting changes in TRACE. We remove trades that are later canceled, correct trades that are later reversed and replaced, eliminate agency transaction duplicates, and address the TRACE data structure change in February 2012; we further remove trades that have a negative reported yield, include a commission, or have a settlement period longer than five days (Bongaerts et al., 2012; Dick-Nielsen, 2009; Dick-Nielsen et al., 2012). Next, we match the resulting cleaned bond transaction data to bond characteristics from FISD using CUSIPs, retain senior unsecured bonds, and discard all bonds that (a) are convertible, puttable, substitutable, or exchangeable; (b) have credit enhancement features; (c) are non-fixed coupon or zero-coupon bonds; or (d) have a duration less than one year. Following Bongaerts et al. (2012), we keep callable bonds in our sample as otherwise the sample size would be significantly reduced. We then make monthly yield observations by retaining for each bond and in each month the median of all yields that are reported on the last available trading day of that month, provided that the last available trading day falls in the last week of that month; otherwise, the monthly yield is set to missing. Next, for a given bond/year-month pair, we compute a monthly credit spread as the bond's end-of-month yield less a benchmark Treasury rate, where the benchmark Treasury rate is computed by interpolating

[16] Treasury yield curve rates data are obtained from the Federal Reserve System's H15.

the two Treasury yield curve rates with the closest maturities to the corporate bond.[16] To remove the influence of outliers, we winsorize monthly credit spreads each month at the 99th percentile.

We then match the monthly credit spread data to our original credit watch data and retain the monthly credit spreads observed in the month ending immediately prior to the credit watch announcement (month 0) and those observed in each of the three months ending immediately after the watch resolution announcement (month 1, 2, and 3). Our objective is to analyze changes in the cost of debt capital from one month before to three months after the credit watch period. Most firms in our sample have multiple bonds outstanding. As noted by Bessembinder et al. (2009, p. 4229), aggregating bonds at the firm level is desirable because a bond-level analysis may result in several empirical issues, such as violation of the independence assumption and greater influence of firms with the highest number of bonds outstanding. We follow their approach and construct credit spreads at the firm level by computing for each firm and in each month a value-weighted average of the credit spreads of available bond issues. Because we are interested in changes in the cost of debt capital conditional on capital constraints, we retain firms for which the WW-index values are nonmissing as of quarter 0. The resulting sample consists of 360 firm-watch/year-month observations. We construct another sample by retaining firms for which sigma (our proxy for information asymmetry) is nonmissing as of quarter 0. The resulting sample consists of 464 firm-watch/year-month observations. These two samples are used in our credit spread analysis in Section 5.4.

Appendix B. Switching regression with endogenous switching

The model comprises a binary outcome equation along with a latent equation that matches watch resolution decisions with firm characteristics and other relevant factors, and a set of two equations that model changes in the firm fundamentals measures of interest in two different regimes. Formally, the model is described by the following set of equations:

$$I_i = 1 \text{ iff } I_i^* > 0, \text{and } I_i = 0 \text{ iff } I_i^* \le 0, \quad \text{where} \tag{B.1}$$

$$I_i^* = \gamma Z_i + u_i; \text{and} \tag{B.2}$$

$$\Delta Y_{1i} = \beta_1 X_i + u_{1i}, \text{and} \tag{B.3}$$

$$\Delta Y_{2i} = \beta_2 X_i + u_{2i}. \tag{B.4}$$

Eq. (B.1) models the observed watch resolution outcomes, in which the binary variable I_i indicates whether a credit watch issued on firm i is resolved with a rating confirmation. Eq. (B.2) is the latent watch resolution equation, where the vector Z_i consists of variables that may help shape watch resolution decisions. Eqs. (B.3) and (B.4) are the fundamentals equations for the rating confirmation and downgrade regimes, respectively. To capture the cumulative effects of watch resolution outcomes, we compute q-quarter changes in a fundamentals measure from quarter 0 to quarter q, where quarter 0 represents the quarter ending prior to the watch period, and $q = 1, 2, 3$, or 4 quarters. Accordingly, the variables ΔY_{1i} and ΔY_{2i} represent q-quarter future changes in a fundamentals measure of firm i in case of a rating confirmation and a rating downgrade, respectively. For a given watch observation either Eq. (B.3) or (B.4) is realized depending on the watch resolution decision for firm i. For example, if a credit watch is resolved with a rating confirmation, we observe ΔY_{1i}, and never ΔY_{2i}, so that only Eq. (B.3) is realized. The vector X_i consists of variables that may affect the pattern of firm fundamentals outcomes. To facilitate model estimation and inferences, we assume that the residuals u_{1i}, u_{2i}, and u_i have a trivariate normal distribution.[17]

A key distinctive feature of the endogenous switching regression model is the explicit modeling of endogeneity by allowing the residuals in the fundamentals equations, Eqs. (B.3) and (B.4), to correlate with the residual in the watch resolution Eq. (B.2). That is, unobserved or missing variables that influence watch resolution decisions are allowed to affect future changes in firm fundamentals outcomes. Formally, this implies that the residual vector has a nondiagonal covariance matrix with the following structure:

$$cov(u_{1i}, u_{2i}, u_i) = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{1u} \\ \sigma_{21} & \sigma_{22} & \sigma_{2u} \\ \sigma_{u1} & \sigma_{u1} & 1 \end{bmatrix}. \tag{B.5}$$

To estimate the switching regression model, it is important to note that Ordinary Least Square OLS estimation of Eqs. (B.3) and (B.4) yields inconsistent estimates given the above residual covariance structure. To see this, we take the expected values of the future changes in a firm's fundamentals measure in Eqs. (B.3) and (B.4), where we apply standard rules for conditional normal

[16] Treasury yield curve rates data are obtained from the Federal Reserve System's H15.

[17] In our empirical tests, Eqs. (B.3) and (B.4) also include industry fixed effects, $Industry_i$, and calendar year fixed effects, $Year_t$, which are not shown here for brevity of presentation.

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variables (see, e.g., Maddala (1983), p. 367). We define ΔY_i as the unconditional future change in the fundamentals measure of firm i and compute the expected values as follows:

$$\begin{aligned} E[\Delta Y_{1i}] &= E\left[\Delta Y_i | I_i^* > 0\right] \\ &= E[\beta_1 X_i + u_{1i} | \gamma Z_i + u_i > 0] \\ &= \beta_1 X_i + E[u_{1i} | u_i > -\gamma Z_i] \\ &= \beta_1 X_i + \sigma_{1u} E[u_i | u_i > -\gamma Z_i] \\ &= \beta_1 X_i + \sigma_{1u} \underbrace{\left(\frac{\phi(\gamma Z_i)}{\Phi(\gamma Z_i)}\right)}_{=Inverse\ \ Mills_{1i}}; \end{aligned} \tag{B.6}$$

$$\begin{aligned} E[\Delta Y_{2i}] &= E\left[\Delta Y_i \, | I_i^* \le 0\right] \\ &= E[\beta_2 X_i + u_{2i} | \gamma Z_i + u_i \le 0] \\ &= \beta_2 X_i + E[u_{2i} | \, u_i \le -\gamma Z_i] \\ &= \beta_2 X_i + \sigma_{2u} E[u_i | u_i \le -\gamma Z_i] \\ &= \beta_2 X_i - \sigma_{2u} \underbrace{\left(\frac{\phi(\gamma Z_i)}{1 - \Phi(\gamma Z_i)}\right)}_{=Inverse\ \ Mills_{2i}}; \end{aligned} \tag{B.7}$$

where σ_{1u} is the covariance between u_{1i} and u_i; σ_{2u} is the covariance between u_{2i} and u_i; $\phi(.)$ is the density function of the standard normal distribution; and $\Phi(.)$ is the cumulative distribution function of the standard normal distribution. The last terms in Eqs. (B.6) and (B.7) are the associated inverse Mills ratios, which result from the nonzero conditional expectation of the residuals. Because of these additional terms, OLS estimation of Eqs. (B.3) and (B.4) yields inconsistent estimates. However, if we augment Eqs. (B.3) and (B.4) with the inverse Mills ratios as additional explanatory variables, OLS estimation will generate consistent estimates. The augmented fundamentals equations are:

$$\Delta Y_{1i} = \beta_1 X_i + \sigma_{1u} Inverse\ Mills_{1i} + \varepsilon_{1i}, \ \text{and} \tag{B.8}$$

$$\Delta Y_{2i} = \beta_2 X_i - \sigma_{2u} Inverse\ Mills_{2i} + \varepsilon_{2i}, \tag{B.9}$$

where ε_{1i} and ε_{2i} are the new residuals, each of which has a zero conditional mean. In light of the above results, the two-stage estimation of the switching regression model is now clear. First, we estimate Eqs. (B.1) and (B.2) using a probit regression and obtain consistent estimates of γ, denoted by . Next, we obtain estimates of the inverse Mills ratios for Eqs. (B.8) and (B.9) by substituting γ for γ. We then estimate Eqs. (B.8) and (B.9) by OLS, yielding consistent estimates of β_1, β_2, σ_{1u}, and σ_{2u}. This two-step estimation procedure was first proposed in Lee (1976) and later discussed in Maddala (1983).

To investigate the effects of watch resolution decisions on firm fundamentals measures while controlling for endogeneity, it is necessary to address the following question: for a firm with a rating confirmation, what would the alternative change in the firm's fundamentals measure be had its rating been downgraded instead? To answer the question, we need an empirical methodology that evaluates for the same firm the effects of switching from an actual rating confirmation to a hypothetical rating downgrade. The above analysis lays the groundwork for answering such a question. What we have to do next is compare the actual change in a fundamentals measure for a firm with a rating confirmation with the predicted change in that measure under a hypothetical rating downgrade scenario. Following Fang (2005), we compute the following difference:

$$\begin{aligned} \underbrace{\Delta Y_{1i}}_{actual} - \underbrace{E\left[\Delta Y_{2i} | I_i^* > 0\right]}_{hypothetical} &= \Delta Y_{1i} - E[\beta_2 X_i + u_{2i} \, | \gamma Z_i + u_i > 0] \\ &= \Delta Y_{1i} - \beta_2 X_i - E[u_{2i} | u_i > -\gamma Z_i] \\ &= \Delta Y_{1i} - \beta_2 X_i - \sigma_{2u} E[u_i \, | u_i > -\gamma Z_i] \\ &= \Delta Y_{1i} - \beta_2 X_i - \sigma_{2u} \left(\frac{\phi(\gamma Z_i)}{\Phi(\gamma Z_i)}\right). \end{aligned} \tag{B.10}$$

The difference in Eq. (B.10) has an intuitive interpretation. For example, if the firm fundamentals measure of interest is profitability, a positive difference can be interpreted as an improvement in profitability for the same firm i. From Eq. (B.10), note that X_i is the vector of characteristics for the firm with a rating confirmation and $\left(\frac{\phi(\gamma Z_i)}{\Phi(\gamma Z_i)}\right)$ is its associated inverse Mills ratio, and the parameters β_2 and σ_{2u} are the coefficients from the fundamentals equation for the rating downgrade regime. Therefore, the hypothetical future change in a fundamentals measure of a firm with rating confirmation is the predicted value from evaluating the firm's characteristics and its associated inverse Mills ratio in the fundamentals equation for the rating downgrade regime. Our inferences with respect to the effects of watch resolution decisions on future changes in firm fundamentals draw upon the key result in Eq. (B.10).

Empirically, we estimate a probit regression that models the decision of a rating confirmation, as described in Eqs. (B.1) and (B.2). The vector Z_i includes all variables used in our propensity score matching tests (see Section 6.2). We also consider other variables that may influence credit watch decisions, but are unlikely to directly affect firm fundamentals outcomes. These are: a dummy variable indicating whether a watch is resolved after Regulation Fair Disclosure came into effect, the natural logarithm of the duration of the watch period, the natural logarithm of the number of instances a firm has been placed under watch in the past, and the natural logarithm of the number of instances a firm has received a watch-preceded rating confirmation in the past. Technically, these variables serve as identification restrictions in the endogenous switching model. Next, we estimate the augmented fundamentals Eqs. (B.8) and (B.9). The vector X_i consists of all variables used in our propensity score matching tests (see Section 6.2). Finally, we compute the empirical analogs of the difference in Eq. (B.10) and report the results in Table 11.

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