Credibility of Mandatory Disclosure by Credit Rating Agencies and Market Feedback

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ABSTRACT

Using the Credit Rating Agency Reform Act of 2006, we examine the effect of the credibility of mandatory disclosure by credit rating agencies (CRAs) on market feedback. We find an increase in investment-price sensitivity for firms affected by the act, and the increase is enhanced when managers have greater incentives to glean information from prices—when firms are exposed to multiple dimensions of uncertainty, have higher growth options, face more competition, have less informed managers, or have higher accounting fraud risk. Our findings suggest that the greater credibility of CRA mandatory disclosure improves managerial learning from stock prices.

JEL Classification: G24, G31, M41
Keywords: *Mandatory disclosure; managerial learning; investment-price sensitivity; corporate investment; informed trading; disclosure credibility; credit ratings; credit rating agency; regulation*

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I. Introduction

The press and politicians often express the need for more precise and credible public firm information following financial turmoil and market failure, which they say will allow capital market participants to reduce information asymmetry and make better decisions. Notable examples of such legislative efforts include the Sarbanes-Oxley Act (2002) and the Dodd-Frank Act (2010). Despite the informational benefits these acts provide for capital market participants (Beyer, Cohen, Lys, and Walther (2010) and Leuz and Wysocki (2016)), the literature provides nuanced evidence on the economic consequences of disclosure regulations for firms. Studies find that mandating firms to disclose (or disseminate) more precise information can lead to *inefficient* investment decisions by discouraging investors' private information production in stock prices and impeding managers' ability to learn from stock prices (Jayaraman and Wu (2019), Bird, Karolyi, Ruchti, and Truong (2021), and Goldstein, Yang, and Zuo (2023)).[1] These studies suggest that regulators should consider both information benefits and real costs in evaluating mandatory disclosure regulation.

Our study extends this literature, which has focused on *firm* disclosures by examining how disclosures by *financial intermediaries* impact managerial learning from stock prices. Intermediaries provide useful information to capital market participants. For example, credit rating agencies (CRAs) inform both stock and bond investors about firms' creditworthiness (Hand, Holthausen, and Leftwich (1992)). In the aftermath of high-profile bankruptcies, accounting scandals, and market failures, regulatory efforts to improve investor confidence about the precision and credibility of this kind of information (e.g., the Credit Rating Agency Reform Act) have arisen (e.g., Skreta and Veldkamp (2009), White (2010), and Goldstein and Yang

[1] This mechanism is referred to as "managerial learning from stock prices" or "market feedback" (Bond, Edmans, and Goldstein (2012)). See Section II.A. for a review of this literature.

(2019)). We contribute to the learning literature by examining the effect of the credibility of mandatory disclosure by CRAs on managerial learning from stock prices.

Our examination represents a joint test of the two propositions. First, we examine how the credibility of mandatory CRA disclosure influences stock price informativeness. Goldstein and Yang (2015) present a model in which informed traders facing multiple uncertainties specialize in analyzing a subset about which they have a comparative advantage but thus expose themselves to risks outside their specialization. Applying this model to our context, if CRA disclosure reveals information about a source of uncertainty that informed traders are less likely to specialize in, those traders will more actively acquire information about uncertainty that they are more likely to specialize in, enhancing stock price informativeness. Conversely, if CRA disclosure reveals information about a source of uncertainty that informed traders specialize in, they will scale back information acquisition, due to a reduction in their informational advantage over uninformed traders, leading to a decline in stock price informativeness.

Second, we explore how the credibility of mandatory CRA disclosure influences managerial learning from stock prices. The impact on learning depends on the type of investor information that CRA disclosure influences. If credit ratings reliably signal firm creditworthiness and investors tend to focus more on uncertainties, such as market demand and competition, then this shift in information acquisition increases managers' reliance on stock prices. This increase occurs as informed traders have a greater competitive advantage in analyzing these uncertainties than do managers. However, if firms' creditworthiness is difficult to assess due to uncertain consumer demand and industry competition, credit ratings will partially reveal information about these factors. This would then discourage investors from acquiring additional information about them and decrease managers' dependence on prices. Taken together, depending on the type of investors' private information that CRA disclosure is more likely to affect, managerial learning either increases or decreases.

To test these predictions, we choose the U.S. Credit Rating Agency Reform Act (CRARA) of 2006 as our setting. (See Section II.C. for details.) Following several high-profile bankruptcies and the revelation of large-scale accounting fraud at Enron and WorldCom, major CRAs came under severe criticism, leading to regulatory and political scrutiny, including SEC reports and congressional and senate hearings. These events damaged the reputation of major CRAs as a reliable source of information on firms' creditworthiness (Sethuraman (2019)). In response, Congress passed CRARA on September 29, 2006, to restore the reputation and enhance the accountability of CRAs.

Before testing our hypotheses, we validate our premise that CRARA improves the credibility of credit ratings. First, we find that the association between changes in firm fundamentals and subsequent changes in credit ratings strengthens after the passage of the law, suggesting that CRAs incorporate changes in firm fundamentals into their rating decisions more promptly post CRARA. Importantly, stock market investors seem to perceive the improved credibility, as Sethuraman (2019) documents that market reactions to changes in credit ratings increased after the law's passage. We complement this evidence by examining the changes in financial reporting credibility. We follow Gipper, Leuz, and Maffett (2020) and proxy for reporting credibility with stock market reactions to unexpected earnings news during short windows around earnings announcements (known as the earnings response coefficient or ERC). We find an increase in ERC after the passage of CRARA, suggesting that investors perceive the credibility of earnings as higher. Given that high-profile bankruptcies and accounting frauds prompted the passage of CRARA, these findings support the premise that the law improves the (perceived) credibility of credit ratings as a source of information about firm creditworthiness, particularly accounting fraud. Finally, we complement the above validation analyses by analyzing details of CRARA and provide institutional evidence consistent with this premise. (See Section II.C and Appendix A.)

Having established that CRARA improves the credibility of credit ratings as a source of information about firms' creditworthiness, we examine the first part of our joint hypotheses. We use a difference-in-differences design with a sample of firms rated by major CRAs as the treatment group and unrated firms as the control group around the passage of CRARA. Using the probability of informed trading (PIN), price nonsynchronicity, and stock illiquidity as proxies for price informativeness, we find that stock price informativeness increases for firms affected by the act relative to control firms following its passage, suggesting that an increase in the credibility of mandatory CRA disclosure helps enhance stock price informativeness. This evidence suggests that investors acquire and trade more on information that they specialize in, presumably because they can obtain better information of firms' creditworthiness post CRARA.

Next, we turn to our second hypothesis regarding the effect of CRA disclosure credibility on managerial learning from stock prices. Following prior research (e.g., Bai, Philippon, and Savov (2016)), we use the investment-price sensitivity framework. In a difference-in-differences design, we find an increase in investment-price sensitivity for treatment firms compared to control firms after CRARA. A parallel trends test shows no pre-trend in the investment-price sensitivity between treatment and control groups before the law's passage. Overall, the results are consistent with managers relying more on stock prices to guide investment decisions after the law passed. We next explore within-treatment firm variation in the increase in investment-price sensitivity. We investigate how this increase is affected by (1) types and dimensions of information that informed traders must gather and (2) the manager's own information. The intuition for the first analysis is that informed traders' information advantage lies in assessing growth opportunities and factors such as competition (e.g., Gao and Liang (2013), Jayaraman and Wu (2019), Goldstein and Yang (2019), and Goldstein et al. (2023)) and aggregating and synthesizing multiple dimensions of information (e.g., Goldstein and Yang (2015), (2019)). The intuition for the second analysis is that managers rely less on investor information when their own information is rich (e.g., Chen, Goldstein, and Jiang (2007), Foucault and Frésard (2014), and Edmans, Jayaraman, and Schneemeier (2017)). Consistent with these intuitions, we find that the increase in investment-price sensitivity strengthens when firms have greater growth opportunities, face more competition, have more segments, are exposed to greater risks, and when managers have poor information.[2]

To further illuminate what type of uncertainty CRARA reduces, we investigate accounting fraud risk as a source of firm-specific uncertainty that informed traders face but that the law reduces. The reasoning is that the damaged reliability of credit ratings prior to CRARA mainly stems from investors' concern about CRAs' inability to detect accounting fraud. We find that CRARA seems to help mitigate this concern, evidenced by an increase in perceived reporting credibility. In response, investors may substitute the information production of factors potentially new to managers and opt out of assessing fraud risk in the post-CRARA era. Indeed, we find a more pronounced increase in investment-price sensitivity among firms with poor earnings quality (i.e., high risk of fraud) in the pre-CRARA era.

[2] We, however, acknowledge that these results are suggestive rather than definitive, because differences between subsamples based on some partitions are not always significant and significant differences are generally observed only for the treatment firms with high levels of informed trading. Furthermore, when we construct the matched control sample, some significant differences disappear.

A concern is the possibility that an increase in investment-price sensitivity might reflect changes in the information possessed by investors. This would result in an increase in the alignment between managers' and investors' information, even though informed managers have not changed their investment policies. To address this concern, we examine the effect of CRARA on future firm performance. The intuition is that, if the increase in investment-price sensitivity stems from increased learning by managers, we expect an increase in future firm performance. Using market-to-book and return on assets, we show that treatment firms do see better future performance. These results demonstrate improved efficiency and thus weigh against common information between the market and managers as an alternative explanation.

Another alternative explanation is that, as credit rating agencies better monitor firms following CRARA, managers may make fewer self-dealing investments, such as empire-building, resulting in increased investment-price sensitivity. To address this concern, we conduct falsification tests and find that the increase in investment-price sensitivity does not vary with the strength of corporate governance.

We also show the robustness of our results to alternative research designs. First, we use entropy balancing (e.g., Hainmueller (2012)) and show that our main results hold. Next, we find our results robust to correcting measurement errors in proxies for investment opportunities (Erickson and Whited (2000), (2002) and Erickson, Jiang, and Whited (2014), (2017)) and alternative definitions of investment opportunities.

Our study makes two important contributions. First, we extend research on the effect of mandatory disclosure on managerial learning from stock prices. Studies primarily have examined how firms' mandatory disclosures impact market-based feedback (e.g., Jayaraman and Wu (2019), Bird et al. (2021), and Goldstein et al. (2023)). In contrast, we examine how the credibility of mandatory disclosures from financial intermediaries, particularly CRAs, influences managerial learning. Our findings suggest that the credibility of mandatory disclosures by CRAs increases managerial learning from stock prices and thus firms' investment efficiency. Our evidence is valuable for assessing the economic consequences of regulations designed to boost investors' confidence in credit ratings and, more generally, regulatory efforts directed at public information provided by financial intermediaries (e.g., Skreta and Veldkamp (2009), White (2010), (2013), and Goldstein and Yang (2019)).

Our findings on the crowding-in effect of managerial learning from stock prices contrast with prior evidence of the adverse effects of mandatory firm disclosures and information dissemination, which have been shown to crowd out managerial learning from stock prices (e.g., Jayaraman and Wu (2019), Bird et al. (2021), and Goldstein et al. (2023)). This contrast highlights that the market feedback effects of mandatory disclosure depend on context, particularly the nature of the disclosure in question. In our study, mandatory CRA disclosure, by reliably signaling firm creditworthiness, motivates investors to acquire more information about such factors as market demand and competition. Since investors have a comparative advantage over managers in analyzing these factors, managerial learning from prices increases. Conversely, if mandatory disclosure provides better signals about market-wide factors, such as industry competition (segment disclosure in Jayaraman and Wu (2019)), and thus reduces information advantage against unsophisticated investors, informed investors will reduce their acquisition of this information, resulting in a decrease in managerial learning from prices.

II. Related Literature, Hypothesis Development, and Setting

A. Related Literature

Our study contributes to the emerging literature that investigates the effects of mandatory disclosure on managerial learning from stock prices. Using the mandatory change to segment disclosures (SFAS 131), Jayaraman and Wu (2019) find a decrease in investment-price sensitivity, with a more pronounced effect for firms with more informed trading and for financially unconstrained firms, consistent with mandatory disclosures reducing market feedback. Bird et al. (2021) and Goldstein et al. (2023) explore the real effects of mandated dissemination of public information by using the staggered implementation of the SEC (Securities and Exchange Commission)'s EDGAR (Electronic Data Gathering, Analysis, and Retrieval) system. They find a decrease in investment-price sensitivity after EDGAR's implementation, particularly when investors have an information advantage, consistent with price-based learning. By focusing on mandatory dissemination as opposed to disclosure, the two studies' findings point to a similar conclusion that reducing informed traders' information advantage via more timely dissemination of public information impedes managerial learning from stock prices.

Our study extends this line of research by focusing on mandatory disclosures from CRAs, rather than firms themselves, and by examining how the credibility of these mandatory disclosures, beyond disclosures alone, influences firm investment efficiency through managerial learning.

B. Hypothesis Development

Our analyses represent a joint test of the two hypotheses: (1) how the credibility of mandatory CRA disclosure affects stock price informativeness and (2) whether the credibility of mandatory CRA disclosure influences managerial learning from stock prices.

Theory predicts that the effect of the credibility of mandatory CRA disclosure on stock price informativeness depends upon how the source of the disclosure is correlated with that of investors' private information. Goldstein and Yang (2015) present a theoretical framework that suggests a favorable impact of mandatory CRA disclosure on stock price informativeness. In their model, informed traders encounter various uncertainties and thus focus on analyzing specific subsets of uncertainties. However, this specialization exposes those traders to risks associated with uncertainties outside their expertise. The model suggests that, as the cost of obtaining information about one source of uncertainty that informed traders do not specialize in decreases, they are more likely to acquire additional private information about another source of uncertainty, increasing stock price informativeness.[3]

If, however, CRA disclosure partially reveals information about uncertainty that informed traders specialize in, that could decrease stock price informativeness. In this situation, CRA disclosure reduces informed traders' information advantage against uninformed traders, and hence informed traders will scale back their information acquisition. Consistent with this prediction, Gao and Liang (2013) present a model where firm value is subject to two sources of

[3] Several examples are consistent with the model of Goldstein and Yang (2015). Goldstein and Yang (2015) discuss fire sales: during the financial crisis of 2008, traditional traders pulled out of the market because of their exposure to risks such as exotic assts and counterparty risks that they do not understand. Lundholm (2021) argues that ETFs allow investors to hedge out exposure to systematic risk, which they do not understand, and thus they acquire more information about firm-specific risk. Gleason, Jenkins, and Johnson (2008) show that the revelation of accounting restatements in a particular company prompts investors to reevaluate the credibility of financial statements released by peers and sell their stocks, consistent with investors pulling out of the market when they face uncertainties that they do not understand.

uncertainties (assets-in-place and growth options), and these two sources are positively correlated. They predict that mandatory disclosure of assets-in-place discourages informed traders' information acquisition about growth opportunities because this disclosure decreases informed traders' information advantage about these opportunities. Given competing forces, we present our first hypothesis associated with stock price informativeness in two alternative forms:

H1a (price informativeness): The credibility of mandatory disclosure by CRAs increases stock price informativeness.

H1b (price informativeness): The credibility of mandatory disclosure by CRAs decreases stock price informativeness.

Learning theories posit that, while managers are arguably the most informed economic agents about sources of uncertainty that drive firm value, they are not perfectly informed about all sources and thus wish to learn from outsiders (Chen et al. (2007), Gao and Liang (2013), Bai et al. (2016), and Goldstein and Yang (2019)). The literature generally views firm-specific information, such as product quality, technology, and idiosyncratic creditworthiness, as well known to managers, whereas they aim to learn about industry distress risk, competition, and economy-wide factors—including macroeconomic conditions and economic policy uncertainty—from the market (e.g., Goldstein and Yang (2019)).

We argue that the effect of the credibility of mandatory CRA disclosure on managerial learning from stock prices depends on what types of investor information in stock prices are crowded out or crowded in by CRA disclosure, as hypothesized above. If credit ratings credibly signal *firm-specific* creditworthiness (i.e., lower cost of information acquisition) and reduce the uncertainty risk-averse traders face, investors are likely to acquire and trade on more information about such uncertainties as market demand and competition, in line with H1a. Since managers know about their own creditworthiness but less about market demand and competition, this substitution between these two types of information in stock prices will increase managerial learning from stock prices.

Note, however, that mandatory CRA disclosure could reduce managerial learning. For instance, if a firm's creditworthiness is difficult to evaluate due to uncertain consumer demand and steeper competition, credible credit ratings not only reliably signal a firm's creditworthiness but also partially reveal information about market demand and industry competition. Consequently, investors acquire less information about these uncertainties, as in H1b. To the extent that consumer demand and tougher competition are information that managers wish to learn from the market, their learning from stock prices decreases with more credible CRA disclosure. Given competing predictions, we present two alternative hypotheses:

H2a (managerial learning): Managerial learning from stock prices increases with the credibility of mandatory disclosure by CRAs.

H2b (managerial learning): Managerial learning from stock prices decreases with the credibility of mandatory disclosure by CRAs.

C. Experimental Setting: The Credit Ratings Agency Reform Act of 2006

CRAs are viewed as gatekeepers in capital markets in that they provide opinions on the creditworthiness of firms. Standard and Poor's states: "Our ratings express the agency's opinion about the ability and willingness of an issuer, such as a corporation or state or city government, to meet its financial obligations in full and on time."

The role of CRAs as gatekeepers was called into question by high-profile accounting frauds in 2002 (e.g., the Enron scandal). Pundits pointed to inaccurate, untimely credit ratings as a contributor to the Enron crisis and called for better regulation (Coskun (2008), Skreta and Veldkamp (2009)). Subsequently, an SEC investigation and congressional and senate hearings pointed out that CRAs ignored fundamental problems, like questionable transactions in 10-Ks and suspect accounting, in determining ratings due to conflicts of interest (Coskun (2008)). The reputation of major CRAs was damaged. This situation led to the passage of the Credit Rating Agency Reform Act (CRARA) in 2006.

CRARA aimed to restore the reputation of CRAs rather than require more disclosures by them, and thus the law serves as an effective setting in which the credibility of firms' credit ratings increases. CRARA was designed to (1) bolster the accountability of CRAs, (2) ensure that sufficient information about the inputs to the rating process is available to the SEC and the public, and (3) increase competition among CRAs.

Our premise is that CRARA, on average, improves the credibility of credit ratings as a source of information about firms' creditworthiness. To assess the plausibility of this premise, we provide both institutional and empirical evidence on each of the two elements of this presumed mechanism.

We conduct institutional analysis concerning the premise that the credibility of credit ratings as a source of firms' creditworthiness increases after the act. Appendix A describes details of the provisions under CRARA. We argue that the provisions associated with the first two objectives will improve the rating credibility perceived by investors. First, the provisions mandating that CRAs disclose conflicts of interest in advance reduce the likelihood that they will inflate ratings or delay downgrades. Policies and procedures that prevent CRAs from misusing material non-public information also serve to proactively discipline CRAs. The provisions that are designed to enhance ratings transparency also discipline CRAs, as details about their procedures and methodologies allow sophisticated investors to assess the credibility of ratings—something infeasible without these disclosures. However, the provisions associated with increasing competition have an unclear impact because the dominance of the three big CRAs did not significantly change after the act's passage. Consequently, we argue that the provisions of the act, on average, restore the credibility of CRAs as a reliable signal of creditworthiness. We provide empirical evidence consistent with this conclusion based on institutional analysis in Section IV.A.

III. Sample and Data Sources

To construct our sample, we obtain data from several sources: firms' accounting information and Standard & Poor's senior debt ratings from Compustat, stock price and return data from CRSP, and probability of informed trading data from Brown and Hillegeist (2007). Our sample covers the period surrounding the passage of CRARA and comprises firm-quarters between October 1, 2004, and June 30, 2008. We drop the third quarter of 2006, the quarter in which CRARA became law (September 29, 2006). This leads to seven quarters each for both the pre-and post-CRARA periods. Our sample ends in the second quarter of 2008 to avoid the effects of the Great Recession of 2008. We exclude all firms that belong to the financial and utility industries (SIC codes 6000–6999 and 4900–4999), which leaves 49,701 firm-quarter observations. Further, we delete observations without the necessary information to calculate variables for our analyses, leading to a sample of 24,344 firm-quarter observations (2,632 firms). Sample size also varies across cross-sectional tests due to the availability of data for partitioning variables.

IV. Research Design and Results

A. Validation Tests of CRARA

We begin by examining whether CRARA improves the credibility of credit ratings as a source of firms' creditworthiness. In our analysis, we take a "market-based approach" by evaluating the overall effects of CRARA relative to the prior regime rather than by separately assessing the impact of specific provisions.

First, we follow prior research (Ayers, Laplante, and McGuire (2010)) and examine the extent to which changes in firm fundamentals are associated with subsequent changes in credit ratings. The motivation for this analysis is that, if CRARA enhances the accountability of CRAs, changes in firm fundamentals prefigure changes in credit ratings after the law's passage. Credit rating letters span from AAA (indicating a strong capacity to pay interest and repay principal) to D (indicating actual default). We translate rating letters into numbers ranging from 21 to 1, where higher numbers indicate better ratings. Since it takes time for credit ratings to reflect changes in firm fundamentals, we measure changes in numerical credit ratings over various time horizons. This analysis is conducted only for firms with credit ratings.

We present the results of estimating ordered logistic regressions, separately for the pre- and post-CRARA periods in Table 1. $\Delta RATING_{t+k}$ denotes changes in Standard & Poor's long-term issuer credit ratings in quarter $t+k$, where k is 1 through 3 as of quarter t. Following Bongaerts, Cremers, and Goetzman (2012), we present McFadden's (1974) pseudo-R^2 for each regression at the bottom of Table 1. Across three different horizons, the pseudo R^2s for the post-CRARA period exceed those for the pre-period. Furthermore, the differences between the pre- and post-CRARA periods increase with the length of windows for measuring changes in credit ratings. These results are consistent with CRAs incorporating changes in firm fundamentals into credit ratings more promptly after CRARA.

INSERT TABLE 1 HERE

Next, we investigate whether investors perceive the quality of credit ratings as higher after the passage of CRARA. To this end, we examine changes in financial reporting credibility.

Our analysis is motivated by the notion that, because investors previously questioned the reliability of credit ratings in assessing firm creditworthiness, especially due to CRAs' failures to detect major accounting frauds, investors would place greater credibility on reported earnings if CRARA has indeed enhanced credit rating quality, as documented above. Following Gipper, Leuz, and Maffett (2020), we proxy for reporting credibility with earnings response coefficients (ERC), measured as stock market reactions to unexpected earnings news during short windows around earnings announcements.

We present the results in Table 2. *CAR_3DAY* (*CAR_4DAY*) is cumulative abnormal return in the three days (four days) centering on quarterly earnings announcements (-1, 0, 1) [(-1, 0, 1, 2)] (relative to a market model-adjusted benchmark, measured as the log of one plus actual return minus the log of one plus expected return (estimated using market models) on a day). *SURPRISE* is earnings surprise, measured as the difference between actual earnings minus mean analyst consensus earnings forecasts immediately preceding the actual earnings announcement, scaled by the stock price at the end of the prior quarter. As evidenced by the positive and significant coefficients on *SURPRISE*TREAT*POST* (*p*-value<.05), ERC increases incrementally among treatment firms after the passage of CRARA, indicating that investors seem to place higher weight on earnings surprises after CRARA. We interpret an increase in ERC among treatment firms as evidence of the law improving the perceived credibility of credit ratings as a source of information about firms' creditworthiness.

INSERT TABLE 2 HERE

B. Effect of CRARA on Stock Price Informativeness (H1)

Having established that the credibility of credit ratings increases, we examine our first hypothesis by comparing changes in stock price informativeness before and after the passage of

CRARA for the treatment group, relative to the control group. Specifically, we estimate the following difference-in-differences models (firm subscripts omitted):

(1) $$PRC\_INF_t = \beta_0 + \beta_1 TREAT*POST + \beta_2 SIZE_t + \beta_3 PRC\_INV_t + \gamma + \delta + \varepsilon_t,$$

where PRC_INF_t represents proxies for stock price informativeness, as described in the following paragraph. *TREAT* is set equal to one for treatment firms and zero otherwise. We categorize a firm as a treatment firm if it is rated by Standard & Poor's, a major rating agency impacted by CRARA, and as a control firm if it is not rated by Standard & Poor's.[4] *POST* is set equal to one for the quarters after CRARA and zero otherwise (i.e., seven quarters in the pre- and post-periods). We follow Jayaraman and Wu (2019) and include firm size (*SIZE*) and the inverse of stock price (*PRC_INV*) as controls. We provide detailed variable definitions in Appendix B. We include firm (γ) and year-quarter (δ) fixed effects, which absorb the effect of *TREAT* and *POST*, respectively. We follow Jayaraman and Wu (2019) and cluster standard errors by industry. A positive (negative) coefficient on β_1 will indicate that CRARA increases (decreases) stock price informativeness for affected firms compared to unaffected ones.

We follow Ferreira, Ferreira, and Raposo (2011) and use the probability of informed trading (PIN) as our primary measure of price informativeness. This measure is derived from a structural market microstructure model, which posits that trades are executed by either noise traders or informed traders. However, empirical proxies that are based on structural models and use order flow data, such as PIN, have been subject to criticism. Collin-Dufresne and Fos (2016) suggest that strategic trading choices may limit the ability of these models to identify informed trading. Duarte, Hu, and Young (2021) find that these models do not match the moments of order

[4] According to Himmelberg and Morgan (1995) and Sethuraman (2019), most bond and commercial paper issues are rated by Standard & Poor's. The control group consists of firms that depend only on equity financing, unrated public debt, private debt, or public debt rated by rating agencies less likely to be affected by CRARA.

flow observed in the data and lead to incorrect inferences about the presence of private information. Therefore, we use alternative price informativeness variables to corroborate our interpretation of the results. Following prior studies (Chen et al. (2007) and Jayaraman and Wu (2019)), we employ stock price nonsynchronicity and Amihud's (2002) illiquidity measure.

Panel A of Table 3 presents the descriptive statistics of the stock price informativeness sample. Means and medians of the three measures of price informativeness are generally consistent with those of prior studies (Morck, Yeung, and Yu (2000), Durnev, Morck, Yeung, and Zarowin (2003), Chen et al. (2007), Jayaraman and Wu (2019), and Goldstein et al. (2023)).

INSERT TABLE 3 HERE

Table 4 reports the results. In Model 1, we find a positive coefficient (p-value<0.01) on *TREAT*POST*, indicating an increase in the probability of informed trading among firms affected by the passage of CRARA compared to unaffected firms. The results from alternative measures of stock price informativeness proxies provide similar inferences. In Model 2, a significant coefficient of 0.018 indicates an increase in stock price nonsynchronicity, suggesting that stock returns co-move less after the passage of CRARA. Furthermore, a significant coefficient of 0.008 indicates a significant increase in the Amihud (2002) measure after CRARA. Taken together, to the extent that our measures capture stock price informativeness, the results in Table 4 provide support for the hypothesis that the credibility of mandatory disclosure by CRAs increases stock price informativeness (H1a).[5]

INSERT TABLE 4 HERE

[5] Measuring price informativeness is inherently challenging due to the non-observability of investors' information and the ability of informed investors to blend in with uninformed order flow. Thus, one can think of our analyses as joint tests of (1) whether our measures capture stock price informativeness and (2) whether CRARA increases it.

The parallel trends assumption is key to the identification of the effect of the disclosure regulation change (i.e., CRARA) on stock price informativeness in a difference-in-differences design (Roberts and Whited (2013)). Although formally testing this assumption is infeasible, we take the advice of Roberts and Whited (2013) and evaluate trends in stock price informativeness around the passage of CRARA.

We define a series of indicator variables equal to one for each quarter surrounding the passage of CRARA. We do not include indicators denoting quarter -1 and +1, and they serve as the benchmark. In Figure 1, we plot the 12 coefficient estimates along with 95% confidence intervals to facilitate visual inspection. Differences in stock price informativeness appear to have increased immediately following the passage of CRARA, particularly in (a) and (b) of Figure 1.

INSERT FIGURE 1 HERE

C. Effect of CRARA on Investment-Price Sensitivity (H2)

1. Research Design

To examine the second part of our joint hypotheses, the effect of the credibility of mandatory CRA disclosure on managerial learning from stock prices, we compare changes in investment-price sensitivity before and after the passage of CRARA for the treatment group relative to the control group. Specifically, we estimate difference-in-differences models as follows (firm subscripts omitted):

$$(2)\quad INV_{t+1} = \beta_0 + \beta_1 Log(M/A)_t + \beta_2 CFO_t + \beta_3 TREAT*POST + \beta_4 Log(M/A)_t*TREAT + \beta_5 Log(M/A)_t*POST + \boldsymbol{\beta_6} Log(M/A)_t*TREAT*POST + \beta_7 CFO_t*TREAT + \beta_8 CFO_t*POST + \beta_9 CFO_t*TREAT*POST + \beta_{10} SIZE_t + \gamma + \delta + \varepsilon_t,$$

where INV_{t+1} denotes future investment, defined as the sum of capital expenditures and research and development expenditures at quarter t+1, scaled by fixed assets at quarter t. *TREAT* and *POST* are defined as in equation (1). We follow Bai et al. (2016) and define a price-based measure of investment opportunities (*Log(M/A)*$_t$) as the natural log of a firm's market capitalization scaled by the total assets.[6] In Section IV.H, we assess the robustness of our results in correcting measurement errors in market-based proxies and for alternative definitions of investment opportunities. *CFO* is a nonprice-based measure of a firm's investment opportunity. *SIZE* is firm size measured by the natural log of the market value of equity. We provide detailed variable definitions in Appendix B. We include firm (γ) and year-quarter (δ) fixed effects, which absorb the effects of *TREAT* and *POST*, respectively. We follow Jayaraman and Wu (2019) and cluster standard errors by industry. If the increase in stock price informativeness associated with CRARA documented in the previous section (H1a) leads managers to rely more on stock prices, we expect β_6 to be positive, consistent with an increase in managerial learning from prices (H2a).

Note that a significant β_6 coefficient is only suggestive of price-based learning for two reasons. First, as described below, treatment and control groups have pre-CRARA differences in characteristics, raising the possibility of time-varying omitted-variable bias. To mitigate this concern, we exploit within-treatment firm variation and run a battery of robustness and falsification tests. Second, investment-price sensitivity indirectly proxies for managerial learning from stock prices (Goldstein et al. (2023)). We help alleviate this concern by examining future performance.

Panel A of Table 3 presents the descriptive statistics of the full sample, where we find the mean value of investment, *INV*, is 33% of lagged net property, plant, and equipment. The mean *Log (M/A)* [*M/A*] is 0.295 [1.34]. The mean *SIZE* is 6.806, indicating that the average market capitalization is about $903 million. Panel B of Table 1 displays pre-CRARA comparisons between treatment and control firms. As expected, the two groups show differences across firm

[6] Bai et al. (2016) note that "the correct functional form is whichever one managers use to extract information from prices. … In practice, we find that taking logs works slightly better because it mitigates skewness in the data."

characteristics. Control firms exhibit a higher investment rate and higher Tobin's *Q* but are smaller than treatment firms. We address the concern of pre-CRARA differences in firm characteristics in Section IV.H.

2. Results

We present the results of estimating equation (2) in Table 5. Model 1 presents the baseline result without treatment, where INV_{t+1} is regressed on *Log(M/A)*, our price-based measure of investment opportunities. We also include *CFO* and *SIZE.* We standardize *Log(M/A)* and *CFO* by subtracting the sample mean and scaling by the standard deviation to infer the coefficient as the marginal effect of one standard deviation. The coefficient on *Log(M/A)* is 0.100 (p-value<0.01), demonstrating that future investment increases by 10.0% in response to a one standard deviation increase in a price-based measure of investment opportunities.

INSERT TABLE 5 HERE

Model 2 shows the impact of CRARA on investment-price sensitivity. The coefficient on *Log(M/A)*TREAT*POST* is positive, 0.020, and significant (p-value<0.05), indicating an increase in investment-price sensitivity after CRARA. We interpret these results as initial evidence that managers increasingly rely on stock prices to guide their investment decisions because stock prices contain more private information they wish to learn after the passage of CRARA. In Model 3, we include a nonprice-based measure for investment opportunities (variables interacted with *CFO*) and find an insignificant coefficient on *CFO*TREAT*POST*. Not only does this result support the price-based learning channel, but it also mitigates the confounding effect of time-varying investment opportunities.

In combination with the results in Table 4, the results in Table 5 suggest that CRARA incentivizes informed traders to gather and trade on information, some of which is new to managers, and hence managers rely more on stock prices after the passage of CRARA.

Figure 2 shows the results of assessing the parallel trends assumption. We plot the coefficients that are obtained from estimating regressions similar to Model 3 of Table 5 by interacting 12 indicator variables equal to one for each quarter surrounding CRARA with *Log (M/A)* in place of *POST*. Differences in investment-price sensitivity appear to have increased two quarters after the passage of CRARA, suggesting that it took a few quarters until managers' investment decisions responded to the newly available private information in prices, presumably due to adjustment costs. This finding comports with those of Jayaraman and Wu (2019). However, treatment and control groups seem to show some modest differences in a few quarters prior to the passage of CRARA. In general, we interpret the results from Figure 2 as not indicating a violation of parallel trends in the pre-treatment period. Nonetheless, we admit there is some concern about time-varying correlated omitted variables. We mitigate this concern by running a battery of cross-sectional and falsification tests and examining future performance in the subsequent sections.

INSERT FIGURE 2 HERE

D. Cross-Sectional Tests: Types of Information Driving the Effects of CRARA on Investment-Price Sensitivity

In this section, we explore whether the treatment effect varies with firm characteristics that correlate with types of information more conducive to managerial learning.

1. Uncertainties Where Investors Have an Informational Advantage

A salient feature of learning models is that investors' information advantage lies in assessing certain types of uncertainties, such as growth opportunities, industry competition, or factors that require market-wide analysis, such as policy uncertainty (Bai et al. (2016), Goldstein and Yang (2019), and Goldstein et al. (2023)). We thus predict that the passage of CRARA facilitates managerial learning more among firms about which investors tend to have an information advantage relative to managers. Studies posit that growth opportunities and product market competition are the types of uncertainties where investors' informational advantage lies (Jayaraman and Wu (2019), Goldstein et al. (2023)). We follow Goldstein et al. (2023) and use firms' market-to-book ratio as a proxy for growth opportunities. We split the *TREAT* indicator into two indicators representing treatment firms with above-median (*TREAT_GROWTH*) and below-median (*TREAT_VALUE*) values of firms' growth opportunities. Then we modify equation (2) by interacting these indicators with *POST* and *Log(M/A)* to examine the varied treatment effect between growth and value firms.

Since competition is complex, we rely on both industry and firm measures. Specifically, we use industry concentration (HHI) and a measure of product similarity provided by Hoberg and Phillips (2016). We then take the average of the ranks of the inverse of HHI and product similarity to construct a composite measure of competition. We partition treatment firms with above-median (*TREAT_HIGHCOMP*) and below-median (*TREAT_LOWCOMP*) values of this competition measure. We interact these indicators with *POST* and *Log(M/A)* to examine the heterogeneous treatment effect between firms with high and low competition.

To better identify the effect of CRARA, we estimate this specification and remaining cross-sectional tests separately for treatment firms with high versus low informed trading (i.e., high and low *PIN* treatment firms) because studies show that managerial learning from prices is more pronounced when informed trading is high (e.g., Chen et al. (2007)).

We present our results in Panel A of Table 6. Consistent with our expectations, in Models 1 and 2, the coefficient on *Log(M/A)*TREAT_GROWTH*POST* of the high *PIN* group is positive (0.049) and significant at the 5% level, whereas the corresponding coefficient of value firms, *Log(M/A)*TREAT_VALUE*POST*, is insignificant. The two coefficients differ at *p*-value=0.039. In Models 3 and 4, we present our results of the differential treatment effect with respect to the level of competition. The coefficient on *Log(M/A)*TREAT_HIGHCOMP*POST* of the high *PIN* group is positive, 0.034, and significant at the 5% level, whereas the coefficient on *Log(M/A)* TREAT_LOWCOMP*POST* is insignificant. However, the difference between the two subsamples is insignificant at the conventional level (*p*-value=0.110).

INSERT TABLE 6 HERE

2. Firms Exposed to Multiple Dimensions of Uncertainties

Learning models assume that firms face multiple kinds of uncertainties, about which informed traders acquire private information to try to profit from trading on the acquired information (Goldstein and Yang (2015), (2019)). This assumption suggests that the effect of CRARA on investment-price sensitivity strengthens among firms with more uncertainties. We test this prediction by employing two proxies. First, we use the overall risk that each firm faces. To measure overall risk, we exploit the measure developed by Hassan, Hollander, van Lent, and Tahoun (2019), which counts the number of risk-related words from the firm's earnings conference call scripts. Second, we use the number of segments (both business and geographic). This proxy dovetails nicely with the conceptual framework of learning models.[7]

[7] Goldstein and Yang ((2015), p. 1737) state: "Obvious examples include multinational firms, for which there is uncertainty originating from the different countries where the firm operates, and conglomerates, for which there is uncertainty about the different industries the firm operates in."

As in the above heterogeneity tests, we split the *TREAT* indicator into two indicators representing treatment firms with above-median (*TREAT_HIGHRISK*) and below-median (*TREAT_LOWRISK*) values of the overall risk measure. Likewise, we split the *TREAT* indicator into two indicators denoting treatment firms with above-median (*TREAT_MORESEG*) and below-median (*TREAT_LESSSEG*) values of the total number of segments. Then we modify equation (2) by interacting these indicators with *POST* and *Log(M/A)*.

We present the results in Panel B of Table 6. The results are consistent with our predictions. Models 1 and 2 present the differential treatment effect between firms with high and low risk. Focusing on Model 1 of the high *PIN* group shows that the coefficient for high-risk firms (*Log(M/A)*TREAT_HIGHRISK*POST*) is positive (0.044) and significant at the 5% level, whereas the corresponding coefficient for low-risk firms (*Log(M/A)*TREAT_LOWRISK*POST*) is insignificant. The two coefficients statistically differ from each other at *p*-value=0.022. Models 3 and 4 present the heterogeneous treatment effect with respect to the number of segments. The coefficient on *Log(M/A)*TREAT_MORESEG*POST* of the high *PIN* group is positive and significant at the 5% level, whereas that on *Log(M/A)*TREAT_LESSSEG*POST* is insignificant. The differences in coefficients between the two groups are significant (*p*-value=0.084).

3. Managers' Own Information

The previous cross-sectional tests exploit firm characteristics associated with types of information in prices that can help managers make investment decisions. However, managers factor into their investment decisions all available information, including their own information, as well as information in stock prices incorporated by informed traders via trading (e.g., Bai et al. (2016)). Studies show that managers' own information moderates their reliance on market feedback (Chen et al. (2007), Bai et al. (2016), and Jayaraman and Wu (2020)). This suggests that the increase in investment-price sensitivity associated with CRARA will be muted when managers are privately better informed about the sources of uncertainty affecting firm value.

To test this prediction, we follow (e.g., Chen et al. (2007)) and use the number of shares bought and sold by CEOs and CFOs (*INSIDER*) and earnings surprises (*MKTSURP*), measured as the absolute abnormal returns around earnings announcements, as proxies for managers' private information. The idea is as follows: managers with more private information trade more, and their greater trading indicates their greater information; managers, for example. know earnings before the announcement, and thus higher (absolute) stock reactions to announcements indicate more managerial information.

We split the *TREAT* indicator into two indicators denoting treatment firms with above-median (*TREAT_HIGHINSIDER* or *TREAT_HIGHMKTSURP*) and below-median (*TREAT_LOWINSIDER* or *TREAT_LOWMKTSURP*) values of insider trading and earnings surprises. Then we modify equation (2) by interacting these indicators with *POST* and *Log(M/A)* to examine the heterogenous treatment effect between firms with high and low managerial information.

We present the results in Panel C of Table 6. The results support our prediction. The coefficient on *Log(M/A)*TREAT_LOWINSIDER*POST* of the high *PIN* group (Model 1) is positive and significant at the 5% level, whereas that for firms with high insider trading (*Log(M/A)*TREAT_HIGHINSIDER*POST*) is insignificant. The two coefficients differ at *p*-value=0.022. We also observe similar patterns in models 3 and 4, with only the coefficient on *Log(M/A)*TREAT_LOWMKTSURP*POST* being significant for the high PIN group. These results indicate that managers' private information moderates the effects of CRARA on managers' reliance on price signals. All the cross-sectional findings substantiate our inferences that the increase in investment-price sensitivity associated with the passage of CRARA is due to price-based learning and helps mitigate the concern of time-varying omitted variable bias.

We, however, hasten to add a caveat that these findings provide suggestive rather than conclusive evidence. Differences across subsamples are not consistently significant, and when they are, they are typically concentrated among treatment firms with high levels of informed trading. Moreover, some of the significant differences vanish once we use the matched control sample, the results that we present in the Online Appendix (Tables OA4).

E. Evidence on a Specific Type of Uncertainty: Accounting Fraud Risk

The results thus far are consistent with CRARA lowering informed traders' uncertainty about firm creditworthiness, acquiring more information that is new to managers, and thus leading to more managerial learning from stock prices. To substantiate this inference, we examine accounting fraud risk as one source of firm-specific creditworthiness.

CRAs' failure to downgrade the credit ratings of firms that were subsequently shown to have committed accounting fraud (e.g., Enron and WorldCom) damaged their reputation as a credible and reliable source of information about creditworthiness. In response, investors are likely to spend more time and effort assessing accounting fraud risk on their own and less collecting information about other aspects of firm value. Consequently, CRARA may restore the credibility of credit ratings as a source of information about firms' accounting fraud risk. This argument is consistent with an increase in reporting credibility in Table 2. Following the passage of CRARA, investors acquire less information about firms' fraud risk and more information about factors that may be new to firm managers. This substitution effect is expected to strengthen among firms whose earnings quality was worse before CRARA.

To capture earnings quality, we follow prior studies (e.g., Ahmed et al. (2020)) and use multiple proxies. First, we use modified Jones discretionary accruals, measured as the absolute value of residuals from the Dechow et al. (1995) model augmented by including nonlinear performance and growth controls (Kothari et al. (2005), Collins et al. (2017)). Second, we use Dechow–Dichev discretionary accruals, measured as the absolute value of residuals from the Dechow and Dichev (2002) model modified by McNichols (2002) with nonlinear performance and growth controls. Thus, lower values of these accrual measures indicate higher EQ. We provide detailed measurements of these variables in Appendix B.

To test our prediction, we split the *TREAT* indicator into two indicators representing treatment firms with below-median (*TREAT_HIGHEQ*) and above-median (*TREAT_LOWEQ*) values of the two accrual measures, respectively. Then we modify equation (2) by interacting these indicators with *POST* and *Log(M/A)* to assess the differential treatment effect on investment-price sensitivity between high versus low EQ firms.

INSERT TABLE 7 HERE

Table 7 presents the results. The results support our prediction that the treatment effect strengthens for firms with pre-CRARA poor earnings quality, especially when there is active informed trading. The coefficients on *Log(M/A)*TREAT_LOWEQ*POST* of the high *PIN* group (Models 1 and 3) are 0.045 and 0.041 and significant at the 1% level, whereas the corresponding coefficients for high EQ firms are insignificant. The differences in the two coefficients between high and low EQ subgroups are statistically significant at the 5% level for Model 1 and at the 10% level for Model 3. In sum, these results suggest that CRARA assuages investors' concerns about firms' accounting fraud risk, leading to an increase in investment-price sensitivity.

F. Future Performance

We interpret an increase in investment-price sensitivity following the passage of the act as consistent with managers learning from investor information, indicating an improvement in real efficiency. However, some concerns still exist. First, an increase in investment-price sensitivity post CRARA may simply reflect changes in information available to investors. In that case, the increase would result from greater alignment between managers' and investors' information, even if managers have not altered their investment policies based on investors' information. Second, an increase in investment-price sensitivity may be consistent with managers increasing investment to cater to overly optimistic investors in the post-CRARA period (Polk and Sapienza (2008)). To assuage these concerns, we test for an improvement in firms' future performance. If price-based learning entails richer information in stock prices that is new to managers after CRARA's passage, we expect an increase in firms' future performance as managers rely more on stock prices.

INSERT TABLE 8 HERE

Table 8 presents the results. We follow Frésard (2010) and measure future performance with industry-adjusted market-to-book (MTB) and return on assets (ROA). We measure ROA over various horizons—one-quarter-ahead ROA ($ROA_{[t+1]}$) and average ROA over the next two and three quarters ($ROA_{[t+1,\ t+2]}$ and $ROA_{[t+1,\ t+3]}$)—and regress these measures on *TREAT*POST* and *SIZE*. Using these measures, we find evidence of improvement in firm performance. In Model 1, we find a significant coefficient on *TREAT*POST*, suggesting that treatment firms experience a significant increase in market-to-book following the passage of the act. In Models 2–4, we also find significant coefficients on *TREAT*POST*, indicating that the treatment firms significantly improve accounting performance after CRARA.

Figure 3 shows the results of assessing the parallel trends assumption. We plot the coefficients that are obtained from estimating regressions by interacting with 12 indicator variables equal to one for each quarter surrounding CRARA in place of *POST* with *TREAT*. Visual inspection suggests that the effect on market-to-book seems to emerge with some delay, whereas the effect on accounting performance appears to rise more rapidly, and that these effects appear to be somewhat sustained in the post-CRARA period.

INSERT FIGURE 3 HERE

In Panel B, we split treatment firms into high and low *PIN* subsamples because managers' reliance on stock prices as a source of information to guide investment decisions strengthens for firms with more informed trading (Chen et al. (2007)). The results support our prediction. The coefficients on *TREAT_HIGHPIN*POST* are positive and significant at the 1% level, whereas the coefficients on *TREAT_LOWPIN*POST* are insignificant. The two coefficients differ significantly (*p*-value<.05 or better). Overall, the results support the argument that the credibility of mandatory disclosure by CRAs improves real efficiency via managerial learning from stock prices.[8]

G. Alternative Explanations

1. Corporate Governance

A compelling alternative explanation is that investment-price sensitivity increases among firms affected by CRARA due to increased monitoring. If CRAs better monitor firms following CRARA, managers may pursue fewer self-dealing investments, such as empire-building, resulting in an increase in investment-price sensitivity. To assess this explanation, we conduct

[8] We also compute industry-unadjusted measures of market-to-book and ROA and find the robust evidence (see Table OA7 of the Online Appendix).

falsification tests by exploring whether the increase in investment-price sensitivity associated with CRARA varies with the strength of corporate governance.

We measure the strength of firms' corporate governance with two proxies: (1) Cain, McKeon, and Solomon's (2017) H-index capturing hostile takeover threats and (2) CEO-chair duality. As in our cross-sectional tests, we split the *TREAT* indicator into two indicators, denoting treatment firms with good governance (*TREAT_GOODGOV*) and those with poor governance (*TREAT_POORGOV*). Firms with above-median values of the H-index are categorized as well-governed firms, while firms with below-median values are categorized as poorly governed. Firms where CEOs are also the chairperson of the board are characterized as poorly governed, while other firms are characterized as well governed. We present the results in Table 9. Across the two measures of governance, we do not find evidence supporting improved monitoring as an alternative explanation.

INSERT TABLE 9 HERE

2. Other Alternative Explanations

We also assess other alternative explanations. First, we evaluate the possibility that CRA disclosure directly benefits managers by providing new information after CRARA. If so, better future performance among treatment firms could be driven by managers learning new information from CRAs, not from stock prices. Second, we assess the Great Recession as an alternative explanation. If the recession significantly limited firms' ability to access capital markets, especially for firms with no credit ratings (Duchin, Ozbas, and Sensoy (2010)), investment-price sensitivity would increase for firms with credit ratings relative to those without. Third, we examine managers' disclosure changes as an alternative explanation. If CRARA results in a decrease in management earnings forecasts (Sethuraman (2019)), reductions in these disclosures will encourage informed traders' private information production (Chen, Ng, and Yang (2021)), resulting in more reliance on stock prices in the post-CRARA period. In the results presented in the online appendix (Tables OA1 – 3), we conclude that these are unlikely explanations.

H. Robustness Tests

INSERT TABLE 10 HERE

To mitigate the concern of pre-CRARA differences between treatment and control groups, we entropy balance treatment and control firms on a set of covariates based on the factors that Standard & Poor's considers when it rates the firms (S&P Global Ratings (2017), (2022)): firm size (*SIZE*), leverage (*DEBT*), asset turnover (*ASSETTURN*), the number of analysts following (*ANALYST*), and uncertainty (*RETVOL*). We augment these covariates with two proxies for financial constraints, the WW index of Whited and Wu (2006) (*WW-INDEX*) and the HP index of Hadlock and Pierce (2010) (*HP-INDEX*), because treatment and control firms likely face different levels of financial constraints. We reweight control firms based on these seven variables in the year prior to the enactment of CRARA to ensure covariate balance across treatment and control samples (Hainmueller (2012), McMullin and Schonberger (2020)). We present the covariate balance between treatment and control firms in Panel A of Table 10. By construction, both samples exhibit no differences across the seven covariates after entropy balancing. We then estimate the entropy-balance-weighted regressions and present the results in Panel B of Table 10. Our results are robust to this alternative research design.[9]

[9] We do not estimate the entropy-balance-weighted regressions for our cross-sectional tests because our focus in those tests is within-treatment firm differences but does not compare treatment firms with control firms. Nonetheless, we present the results of cross-sectional tests using the entropy-balance-weighted regressions in Tables OA4–OA5 of the online appendix. We acknowledge that some of the significant differences become insignificant: high versus low number of segments and high versus low level of insider trading.

Next, we address measurement errors present in market-based proxies for investment opportunities (Erickson and Whited (2000), (2006), (2012)) by using a method of Erickson et al. (2014). This method leverages higher-order cumulants derived from the distribution of market-to-book, aiming to address the impact of fluctuations in market values overlooked by managers. We also show the robustness of our results to alternative definitions of market-based investment opportunities. For our analyses, we follow Bai et al. (2016) and use the log of the market value of equity to total assets (*Log(M/A)*). We assess whether our results are sensitive to the unlogged M/A and the traditional Tobin's *Q*. In Table 11, we find our results are robust to the correction of measurement error in investment opportunities and alternative definitions of investment opportunities. We also assess the robustness of the results from cross-sectional tests and find that the significant differences we report in Table 5 remain, with an exception for high versus low levels of insider trading. See the online appendix (Tables OA6).

INSERT TABLE 11 HERE

V. Conclusion

This paper examines the effects of the credibility of mandatory disclosure by CRAs on stock price informativeness and managerial learning from stock prices. Using CRARA in 2006 as a setting, we find increases in stock price informativeness and investment-price sensitivity for affected firms compared to control firms. Cross-sectional analyses show the increase in investment-price sensitivity strengthens for growth firms, firms confronting more competition, firms with multiple uncertainties, firms with poorer managerial information, and firms with poor earnings quality. Further, affected firms experience an improvement in future performance compared to control firms. These findings contribute to the managerial learning literature by examining the credibility of mandatory disclosures from an information intermediary, rather than focusing on mandatory disclosures by firms.

We add several caveats and avenues for future research. First, our study is subject to the inherent challenge that information in stock prices, not to mention information type, is unobservable. As such, our findings are subject to the possibility that correlated omitted factors are responsible for our results. Nonetheless, the detailed assessment of alternative explanations and the results of improved future performance support price-based learning. Relatedly, readers should exercise caution in drawing causal inferences because having an S&P credit rating is endogenous and the market feedback effect of mandatory disclosures, either by firms or information intermediaries, is context specific. Thus, we believe that our results should be interpreted in the context of CRARA, and a different conclusion may arise in other settings because, as highlighted by Goldstein and Yang (2019), whether disclosures improve or impede managerial learning depends upon the type of information being disclosed by a given intermediary. We leave this for future research. Another interesting question for future research is how disclosures by CRAs affect managerial learning from bond prices.

Appendix A.
Details on the Provisions of the Credit Rating Agency Reform Act of 2006

This appendix provides details of the provisions from the Senate Report 109–326 and Public Law 109-291 regarding Credit Rating Agency Reform Act of 2006.

Title:	Credit Rating Agency Reform Act of 2006
Enacted:	September 29, 2006
Purpose of the legislation:	To improve ratings quality for the protection of investors and in the public interest by fostering accountability, transparency, and competition in the credit rating agency industry.
Overview of the regulatory landscape	The largest NRSROs [10] (Nationally Recognized Statistical Rating Organizations)", S&P and Moody's, wield enormous power in the global capital markets system. Their ratings affect the cost of capital and the structure of transactions for debt issuers, and determine which securities may be purchased by money market mutual funds, banks, credit unions, insurers, state pension funds, local governments, and local school boards. Regulatory actions have tended to insulate industry leaders from competition. Yet, once accorded this privileged status, they are virtually unregulated. Following corporate scandals at Enron, WorldCom, and elsewhere, Congress and the securities regulators adopted new rules governing the conduct of public companies, corporate boards and officers, accountants, stock research analysts, investment bankers, and attorneys. Rating agencies are not subject to similar regulation in spite of widespread criticism for failing to warn investors about several of the largest bankruptcies in U.S. history, conflicts of interest, anticompetitive and abusive business practices, and an absence of transparency, regulatory oversight, and meaningful competition.
Details of the provisions of CRARA:	❖ Credit rating agencies that choose to register as NRSROs must disclose important information such as ratings performance, conflicts of interest, and the procedures used in determining ratings (SEC. 15E (1)(B)(i)). ❖ CRAs should provide the procedures and methodologies that they use in determining credit ratings (SEC. 15E (1)(B)(ii)). ❖ CRAs should provide policies or procedures adopted and implemented to prevent the misuse of material, nonpublic information (SEC. 15E (1)(B)(iii)). ❖ CRAs should provide an organizational structure of the agency (SEC. 15E (1)(B)(iv)). ❖ CRAs should provide whether or not they have in effect a code of ethics, if not, the reason therefor (SEC. 15E (1)(B)(v)).

[10] NRSROs are credit rating agencies approved by the SEC to provide information that financial firms should depend on for regulatory purposes.

	❖ CRAs should provide any conflict of interest related to the issuance of credit rating by the rating agency (SEC. 15E (1)(B)(vi)). ❖ On a confidential basis, CRAs should provide a list of the 20 largest issuers and subscribers that use the credit rating services of the applicant, by amount of net revenues (SEC. 15E (1)(B)(viii)). ❖ CRAs should provide any other information and documents concerning the applicant and any person associated with such applicant as the Commission may prescribe as necessary or appropriate in the public interest or for the protection of investors (SEC. 15E (1)(B)(x)).

Appendix B.
Variable Definitions and Data Sources

Outcome Variables	
CAR_3DAY	Cumulative abnormal return in the three-day period centering on quarterly earnings announcement dates (-1, 0, 1). Abnormal return is measured as the natural logarithm of one plus actual return of firm *i* on day *d* minus the natural logarithm of one plus expected return of firm *i* on day *d*. Expected returns are estimated using a market model which is estimated from 90 calendar days prior to the quarterly earnings announcement date to 28 calendar days prior to the quarterly earnings announcement date. We start from 90 days prior to the earnings announcement date to avoid any effect of previous quarterly earnings announcements and estimate until 28 days prior to the quarterly earnings announcement date to prevent any anticipation of upcoming earnings surprises. Source: CRSP Daily Stock File, Compustat Fundamentals Quarterly
CAR_4DAY	Cumulative abnormal return in the three-day period centering on quarterly earnings announcement dates (-1, 0, 1, 2). Abnormal return is measured as the natural logarithm of one plus actual return of firm *i* on day *d* minus the natural logarithm of one plus expected return of firm *i* on day *d*. Expected returns are estimated using a market model which is estimated from 90 calendar days prior to the quarterly earnings announcement date to 28 calendar days prior to the quarterly earnings announcement date. We start from 90 days prior to the earnings announcement date to avoid any effect of previous quarterly earnings announcements and estimate until 28 days prior to the quarterly earnings announcement date to prevent any anticipation of upcoming earnings surprises. Source: CRSP Daily Stock File, Compustat Fundamentals Quarterly
$\Delta RATING_{t+k}$	Changes in credit rating over future horizons, where k = 1, 2, and 3. Standard & Poor's rates an issuer's long-term debt from AAA (indicating a strong capacity to pay interest and repay principal) to D (indicating actual default). We translate rating letters into numbers (1 to 21), with a larger number indicating a better rating. Source: Standard & Poor's senior debt ratings from Compustat Fundamentals Quarterly
PIN	The probability of informed trading, which measures the ratio of trades by informed traders as a proportion of total trades in the stock. It is expressed in percentage points. *PIN* data is obtained from Brown and Hillegeist (2008): Source: https://scholar.rhsmith.umd.edu/sbrown/pin-data
NONSYNC	Return nonsynchronicity, calculated as the log of one minus the R2 from firm-specific regressions of weekly stock returns on the weekly market and industry (both current and lagged) returns over the year. Source: CRSP
ILLIQUIDITY	The log of stock illiquidity. Following Amihud (2002), it is measured as the average of the ratio of daily unsigned stock returns scaled by dollar trading volume multiplied by 10^6. Source: CRSP
INV_{t+1}	Future investment, measured as the sum of capital expenditures and research and development (RandD) expenses for a firm *i* in quarter *t+1* scaled by the net property, plant, and equipment as of the end of quarter *t*. Source: Compustat Fundamentals Quarterly
ROA	Following Frésard (2010), industry-adjusted return on assets (ROA) is measured as the ratio of operating income before depreciation and amortization expenses to total assets. Source: Compustat Fundamentals Quarterly
MTB	Following Frésard (2010), industry-adjusted market-book ratio (MTB) is measured as market value of equity plus book value of assets minus book value of equity minus deferred taxes, scaled by total assets. Source: Compustat Fundamentals Quarterly

Explanatory and Partitioning Variables	
TREAT	An indicator variable equals one for firms whose long-term debt is rated by Standard & Poor's and to zero otherwise. Source: Compustat Standard & Poor's Senior Debt Ratings
POST	An indicator variable equal to one for the quarters 2006 4Q to 2008 2Q to denote the post-CRARA period and to zero otherwise
SURPRISE	Earnings surprise, defined as the difference between actual earnings minus mean analyst consensus forecast immediately preceding the actual earnings announcement, scaled by the stock price at the end of the prior quarter. Source: IBES Detail History
AT	Natural logarithm of firm *i*'s total assets at quarter *t*. Source: Compustat Fundamentals Quarterly
BTM	Firm *i*'s book value of equity divided by its market value of equity. Source: Compustat Fundamentals Quarterly
CFO	Firm *i*'s Cash flow from operations deflated by total assets. Source: Compustat Fundamentals Quarterly
LEV	Long-term debt deflated by total assets at the end of quarter *t-1*. Source: Compustat Fundamentals Quarterly
TIER	Firm *i*'s times-interest earned ratio, where the ratio is calculated as operating income before depreciation and interest expense divided by interest expense, both at the end of quarter *t*. Source: Compustat Fundamentals Quarterly
RND	Firm *i*'s research and development expense at quarter *t* deflated by total assets at quarter *t-1*. Source: Compustat Fundamentals Quarterly
EARNINGS	Earnings before extraordinary items at quarter *t*, deflated by total assets at quarter *t-1*. Source: Compustat Fundamentals Quarterly
SD_ROA	Firm *i*'s standard deviation of ROA using five quarters data from quarter *t-4* to *t*. ROA is net income before extraordinary items at quarter *t* deflated by total assets at *t-1*. Source: Compustat Fundamentals Quarterly
LOSS	An indicator variable equals to one if firm *i*'s basic earnings before extraordinary items is less than zero in quarter *t*, zero otherwise. Source: Compustat Fundamentals Quarterly
CAPINT	Firm *i*'s capital intensity, calculated as property, plant, and equipment net of depreciation at quarter *t*, deflated by total assets at the end of *t-1*. Source: Compustat Fundamentals Quarterly
M/A	Market capitalization for firm *i* at quarter *t* divided by total assets. Source: Compustat Fundamentals Quarterly
Log(M/A)	The natural log of market capitalization for firm *i* at quarter *t* divided by total assets. Source: Compustat Fundamentals Quarterly
Q	The ratio of market value of equity plus book value of debt to total assets
DEBT	Firm *i*'s long-term debt plus short-term debt, scaled by total assets in quarter *t*. Source: Compustat Fundamentals Quarterly
ASSETTURN	Firm *i*'s quarterly sales scaled by total assets. Source: Compustat Fundamentals Quarterly
ANALYST	Number of analysts following for firm *i* in a quarter *t*. Source: IBES Summary History
WW-INDEX	Financial constraint index of Whited and Wu (2006).

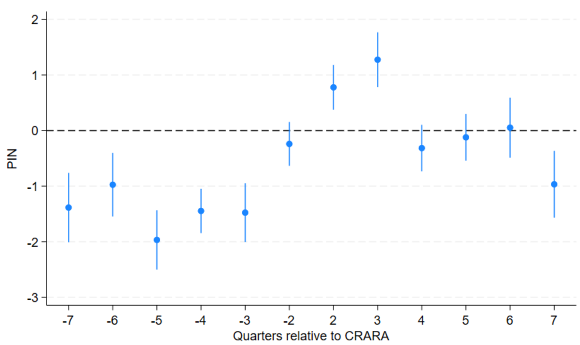
	It is defined as (-0.091**CF*) - (0.062**DIVPOS*) + (0.021**TLTD*) - (0.044**LNTA)* + (0.102**ISG*) - (0.035**SG*), where *CF* is the ratio of cash flow to total assets, *DIVPOS* is an indicator that takes the value of one if the firm pays cash dividend, *TLTD* is the ratio of the long-term debt to total assets, *LNTA* is the natural log of total assets, *ISG* is the firm's three-digit industry sales growth, and *SG* is firm sales growth.
HP-INDEX	Financial constraint index of Hadlock and Pierce (2010). It is measured as (-0.737**Size*) + (0.043*$Size^2$)-(0.040**Age*), where *Size* equals the log of total assets and *Age* is the number of years the firm is listed with a non-missing stock price on Compustat. In calculating this index, *Size* is winsorized at the log of $4.5 billion, and *Age* is winsorized at thirty-seven years.
TREAT_HIGHPIN	An indicator variable equals one for treatment firms with the above-median value of the probability of informed trading (PIN) as of the last quarter of the pre-period (2006 Q2) and zero otherwise. *PIN* data is obtained from Brown and Hillegeist (2008).
TREAT_LOWPIN	An indicator variable equals one for treatment firms with the below-median value of PIN as of the last quarter of the pre-period (2006 Q2) and to zero otherwise. *PIN* data is obtained from Brown and Hillegeist (2008).
TREAT_LOWEQ	An indicator variable equals one for treatment firms with the above-median value of a discretionary accrual measure as of the last quarter of the pre-period (2006 Q2) and to zero otherwise. We employ two versions of discretionary accruals as earnings quality proxies. We calculate working capital accruals from the statement of cash flows following Hribar and Collins (2002). We follow Ahmed et al. (2020) and use the absolute values of discretionary accruals that are estimated based on modified Jones and modified Dechow-Dichev models. Source: Compustat Fundamentals Quarterly <u>Modified Jones model:</u> $Working\ capital\ accrual_t = \beta_0 + \beta_1 Adj\_\Delta sales_t + \beta_2 Inverse\_Assets_{t-1} + \beta_3 PPE_t + \Sigma\beta_{4,k} ROA\_Dummy_{k,t} + \Sigma\beta_{5,k} Salesgrowth\_Dummy_{k,t} + \Sigma\beta_{6,k} MTB\_Dummy_{k,t-1} + \varepsilon_t$ <u>Modified Dechow-Dichev model:</u> $Working\ capital\ accrual_t = \beta_0 + \beta_1 CFO_{t-1} + \beta_2 CFO_t + \beta_3 CFO_{t+1}\ \beta_4 PPE_t + \beta_5 \Delta sales_t\ \Sigma\beta_{6,k} ROA\_Dummy_{k,t} + \Sigma\beta_{7,k} Salesgrowth\_Dummy_{k,t} + \Sigma\beta_{8,k} MTB\_Dummy_{k,t-1} + \varepsilon_t$ *Adj_Δsales* is the changes in sales minus receivables between quarter *t* – 4 and *t*, scaled by lagged total assets; *Inverse_Assets* is the inverse of lagged total assets; *PPE* is gross property, plant and equipment scaled by lagged total assets; *ROA_Dummy* is an indicator variable equal to one when firm *i*'s *ROA* is in *k*th quintile of *ROA*, and zero otherwise; *Salesgrowth_Dummy* is an indicator variable equal to one when firm i's sales growth is in *k*th quintile of sales growth, and zero otherwise; *MTB_Dummy* is an indicator variable equal to one when firm i's lagged *MTB* is in *k*th quintile of *MTB*, and zero otherwise. These models are estimated for each two-digit SIC industry and each quarter with a minimum of 10 observations.
TREAT_HIGHEQ	An indicator variable equals one for treatment firms with the below-median value of a discretionary accrual measure as of the last quarter of the pre-period (2006 Q2) and to zero otherwise. We employ two versions of discretionary accruals as earnings quality proxies. We calculate working capital accruals from the statement of cash flows following Hribar and Collins (2002). We follow Ahmed et al. (2020) and use the absolute values of discretionary accruals that are estimated based on modified Jones and modified Dechow-Dichev models. Source: Compustat Fundamentals Quarterly See the definition of *TREAT_LOWEQ* for discretionary accrual models
TREAT_HIGHINSIDER	An indicator variable equals to one for treatment firms with above-median value of insider trading activities as of the last quarter of the pre-period (2006 Q2), and to zero otherwise.

	Insider trading activities are measured as the total number of transactions (both buys and sells) by management, deflated by the beginning-of-quarter market capitalization. Source: Thomson Reuters Insiders
TREAT_LOWINSIDER	An indicator variable equals to one for treatment firms with below-median value of insider trading activities as of the last quarter of the pre-period (2006 Q2), and to zero otherwise. Insider trading activities are measured as the total number of transactions (both buys and sells) by management, deflated by the beginning-of-quarter market capitalization. Source: Thomson Reuters Insiders
TREAT_HIGHMKTSURP	An indicator variable equals one for treatment firms with the above-median value of earnings surprise. Earnings surprise, following Chen et al. (2007), is measured as the abnormal stock returns in the three-day period centering on each of the four quarterly earnings announcement dates in the year before the shock. Then, use the average of absolute abnormal returns as a proxy for the earnings surprise. Source: CRSP, Compustat Fundamentals Quarterly
TREAT_LOWMKTSURP	An indicator variable equals one for treatment firms with the below-median value of earnings surprise. Earnings surprises, following Chen et al. (2007), is measured as the abnormal stock returns in the three-day period centering on each of the four quarterly earnings announcement dates in the year before the shock. Then, use the average of absolute abnormal returns as a proxy for the earnings surprise. Source: CRSP, Compustat Fundamentals Quarterly
TREAT_HIGHRISK	An indicator variable equals one for treatment firms with the above-median value of firms' overall risk measure as of the last quarter of the pre-period (2006 Q2) and to zero otherwise. The data about overall risk is obtained from Hassan et al. (2019). https://www.firmlevelrisk.com/download
TREAT_LOWRISK	An indicator variable equals one for treatment firms with the below-median value of firms' overall risk measure as of the last quarter of the pre-period (2006 Q2) and to zero otherwise. The data about overall risk is obtained from Hassan et al. (2019). https://www.firmlevelrisk.com/download
TREAT_MORESEG	An indicator variable equals one for treatment firms with the above-median value of the number of segments as of the last fiscal year of the pre-period and to zero otherwise. The number of segments is the number of geographic segments plus the number of business segments. Source: Compustat Historical Segments
TREAT_LESSSEG	An indicator variable equals one for treatment firms with the below-median value of the number of segments as of the last fiscal year of the pre-period and to zero otherwise. The number of segments is the number of geographic segments plus the number of business segments. Source: Compustat Historical Segments
TREAT_GROWTH	An indicator variable equals one for treatment firms with the above-median value of market-to-book ratio as of the last quarter of the pre-period (2006 Q2) and to zero otherwise. Source: Compustat Fundamentals Quarterly
TREAT_VALUE	An indicator variable equals one for treatment firms with the below-median value of market-to-book ratio as of the last quarter of the pre-period (2006 Q2) and to zero otherwise. Source: Compustat Fundamentals Quarterly
TREAT_HIGHCOMP	An indicator variable equals one for treatment firms with the above-median value of average ranks of two competition measures (the inverse of industry concentration and total product similarity) as of the last fiscal year of the pre-period and to zero otherwise. Data about industry concentration and total product similarity are obtained from the Hoberg-Phillips data library. http://hobergphillips.tuck.dartmouth.edu/
TREAT_LOWCOMP	An indicator variable equals one for treatment firms with the below-median value of average ranks of two competition measures (the inverse of industry concentration and total product similarity) as of the last fiscal year of the pre-period and to zero otherwise. Data about industry

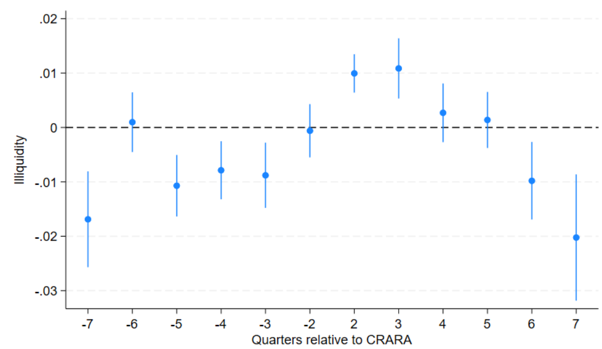
	concentration and total product similarity are obtained from the Hoberg-Phillips data library. http://hobergphillips.tuck.dartmouth.edu/
TREAT_GOODGOV	An indicator variable equals one for treatment firms with the above-median value of the hostile takeover index or firms with no CEO-chair duality status as of the last quarter of the pre-period (2006 2Q). The hostile takeover measure was obtained from Cain, McKeon, and Solomon (2017). CEO duality source: Execucomp
TREAT_POORGOV	An indicator variable equals one for treatment firms with the below-median value of the hostile takeover index or firms with CEO-chair duality status as of the last quarter of the pre-period (2006 2Q). The hostile takeover measure was obtained from Cain, McKeon, and Solomon (2017). CEO duality source: Execucomp
Control Variables	
CFO	Cash flows from operations available from the cash flow statement scaled by the quarter-end book value of total assets of firm *i* in quarter *t*. Source: Compustat Fundamentals Quarterly
SIZE	The natural logarithm of firm *i*'s market value of equity as of the end of quarter *t*. Source: Compustat Fundamentals Quarterly
PRC_INV	The inverse of stock price. Source: CRSP

FIGURE 1: The Incremental Effect on Price Informativeness by Event Time

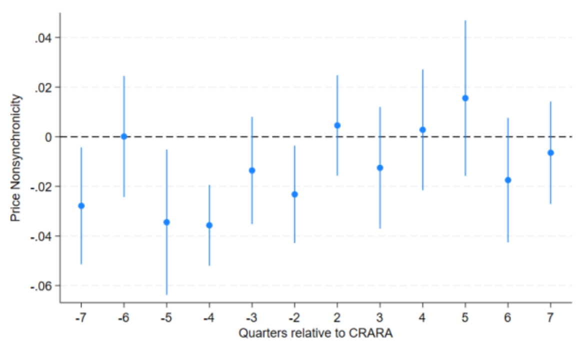
Figure 1 shows difference-in-differences coefficients on price informativeness for each event-time. In Panels (a), (b), and (c), the measures of price informativeness are PIN, illiquidity, and price non-synchronicity, respectively. We define *QTR(-7)* as an indicator variable equal to one for observations in the seven quarters before CRARA and zero otherwise. The remaining indicators are defined analogously. *QTR(-1)* and *QTR(+1)* are omitted, serving as the benchmark. The dots (lines) represent coefficient estimates (95% confidence intervals).



(a) PIN



(b) Illiquidity



(c) Price non-synchronicity

FIGURE 2: The Incremental Effect on Investment-Price Sensitivity by Event Time

Figure 2 shows difference-in-differences coefficients on investment-price sensitivity for each event-time. We define *QTR(-7)* as an indicator variable equal to one for observations in the seven quarters before CRARA and zero otherwise. The remaining indicators are defined analogously. *QTR(-1)* and *QTR(+1)* are omitted, serving as the benchmark. The dots (lines) represent coefficient estimates (95% confidence intervals).

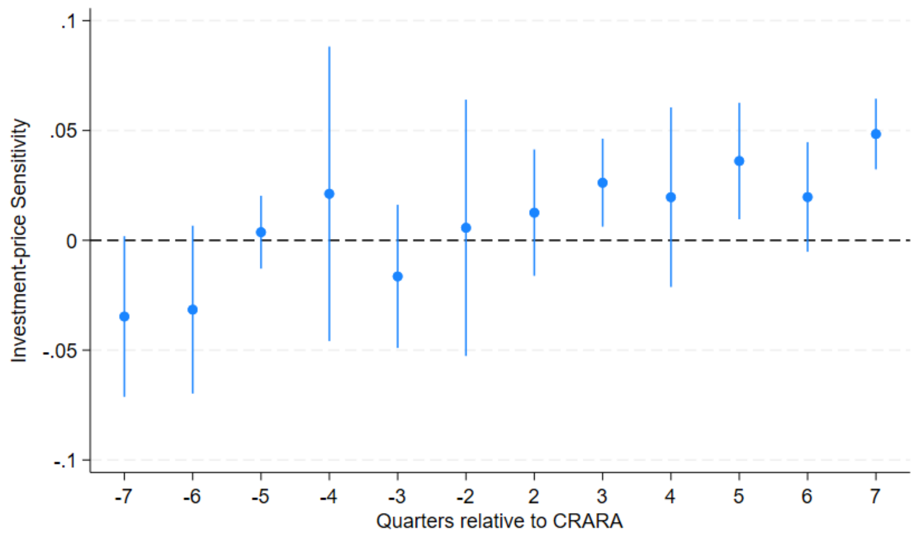
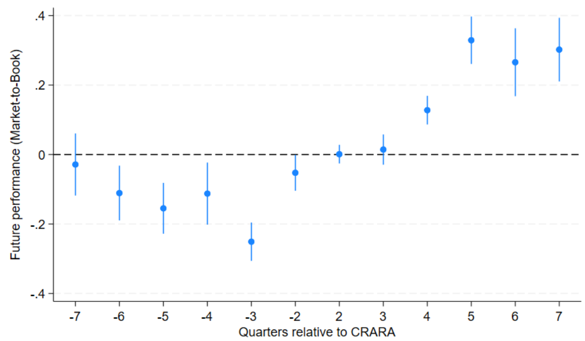
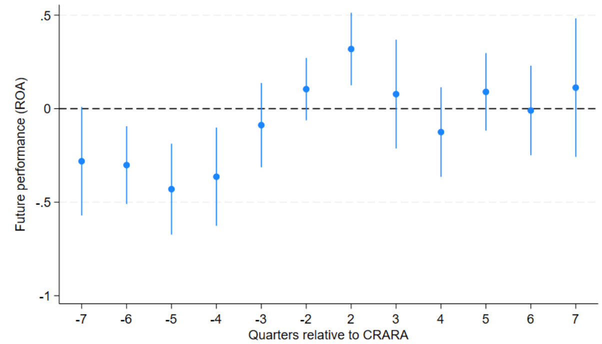


FIGURE 3: The Incremental Effect on Future Performance by Event Time

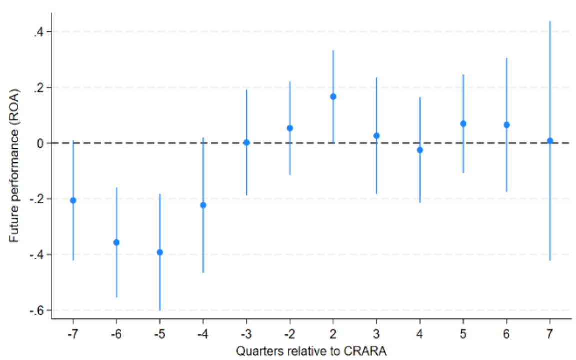
Figure 3 shows difference-in-differences coefficients on future performance for each event-time. As measures of future performance, Panels (a)–(d) use the market-to-book ratio at t+1, ROA at t+1, average ROA over t+1 and t+2, and average ROA over t+1 to t+3. We define *QTR(-7)* as an indicator variable equal to one for observations in the seven quarters before CRARA and zero otherwise. The remaining indicators are defined analogously. *QTR(-1)* and *QTR(+1)* are omitted, serving as the benchmark. The dots (lines) represent coefficient estimates (95% confidence intervals).



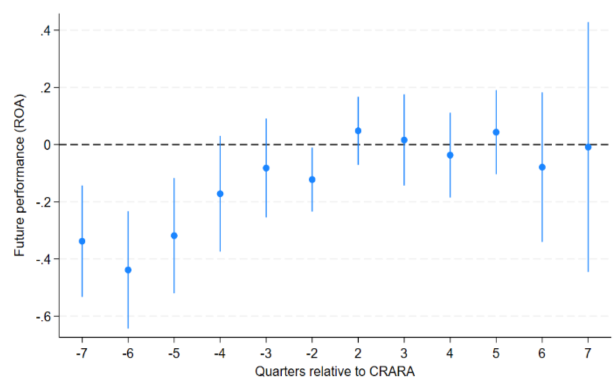
(a) Market-to-book ratio



(b) ROA_{t+1}



(c) $ROA_{[t+1, t+2]}$



(d) $ROA_{[t+1, t+3]}$

TABLE 1
The Effect of the Credit Rating Agency Reform Act on the Relation between Credit Ratings and Firm Fundamentals

Table 1 presents results examining whether the relation between changes in firm fundamentals and subsequent changes in credit ratings differs between the pre-CRARA and post-CRARA periods. The dependent variable is the change in credit rating over future horizons, denoted $\Delta Rating_{t+k}$. For k = 1, 2, and 3, $\Delta Rating_{t+k}$ measures the extent of rating change between quarter *t* and quarter *t+k*, and the independent variables are changes in firm fundamentals from quarter *t-1* to quarter *t*. Regressions are estimated using ordered logit, and reported fit statistics are McFadden (1974)'s pseudo-R^2. See Appendix B for detailed variable definitions. The t-statistics, computed using robust standard errors clustered at the two-digit SIC industry level, are presented in parentheses below the coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	$\Delta Rating_{t+1}$		$\Delta Rating_{t+2}$		$\Delta Rating_{t+3}$	
	Pre	*Post*	*Pre*	*Post*	*Pre*	*Post*
	1	2	3	4	5	6
ΔAT	0.365	2.156*	0.911	1.647*	1.359**	2.144***
	(0.361)	(1.843)	(1.154)	(1.936)	(2.072)	(3.004)
ΔBTM	0.117	-0.605	-0.481	-0.944***	-0.903***	-1.254***
	(0.247)	(-1.383)	(-1.425)	(-3.043)	(-3.175)	(-4.600)
ΔSD_ROA	-11.41	-1.643	-13.55	-10.53*	-11.99	-15.48***
	(-1.073)	(-0.216)	(-1.493)	(-1.927)	(-1.541)	(-3.445)
ΔLEV	-3.363**	-5.057***	-3.099***	-4.197***	-3.602***	-4.686***
	(-2.291)	(-4.024)	(-2.817)	(-3.949)	(-3.768)	(-5.303)
ΔRND	-4.077	2.005	-1.628	7.497	3.247	2.580
	(-0.333)	(0.185)	(-0.182)	(0.928)	(0.466)	(0.489)
ΔEARNINGS	-0.701	0.585	0.991	0.404	-0.105	0.115
	(-0.173)	(0.181)	(0.328)	(0.130)	(-0.043)	(0.055)
ΔCFO	-2.592	-2.249	-2.804**	-1.880	-1.427	-1.285
	(-1.272)	(-1.255)	(-2.346)	(-1.276)	(-1.582)	(-1.382)
LOSS	-1.087***	-1.261***	-1.150***	-1.153***	-1.087***	-1.161***
	(-4.346)	(-5.850)	(-5.286)	(-6.610)	(-5.581)	(-6.989)
ΔTIER	-0.383**	-0.067	-0.097	0.021	0.073	-0.009
	(-2.140)	(-0.394)	(-0.806)	(0.171)	(0.855)	(-0.093)
ΔCAPINT	3.049	4.854***	4.180***	3.046**	3.638**	3.086**
	(1.411)	(2.845)	(2.632)	(2.366)	(2.564)	(2.440)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3,301	3,391	3,301	3,388	3,301	3,382
Pseudo R^2	0.056	0.058	0.058	0.068	0.060	0.082

TABLE 2
The Effect of the Credit Rating Agency Reform Act on Financial Reporting Credibility

Table 2 presents the results of examining changes in financial reporting credibility around the passage of the CRARA. *CAR_3DAY* denotes abnormal return in the three-day period centering on earnings announcement dates (-1, 0, 1). *CAR_4DAY* denotes abnormal return in the four-day period centering on earnings announcement dates (-1, 0, 1, 2). *SURPRISE* denotes surprises. *TREAT* denotes rated firms that are affected by the passage of the CRARA and to zero otherwise. *POST* denotes the post-CRARA era. *PRC_INV* is the inverse of stock price. *SIZE* is a firm size. *BTM* is the book-to-market ratio. *EARNINGS* denotes a firm *i*'s earnings deflated by total assets. See Appendix B for detailed variable definitions and data sources. The sample period covers 2004 4Q – 2008 2Q. 2006 3Q (the quarter in which the CRARA was passed) is dropped. The t-statistics, computed using robust standard errors clustered at the two-digit SIC industry level, are presented in parentheses below the coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	*CAR_3DAY*	*CAR_4DAY*
	1	2
SURPRISE*TREAT*POST	**0.188****	**0.214****
	(2.013)	**(2.303)**
SURPRISE	0.231***	0.233***
	(6.813)	(6.235)
*TREAT*POST*	0.002	0.003
	(0.877)	(1.216)
*SURPRISE*TREAT*	0.054	0.077
	(0.766)	(0.848)
*SURPRISE*POST*	-0.129***	-0.110**
	(-3.605)	(-2.608)
TREAT	0.001	0.015
	(0.033)	(0.443)
SIZE	-0.043***	-0.047***
	(-7.107)	(-7.908)
PRC_INV	-0.024	-0.029
	(-1.524)	(-1.652)
BTM	0.028**	0.038***
	(2.233)	(3.015)
EARNINGS	0.064	0.064
	(1.588)	(1.403)
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Clustering	Industry	Industry
N	23,144	23,144
R^2	0.164	0.168

TABLE 3
Descriptive Statistics

Table 3 presents summary statistics for the variables used in our analyses. Panel A presents summary statistics for the full sample, and Panel B shows pre-CRARA summary statistics of treatment and control regarding variables that are used in investment-price sensitivity and informed trading analyses. The sample is comprised of 24,344 firm-quarter observations for 2,632 unique firms over the period 2004 4Q-2008 2Q, which corresponds to 7 quarters before and 7 quarters after the passage of CRARA (2006 3Q, the quarter in which CRARA was passed, is dropped). Continuous variables are winsorized at the 1st and 99th percentiles, except *CAR_3DAY* and *CAR_4DAY*. Variable definitions are provided in Appendix B. ***, **; and * in Panel B indicate the significance of the difference in means (two-tailed t-tests) and medians (Wilcoxon signed-rank tests) between treatment and control firms at the 1%, 5%, and 10% levels, respectively.

Panel A: Full sample

	Obs.	Mean	Median	SD	Min	Max
H1 (Table 4)						
PIN	22,534	14.775	12.883	7.736	1.606	42.071
NONSYNC	24,086	0.410	0.413	0.269	0.000	0.998
ILLIQUIDITY	22,534	0.037	0.003	0.115	0.000	0.875
SIZE	22,534	6.788	6.642	1.657	3.355	11.205
PRC_INV	22,534	0.100	0.049	0.139	0.010	1.020
H2 (Table 5)						
$INV_{(t+1)}$	24,344	0.330	0.090	0.786	0.000	8.563
TREAT	24,344	0.332	0.000	0.471	0.000	1.000
POST	24,344	0.507	0.000	0.500	0.000	1.000
Log(M/A)	24,344	0.295	0.291	0.757	-1.793	2.150
CFO	24,344	0.020	0.022	0.050	-0.232	0.161
SIZE	24,344	6.806	6.658	1.675	3.355	11.205
PRC_INV	24,344	0.099	0.049	0.143	0.010	1.020
Validation Tests						
SURPRISE	23,184	-0.003	0.000	0.047	-0.354	0.179
CAR_3DAY	23,184	-0.006	-0.001	0.094	-1.001	0.564
CAR_4DAY	23,184	-0.007	-0.002	0.100	-1.210	0.660

Panel B: Pre-period description

	Treatment firms		Control firms	
	Mean	Median	Mean	Median
INV	0.093***	0.052***	0.452	0.143
Log(M/A)	-0.039***	-0.034***	0.531	0.511
CFO	0.026***	0.025***	0.016	0.020
SIZE	8.079***	7.978***	6.054	5.987
PRC_INV	0.053***	0.031***	0.122	0.068
PIN	11.113***	10.090***	16.564	14.564

TABLE 4
The Effect of the Credit Rating Agency Reform Act on Stock Price Informativeness

Table 4 presents the results of examining the effect of the Credit Rating Agency Reform Act on informed trading. *PIN* denotes the probability of informed trading. *NONSYNC* denotes return non-synchronicity, calculated as the log of one minus the R^2 from firm-specific regressions of weekly stock returns on the weekly market and industry (both current and lagged) returns over the year. *ILLIQUIDITY* denotes the log of stock illiquidity. It is defined, following Amihud (2002), as the average of the ratio of daily unsigned stock returns scaled by dollar trading volume multiplied by 10^6. *TREAT* denotes firms that are affected by the passage of CRARA and to zero otherwise. *POST* denotes the post-CRARA era. *PRC_INV* is the inverse of stock price. *SIZE* is a firm size. See Appendix B for detailed variable definitions and data sources. The sample period covers 2004 4Q – 2008 2Q. 2006 3Q (the quarter in which CRARA was passed) is dropped. The t-statistics, computed using robust standard errors clustered at the two-digit SIC industry level, are presented in parentheses below the coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	*PIN*	*NONSYNC*	*ILLIQUIDITY*
	1	2	3
TREAT*POST	**1.412*** **	**0.018** **	**0.008*** **
	(6.818)	**(2.244)**	**(3.656)**
SIZE	-2.780***	-0.036***	0.337***
	(-12.19)	(-4.546)	(8.450)
PRC_INV	11.360***	0.035	-0.017***
	(7.823)	(1.426)	(-3.170)
Firm FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Clustering	Industry	Industry	Industry
N	22,534	24,086	22,534
R^2	0.744	0.600	0.770

TABLE 5
The Effect of the Credit Rating Agency Reform Act on Investment-Price Sensitivity

Table 5 presents the results of examining the effect of the Credit Rating Agency Reform Act on investment-price sensitivity. *TREAT* denotes firms that are affected by the passage of CRARA and to zero otherwise. *POST* denotes the post-CRARA era. INV_{t+1} is future investment, defined as the sum of capital expenditure and R&D expense in the quarter *t+1* scaled by the net property, plant, and equipment at the quarter *t*. *Log(M/A)* is the log of firm market capitalization scaled by total assets at the quarter *t*. *CFO* denotes cash flows from operations scaled by total assets, and *SIZE* is firm size. See Appendix B for detailed variable definitions and data sources. The sample period covers 2004 4Q – 2008 2Q. 2006 3Q (the quarter in which CRARA was passed) is dropped. The t-statistics, computed using robust standard errors clustered at the two-digit SIC industry level, are presented in parentheses below the coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	INV_{t+1}		
	1	2	3
Log(M/A)	0.100***	0.120***	0.122***
	(6.539)	(7.280)	(7.394)
CFO	0.000	0.001	-0.010
	(0.084)	(0.121)	(-1.355)
*TREAT*POST*		0.000	0.004
		(-0.090)	(0.597)
*Log(M/A)*TREAT*		-0.085***	-0.086***
		(-3.675)	(-3.737)
*Log(M/A)*POST*		-0.019***	-0.021***
		(-3.265)	(-3.265)
Log(M/A)*TREAT*POST		**0.020****	**0.022****
		(2.037)	**(2.090)**
*CFO*TREAT*			0.005
			(0.813)
*CFO*POST*			0.025
			(1.536)
*CFO*TREAT*POST*			-0.022
			(-1.516)
SIZE	-0.043**	-0.038**	-0.041**
	(-2.613)	(-2.330)	(-2.403)
Firm FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Clustering	Industry	Industry	Industry
N	24,344	24,344	24,344
R^2	0.877	0.877	0.877

TABLE 6
Cross-Sectional Tests: Types of Information Driving the Effects of the Credit Rating Agency Reform Act on Investment-Price Sensitivity

Table 6 presents the results of conducting cross-sectional tests based on types of information that drive the effect of CRARA on managerial learning from stock prices. In Panel A, we partition firms based on uncertainties where informed traders have an information advantage. In Panel B, we partition treatment firms based on the number of dimensions of uncertainties. In Panel C, we partition firms based on the managers' information set. In Models 1 and 2 of Panel A, we split the *TREAT* indicator into *TREAT_GROWTH* and *TREAT_VALUE* depending on whether the firm has above- or below-median values of market-to-book ratio as of the last quarter of the pre-period (2006 2Q). In Models 3 and 4 of Panel A, we split the *TREAT* indicator into *TREAT_HIGHCOMP* and *TREAT_LOWCOMP* depending on whether the firm has above- or below-median values of the competition measure in the last fiscal year before the passage of CRARA. In Models 1 and 2 of Panel B, we split the *TREAT* indicator into *TREAT_HIGHRISK* and *TREAT_LOWRISK* depending on whether the firm has above- or below-median values of the overall risk measure of Hassan et al. (2019) as of the last quarter of the pre-period (2006 2Q). In Models 3 and 4 of Panel B, we split the *TREAT* indicator into *TREAT_MORESEG* and *TREAT_LESSSEG* depending on whether the firm has above- or below-median values of the number of segments in the last fiscal year before the passage of CRARA. In Panel C, we partition the *TREAT* indicator into *TREAT_HIGHINSIDER* and *TREAT_LOWINSIDER,* and *TREAT_HIGHMKTSURP* and *TREAT_LOWMKTSURP* based on the pre-period median value of insider trading activities and earnings surprise. We tabulate only the relevant coefficients for brevity. See Appendix B for detailed variable definitions and data sources. The sample period covers 2004 4Q – 2008 2Q. 2006 3Q (the quarter in which CRARA was passed) is dropped. The t-statistics, computed using robust standard errors clustered at the two-digit SIC industry level, are presented in parentheses below the coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Uncertainties where Informed Investors Have an Informational Advantage

Dependent Variable =	INV_{t+1}			
	High PIN 1	*Low PIN* 2	*High PIN* 3	*Low PIN* 4
Log(M/A)*TREAT_GROWTH*POST **[a]**	**0.049****	-0.003		
	(2.275)	(-0.170)		
*Log(M/A)*TREAT_VALUE*POST* [b]	-0.006	0.021		
	(-0.440)	(0.915)		
Log(M/A)*TREAT_HIGHCOMP*POST **[a]**			**0.034****	-0.005
			(2.667)	(-0.266)
*Log(M/A)*TREAT_LOWCOMP*POST* [b]			0.009	0.012
			(0.905)	(0.718)
p-value of [a] = [b]	0.039	0.016	0.110	0.051
Controls (See Model 3 in Table 5)	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
N	11,428	11,489	10,964	11,005
R^2	0.883	0.807	0.861	0.819

Panel B. Firms Exposed to Multiple Dimensions of Uncertainties

Dependent Variable =	INV_{t+1}			
	High PIN 1	*Low PIN* 2	*High PIN* 3	*Low PIN* 4
***Log(M/A)*TREAT_HIGHRISK*POST* [a]**	**0.044****	-0.007		
	(2.459)	(-0.318)		
*Log(M/A)*TREAT_LOWRISK*POST* [b]	0.012	0.012		
	(1.051)	(0.821)		
***Log(M/A)*TREAT_MORESEG*POST* [a]**			**0.036****	0.003
			(2.524)	(0.178)
*Log(M/A)*TREAT_LESSSEG*POST* [b]			0.010	0.009
			(0.957)	(0.524)
p-value of [a] = [b]	0.022	0.076	0.084	0.342
Controls (See Model 3 in Table 5)	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
N	10,578	10,622	11,381	11,436
R^2	0.880	0.817	0.879	0.821

Panel C. Managerial Information Set

Dependent Variable =	INV_{t+1}			
	High PIN 1	*Low PIN* 2	*High PIN* 3	*Low PIN* 4
*Log(M/A)*TREAT_HIGHINSIDER*POST* [a]	0.010	-0.018		
	(0.785)	(-0.648)		
***Log(M/A)*TREAT_LOWINSIDER*POST* [b]**	**0.026****	0.006		
	(2.349)	(0.314)		
*Log(M/A)*TREAT_HIGHMKTSURP*POST* [a]			0.007	0.006
			(0.900)	(0.307)
***Log(M/A)*TREAT_LOWMKTSURP*POST* [b]**			**0.030***	0.012
			(1.818)	(0.764)
p-value of [a] = [b]	0.022	0.076	0.116	0.371
Controls (See Model 3 in Table 5)	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
N	10,578	10,622	10,923	10,936
R^2	0.880	0.817	0.872	0.809

TABLE 7
Role of Accounting Fraud Risk

Table 7 reports the results of examining whether the effect of CRARA on investment-price sensitivity varies by accounting fraud risk. We split the *TREAT* indicator into *TREAT_HIGHEQ* and *TREAT_LOWEQ* based on the pre-period median values of earnings quality proxies. For earnings quality proxies, we employ the absolute value of modified Jones discretionary accruals and the absolute value of modified Dechow-Dichev discretionary accruals. We tabulate only the relevant coefficients for brevity. See Appendix B for detailed variable definitions and data sources. The sample period covers 2004 4Q – 2008 2Q. 2006 3Q (the quarter in which CRARA was passed) is dropped. The t-statistics, computed using robust standard errors clustered at the two-digit SIC industry level, are presented in parentheses below the coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	INV_{t+1}			
Proxy for Earnings Quality =	*Discretionary Accruals (Modified Jones)*		*Discretionary Accruals (Modified Dechow-Dichev)*	
	High PIN	*Low PIN*	*High PIN*	*Low PIN*
	1	2	3	4
*Log(M/A)*TREAT_HIGHEQ*POST* [b]	0.019	0.010	0.018	0.0148
	(1.216)	(0.554)	(1.129)	(1.206)
***Log(M/A)*TREAT_LOWEQ*POST* [a]**	**0.045*****	-0.013	**0.041*****	-0.007
	(2.677)	(-0.636)	**(2.766)**	(-0.318)
p-value of [a] = [b]	0.044	0.123	0.072	0.137
Controls (See Model 3 in Table 5)	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
N	8,519	8,564	8,519	8,578
R^2	0.883	0.827	0.883	0.827

TABLE 8
Future Performance

Table 8 reports the results of examining future firm performance. Panel A presents results for the full sample, while Panel B reports results separately for firms with high and low probability of informed trading (PIN). Each panel includes four model specifications. Following Frésard (2010), we use the industry-adjusted market-to-book ratio and ROA as measures of firm performance. The dependent variable in Model 1 is the market-to-book ratio at quarter t+1; in Model 2, ROA at quarter t+1; in Model 3, the average ROA over quarters t+1 and t+2; and in Model 4, the average ROA over quarters t+1 through t+3. *TREAT* denotes firms that are affected by the passage of CRARA and equals zero otherwise. *POST* denotes the post-CRARA era. In Panel B, we split the TREAT indicator into *TREAT_HIGHPIN* and *TREAT_LOWPIN* based on whether the firm's PIN in the pre-period is above or below the sample median. SIZE denotes firm size. See Appendix B for detailed variable definitions and data sources. The sample period covers 2004 Q4 to 2008 Q2, excluding 2006 Q3 (the quarter in which CRARA was passed). The t-statistics, computed using robust standard errors clustered at the two-digit SIC industry level, are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Full Sample

Dependent Variable=	MTB_{t+1}	ROA_{t+1}	$ROA_{[t+1, t+2]}$	$ROA_{[t+1, t+3]}$
	1	2	3	4
TREAT*POST	**0.243*****	**0.003*****	**0.003*****	**0.002****
	(7.096)	**(2.908)**	**(2.741)**	**(2.399)**
SIZE	0.578***	0.009***	0.007***	0.005***
	(9.001)	(7.722)	(4.856)	(3.513)
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
N	24,330	23,645	23,541	23,414
R^2	0.803	0.776	0.810	0.834

Panel B. High vs. Low PIN Subsamples

Dependent Variable=	MTB_{t+1}	ROA_{t+1}	$ROA_{[t+1, t+2]}$	$ROA_{[t+1, t+3]}$
	1	2	3	4
***TREAT_HIGHPIN*POST* [a]**	**0.277*****	**0.004*****	**0.004*****	**0.004*****
	(7.373)	**(3.913)**	**(3.779)**	**(3.496)**
*TREAT_LOWPIN*POST* [b]	0.212***	0.001	0.001	0.001
	(5.832)	(1.357)	(0.925)	(0.499)
SIZE	0.581***	0.009***	0.007***	0.005***
	(9.053)	(7.732)	(4.879)	(3.546)
p-value of [a] = [b]	0.047	0.009	0.007	0.007
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
N	24,215	23,531	23,428	23,302
R^2	0.803	0.776	0.810	0.834

TABLE 9
Alternative Explanation: Governance

Table 9 reports the results of examining whether improved governance after CRARA is an alternative explanation. For corporate governance proxies, in Models 1 and 2, we use the hostile takeover measure of Cain, McKeon, and Solomon (2017). We split the *TREAT* indicator into *TREAT_GOODGOV (TREAT_POORGOV)* depending on whether the firm has above- (below-) median values of the hostile takeover measure as of the last quarter of the pre-period (2006 2Q). In Models 3 and 4, CEO-Chair Duality is an indicator variable that equals one if a firm's CEO is also the chairman of the board. We split the *TREAT* indicator into *TREAT_GOODGOV* and *TREAT_POORGOV* depending on a firm's CEO duality status (poor governance for duality firms). We tabulate only the relevant coefficients for brevity. See Appendix B for detailed variable definitions and data sources. The sample period covers 2004 4Q – 2008 2Q. 2006 3Q (the quarter in which CRARA was passed) is dropped. The t-statistics, computed using robust standard errors clustered at the two-digit SIC industry level, are presented in parentheses below the coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	INV_{t+1}			
Proxy for Governance =	*Hostile Takeover*		*CEO-Chair Duality*	
	High PIN	*Low PIN*	*High PIN*	*Low PIN*
	1	2	3	4
*Log(M/A)*TREAT_GOODGOV*POST* [b]	0.024*	0.008	0.017*	0.006
	(1.959)	(0.515)	(1.772)	(0.224)
*Log(M/A)*TREAT_POORGOV*POST* [a]	0.010	0.015	0.020**	0.027
	(0.749)	(0.694)	(2.306)	(1.016)
p-value of [a] = [b]	0.241	0.506	0.822	0.046
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
N	10,546	10,601	6,309	6,325
R^2	0.889	0.814	0.901	0.725

TABLE 10
Matching Analysis: Entropy Balancing

Table 10 presents the results of conducting entropy balancing. Panel A presents summary statistics and covariate distribution before and after entropy balancing between treatment firms and control firms in the quarter prior (2Q 2006) to the passage of CRARA. ***, **, and * in Panel A indicate the significance of the difference in means (t-tests) between treatment and control firms at the 1%, 5%, and 10% levels, respectively. Panel B presents the results of estimating the entropy-balance-weighted regressions. For these analyses, we only keep firms that exist in 2Q 2006 to conduct entropy balancing. *TREAT* denotes firms that are affected by the passage of CRARA and to zero otherwise. *POST* denotes the post-CRARA era. INV_{t+1} is future investment, defined as the sum of capital expenditure and R&D expense in the quarter *t+1* scaled by the net property, plant, and equipment at the quarter *t*. *Log(M/A)* is the log of firm market capitalization scaled by total assets at the quarter *t*. *CFO* denotes cash flows from operations scaled by total assets, and *SIZE* is firm size. See Appendix B for detailed variable definitions and data sources. The sample period covers 2004 4Q – 2008 2Q. 2006 3Q (the quarter in which CRARA was passed) is dropped. The t-statistics, computed using robust standard errors clustered at the two-digit SIC industry level, are presented in parentheses below the coefficients. ***, **, and * in Panel B indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Entropy Balancing on the Sample Used for Investment-Price Sensitivity Analysis

	Prior to balancing		After balancing	
	Treatment Firms	Control Firms	Treatment Firms	Control Firms
SIZE	8.110***	6.119	8.110	8.110
DEBT	0.301***	0.124	0.301	0.301
ASSETTURN	0.282	0.281	0.282	0.282
ANALYST	2.237***	1.630	2.237	2.237
RETVOL	0.021***	0.028	0.021	0.021
WW-INDEX	0.272***	0.394	0.272	0.272
HP-INDEX	-3.892***	-3.205	-3.893	-3.893

Panel B. Entropy-Balance-Weighted Regressions

Dependent Variable =		INV_{t+1}	
	1	2	3
Log(M/A)	0.057**	0.067***	0.068***
	(2.643)	(2.842)	(2.830)
CFO	-0.062	-0.046	-0.136
	(-0.648)	(-0.585)	(-1.463)
*TREAT*POST*		-0.009	-0.009
		(-0.634)	(-0.651)
*Log(M/A)*TREAT*		-0.009	-0.009
		(-0.386)	(-0.374)
*Log(M/A)*POST*		-0.033**	-0.035**
		(-2.201)	(-2.388)
Log(M/A)*TREAT*POST		**0.032****	**0.032****
		(2.183)	**(2.193)**
*CFO*TREAT*			0.063
			(0.705)
*CFO*POST*			0.150
			(1.171)
*CFO*TREAT*POST*			-0.026

			(-0.154)
SIZE	-0.027	-0.023	-0.023
	(-1.483)	(-1.211)	(-1.193)
Firm FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Clustering	Industry	Industry	Industry
N	19,735	19,735	19,735
R^2	0.768	0.768	0.769

TABLE 11
Measurement Errors in Market-Based Proxies for Investment Opportunities and Alternative Definitions of Investment Opportunities

Table 11 presents the results of examining the robustness of correcting measurement errors in market-based proxies for investment opportunities and alternative definitions of investment opportunities. To correct measurement errors, we use a method introduced by Erickson et al. (2014). For alternative definitions, we use the market value of equity scaled by total assets (*M/A*) and Tobin's *Q* as explanatory variables in Models 1 and 2, respectively. *TREAT* denotes firms affected by the passage of CRARA and to zero otherwise. *POST* denotes the post-CRARA era. INV_{t+1} is investment in quarter $t+1$ scaled by the net plant property, , and equipment at the quarter *t*. *CFO* denotes cash flows from operations scaled by total assets; *SIZE* is the log of a firm's market value of equity. The sample period covers 2004 4Q – 2008 2Q. 2006 3Q (the quarter in which CRARA was passed) is dropped. The t-statistics are presented in parentheses below the coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	INV_{t+1}	
	1	2
M/A	0.310***	
	(93.79)	
Q		0.300***
		(98.96)
CFO	-0.289***	-0.282***
	(-8.001)	(-7.821)
*TREAT*POST*	-0.122***	-0.142***
	(-6.250)	(-7.253)
*M/A*TREAT*	-0.139***	
	(-22.24)	
*M/A*POST*	-0.004	
	(-0.522)	
M/A*TREAT*POST	**0.017****	
	(1.980)	
*Q*TREAT*		-0.143***
		(-25.08)
*Q*POST*		0.002
		(0.381)
Q*TREAT*POST		**0.016****
		(2.111)
*CFO*TREAT*	1.698***	1.387***
	(3.838)	(3.119)
*CFO*POST*	-0.558	-0.611
	(-0.920)	(-1.006)
*CFO*TREAT*POST*	2.831***	3.188***
	(3.739)	(4.185)
SIZE	-0.085***	-0.085***
	(-13.68)	(-13.62)
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Clustering	Industry	Industry
N	24,195	24,129
Pseudo R^2	0.173	0.167

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ONLINE APPENDIX

Credibility of Mandatory Disclosure by Credit Rating Agencies and Market Feedback

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This online appendix provides supplementary results for the paper titled "Credibility of Mandatory Disclosure by Credit Rating Agencies and Market Feedback." First, we present results addressing potential alternative explanations for our findings, including direct learning from credit rating agencies (Table OA1), the Great Recession (Table OA2), and earnings guidance (Table OA3). Second, we present cross-sectional results using the entropy-balanced sample (Tables OA4 and OA5). Third, we present cross-sectional results using specifications that mitigate measurement error in market-based proxies (Table OA6). Finally, we present results on future firm performance using industry-unadjusted measures (Table OA7).

TABLE OA 1
Alternative Explanation: Managers Learn Directly from Credit Rating Agencies

This table examines whether managers' direct learning from credit rating agencies provides an alternative explanation for the main results. In Models (1) and (2), *INSIDER* is the natural log of the management's selling and buying during the quarter scaled by total assets. In Models (3) and (4), *MKTSURP* is an earnings surprise measure following Chen et al. (2007). It is measured as the absolute abnormal stock returns in the three-day period centering on quarterly earnings announcement dates. Abnormal return is measured as the natural logarithm of one plus the actual return of *i* on day *d* minus the natural logarithm of one plus the expected return of firm *i* on day *d*. Expected returns are estimated using a market model, which is estimated from 90 calendar days prior to the quarterly earnings announcement date to 28 calendar days prior to the quarterly earnings announcement date. We start 90 days before the earnings announcement date to avoid any effect of the previous quarterly earnings announcement and estimate until 28 days before the quarterly earnings announcement date to prevent any anticipation of upcoming earnings surprises.

Dependent Variable =	*INSIDER*		*MKTSURP*	
	1	2	3	4
TREAT*POST	**0.082**	**-0.007**	**0.000**	**-0.001**
	(1.385)	**(-0.123)**	**(0.219)**	**(-0.445)**
SIZE		0.319***		0.005
		(4.318)		(0.994)
RET_QTR		0.185		-0.006
		(1.654)		(-0.578)
ROA		-0.014**		-0.008***
		(-2.021)		(-2.692)
RETVOL		10.080***		0.0015***
		(6.267)		(2.964)
ILLIQUIDITY		-0.038		0.351***
		(-0.203)		(5.498)
BTM		-1.056***		-0.016***
		(-3.921)		(-4.150)
EARNINGS		2.022***		-0.013
		(4.598)		(-1.579)
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
N	24,344	24,202	23,291	23,154
R^2	0.336	0.350	0.251	0.257

TABLE OA 2
Alternative Explanation: The Great Recession

This table reports the results of examining the Great Recession as an alternative explanation. In Panel A, we report the results from estimating difference-in-differences regressions concerning debt financing around the CRARA. *Debt financing* is defined as cash proceeds from the issuance of long-term debt in the quarter *t*, deflated by lagged total assets. In Panel B, we provide the results of estimating the entropy-balance-weighted regression of equation (1). We reweight firms based on three input variables that we used to construct a financial constraint index (the WW index of Whited and Wu (2006), the HP index of Hadlock and Pierce (2010), and the inverse of market capitalization) in the quarter prior to the passage of the CRARA. We tabulate only the relevant coefficients for brevity. The sample period covers 2004 4Q – 2008 2Q. 2006 3Q (the quarter in which the CRARA was passed) is dropped. The t-statistics, computed using robust standard errors clustered at the two-digit SIC industry level, are presented in parentheses below the coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Debt financing

Dependent Variable =	*Debt Financing*
TREAT*POST	**-0.003**
	(-0.884)
Log(M/A)	0.008***
	(4.257)
CFO	-0.000
	(-0.372)
SIZE	-0.001
	(-1.432)
PRC_INV	0.006
	(1.027)
Firm FE	Yes
Year-Quarter FE	Yes
Clustering	Industry
N	24,229
R^2	0.349

Panel B. Matched on financial constraint measures

Dependent Variable =	INV_{t+1}
Log(M/A)*TREAT*POST	**0.033****
	(2.212)
Controls (See Model 3 in Table 5)	Yes
Firm FE	Yes
Year-Quarter FE	Yes
Clustering	Industry
N	19,419
R^2	0.759

TABLE OA 3
Alternative Explanation: Controlling for Voluntary Earnings Guidance

This table reports the results of examining voluntary earnings guidance as an alternative explanation. *GUIDANCE* is an indicator variable equal to one if a firm provides earnings guidance in a given quarter and zero otherwise. INV_{t+1} is future investment, defined as the sum of capital expenditure and R&D expense in the quarter *t+1* scaled by the net property, plant, and equipment at the quarter *t*. *Log(M/A)* is the log of firm market capitalization scaled by total assets at the quarter *t*. *CFO* denotes cash flows from operations scaled by total assets. The sample period covers 2004 4Q – 2008 2Q. 2006 3Q (the quarter in which the CRARA was passed) is dropped. The t-statistics, computed using robust standard errors clustered at the two-digit SIC industry level, are presented in parentheses below the coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	INV_{t+1}
Log(M/A)	0.123***
	(7.401)
CFO	-0.0100
	(-1.321)
*TREAT*POST*	0.014*
	(1.843)
*Log(M/A)*TREAT*	-0.087***
	(-3.844)
*Log(M/A)*POST*	-0.021***
	(-3.226)
Log(M/A)*TREAT*POST	**0.024****
	(2.290)
*CFO*TREAT*	0.005
	(0.773)
*CFO*POST*	0.024
	(1.476)
*CFO*TREAT*POST*	-0.022
	(-1.447)
SIZE	-0.041**
	(-2.450)
GUIDANCE	0.003
	(0.370)
*GUIDANCE*TREAT*	0.004
	(0.359)
*GUIDANCE*POST*	0.009
	(0.967)
*GUIDANCE*TREAT*POST*	-0.019
	(-1.511)
Firm FE	Yes
Year-Quarter FE	Yes
Clustering	Industry
N	24,344
R^2	0.877

TABLE OA 4
Cross-Sectional Tests using Entropy-Balanced Sample: Types of Information Driving the Effects of the Credit Rating Agency Reform Act on Investment-Price Sensitivity

This table presents the results of conducting cross-sectional tests based on types of information that drive the effect of the CRARA on managerial learning from stock prices with the entropy-balanced sample. Treatment and control are reweighted based on firm size, level of debt, asset turnover, number of analysts, return volatility, and financial constraint measures (WW-index and HP-index) in the last quarter before the passage of CRARA. In Panel A, we partition firms based on uncertainties where informed traders have an information advantage. In Panel B, we partition treatment firms based on the number of dimensions of uncertainties. In Panel C, we partition firms based on the managers' information set. In Models (1) and (2) of Panel A, we split the *TREAT* indicator into *TREAT_GROWTH* and *TREAT_VALUE* depending on whether the firm has above- or below-median values of market-to-book ratio as of the last quarter of the pre-period (2006 2Q). In Models (3) and (4) of Panel A, we split the *TREAT* indicator into *TREAT_HIGHCOMP* and *TREAT_LOWCOMP* depending on whether the firm has above- or below-median values of the competition measure in the last fiscal year before the passage of the CRARA. In Models (1) and (2) of Panel B, we split the *TREAT* indicator into *TREAT_HIGHRISK* and *TREAT_LOWRISK* depending on whether the firm has above- or below-median values of the overall risk measure of Hassan et al. (2019) as of the last quarter of the pre-period (2006 2Q). In Models (3) and (4) of Panel B, we split the *TREAT* indicator into *TREAT_MORESEG* and *TREAT_LESSSEG* depending on whether the firm has above- or below-median values of the number of segments in the last fiscal year before the passage of the CRARA. In Panel C, we partition the *TREAT* indicator into *TREAT_HIGHINSIDER* and *TREAT_LOWINSIDER,* and *TREAT_HIGHMKTSURP* and *TREAT_LOWMKTSURP* based on the pre-period median value of insider trading activities and earnings surprise. We tabulate only the relevant coefficients for brevity. The sample period covers 2004 4Q – 2008 2Q. 2006 3Q (the quarter in which the CRARA was passed) is dropped. The t-statistics, computed using robust standard errors clustered at the two-digit SIC industry level, are presented in parentheses below the coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Uncertainties where informed investors have an informational advantage

Dependent Variable =	INV_{t+1}			
	High PIN	*Low PIN*	*High PIN*	*Low PIN*
	1	2	3	4
***Log(M/A)*TREAT_GROWTH*POST* [a]**	**0.041***	0.000		
	(1.849)	(0.010)		
*Log(M/A)*TREAT_VALUE*POST* [b]	-0.016	0.023		
	(-0.740)	(1.428)		
***Log(M/A)*TREAT_HIGHCOMP*POST* [a]**			**0.009**	0.001
			(0.637)	(0.042)
*Log(M/A)*TREAT_LOWCOMP*POST* [b]			0.006	0.016
			(0.423)	(1.656)
p-value of [a] = [b]	0.088	0.203	0.825	0.104
Controls (See Model 3 in Table 5)	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
N	8,875	9,842	9,031	9,909
R^2	0.794	0.752	0.788	0.752

TABLE OA 4 (continued)
Cross-Sectional Tests using Entropy-Balanced Sample: Types of Information Driving the Effects of the Credit Rating Agency Reform Act on Investment-Price Sensitivity

Panel B. Firms that are exposed to multiple dimensions of uncertainties

Dependent Variable =	INV_{t+1}			
	High PIN	*Low PIN*	*High PIN*	*Low PIN*
	1	2	3	4
***Log(M/A)*TREAT_HIGHRISK*POST* [a]**	**0.035***** **(2.747)**	-0.002 (-0.117)		
*Log(M/A)*TREAT_LOWRISK*POST* [b]	0.002 (0.143)	0.019* (2.003)		
***Log(M/A)*TREAT_MORESEG*POST* [a]**			**0.019** **(1.464)**	0.006 (0.594)
*Log(M/A)*TREAT_LESSSEG*POST* [b]			0.010 (0.957)	0.009 (0.524)
p-value of [a] = [b]	0.036	0.065	0.284	0.205
Controls (See Model 3 in Table 5)	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
N	8,735	9,439	9,171	10,093
R^2	0.796	0.748	0.789	0.752

Panel C. Managerial information set

Dependent Variable =	INV_{t+1}			
	High PIN	*Low PIN*	*High PIN*	*Low PIN*
	1	2	3	4
*Log(M/A)*TREAT_HIGHINSIDER*POST* [a]	0.017 (1.302)	-0.042 (-1.297)		
***Log(M/A)*TREAT_LOWINSIDER*POST* [b]**	**0.033***** **(3.936)**	0.001 (0.045)		
*Log(M/A)*TREAT_HIGHMKTSURP*POST* [a]			0.004 (0.282)	0.008 (0.728)
***Log(M/A)*TREAT_LOWMKTSURP*POST* [b]**			**0.017** **(1.520)**	0.013 (1.229)
p-value of [a] = [b]	0.142	0.258	0.364	0.520
Controls (See Model 3 in Table 5)	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
N	6,964	6,654	9,068	9,996
R^2	0.851	0.780	0.794	0.752

TABLE OA 5
Role of Accounting Fraud Risk Analysis using Entropy-Balanced Sample

This table reports the results of examining whether the effect of the CRARA on investment-price sensitivity varies by accounting fraud risk with the entropy-balanced sample. Treatment and control are reweighted based on firm size, level of debt, asset turnover, number of analysts, return volatility, and financial constraint measures (WW-index and HP-index) in the last quarter before the passage of CRARA. We split the *TREAT* indicator into *TREAT_HIGHEQ* and *TREAT_LOWEQ* based on the pre-period median values of earnings quality proxies. For earnings quality proxies, we employ the absolute value of modified Jones discretionary accruals and the absolute value of modified Dechow-Dichev discretionary accruals. We tabulate only the relevant coefficients for brevity. The sample period covers 2004 4Q – 2008 2Q. 2006 3Q (the quarter in which the CRARA was passed) is dropped. The t-statistics, computed using robust standard errors clustered at the two-digit SIC industry level, are presented in parentheses below the coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	INV_{t+1}			
Proxy for Earnings Quality =	*Discretionary Accruals (Modified Jones)*		*Discretionary Accruals (Modified Dechow-Dichev)*	
	High PIN	*Low PIN*	*High PIN*	*Low PIN*
	1	2	3	4
*Log(M/A)*TREAT_HIGHEQ*POST* [b]	0.033***	0.013	0.031**	0.018
	(2.738)	(0.913)	(2.557)	(1.617)
***Log(M/A)*TREAT_LOWEQ*POST* [a]**	**0.068*** **	-0.009	**0.063*** **	-0.010
	(3.794)	(-0.632)	**(3.759)**	(-0.671)
p-value of [a] = [b]	0.029	0.140	0.032	0.047
Controls (See Model 3 in Table 5)	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
N	6,984	6,821	6,984	6,835
R^2	0.731	0.769	0.731	0.769

TABLE OA 6
Cross-Sectional Tests Mitigating Measurement Errors in Market-Based Proxies

This table presents the results of cross-sectional tests based on the types of information that drive the effect of the CRARA on managerial learning from stock prices, mitigating measurement error in market-based proxies using the method introduced by Erickson et al. (2014). For alternative proxies, we use the market value of equity scaled by total assets (*M/A*) and Tobin's *Q*, defined as the ratio of the market value of equity plus the book value of debt to total assets. Panels A1, B1, and C1 use *M/A* as the market-based proxy, while Panels A2, B2, and C2 use Tobin's *Q*. In each panel, we examine heterogeneous effects of CRARA based on firm characteristics. In Panel A, we partition firms based on the nature of uncertainty where informed traders have an information advantage. In Models (1) and (2) of A1 and A2, we split the *TREAT* indicator into *TREAT_GROWTH* and *TREAT_VALUE* based on whether the firm's market-to-book ratio as of the last quarter of the pre-period (2006Q2) is above or below the median. In Models (3) and (4), we split *TREAT* into *TREAT_HIGHCOMP* and *TREAT_LOWCOMP* based on the firm's competition measure in the last fiscal year before CRARA. In Panel B, we examine variation in the number of uncertainty dimensions. In Models (1) and (2) of B1 and B2, we split *TREAT* into *TREAT_HIGHRISK* and *TREAT_LOWRISK* based on the overall risk measure of Hassan et al. (2019) as of 2006 Q2. In Models (3) and (4), we split *TREAT* into *TREAT_MORESEG* and *TREAT_LESSSEG* based on the number of business segments in the last fiscal year before CRARA. Panel C partitions firms based on the managers' information set. Specifically, we split the *TREAT* indicator into *TREAT_HIGHINSIDER* and *TREAT_LOWINSIDER*, and *TREAT_HIGHMKTSURP* and *TREAT_LOWMKTSURP*, based on pre-period medians of insider trading activity and earnings surprises, respectively. We tabulate only the relevant coefficients for brevity. The sample period covers 2004 Q4 to 2008 Q2, excluding 2006 Q3 (the quarter in which the CRARA was passed). The t-statistics, computed using robust standard errors clustered at the two-digit SIC industry level, are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A1. Results using M/A - Uncertainties where informed investors have an informational advantage

Dependent Variable =	INV_{t+1}			
	High PIN 1	*Low PIN* 2	*High PIN* 3	*Low PIN* 4
M/A*TREAT_GROWTH*POST **[a]**	0.084***	0.036		
	(3.343)	(1.270)		
*M/A*TREAT_VALUE*POST* [b]	-0.053	-0.009		
	(-1.381)	(-0.168)		
M/A*TREAT_HIGHCOMP*POST **[a]**			0.060***	-0.004*
			(6.566)	(-1.889)
*M/A*TREAT_LOWCOMP*POST* [b]			-0.027	-0.007
			(-1.378)	(-0.634)
p-value of [a] = [b]	0.008	0.521	0.000	0.803
Controls (See Model 3 in Table 5)	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
N	11,524	11,529	11,279	11,286
R^2	0.007	0.014	0.004	0.003

TABLE OA 6 (continued)
Cross-Sectional Tests Mitigating Measurement Errors in Market-Based Proxies

Panel A2. Results using Q - Uncertainties where informed investors have an informational advantage

Dependent Variable =	INV_{t+1}			
	High PIN	*Low PIN*	*High PIN*	*Low PIN*
	1	2	3	4
***Q*TREAT_GROWTH*POST* [a]**	0.026	0.058**		
	(1.170)	(2.262)		
*Q*TREAT_VALUE*POST* [b]	-0.045	0.003		
	(-1.319)	(0.063)		
***Q*TREAT_HIGHCOMP*POST* [a]**			0.126***	0.039
			(4.669)	(1.272)
*Q*TREAT_LOWCOMP*POST* [b]			-0.075	-0.047
			(-1.274)	(-1.110)
p-value of [a] = [b]	0.133	0.416	0.003	0.148
Controls (See Model 3 in Table 5)	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
N	11,495	11,496	11,064	11,060
R^2	0.005	0.014	0.002	0.015

Panel B1. Results using M/A - Firms that are exposed to multiple dimensions of uncertainties

Dependent Variable =	INV_{t+1}			
	High PIN	*Low PIN*	*High PIN*	*Low PIN*
	1	2	3	4
***M/A*TREAT_HIGHRISK*POST* [a]**	0.093***	0.060**		
	(3.507)	(2.219)		
*M/A*TREAT_LOWRISK*POST* [b]	-0.007	-0.026		
	(-0.159)	(-0.636)		
***M/A*TREAT_MORESEG*POST* [a]**			0.107***	0.064**
			(4.131)	(2.280)
*M/A*TREAT_LESSSEG*POST* [b]			-0.113*	-0.045
			(-1.844)	(-1.104)
p-value of [a] = [b]	0.073	0.129	0.001	0.055
Controls (See Model 3 in Table 5)	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
N	10,718	10,730	11,524	11,524
R^2	0.007	0.012	0.005	0.013

TABLE OA 6 (continued)
Cross-Sectional Tests Mitigating Measurement Errors in Market-Based Proxies

Panel B2. Results using Q - Firms that are exposed to multiple dimensions of uncertainties

Dependent Variable =	INV_{t+1}			
	High PIN	*Low PIN*	*High PIN*	*Low PIN*
	1	2	3	4
***Q*TREAT_HIGHRISK*POST* [a]**	0.120***	0.067**		
	(4.478)	(2.259)		
*Q*TREAT_LOWRISK*POST* [b]	-0.076	-0.019		
	(-1.049)	(-0.445)		
***Q*TREAT_MORESEG*POST* [a]**			0.056**	0.038
			(2.356)	(1.551)
*Q*TREAT_LESSSEG*POST* [b]			-0.116*	-0.033
			(-1.918)	(-0.885)
p-value of [a] = [b]	0.015	0.155	0.009	0.167
Controls (See Model 3 in Table 5)	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
N	10,689	10,702	11,343	11,343
R^2	0.007	0.012	0.004	0.015

Panel C1. Results using M/A - Managerial information set

Dependent Variable =	INV_{t+1}			
	High PIN	*Low PIN*	*High PIN*	*Low PIN*
	1	2	3	4
*M/A*TREAT_HIGHINSIDER*POST* [a]	-0.507***	-0.022		
	(-10.07)	(-0.859)		
***M/A*TREAT_LOWINSIDER*POST* [b]**	0.018	0.006		
	(0.677)	(0.140)		
*M/A*TREAT_HIGHMKTSURP*POST* [a]			-0.004	0.046
			(-0.265)	(1.639)
***M/A*TREAT_LOWMKTSURP*POST* [b]**			0.016	-0.066*
			(0.399)	(-1.702)
p-value of [a] = [b]	0.000	0.456	0.674	0.047
Controls (See Model 3 in Table 5)	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
N	8,615	8,627	11,596	11,600
R^2	0.008	0.012	0.007	0.013

TABLE OA 6 (continued)
Cross-Sectional Tests Mitigating Measurement Errors in Market-Based Proxies

Panel C2. Results using Q - Managerial information set

Dependent Variable =	INV_{t+1}			
	High PIN 1	*Low PIN* 2	*High PIN* 3	*Low PIN* 4
*Q*TREAT_HIGHINSIDER*POST* [a]	0.195***	-0.017		
	(4.224)	(-0.639)		
***Q*TREAT_LOWINSIDER*POST* [b]**	-0.043	-0.081		
	(-1.230)	(-1.482)		
*Q*TREAT_HIGHMKTSURP*POST* [a]			0.001	0.031
			(0.044)	(1.150)
***Q*TREAT_LOWMKTSURP*POST* [b]**			0.026	-0.074*
			(0.733)	(-1.719)
p-value of [a] = [b]	0.000	0.360	0.571	0.047
Controls (See Model 3 in Table 5)	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
N	8,593	8,601	11,567	11,566
R^2	0.005	0.012	0.007	0.013

TABLE OA 7
Future Performance (Using Industry-Unadjusted Measures)

This table reports the results of examining future firm performance (Table 8 of our main draft) using industry-unadjusted measures. Panel A presents results for the full sample, while Panel B reports results separately for firms with high and low probability of informed trading (PIN). Each panel includes four model specifications. The dependent variable in Model (1) is the market-to-book ratio at quarter t+1; in Model (2), ROA at quarter t+1; in Model (3), the average ROA over quarters t+1 and t+2; and in Model (4), the average ROA over quarters t+1 through t+3. *TREAT* denotes firms that are affected by the passage of the CRARA and equals zero otherwise. *POST* denotes the post-CRARA era. In Panel B, we split the TREAT indicator into *TREAT_HIGHPIN* and *TREAT_LOWPIN* based on whether the firm's PIN in the pre-period is above or below the sample median. SIZE denotes firm size. See Appendix B for detailed variable definitions and data sources. The sample period covers 2004 Q4 to 2008 Q2, excluding 2006 Q3 (the quarter in which the CRARA was passed). The t-statistics, computed using robust standard errors clustered at the two-digit SIC industry level, are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Whole sample

Dependent Variable =	MTB_{t+1}	ROA_{t+1}	$ROA_{[t+1,\ t+2]}$	$ROA_{[t+1,\ t+3]}$
	(1)	(2)	(3)	(4)
TREAT*POST	0.244***	0.003***	0.002**	0.002**
	(7.088)	(2.888)	(2.643)	(2.294)
SIZE	0.583***	0.009***	0.006***	0.005***
	(8.973)	(7.901)	(4.870)	(3.537)
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
N	24,330	23,645	23,541	23,414
R^2	0.826	0.806	0.833	0.852

Panel B. High vs. Low PIN Subsamples

Dependent Variable =	MTB_{t+1}	ROA_{t+1}	$ROA_{[t+1,\ t+2]}$	$ROA_{[t+1,\ t+3]}$
	(1)	(2)	(3)	(4)
***TREAT_HIGHPIN*POST* [a]**	0.277***	0.004***	0.004***	0.004***
	(7.360)	(3.917)	(3.677)	(3.331)
*TREAT_LOWPIN*POST* [b]	0.213***	0.001	0.001	0.000
	(5.849)	(1.320)	(0.859)	(0.417)
SIZE	0.586***	0.009***	0.007***	0.005***
	(9.025)	(7.914)	(4.894)	(3.571)
p-value of [a] = [b]	0.0488	0.009	0.008	0.009
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
N	24,215	23,531	23,428	23,302
R^2	0.826	0.806	0.833	0.852