Mandatory Disclosure by Credit Rating Agencies and Investment Sensitivity to Stock Price: A Managerial Learning Perspective

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ABSTRACT

We study the effect of mandatory disclosure by credit rating agencies (CRAs) on investment-price sensitivity. We use the Credit Rating Agency Reform Act (CRARA) in 2006 as a mandatory disclosure setting for CRAs and find an increase in investment-price sensitivity for firms affected by the CRARA. In line with the CRARA alleviating investors' concern about firm-specific accounting fraud risk, the increase is more pronounced among firms suspected to engage in more earnings management. The sensitivity of investment to stock prices is also more marked among firms with multiple dimensions of uncertainty, firms with higher growth options, firms facing steeper competition, or firms in which managers are less privately informed. Our findings are consistent with managers' reliance on stock prices increasing when stock prices become more informative to managers' investment decisions after the CRARA. Corroborating improved investment efficiency, we further find an increase in future profitability for firms affected by the CRARA.

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The press and politicians often express the need for more precise public information following financial turmoil and market failure, allowing capital market participants to reduce information asymmetry and thus make more informed and efficient decisions (e.g., the Sarbanes-Oxley Act and the Dodd-Frank Act). While prior research provides evidence on the benefits of mandatory disclosures in financial markets such as reducing the cost of capital (e.g., see Leuz and Wysocki (2016), Goldstein and Yang (2017) for a review), recent literature provides more nuanced evidence on the economic consequences of new disclosure regulations. 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 thus impeding managers' ability to learn from the market (see Section I for the literature review).[1]

Our contribution to this nascent research is twofold. First, financial intermediaries provide useful information to capital market participants (e.g., Kothari, So, and Verdi (2016)), and regulatory efforts to improve investors' confidence about the precision and credibility of such information (e.g., the Credit Rating Agency Act and MiFID II) have been reinforced overtime (e.g., Skreta and Veldkamp (2009), White (2010), Goldstein and Yang (2019)). However, the real effects of regulations toward financial intermediaries via market feedback have drawn little attention, and we fill this void by studying a regulation directed toward credit ratings provided by credit rating agencies (CRAs). We provide evidence that the effect of mandatory disclosures on investment efficiency via market feedback critically hinges on the specific attributes of the information being disclosed (e.g., Goldstein and Yang (2019)). We assess the potential that CRAs' mandatory disclosure concerning firms' creditworthiness complements information production by informed traders, thus increasing price-based learning, while extant evidence supports that firm

[1] See e.g., Goldstein and Yang (2017), Jayaraman and Wu (2019), Goldstein, Yang, and Zuo (2020), and Bird, Karolyi, Ruchti, and Truong (2020).

mandatory disclosure substitutes for informed traders' private information production, resulting in a decrease in managerial learning (e.g., Jayaraman and Wu (2019), Goldstein, Yang, and Zuo (2020)).

Goldstein and Yang (2019) develop a model of two types of uncertainties in which disclosures are made by a third-party, and capital providers are decision makers. In their model, decision makers know more about one uncertainty (i.e., the known factor), but know less about the other uncertainty relative to the market as a whole (i.e., the unknown factor) and thus want to learn from the market.[2] Informed traders collect and trade on information about two types of uncertainties, and two sources of information are substitutes, suggesting that more disclosure about the known factor leads informed traders to collect more information on the unknown factor and vice versa.

We extend Goldstein and Yang's (2019) model to a case in which decision makers are firm managers and disclosures are made by credit rating agencies. In this case, if credit ratings provided by CRAs are primarily concerned with the known factor, including firm-specific information such as product quality, technology, and firm-specific creditworthiness, which Goldstein and Yang (2019) name "good disclosure", more accurate ratings can encourage informed traders to shift their focus to producing more private information about the unknown factor, including industry-distress risk, industry competition, consumer demand, the geopolitical environment and economy-wide factors. We expect this shift to improve real efficiency by facilitating managerial learning. In

[2] It is also pertinent to note that the learning from the market channel does not necessarily require an assumption that managers are less informed than the market as a whole. Rather, to the extent that managers are not *perfectly* informed about all aspects of firm value, information in prices has the potential to guide managerial actions (see Bond, Edmans, and Goldstein (2012) for a review of this literature). The idea that managers glean information useful to their decisions from stock prices is also supported by survey evidence. In response to Goldstein, Liu, and Yang's (2021) survey, about three-quarters of firms that answered to closely follow own stock prices report that learning information from prices is the primary reason.

contrast, if CRA disclosures were primarily concerned with the unknown factor, which Goldstein and Yang (2019) refer to as "bad disclosure," informed traders likely spend more resources producing information that is already known to managers, thus impeding real efficiency via a reduction in market feedback. Thus, the effect of CRA disclosures on real efficiency via managerial learning depends on whether such disclosure is a type of "good disclosure" versus "bad disclosure" and we take this prediction to the data.

We use the U.S. Credit Rating Agency Reform Act (CRARA) in 2006 as the setting for our tests (Section I.C. for details). Following several high-profile bankruptcies and the subsequent revelation of accounting frauds including Enron and WorldCom, major CRAs came under severe criticism as Enron's bonds were rated investment grade until a few days before Enron filed for bankruptcy. In response to this call, Congress passed the CRARA on September 29, 2006 to restore the reputation of CRAs and build up investor confidence in their ratings by enhancing the accountability of CRAs rather than changing the content of credit ratings.

Our premise underlying this setting is that the CRARA improves investors' *perception* of the quality of credit ratings as a precise and reliable source of *firm-specific* creditworthiness, namely accounting fraud risk rather than industry and market-wide distress. There is strong evidence in support of this premise. Huang, Kraft, and Wang (2019) show that credit rating agencies downgrade firms that are subsequently shown to have engaged in accounting fraud, pointing to credit rating agencies' ability to detect accounting fraud in advance. Supporting the notion that the CRARA increases the (perceived) quality of credit ratings as a reliable source of fraud risk, Sethuraman (2019) documents that the stock market reactions to changes in credit ratings increased after the passage of the CRARA.

The increased credibility of credit ratings as a source of firms' accounting fraud risk will allow investors to collect more information about uncertainties that are new to managers (i.e., the unknown factor), thus improving investment efficiency. In the pre-CRARA era, during which credit ratings were a noisy signal of accounting fraud risk, informed traders such as institutional investors likely had to assess such risk on their own, as suggested by Hribar, Jenkins, and Wang (2004), while scaling back information production of factors that are less known to firm managers such as the geopolitical environment for multinationals (e.g., Goldstein and Yang (2015)). If the CRARA improves the credibility of ratings, and investors place a higher weight on those ratings, consistent with the findings in Sethuraman (2019), then we expect them to shift more resources to produce information about uncertainties that are useful to managers' decisions. This substitution between two sources of information in stock prices will increase investment efficiency via improved managerial learning.

We test our prediction using a sample of firms that are rated by major credit rating agencies as the treatment group and unrated firms as the control group around the passage of the CRARA. Specifically, we follow prior research (e.g., Foucault and Frésard (2014), Bai, Philippon, and Savov (2016)) and use the investment-price sensitivity framework, where we regress future investment on current-period price. In a difference-in-differences design, we find a more marked increase in investment-price sensitivity for treatment firms relative to control firms. [3] In falsification tests, we find neither similar results using lagged investment (past investment) nor any change in the sensitivity of future investment to current cash flow, a non-price measure of investment opportunities.

[3] We also examine parallel-trends in the treatment effect. The results suggest that the investment-price sensitivity is indifferent between treatment and control groups in the pre-CRARA era.

While suggestive of price-based learning, the results are subject to some concerns. First, we cannot directly test whether the increase in investment-price sensitivity is due to informed traders producing more (less) private information about unknown (known) factor into prices because such information in prices is unobservable. Second, treatment (i.e., rated firms) and control (i.e., unrated firms) groups are different in many aspects particularly accessibility to capital markets. As with prior studies (Foucault and Frésard (2014), Edmans, Jayaraman, and Schneemeier (2017)), we substantiate our inference by addressing whether the investment-price sensitivity varies by firm-level characteristics that correlate with substitution between investors' information production about the known and unknown factors. Evidence on within-treatment variation helps mitigate concerns of uncontrolled heterogeneity between treatment and control firms.

We begin by validating the claim that the CRARA mitigates investors' concerns about accounting fraud risk, which was heightened following the high-profile accounting scandals that largely gave rise to the CRARA. If this claim is valid, we predict a more pronounced increase in investment-price sensitivity among firms that are suspected of engaging in earnings management in the pre-CRARA era because informed traders potentially substitute the information production of factors new to managers and away from assessing fraud risk. To test this prediction, we differentiate between firms with high and low levels of discretionary accruals (a proxy for earnings management).[4] Indeed, the investment-price sensitivity is higher when firms exhibit high accounting fraud risk in the pre-CRARA era.

[4] We run this test (also all cross-sectional tests described below) separately for subsamples with high and low amounts of informed trading because price-based learning occurs dominantly among firms with active informed trading (e.g., Chen et al. (2007)). In support of this claim, we find a statistically significant increase in investment-price sensitivity for firms with more informed trading, whereas the result for firms with low informed trading is insignificant (un-tabulated).

Further, we exploit the idea that informed traders' information advantage lies in assessing growth opportunities vis-à-vis assets-in-places, and factors such as competition and product demand vis-à-vis production technology (e.g., Gao and Liang (2013), Jayaraman and Wu (2019), Goldstein and Yang (2019), Goldstein et al. (2020)). In the post-CRARA era, if prices become more informative with respect to investment decisions for firms with greater growth opportunities and firms facing steeper competition, then we expect the investment-price sensitivity associated with the passage of the CRARA will be stronger for those firms. We find results in support of this prediction.

Another implication of learning models with disclosure is that managerial learning from prices is especially important when firms are exposed to, and informed traders need to collect, multiple dimensions of information (e.g., Goldstein and Yang (2015, 2019)). Relative to managers of domestic firms, managers of multinationals are unlikely perfectly informed about all dimensions of uncertainties including the geopolitical and macroeconomic environment of multiple regions, and private information in prices impounded by informed traders is a likely a more useful signal to decision makers. Consistent with this implication, we find a more pronounced increase in investment-price sensitivity when firms have more segments (both geographical and business) and more risks. Learning models also suggest that managers' incentives to learn from prices decline with their own information (e.g., Chen, Goldstein, and Jiang (2007), Gao and Liang (2013), Foucault and Frésard (2014)). Indeed, we find a stronger increase in investment-price sensitivity when managers have a poor managerial information set. Taking all the cross-sectional heterogeneity results together, the results substantiate our inference that the increase in investment-price sensitivity is due to price-based learning, and also helps mitigate concerns about omitted variable bias (i.e., time-varying events concurrent with the passage of the CRARA).

An increase in investment sensitivity implies more efficient investment, but is not a direct test of investment efficiency. We follow prior studies (Jayaraman and Wu (2019), Goldstein et al. (2020)) and also examine the effect of the CRARA on future profitability. We find that treatment firms experience an increase in future performance, measured by return on assets, and this effect is more pronounced for firms with higher informed trading. This result corroborates our inference that the increase in investment sensitivity in the post-CRARA era is indicative of improved efficiency rather than a symptom of agency problems such as empire-building.

Finally, we explore several alternative explanations. First, one may be concerned that investment-price sensitivity increased because the CRARA eased financing frictions for firms with credit ratings. We mitigate this concern by comparing financially constrained and unconstrained treatment firms. We find a more pronounced increase among *unconstrained* firms. This result is in line with the learning-based explanation that unconstrained firms' investment is more responsive to changes in information in prices that is newly available to managers (e.g., Jayaraman and Wu (2019)). Second, the financial crisis of 2008 can also be an alternative explanation in that firms with credit ratings (i.e., treatment firms) are less adversely affected by the crisis, exhibiting relatively higher investment-price sensitivity. We address this concern in several ways. First, as discussed, our cross-sectional tests show predictable heterogeneity in the treatment effect, which is hard to reconcile with the confounding effect of the financial crisis of 2008. Second, we repeat our main tests after dropping all observations in 2008 and find the results hold. Third, we use entropy balancing (e.g., Hainmueller (2012)) to identify control firms that have similar levels of financial constraints as treatment firms in the pre-CRARA period. Our main inferences remain unaffected using this alternative research design. Finally, we examine debt financing as a falsification test, and find little difference in debt financing between treatment and control firms around the passage of the CRARA.

Our study makes two important contributions. First, we demonstrate the real effects of mandatory disclosures provided by financial intermediaries, credit rating agencies, via a managerial learning channel. In contrast, prior studies focus exclusively on disclosures provided by firms (e.g., Jayaraman and Wu (2019), Goldstein et al. (2020)). Our evidence is important to assess the economic consequences of increasing regulatory efforts directed at public information provided by financial intermediaries (e.g., Skreta and Veldkamp (2009), White (2010, 2013), Goldstein and Yang (2019)).[5] Second, our findings that regulations designed to boost investors' confidence in credit ratings as a source of firm-level creditworthiness improves firms' investment efficiency contrast with prior evidence on the adverse effects of mandatory firm disclosures and dissemination on managerial learning (e.g., Jayaraman and Wu (2019), Goldstein et al. (2020)). These contrasting findings highlight that the real effects of mandatory disclosure likely depend upon the nature of the disclosure being considered. This knowledge should be helpful to policymakers in considering the implications of future changes in firm disclosure requirements or information provided by financial intermediaries for firms' investment via a market feedback effect channel.

I. Related Literature, Conceptual Framework, Setting, and Hypothesis

A. Related Literature

Dating back to Hayek (1945), economists are aware market prices are a key source of information for real decision makers (e.g., managers). This information is delivered to the manager via price formation, thereby providing price-based feedback to managerial decisions. Studies term

[5] The analyst industry has also experienced increasing regulation over the past two decades (e.g., Reg FD, the Global settlement, and MiFID II).

this as managerial learning or market feedback (Bond, Edmans, and Goldstein (2012), Chen et al. (2007), Jayaraman and Wu (2019)). Recent theories on the real effects of disclosures via the interaction with market feedback suggest that public disclosures released by firms discourage or encourage informed traders' incentives to produce private information, which may be useful to managers in guiding their investment decisions (e.g., Goldstein and Yang (2017) for a review).

Our study is related to the growing literature that empirically investigates these implications. Jayaraman and Wu (2019) use the mandatory change to segment disclosures (SFAS 131) and 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 decreasing investment efficiency via reduced market feedback. Further, Goldstein et al. (2020) explore the real effects of mandated dissemination of public information by using the staggered implementation of the SEC's EDGAR system. Goldstein et al. (2020) find a decrease in investment-price sensitivity, with a stronger effect for firms with more growth opportunities. Although Goldstein et al. (2020) focus on mandatory dissemination as opposed to disclosure, their findings point to a similar conclusion that reducing informed traders' information advantage via more timely dissemination of public information reduces managerial learning from stock prices.[6]

As discussed in the introduction, our study extends these papers in a few ways. First, we examine how mandatory disclosures by credit rating agencies, a third-party to the firm, affect the firm's investment efficiency via the managerial learning channel. Second, we address the implication from recent theories that whether mandatory disclosures facilitate or impede

[6] Bird et al. (2020) use the same setting and draw similar inferences as Goldstein et al. (2020). In contrast, Hillegeist, Kausar, Kraft, and Park (2020) find that mandatory reporting frequency is positively associated with investment-price sensitivity over the period 1951-1974

managerial learning from stock prices ultimately depends upon the type of information being disclosed (e.g., Goldstein and Yang (2019)).

B. Theoretical Framework

Disclosure theories with managerial learning assume that, while managers are arguably the most informed economic agent about sources of uncertainty that drive firm value, they are not perfectly informed about all sources and thus wish to learn from outsiders (Bai et al. (2016)). Going back to at least Hayek (1945), market prices such as stock prices are believed to aggregate information that is otherwise dispersed among outsiders. Informed traders in stock markets have incentives to acquire and trade on private information as long as expected profits outweigh the associated costs (e.g., Glosten and Milgrom (1985), Kyle (1985)). Traders' private information gets into stock prices via the trading process, and managers can glean the information from prices to guide their investment decisions.[7] In such scenarios, disclosure can encourage or hinder managerial learning from stock prices by stimulating or impeding the private information production of informed traders (e.g., Goldstein and Yang (2019)). Studies discussed in the previous section provide evidence supporting the *negative* consequences of mandatory disclosures on managerial learning via their dampening impact on private information production.

However, how mandatory disclosures influence investment efficiency via managerial learning from the market likely depends on the nature of the disclosure being mandated (e.g., Goldstein and Yang (2019)). Goldstein and Yang (2019) describe a model in which information is disclosed by a third-party, such as credit rating agencies, the decision makers are capital providers, and there exist two dimensions of factors. Goldstein and Yang (2019) assume that the future firm

[7] For example, Luo (2005) finds that firms are more likely to withdraw from the announced M&A when the stock market responds more negatively to an M&A announcement (see Bond et al. (2012) for a review of this literature). Also, see Goldstein, Liu, and Yang's (2021) for survey evidence.

value is a function of these two types of information that real decision makers can use: a factor, about which decision makers know better than the market (i.e., *the known factor*) and a factor, about which decision makers have more limited knowledge than the market and want to learn from prices (i.e., *the unknown factor*). In Goldstein and Yang's (2019) framework, informed traders incur costs to acquire information about both factors, and the known and unknown factors are substitutes.

We extend the implications of Goldstein and Yang (2019) to a case in which the decision makers are firm managers who want to glean value-relevant information from stock prices in making investment decisions, and disclosures are made by credit rating agencies. If information about one factor is "freely" disclosed by credit rating agencies, informed traders spend more (less) resources acquiring information about the other factor (the disclosed factor), namely substitution between information production about the known factor and the unknown factor. Under these scenarios, the effect of the provision of information by CRAs on managerial learning depends upon the type of information contained in credit ratings. If credit ratings provide information about the known factor, informed traders acquire more information about the unknown factor from which managers can learn to improve investment decisions. In contrast, if the type of information being disclosed by CRAs concerns the unknown factor, informed traders acquire more (less) information about the known (unknown) factor, which obstructs managerial learning.[8] It is ex ante difficult to ascertain whether information by credit ratings is the type of information that managers know better than the market (the known factor) or the type of information that the market has

[8] Information about the known factor includes firm-specific information such as product quality, technology, and idiosyncratic creditworthiness, accounting information, and corporate events, while the unknown factors include industry-distress risk, industry competition, and economy-wide factors including general macroeconomic conditions and economic policy uncertainty (e.g., Goldstein and Yang (2019)).

comparative advantage at (the unknown factor).[9] Rather, it likely depends on the nature of disclosure being regulated as well as the circumstances leading to a specific regulation. In the next section, we describe our empirical setting and develop our hypothesis specific to the setting.

C. Setting and Hypothesis

We select the Credit Rating Agency Reform Act (CRARA) in 2006 as our setting. Credit rating agencies (CRAs) are viewed as gatekeepers in capital markets primarily by providing opinions on the creditworthiness of firms that seek debt financing. Standard and Poor's state: "Credit ratings are opinions about credit risk. 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…Ratings are provided by credit rating agencies which specialize in evaluating credit risk…" In support of the economic significance of credit ratings, prior studies show that credit ratings affect various firm policies including capital structure decisions and access to credit markets (Kisgen (2006), Tang (2009)).

However, the CRAs' role as a gatekeeper has been called into question. In the wake of high-profile accounting frauds in 2002 (e.g., the Enron scandal), some pundits pointed to inaccurate, untimely credit ratings as one of the main causes of the Enron crisis and called for regulatory actions. (Coskun (2008), Skreta and Veldkamp (2009)). Subsequently, the SEC's investigation and several congressional and senate hearings pointed out that CRAs were inattentive to fundamental problems, like questionable transactions in 10-Ks and suspect accounting in determining ratings (Coskun (2008)). Severe criticism regarding conflicts of interest and abusive practice in the credit rating industry undermined the reputation of major CRAs. Accordingly,

[9] Credit ratings are generally a function of both firm-specific creditworthiness, and industry- and market-wide factors. See S&P's guide to credit rating manual: https://www.spglobal.com/ratings/_division-assets/pdfs/guide_to_credit_rating_essentials_digital.pdf

investors raised severe concern that credit ratings are not a precise and reliable source of creditworthiness for firms, eventually leading to the passage of the CRARA. The CRARA is designed to bolster accountability of CRAs, provide sufficient information of inputs to the rating process to the SEC and the public, and increase competition among CRAs. However, the CRARA does not directly regulate the content in credit ratings (Coskun (2008)).

At the time the CRARA was passed, investors' concerns about firms' accounting fraud risk were elevated after a number of notable high-profile accounting fraud scandals. The CRARA was implemented to mitigate these concerns, at least to some extent. In support of this objective, Sethuraman (2019) finds a marked increase in the stock market reactions to rating changes, suggesting investors place a greater weight on rating changes after the passage of the CRARA. Higher reliance on credit ratings as a credible signal of accounting fraud risk likely allows informed traders to spend fewer resources assessing firms' fraud risk on their own and instead more resources evaluating other factors such as investment opportunities, industry competition, and the geopolitical environment. Because managers already know well their own accounting fraud risk, but care to learn more about the latter factors, the shift in information production by informed traders will motivate managers to rely more on price signals in making investment decisions after the CRARA. Further, this reliance on prices will be more pronounced among firms with higher exposure to uncertainties about which the market as a whole likely has a comparative information advantage (e.g., firms with higher growth opportunities and firms that are exposed to multiple dimensions of uncertainties). This discussion leads to our hypothesis:

Hypothesis 1: Investment-price sensitivity increases after the passage of the Credit Rating Agency Reform Act of 2006.

II. Data and Research Design

A. 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, probability of informed trading (PIN) data from Brown and Hillegeist (2007), and earnings guidance data from I/B/E/S. Our sample covers the period surrounding the passage of the CRARA Act and comprises firm-quarters between October 1, 2004, and Jun 30, 2008. We drop the third quarter of 2006, the quarter in which the CRARA was signed into law (September 29th, 2006). This leads to seven quarters each for both pre- and post-CRARA period. We stop our sample at the second quarter of 2008 to avoid the effects of the Great Recession of 2008. We then exclude all firms that belong to the financial and utility industries (SIC codes 6000-6999 and 4900-4999, respectively), which leaves 49,701 firm-quarter observations. Then, we delete observations without necessary information to calculate variables for our analyses, leading to a sample of 24,344 firm-quarter observations. Sample size also varies across cross-sectional tests due to the availability of additional partitioning variables including PIN.

We categorize a firm as a treatment firm if the firm is rated by Standard & Poor's, a major rating agency that has been impacted by the CRARA, and if a firm is not rated by Standard & Poor's, the firm is categorized as a control firm.[10] The control firms consist of firms that depend only on equity financing, unrated public debt, private debt, or public debt rated by rating agencies that are less likely to be affected by the CRARA. This leads to 8,075 firm-quarter observations for the treatment group and 16,269 observations for the control group. It is pertinent to note that by construction treatment and control groups differ across many dimensions particularly accessibility

[10] According to Himmelberg and Morgan (1995) and Sethuraman (2019), most bond and commercial paper issues are rated by Standard & Poor's.

to public capital markets. Since this heterogeneity can confound our inference, we run a battery of robustness and falsification tests in Section IV.

B. Research Design and Variable Definitions

To examine our main hypothesis, we compare changes in investment-price sensitivity before and after the passage of the CRARA for the treatment group, relative to the control group. Following prior studies (Bai et al. (2016), Edmans et al. (2017), Jayaraman and Wu (2019)) we measure investment-price sensitivity in a generalized difference-in-differences design by estimating the following equation with firm subscripts omitted:

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

Where INV_{t+1} denotes future investment, defined as the sum of capital expenditures and research and development expenditures at year t+1, scaled by fixed assets at year t. *TREAT* is set equal to one for treatment firms and to zero otherwise. *POST* is set equal to one for the quarters after the CRARA, and to zero otherwise. 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. 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. *CFO* is a non-price-based measure of a firm's investment opportunity. *SIZE* is firm size measured by the natural log of the market value of equity. See the Appendix for variable definitions. Our coefficient of interest is β_6. If investment-price sensitivity increases for treatment firms relative to control firms after the passage of the CRARA, we expect β_6 to be positive.

Table I presents the descriptive statistics of the full sample, where we find the mean value of investment, *INV*, is 33% of lagged total assets. 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 millions. The mean *TREAT* is 0.332, suggesting that about one third of firm-quarter observations are treated (i.e., have with credit ratings).

INSERT TABLE I

III. Results

A. Effect of the CRARA on Investment-Price Sensitivity

We present the results of estimating equation (1) in Table II. 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* following the specification of Jayaraman and Wu (2019). We standardize *Log(M/A)* and *CFO* by, for each variable, subtracting its sample mean and scaling by its standard deviation, to infer the coefficient as a marginal effect of one standard deviation. The coefficient on *Log(M/A)* is 0.124 (p-value<0.01), demonstrating that future investment increases by 12.4% in response to one standard deviation increase in a price-based measure of investment opportunities. The estimate is similar to that of prior studies (e.g., Jayaraman and Wu (2019)).

INSERT TABLE II

Model 2 shows the impact of the 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 in the post-CRARA period. We interpret these results as preliminary evidence that managers increase their dependency on stock prices to guide their investment decisions because of more private information in stock prices that they wish to learn after the passage of the CRARA.

In Model 3, we include a non-price-based measure for investment opportunities (variables interacted with *CFO*) and find an insignificant coefficient on *CFO*TREAT*POST*. Not only does this result strengthen the price-based learning channel, but also mitigates the confounding effect of time-varying investment opportunities. To further provide corroborating evidence, in Models 4-6, we present our results using past investment (INV_{t-1}) as a dependent variable. If the positive coefficient on *Log(M/A)*TREAT*POST* is indeed due to managerial learning from prices, we expect no results using past investment because managers cannot learn from information that is yet to be impounded into prices. The results support our prediction.

The parallel trends assumption is key to the identification of the effect of the disclosure regulation change (i.e., the CRARA) on investment-price sensitivity in a generalized difference-in-differences design (Roberts and Whited (2013)). We assume both the treatment and control groups would have experienced similar trends in investment-price sensitivity, absent the CRARA. Although formally testing this assumption is impossible, we take the advice of Roberts and Whited (2013) and evaluate trends in investment-price sensitivity around the passage of the CRARA.

To test this assumption, we follow prior studies (e.g., Jayaraman and Wu (2019)) and partition the *POST* indicator into several indicators to separate periods surrounding the passage of the CRARA. We define *QUARTER(t-4, t-3)* as an indicator variable equal to one for observations in the four or three quarters before the CRARA, and to zero otherwise. Remaining quarter indicators are defined analogously. We do not include an indicator variable denoting the three quarters at the beginning of the pre-CRARA era, and they serve as the benchmark. We then estimate regressions similar to Model 3 of Table III, with relevant coefficients tabulated only.

In Figure 1, we plot the five coefficient estimates for investment-price sensitivity along with 95% confidence intervals to facilitate visual inspection. Investment-price sensitivity appears to increase two quarters after the passage of the CRARA, suggesting that it took a few quarters until managers' investment decisions responded to newly available private information in prices, in line with the finding of Jayaraman and Wu (2019) (presumably due to adjustment costs). In general, we interpret the results from Figure 1 as indicating parallel trends in the pre-treatment period.

INSERT FIGURE 1

B. Ex Post Validation Test: Does the CRARA Concern Firm-Specific Creditworthiness?

The premise underlying our hypothesis is that while informed traders collect information to assess firm-level accounting fraud risk on their own, they are able to reduce information production about fraud risk after the passage of the CRARA, which allows them to produce more information about factors that may guide investment decisions. Validating this claim ex ante is infeasible because the private information in stock prices is unobservable. We circumvent this problem by estimating an ex post validation test. Specifically, we assess whether the increase in investment-price sensitivity is more pronounced for firms that appear to be engaged in more earnings management, which we label high earnings management (EM) firms.

Our expectation is based on the circumstances leading up to the passage of CRARA. In the early 2000s, credit rating agencies' failure to downgrade the credit ratings of firms that were revealed to engage in accounting fraud (e.g., Enron and WorldCom scandals) damaged their reputation as a credible and reliable source of information about firms' accounting fraud risk. In the absence of this information source, we anticipate investors were likely to spend more time and effort assessing firms' accounting fraud risk on their own, and as such, devote fewer resources to collecting information about other aspects of firm value. If the CRARA restores the reputation of CRAs, and thus increases investor confidence in ratings, investors will begin to acquire less information about firms' fraud risk and more information about factors that may be new to firm managers. We expect this substitution to be most pronounced for firms that appear to be engaged in earnings management, where investors were likely devoting relatively more time and effort in assessing the likelihood of fraud risk prior to the CRARA. Consequently, we expect firms that appear to be engaged in more earnings management will exhibit a greater increase in investment-price sensitivity post CRARA.

To capture the extent to which firms engage in earnings management, we follow prior studies (e.g., Bergstresser and Philippon (2006), Ahmed et al. (2020)) and use three measures of earnings management. We use working capital accruals and two versions of discretionary accruals as proxies for earnings management.[11] First, we use the modified Jones discretionary accruals, measured as the absolute value of residuals from the Dechow, Sloan, and Sweeney (1995) model augmented by including nonlinear performance and growth controls (Kothari, Leone, and Wasley (2005), Collins, Pungaliya, and Vijh (2017)). Second, we use the 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.[12] See the Appendix for detailed measurements of these variables.

To test our prediction, we split the *TREAT* indicator into two indicators representing treatment firms with above-median (*TREAT_HIGHEM*) and below-median (*TREAT_LOWEM*) values of the three earnings management proxies, respectively. Then, we modify equation (1) by interacting these indicators with *POST* and *Log(M/A)* to assess the differential treatment effect on

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[11] We follow Hribar and Collins (2002) and calculate working capital accruals from the statement of cash flows.

[12] Subsequent to high-profile accounting scandals in the early- to mid-2000s, investors were concerned not only about income-increasing earnings management but also about income-decreasing earnings management (i.e., big bath accounting) since both types of earnings management hinder investors from assessing the true creditworthiness of firms. Thus, we use the absolute values of discretionary accruals as a proxy for earnings management (e.g., Bergstresser and Philippon (2006)).

investment-price sensitivity between high versus low EM firms. 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 prior studies show that managerial learning is more pronounced when informed trading is high (e.g., Chen et al. (2007)).[13]

INSERT TABLE III

Table III presents the results. The results support our prediction that the treatment effect is present for firms with greater earnings management, especially when there is active informed trading. The coefficients on *Log(M/A)*TREAT_HIGHEM*POST* of the high *PIN* group (Models 1, 3, and 5) are 0.030, 0.045, and 0.041 and significant at the 5% level or higher, whereas the corresponding coefficients for low EM firms are insignificant. The differences in the two coefficients between high and low EM subgroups are statistically significant at the 5% level for Models 1 and 2 and at the 10% level for model 3. In sum, these results validate our claim that the CRARA assuages investors' concern about firm-specific creditworthiness.

C. Cross-Sectional Tests

Although the increase in investment-price sensitivity provides initial evidence on the effect of the CRARA on managerial learning, the results in Table II could be attributable to time-varying correlated omitted factors during the sample period. This is especially so because we cannot observe the private information in prices not to mention its types. In this section, we mitigate this concern by exploring whether the treatment effect varies by firm-characteristics that correlate with managerial learning around the passage of the CRARA.

C.1. Uncertainties Where Investors' Have an Informational Advantage

[13] In an untabulated test, we also find a more pronounced increase in investment-price sensitivity for firms with high levels of PIN. The results are available upon request.

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 (e.g., policy uncertainty) (Bai et al. (2016), Goldstein and Yang (2019), Goldstein et al. (2020)). We thus predict that the passage of the CRARA facilitates managerial learning to a larger extent among firms about which investors as a whole tend to have an information advantage relative to managers. Prior studies posit that growth opportunities and product market competition are the type of uncertainties that investors' informational advantage lies with (e.g., Jayaraman and Wu (2019), Goldstein et al. (2020)). We follow Goldstein et al. (2020) and use firm's 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 (1) by interacting these indicators with *POST* and *Log(M/A)* to examine the varied treatment effect between growth and value firms.

Since competition is multi-faceted, we rely on both industry-level and firm-level measures of competition. Specifically, we use industry concentration (HHI) and 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 *(TEAT_LOWCOMP)* values of this competition measure. Then, we interact these indicators with *POST* and *Log(M/A)* to examine the variant treatment effect between firms with high and low competition.

We present our results in Panel A of Table IV. 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 are different 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 two subsamples is insignificant at the conventional level (p-value=0.110). Overall, the results support the notion that the increase in investment-price sensitivity is due to learning.

INSERT TABLE IV

C.2. Firms that Are Exposed to Multiple Dimensions of Uncertainties

Learning models assume that firm value is exposed to multiple dimensions of uncertainties, about which informed traders acquire private information to make profits from trading on the acquired information (Goldstein and Yang (2015, 2019)). This assumption suggests that the effect of the CRARA on investment-price sensitivity is likely more pronounced among firms with multi-dimensional uncertainties. We employ two proxies to capture multi-dimensional uncertainties. First, we use the overall risk that each firm is exposed to. To measure each firm's overall risk, we exploit the overall risk measure developed by Hassan, Hollander, van Lent, and Tahoun (2019), which assess a firm's overall risk by counting the number of risk-related words from 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. 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."

Similar to 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 *TREAT* indicator into two indicators denoting treatment firms with above-median (*TREAT_MORE_SEG*) and below-median (*TREAT_LESS_SEG*) values of the total number of segments. Then, we modify equation (1) by interacting these indicators with *POST* and *Log(M/A)*.

We present the results in Panel B of Table IV. 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 are statistically different from each other at p-value=0.022. Models (3) and (4) present the heterogenous treatment effect with respect to the number of segments. The coefficient on *Log(M/A)*TREAT_MORE_SEG*POST* of the high *PIN* group is positive and significant at the 5% level, whereas the coefficient on *Log(M/A)*TREAT_LESS_SEG*POST* is insignificant. The differences in coefficients between the two groups are significant (p-value=0.084). Taken together, these results reinforce our inferences from our main result of an increase in investment-price sensitivity due to price-based learning.

C.3. Managers' Own Information Set

The previous cross-sectional tests exploit firm characteristics that are associated with an increase in information in prices that is useful to managers' 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 the trading process (e.g., Bai et al. (2016)). Prior studies show that managers' own information moderates their reliance on market feedback (Chen et al. (2007), Bai et al. (2016), Jayaraman and Wu (2020)). This suggests that the increase in investment-price sensitivity associated with the CRARA will be muted when managers are privately more informed about the sources of uncertainty affecting firm value.

To test this prediction, we follow prior research (e.g., Chen et al. (2007), Jayaraman and Wu (2020)) and use the number of shares bought and sold by CEOs and CFOs in the pre-CRARA era as a proxy for managers' private information (*INSIDER*). Similar to the above cross-sectional tests, we split the *TREAT* indicator into two indicators denoting treatment firms with above-median (*TREAT_HIGHINSIDER*) and below-median (*TREAT_LOWINSIDER*) values of insider trading. Then, we modify equation (1) by interacting these indicators with *POST* and *Log(M/A)* to examine the heterogenous treatment effect between firms with high and low managers' information set.

We present the result in Panel C of Table IV. 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 the coefficient for firms with high insider trading (*Log(M/A)*TREAT_HIGHINSIDER*POST*) is insignificant. The two coefficients are different at p-value=0.084. These results indicate that managers' private information set moderates the positive effects of the CRARA on managers' reliance on price signals. Taken together, all the cross-sectional findings substantiate our inferences that the increase in investment-sensitivity documented in Table II is due to a price-based learning mechanism, and helps mitigate the concern that the increase is due to time-varying omitted variables.

D. Future Performance

Although an increase in investment-price sensitivity indicates an improvement in real efficiency, it is not a direct gauge. Following prior studies on managerial learning (Chen et al. (2007), Jayaraman and Wu (2019)), we test for an improvement in firms' future performance to add further support to the impact of managerial learning on real efficiency. If a price-based measure entails richer information that is new to managers in the post-CRARA era, we expect an increase in firms' future performance as managers rely more on stock prices. We measure future performance with average ROA over the next three quarters (ROA_{t+3}) and regress it on *TREAT*POST* and *SIZE*.

Table V presents the results. We find a significant increase in firm performance in the next three quarters (p-value <0.01). In Model 2 of Table V, we split treatment firms into high *PIN* and low *PIN* subsamples because managers' reliance on stock prices as a source of information to guide investment decisions is stronger for firms with more informed trading (e.g., Chen et al. (2007)). The results are in line with our prediction. The coefficient on *TREAT_HIGHPIN*POST* is 0.353 and significant at the 1% level, whereas the coefficient on *TREAT_LOWPIN*POST* is insignificant. The difference between the two coefficients is statistically significant (*p*-value=0.057). Overall, the results provide support for the proposition that mandatory disclosure by credit rating agencies in the context of the CRARA improves real efficiency via a managerial learning channel.

INSERT TABLE V

IV. Alternative Explanations

All the findings thus far point to managerial learning as a mechanism by which investment-price sensitivity increases for firms affected by the CRARA. In this section, we further rule out a few alternative explanations. First, we assess the validity of an alternative explanation that the increase in investment-price sensitivity associated with the CRARA is driven by easing of financing constraints in the post-CRARA era. Second, we evaluate the differential accessibility to capital markets between treatment and control firms during the Great Recession of 2008 as another alternative explanation.

A. Eased Financing Constraints

An alternative explanation is that the CRARA relaxed financial constraints by improving investor confidence in credit ratings, and that these eased financing constraints contributed to an increase in investment-price sensitivity. To assess the validity of this explanation, we follow prior studies (e.g., Edmans et al. (2017), Jayaraman and Wu (2019)) and conduct a falsification test that exploits financial constraints. If the channel by which the sensitivity increased is eased financing constraints, we expect to observe a more marked increase in the investment-price sensitivity for financially constrained firms. The intuition is that if the CRARA improves the credibility of credit ratings publicly available to the capital providers (e.g., such as banks or equity investors), constrained firms will be able to better exploit investment opportunities after the passage of the CRARA. In contrast, if managerial learning is the primary mechanism, we expect the opposite is true: a more pronounced increase in the sensitivity for unconstrained firms. This is because prior studies have shown that unconstrained firms are better able to adjust their investment with regards to price-based signals (e.g., Chen et al. (2007), Edmans et al. (2017), Bakke and Whited (2010), Jayaraman and Wu (2019)).

To test this prediction, we need a proxy for financial constraints. Given the difficulty of measuring financial constraints, we follow Li (2011) and construct a proxy based on average ranks of three commonly used measures: the WW index of Whited and Wu (2006), the HP index of

Hadlock and Pierce (2010), and the inverse of market capitalization. Similar to the above cross-sectional tests, we split the full sample into high *PIN* and low *PIN* groups. Then, we rank treatment firms into quintiles based on each measure and take the average of the ranks to construct a composite measure of financial constraints. Next, we partition the treatment group into financially constrained (above median) and unconstrained firms (below median) based on the median value of the composite measure.

Table VI presents the results. The coefficient on *Log(M/A)*TREAT_UNCONS*POST* of the high *PIN* group is 0.035 and statistically significant (p-value<0.05), whereas that of financial constrained firms is insignificant. The insignificant coefficient for constrained firms is inconsistent with the explanation that relaxed financing constraints are driving the increase in investment-price sensitivity. Rather, the more pronounced increase in the investment-price sensitivity for unconstrained firms offers further support to price-based learning as a key mechanism.

INSERT TABLE VI

B. The Differential Accessibility to Capital Markets between Treatment and Control Firms during the Great Recession

Another alternative explanation is that our results are driven by the financial crisis of 2008. The Great Recession significantly limited firms' ability to access capital markets especially for firms with no credit ratings (Duchin, Ozbas, and Sensoy (2010)). In this scenario, investment-price sensitivity increases for firms with credit ratings relative to firms with no credit ratings. This explanation seems to pose a threat because, by construction, rated firms comprise our treatment group and unrated firms comprise our control group.

We alleviate this concern in various ways. First, we already show cross-sectional variations within treatment firms, consistent with price-based learning. For the Great Recession to be a viable explanation, it should limit access to credit capital to a greater extent among firms with credit ratings only when they are suspected to engage in *less* earnings management; have lower growth options; face *weak* competition; are exposed to a *smaller* number of uncertainties and risks; are characterized by *better* managers' information set. Some scenarios are counter-intuitive: the Great Recession should have a more severe impact on firms with high accounting fraud risk, high competition, and a higher number of risks. Second, to minimize the effect of the Great Recession, we drop all observations in 2008 from the post-CRARA period and repeat our main tests. The results hold.

Next, we identify control firms that have similar levels of financial constraints as treatment firms in the pre-CRARA era and repeat our main tests. Specifically, we use entropy balancing to reweight control firm-quarters based on three input variables that we used to construct a financial constraint index in the previous section (the WW index of Whited and Wu (2006), the HP index of Hadlock and Pierce (2010), and the inverse of market capitalization) and Altman's Z-Score in the quarters prior to the passage of the CRARA to ensure treatment and control samples have the same level of financial constraints just prior to the passage of the CRARA (Hainmuller (2012)). We assign weights to control firms across the remaining quarters in the panel. We repeat Model (3) of Table II (i.e., a full specification) by estimating entropy-balance-weighted regression models of equation (1) and report the results in Table VII. Our inferences remain unaffected. The coefficient on *Log(M/A)*TREAT*POST* is positive and significant at the 5% level. Overall, we conclude the Great Recession is unlikely to drive our results.

INSERT TABLE VII

Finally, we run a falsification test using financing activities as the outcome variable. If the Great Recession is responsible for investment-price sensitivity associated with the CRARA, we should observe that treatment firms (i.e., rated firms) "enjoy" greater access to external capital than control firms (i.e., unrated firms). To test this prediction, we run model (1) of Table II by replacing investment with financing variables and report the results in Table VIII. Across the board, we find no evidence supporting the assertion that differential access to capital market drives investment-price sensitivity associated with the CRARA. In sum, several falsification tests along with cross-sectional tests in previous sections point in the same direction. The increase in investment-price sensitivity for rated firms around the CRARA is unlikely due to either eased financial constraints or the Great Recession.

INSERT TABLE VIII

V. Conclusion

This paper examines the real effects of mandatory disclosure by credit rating agencies via the managerial learning channel. In a difference-in-differences design using the U.S. Credit Rating Agency Reform Act (CRARA) in 2006 as a setting, we provide the following findings. First, we observe an increase in investment-price sensitivity for treatment firms relative to control firms. The increase is more pronounced for firms that are suspected to engage in greater earnings management, growth firms, firms confronting steeper competition, firms with multiple uncertainties, and firms with poorer managerial information sets. These results are consistent with price-based learning. Supporting investment efficiency, affected firms' future profitability increases. Additional analyses show that neither relaxed financing constraints nor the Great Recession explain our results. We contribute to the literature by testing how mandatory disclosures by *credit rating agencies*, a financial intermediary, affect real efficiency via the managerial learning channel as opposed to existing evidence concerned with mandatory disclosures by *firms*. Our results also suggest that whether mandatory disclosures hinder or improve managerial learning from stock prices depends on the nature of the information being disclosed, as opposed to extant studies pointing to the adverse effect of mandatory firm disclosures on real efficiency (Jayaraman and Wu (2019), Goldstein et al. (2020)).

We add several caveats. First, we are subject to the inherent challenge that information in stock prices, not to mention information types, is unobservable. As such, our findings are subject to the possibility that correlated omitted factors are responsible for our results, and should not be viewed as identifying the causal effects of the CRARA on investment-price sensitivity. Nonetheless, the extensive evidence of within-treatment variations, and the detailed assessment of alternative explanations provide support to price-based learning. Second, we highlight that the real effects of mandatory disclosures either by firms and intermediaries is context specific. Thus, we believe that our results should be interpreted in the context of the CRARA, and a different conclusion can 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. Finally, we cannot completely rule out the possibility that our results are driven by managers directly learning from credit rating agencies. This explanation is unlikely because in the rating process CRAs obtain some information directly from managers, and thus managers are well informed about their own firms' fraud risk conveyed by credit ratings. In this case, the CRARA simply increases the credibility of credit ratings with respect to investors, and less likely expands the managers' information set. Nonetheless, given that the managers' information set is unobservable, we cannot completely rule out this explanation.

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Appendix
Variable Definitions and Data Sources

Outcome Variables	
INV_{t+1}	Future investment measured as the sum of capital expenditures and research and development (R&D) expense for firm *i* in quarter *t+1* scaled by the net property, plant, and equipment as of the end of quarter *t*. Source: Compustat
INV_{t-1}	Past investment measured as the sum of capital expenditures and research and development (R&D) expense for firm *i* in quarter *t-1* scaled by the net property, plant, and equipment as of the end of quarter *t*. Source: Compustat
ROA_{t+3}	The average return on assets over the subsequent 3 quarters (t+1 ~ t+3). ROA is measured as the ratio of earnings before interest, taxes, depreciation, and amortization (EBITDA) to market value of assets, multiplied by 100. Source: Compustat
Debt Financing	Debt financing is defined as cash proceeds from the issuance of long-term debt, scaled by total assets. Source: Compustat
Net Debt Financing	Net debt financing is measured as cash proceeds from the issuance of long-term debt less cash payments for long term debt reductions plus the net change in current debt, deflated by total assets following Bradshaw, Richardson, and Sloan (2006). Source: Compustat
Debt and Equity Financing	Debt and equity financing is defined as cash proceeds from the issuance of long-term debt plus cash proceeds from the sale of common and preferred stock, deflated by total assets. Source: Compustat

Explanatory and Partitioning Variables	
TREAT	An indicator variable equal to one for firms rated by Standard & Poor's and to zero otherwise. Source: Compustat Ratings Database
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
Log(M/A)	The natural log of market capitalization for firm *i* at quarter *t* divided by total assets at *t*. Source: Compustat
TREAT_HIGHPIN	An indicator variable equal to one for treatment firms with above-median value of the probability of informed trading (*PIN*) as of the last quarter of the pre-period (2006 Q2), and to zero otherwise. The data about *PIN* is obtained from Brown and Hillegeist (2008). https://scholar.rhsmith.umd.edu/sbrown/pin-data
TREAT_LOWPIN	An indicator variable equal to one for treatment firms with below-median value of *PIN* as of the last quarter of the pre-period (2006 Q2), and to zero otherwise. The data about *PIN* is obtained from Brown and Hillegeist (2008). https://scholar.rhsmith.umd.edu/sbrown/pin-data
TREAT_HIGHEM	An indicator variable equal to one for treatment firms with above-median value of an earnings management proxy as of the last quarter of the pre-period (2006 Q2), and to zero otherwise. We employ working capital accruals and two versions of discretionary accruals as earnings management 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

Modified Jones model:

$$Working\ capital\ accrual_t = \beta_0 + \beta_1 Adj\_\Delta sales_t + \beta_2 Inverse\_Assets_{t-1} + \beta_3 PPE_t + \Sigma\beta_{4,k} ROA\_Dummy_{k,t} + \Sigma\beta_{5,k} Salesgrowth\_Dummy_{k,t} + \Sigma\beta_{6,k} MTB\_Dummy_{k,t-1} + \varepsilon_t$$

Modified Dechow-Dichev model:

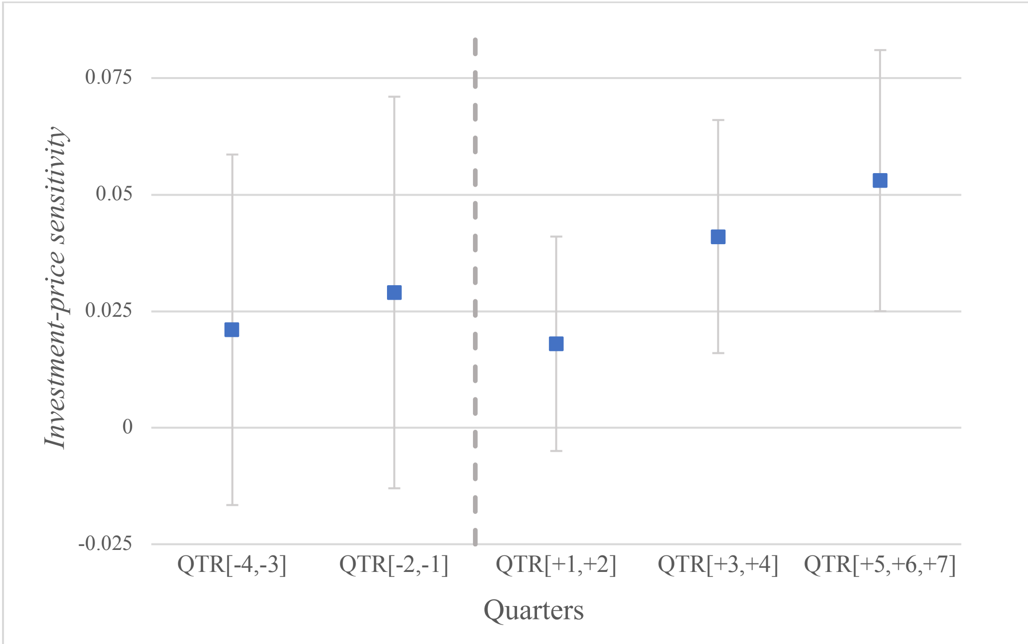
$$Working\ capital\ accrual_t = \beta_0 + \beta_1 CFO_{t-1} + \beta_2 CFO_t + \beta_3 CFO_{t+1}\ \beta_4 PPE_t + \beta_5 \Delta sales_t\ \Sigma\beta_{6,k} ROA\_Dummy_{k,} \Sigma\beta_{7,k} Salesgrowth\_Dummy_{k,t} + \Sigma\beta_{8,k} MTB\_Dummy_{k,t-1} + \varepsilon_t$$

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 1 when firm *i*'s *ROA* is in *k*th quintile of *ROA*, and 0 otherwise; *Salesgrowth_Dummy* is an indicator variable equal to 1 when firm i's sales growth is in *k*th quintile of sales growth, and 0 otherwise; *MTB_Dummy* is an indicator variable equal to 1 when firm i's lagged *MTB* is in *k*th quintile of *MTB*, and 0 otherwise. These models are estimated for each two-digit SIC industry and each quarter with a minimum of 10 observations.

TREAT_LOWEM	An indicator variable equal to one for treatment firms with below-median value of an earnings management proxy as of the last quarter of the pre-period (2006 Q2), and to zero otherwise. We employ working capital accruals and two versions of discretionary accruals as earnings management 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 See the definition of *TREAT_HIGHEM* for discretionary accrual models
TREAT_HIGHINSIDER	An indicator variable equal 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 sum of total sell and buy of management, deflated by the beginning-of-quarter market capitalization. Source: Thomson Reuters
TREAT_LOWINSIDER	An indicator variable equal 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 sum of total sell and buy of management, deflated by the beginning-of-quarter market capitalization. Source: Thomson Reuters
TREAT_HIGHRISK	An indicator variable equal to one for treatment firms with 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 equal to one for treatment firms with 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_MORE_SEG	An indicator variable equal to one for treatment firms with 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 Segment

TREAT_LESS_SEG	An indicator variable equal to one for treatment firms with 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 Segment
TREAT_GROWTH	An indicator variable equal to one for treatment firms with 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
TREAT_VALUE	An indicator variable equal to one for treatment firms with 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
TREAT_HIGHCOMP	An indicator variable equal to one for treatment firms with 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 equal to one for treatment firms with 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_CONS	An indicator variable equal to one for treatment firms with above-median value of average ranks of three measures of financial constraints (WW-index, HP-index, and the inverse of market capitalization) as of the last quarter of the pre-period (2006 Q2), and to zero otherwise. Source: Compustat
TREAT_UNCONS	An indicator variable equal to one for treatment firms with below-median value of average ranks of three measures of financial constraints (WW-index, HP-index, and the inverse of market capitalization) as of the last quarter of the pre-period (2006 Q2), and to zero otherwise. Source: Compustat
Control Variables	
CFO	Cash flows from operations available from the cash flow statement scaled by quarter-end book value of total assets of firm i in quarter t. Source: Compustat
SIZE	The natural logarithm of firm i's market value of equity as of the end of quarter t. Source: Compustat

Figure 1: The incremental effect on investment-price sensitivity by event time



This figure shows differences-in-difference coefficients on investment-price sensitivity for each event-time. We define *QTR(t-4, t-3)* as an indicator variable equal to one for observations in the four or three quarters before the CRARA, and to zero otherwise. Remaining indicators are defined analogously. The first three quarters in the pre-CRARA period are omitted, serving as the benchmark. The dots (lines) represent coefficient estimates (95% confidence intervals).

Table I
Descriptive Statistics

This table presents summary statistics for the variables used in our analyses. The sample consists of 24,344 firm-quarter observations for 2,657 unique firms over the period 2004 4Q - 2008 2Q that corresponds to 7 quarters before and 7 quarters after the passage of the CRARA. 2006 3Q (the quarter in which the CRARA was passed) is dropped. All continuous (unlogged) variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in the Appendix.

	Obs.	Mean	Median	SD	Min	Max
TREAT	24,344	0.332	0.000	0.471	0.000	1.000
POST	24,344	0.507	1.000	0.500	0.000	1.000
INV	24,344	0.330	0.090	0.786	0.000	8.563
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

Table II
Effect of the Credit Rating Agency Reform Act on Investment-Price Sensitivity

This table presents results of examining the effect of the Credit Rating Agency Reform Act on investment-price sensitivity. The dependent variables in Models 1 to 3 are 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* (INV_{t+1}). The dependent variables in Models 4 to 6 are past 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* (INV_{t-1}). *TREAT* denotes firms that are affected by the passage of the CRARA, and to zero otherwise. *POST* denotes the post-CRARA era. *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 the Appendix for detailed variable definitions and data sources. We standardize *Log(M/A)* and *CFO* by, for each variable, subtracting its sample mean and scaling by its standard deviation. 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 coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	Future investment (INV_{t+1})			Past investment (INV_{t-1})		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(M/A)	0.124***	0.149***	0.153***	-0.106	-0.072	-0.044
	(6.539)	(7.280)	(7.394)	(-0.815)	(-0.686)	(-0.502)
CFO	0.005	0.007	-0.135	-0.673	-0.665	-2.154
	(0.084)	(0.121)	(-1.355)	(-1.435)	(-1.443)	(-1.404)
*TREAT*POST*		-0.000	0.004		-0.006	0.026
		(-0.090)	(0.597)		(-0.549)	(1.439)
*Log(M/A)*TREAT*		-0.085***	-0.086***		-0.047	-0.057
		(-3.675)	(-3.737)		(-1.473)	(-1.582)
*Log(M/A)*POST*		-0.019***	-0.021***		-0.129	-0.142
		(-3.265)	(-3.265)		(-1.281)	(-1.423)
Log(M/A)*TREAT*POST		**0.020****	**0.022****		**0.113**	**0.122**
		(2.037)	**(2.090)**		**(1.363)**	**(1.589)**
*CFO*TREAT*			0.064			1.964
			(0.817)			(1.298)
*CFO*POST*			0.327			2.803
			(1.536)			(1.443)
*CFO*TREAT*POST*			-0.296			-2.377
			(-1.517)			(-1.656)
SIZE	-0.043**	-0.038**	-0.041**	0.127	0.162	0.137
	(-2.613)	(-2.330)	(-2.403)	(0.902)	(0.969)	(0.946)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry	Industry	Industry
Observations	24,344	24,344	24,344	24,337	24,337	24,337
R^2	0.874	0.874	0.874	0.908	0.908	0.909

Table III

Does the Credit Rating Agency Reform Act Reduce Investors' Concern about Earnings Management? Ex Post Validation

This table reports the results of testing whether the effect of the CRARA on investment-price sensitivity varies by the extent of earnings management. We split the *TREAT* indicator into *TREAT_HIGHEM* and *TREAT_LOWEM* based on the pre-period median value of earnings management proxies. For earnings management proxies, we employ working capital accruals, modified Jones discretionary accruals, and modified Dechow-Dichev discretionary accruals. We tabulate only the relevant coefficients for brevity. See the Appendix 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 coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	INV_{t+1}					
Proxy for Earnings Management =	*Working Capital Accruals*		*Discretionary Accruals (Modified Jones)*		*Discretionary Accruals (Modified Dechow-Dichev)*	
	High PIN	*Low PIN*	*High PIN*	*Low PIN*	*High PIN*	*Low PIN*
	(1)	(2)	(3)	(4)	(5)	(6)
***Log(M/A)*TREAT_HIGHEM*POST* [a]**	**0.030****	-0.004	**0.045*****	-0.013	**0.041*****	-0.007
	(2.579)	(-0.209)	**(2.677)**	(-0.636)	**(2.766)**	(-0.318)
*Log(M/A)*TREAT_LOWEM*POST* [b]	0.004	0.007	0.019	0.010	0.018	0.0148
	(0.444)	(0.447)	(1.216)	(0.554)	(1.129)	(1.206)
p-value of [a] = [b]	0.023	0.309	0.044	0.123	0.072	0.137
Controls (See Table II)	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry	Industry	Industry
Observations	10,748	10,795	8,519	8,564	8,519	8,578
R^2	0.880	0.817	0.883	0.827	0.883	0.827

Table IV
Cross-Sectional Tests

This table presents the results of cross-sectional tests based on uncertainties where informed traders have an information advantage, multiple dimensions of uncertainties, and managerial 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_MORE_SEG and TREAT_LESS_SEG* depending on whether the firm has above- or below-median values of the number of segments (business plus geographic) 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* based on the pre-period median value of insider trading activities. We tabulate only the relevant coefficients for brevity. See the Appendix 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 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]**	**0.049****	-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 Table II)	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
Observations	11,428	11,489	10,964	11,005
R^2	0.883	0.807	0.861	0.819

Table IV—*continued*

Cross-sectional tests

Panel B: Firms that are 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_MORE_SEG*POST* [a]**			**0.0356****	0.003
			(2.524)	(0.178)
*Log(M/A)*TREAT_LESS_SEG*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 Table II)	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
Observations	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)
*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)
p-value of [a] = [b]	0.084	0.320
Controls (See Table II)	Yes	Yes
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Clustering	Industry	Industry
Observations	8,602	8,661
R^2	0.888	0.815

Table V
Future Performance

This table reports the results of examining future firm performance. The dependent variable (ROA_{t+3}) is average return on assets over the subsequent 3 quarters. *TREAT* denotes firms that are affected by the passage of the CRARA, and to zero otherwise. *POST* denotes the post-CRARA era. In Model (2), we split the *TREAT* indicator into *TREAT_HIGHPIN* and *TREAT_LOWPIN* depending on whether the firm has above- or below-median values of the probability of informed trading (*PIN*) in the pre-period. *SIZE* denotes firm size. See the Appendix 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 coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	ROA_{t+3}	
	(1)	(2)
TREAT*POST	**0.220***** **(2.860)**	
***TREAT_HIGHPIN*POST* [a]**		**0.353***** **(4.737)**
*TREAT_LOWPIN*POST* [b]		0.091 (0.744)
SIZE	0.387*** (2.851)	0.387*** (2.868)
p-value of [a] = [b]		0.057
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Clustering	Industry	Industry
Observations	24,344	24,229
R^2	0.735	0.735

Table VI
Alternative Explanation: Eased Financing Constraints

This table presents the results of cross-sectional tests based on financial constraints. We partition the sample into the *High PIN* and *Low PIN* subsamples based on the pre-period median value of *PIN*. Then we split the *TREAT* indicator into *TREAT_CONS* and *TREAT_UNCONS* depending on whether the firm has above- or below-median values of average ranks of the three measures of financial constraints (the WW-index, the HP-index, the inverse of market capitalization). We tabulate only the relevant coefficients for brevity. See the Appendix 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 coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	INV_{t+1}	
	High PIN	*Low PIN*
	(1)	(2)
***Log(M/A)*TREAT_UNCONS*POST* [a]**	**0.035****	0.009
	(2.115)	(0.453)
*Log(M/A)*TREAT_CONS*POST* [b]	0.002	0.012
	(0.238)	(0.521)
p-value of [a] = [b]	0.057	0.795
Controls (See Table II)	Yes	Yes
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Clustering	Industry	Industry
Observations	11,588	11,665
R^2	0.885	0.805

Table VII
Alternative Explanation: Differential Accessibility to Capital Markets between Treatment and Control Firms during the Great Recession of 2008

This table reports the results from estimating entropy-balanced regressions of equation (1). We use entropy balancing to reweight control firm-quarters 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) and Altman's Z-Score in the quarter prior to the passage of the CRARA. The dependent variable 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* (INV_{t+1}). *TREAT* denotes firms that are affected by the passage of the CRARA, and to zero otherwise. *POST* denotes the post-CRARA era. *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 the Appendix for detailed variable definitions and data sources. We standardize *Log(M/A)* and *CFO* by, for each variable, subtracting its sample mean and scaling by its standard deviation. 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 coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	INV_{t+1} (1)
Log(M/A)	0.114***
	(3.479)
CFO	0.100
	(0.434)
*TREAT*POST*	0.022
	(1.255)
*Log(M/A)*TREAT*	-0.053*
	(-1.949)
*Log(M/A)*POST*	-0.051**
	(-2.133)
Log(M/A)*TREAT*POST	**0.051****
	(2.203)
*CFO*TREAT*	-0.212
	(-0.917)
*CFO*POST*	0.784
	(1.045)
*CFO*TREAT*POST*	-0.699
	(-1.017)
SIZE	-0.031***
	(-3.078)
Firm FE	Yes
Year-Quarter FE	Yes
Clustering	Industry
Observations	15,700
R^2	0.770

Table VIII
Falsification Test: Debt Financing

This table reports the results from estimating differences-in-difference regressions with respect to financing around the CRARA. The dependent variables are debt financing, net debt financing, and debt and equity financing. Debt financing is defined as cash proceeds from the issuance of long-term debt, deflated by total assets. Net debt financing is defined as cash proceeds from the issuance of long-term debt less cash payments for long term debt reductions plus the net change in current debt, deflated by total assets. Debt and equity financing is defined as cash proceeds from the issuance of long-term debt plus cash proceeds from sale of common and preferred stock, deflated by total assets. *TREAT* denotes firms that are affected by the passage of the CRARA, and to zero otherwise. *POST* denotes the post-CRARA era. *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 the Appendix for detailed variable definitions and data sources. We standardize *Log(M/A)* and *CFO* by, for each variable, subtracting its sample mean and scaling by its standard deviation. 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 coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	Debt Financing	Net Debt Financing	Debt and Equity Financing
	(1)	(2)	(3)
TREAT*POST	**-0.001**	**0.002**	**0.003**
	(-0.361)	**(0.785)**	**(1.081)**
Log(M/A)	-0.030***	-0.022***	-0.034***
	(-6.757)	(-6.055)	(-4.710)
CFO	-0.006**	-0.016***	-0.008**
	(-2.517)	(-5.629)	(-2.633)
SIZE	-0.027***	0.020***	0.044***
	(6.422)	(5.215)	(6.671)
Firm FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Clustering	Industry	Industry	Industry
Observations	24,229	24,229	24,229
R^2	0.349	0.183	0.322