Short Selling Threat and Real Activity Manipulation: Evidence from a Natural Experiment

Abstract

In this paper, we investigate whether and how short selling threat affects real activity manipulation. Using a regulatory experiment (Regulation SHO) that removes short selling restrictions on randomly selected pilot firms, we find that real activity manipulation is significantly reduced for pilot firms in response to increased short selling threat during the experiment period. The reduction effect is stronger for pilot firms with a transparent financial reporting strategy, a high level of negative financial reporting sentiment, and bad news. Our finding confirms short sellers' monitoring effect on opportunistic behavior, even for real activity manipulation that is difficult to detect.

Keywords: Short Selling Threat; Real Earnings Management; Regulation SHO

1. Introduction

This paper examines whether and how firms manipulate real activities in response to a regulation shock that increases short selling threat. The extant literature (e.g., Roychowdhury 2006; Cohen, Dey, and Lys 2008; Cohen and Zarowin 2010; Zang 2012) suggests that managers exercise discretion not only via their choice of accounting estimates and methods (i.e., accrual-based earnings management), but also through real activities manipulation (RAM) (i.e., real earnings management). These activities include cutting prices to boost current-period sales, overproducing to lower fixed costs per unit and reduce the cost of goods sold, and opportunistically reducing discretionary expenses such as advertising expenses, research and development expenses, and general and administrative expenses. As these activities occur through real operating decisions rather than accounting method choices, it is difficult for auditors, regulators, and average investors to detect RAM. As such, RAM is a hidden tool for managers to reflect their behavior and attitude toward financial reporting (Kim and Park 2014). In their survey, Graham, Harvey, and Rajgopal (2005) find that managers prefer RAM to accrual-based earnings manipulation.

However, the impact of short selling threat on RAM may not be straightforward. On one hand, RAM involves changing firms' underlying operations and exposing firms to real economic costs (Vorst 2016). The extant literature shows that RAM, which involves inefficient economic activities, has a negative impact on firms' future operating performance and market valuation (e.g., Graham et al. 2005; Cohen and Zarowin 2010; Eldenburg, Gunny, Hee, and Soderstrom 2011). Park (2017) finds that short sellers, as well-informed and sophisticated investors, can identify overvalued firms that have engaged in RAM. Under short selling threat, if managers manipulate earnings by increasing abnormal business activities, such as boosting sales and increasing production, short sellers could reveal such abnormal activities to the stock market, thereby reverting the gains from inflated earnings. Given that short sellers facilitate the processing of unfavorable information (e.g., Chang, Cheng, and Yu 2007; Karpoff and Lou 2010; Boehmer and Wu 2013) and that the impact of negative information can be quickly reflected in stock prices, managers could have an incentive to reduce RAM that has a severe negative impact on stock prices.

On the other hand, prior studies show that accrual earnings management reflects managers' intentional accounting misconduct and has an immediate negative impact on stock prices once it is revealed (e.g., Hutton, Marcus, and Tehranian 2009; Massa, Zhang, and Zhang 2015; Zhu 2016). Short sellers have the incentive to reveal inappropriate accounting practices to the capital market to trade for investment returns (e.g., Desai, Krishnamurthy, and Venkataraman 2006; Karpoff and Lou 2010). Under increased monitoring pressure from short sellers, managers decrease accrual-based earnings management to avoid the potential negative impact (Fang, Huang, and Karpoff 2016). However, prior studies also show that, when facing a greater short selling threat, target firms are still under pressure to meet earnings expectations or benchmarks in the capital market (e.g., Grullon, Michenaud, and Weston 2015; Hong and Stein 2003). Compared to accrual earnings management, RAM is a more hidden tool to hold up bad news and deviate from normal business operations, and its negative impact on future performance tends to be incorporated into stock prices with a delay (e.g., Li 2012; Khurana, Pereira, and Zhang 2018). Therefore, in response to the increased capital market pressure, managers may switch from accrual-based earnings management to RAM to mitigate the potentially immediate negative impact as well as meet earnings targets.

We use a unique setting of regulation changes to empirically test the effect of short selling threat on RAM. From 2004 to 2007, the SEC initiated a pilot program under Rule 202T of Regulation SHO, which suspends the price test that limits the short selling price. In fact, the suspension of the price test alleviates restrictions on short selling, thereby accelerating downward spiraling stock prices. One-third of firms in the Russel 3,000 were selected by the SEC as pilot firms placed under increased short selling threat during the program. This quasi-natural experiment offers an ideal setting in which the SEC randomly assigned treatment and control groups. The sudden regulation change provided an exogenous shock to the short selling threat of pilot firms. Following the recent literature using the same setting (e.g., Fang et al. 2016; Gao, He, and Wu 2016; Hope, Hu, and Zhao 2017), we adopt a difference-in-differences (DID) method to analyze whether and how RAM is affected by increased short selling threat.

We start the analysis using modified RAM measures (Roychowdhury 2006; Cohen et al. 2008; Francis et al. 2016; Chen, Hribar, and Melessa 2018). The three individual RAM measures broadly cover common economic activities that can be implemented to inflate earnings. First, managers can accelerate the timing of sales through increased price discounts or more lenient credit terms, leading to inflated earnings and low cash flow in the current period. Second, managers can lower the cost of goods sold through increased production. However, the production cost will be abnormally inflated. Lastly, managers can reduce discretionary expenses, such as advertising expenses, research and development expenses, and SG&A expenses, to inflate earnings.

We find that pilot firms increase abnormal cash flows and decrease abnormal production costs during the SHO program, but do not substantially change abnormal discretional expenses. The changes of abnormal cash flows and abnormal production costs indicate that short selling threat constrains firms' RAM.

Along with Fang et al.'s (2016) findings, our paper shows that both accrual-based earnings management and RAM of pilot firms decrease during the SHO program period. This is contrary to the substitute relationship identified in the literature between RAM and accrual-based earnings management (e.g., Cohen et al. 2008; Chan, Chen, Chen, and Yu 2014). We replicate the test conducted by Fang et al. (2016) and validate the decrease of accrual-based earnings management. We further find that our main result holds after including accrual-based earnings management as an additional control variable in our baseline model. These two robustness tests do not support the substitute relationship between accrual-based earnings management and RAM.

RAM has a severe negative impact on firm value if revealed by short sellers. It is likely that managers of pilot firms reduce the disclosure of negative information by reducing RAM. As such, we further test whether the reduction of RAM under short selling threat is affected by firms' transparent financial reporting strategy, negative financial reporting sentiment, and bad news. We use the number of voluntary 8-K items as a proxy for reporting transparency (Cooper, He, and Plumlee 2018), the percentage of negative words as the measure for negative sentiment (Loughran and McDonald 2014), and the changes in market value as the measure for bad news. We find that pilot firms with transparent financial reporting, a high level of negative sentiment, and bad news reported reduce RAM more than other firms.

This paper makes two major contributions to the literature. First, we contribute to the research on real earnings management. In light of Graham et al.'s (2005) survey evidence that managers prefer real activities manipulation, several notable studies examine determinants of RAM, especially from a governance perspective (e.g., Bushee 1998; Carcello, Hollingsworth, Klein, and Neal 2006; Chen, Cheng, Lo, and Wang 2015; Cheng, Lee, and Shevlin 2016). We extend this line of research by examining how capital market participants (i.e., short sellers) affect real earnings management. Our finding that short selling threat reduces RAM, along with Fang et al.'s (2016) finding that short selling threat decreases accrual-based earnings management, paints a more complete picture of how short selling threat affects *total* earnings management. Our study also suggests that RAM and accrual earnings management might not necessarily be substituted as indicated in the prior literature.

Second, our paper contributes to the understanding of the effective monitoring role of short sellers in the capital market. Traditional short selling studies mainly focus on stock price discovery and short sellers' information efficiency role (e.g., Diamond and Verrecchia 1987; Duffie, Garleanu, and Pedersen 2002; Saffi and Sigurdsson 2011; Boehmer and Wu 2013). More recently, several short selling regulatory changes around the world have provided scholars with opportunities to explore how short selling threat affects corporate reporting decision-making. Using Regulation SHO in the United States, Fang et al. (2016) find that increased short selling threat leads to reduced accrual-based earnings management, and Li and Zhang (2015) document that short selling pressure reduces the precision of bad news forecasts and the readability of bad news annual reports. Our study complements this line of research by showing another effective monitoring role of short sellers on corporate real earnings management.

Finally, our paper corresponds to the ongoing tension between the SEC and investors regarding the effect of short selling. In a public speech, SEC Chairman Jay Clayton supported the practice of short selling and argued against billionaire Leon Cooperman, who called on the SEC to reinstate the uptick rule (Belvedere 2020). The SEC implemented the temporary Rule 202T of Regulation SHO to evaluate the overall effectiveness of the uptick rule. We find that unrestricted short selling reduces RAM, especially abnormal sales and production activities. These findings align with regulators' position that short selling practices enhance market integrity.[1]

The remainder of the paper is organized as follows. Section 2 provides a literature review and develops the hypothesis. Section 3 describes our research design, the data selection process,

[1] The SEC also summarizes the key points of Regulation SHO on its website: https://www.sec.gov/investor/pubs/regsho.htm

measures, and summary statistics. Section 4 presents the empirical results, including the baseline regression results, subsample analyses, and tests of alternative explanations. We provide a conclusion in Section 5.

2. Background, Literature Review, and Hypothesis Development

2.1. Background: Short Selling and the SHO Pilot Program

Both academic researchers and regulators have long recognized short sellers' negative impact on target firms' performance. Short sellers target firms with low ratios of fundamentals (such as earning and book values) to market values. These firms are known to have systematically lower future stock returns (e.g., Dechow, Hutton, Meulbroek, and Sloan 2001). Since the 1930s, regulators in the United States have developed restrictions on short selling, such as short-sale price tests, to avoid downward spiraling stock prices. The tick test initiated in 1938 and applied to firms listed on the New York Stock Exchange (NYSE) stipulates that a short sale can only occur at a price above the most recently traded price (plus tick) or at the most recently traded price if that price exceeds the last different price (zero-plus tick).[2]

In July 2004, the SEC initiated a pilot program under Rule 202T of Regulation SHO in which Russell 3000 index stocks[3] (as of June 25, 2004) were sorted into three groups—AMEX, NASDAQ, and NYSE—and ranked within each group from the highest to the lowest based on the average daily dollar trading volume from June 2003 to May 2004. The SEC selected every third stock in each group as a pilot stock. These pilot stocks were exempted from the tick test from May 2, 2005, to August 6, 2007. The pilot program represents an exogenous shock to the probability of

[2] The official document for the "tick test" is SEC Rule 10a-1.
[3] The initial sample excluded stocks that were not previously subject to price tests (i.e., not listed on NYSE, AMEX, or NASDAQ-NM) and stocks that went public or had spin-offs after April 30, 2004.

selling short in pilot firms; consequently, it becomes a natural experiment for researchers to test how short selling threat affects corporate behaviors (e.g., Grullon et al. 2015; Fang et al. 2016).

2.2. Real Activities Manipulation and Accruals-Based Earnings Management

Healy and Wahlen (1999, page 368) state that "Earnings management occurs when managers use judgment in financial reporting and in structuring transactions to alter financial reports to either mislead some stakeholders about the underlying economic performance of the company or to influence contractual outcomes that depend on reported accounting practices." RAM has the same purpose as accrual-based earnings management, although the purpose is achieved in different ways. Accrual-based earnings management changes the accounting methods or estimates used when presenting a given transaction in the financial statements (Zang 2012) whereas RAM changes the timing or structuring of operation, investment, or financing transactions (Zang 2012). These economic transactions include cutting prices to boost sales, increasing production to lower fixed costs per unit to reduce the cost of goods sold, and reducing discretionary expenses such as advertising expenses or general and administrative expenses.

The survey evidence by Graham et al. (2005) shows that managers actually prefer real activities manipulation, especially when there is a regulatory change that intends to improve earnings quality (Ewert and Wagenhofer 2005). Several recent studies support a substitute relationship between accrual-based earnings management and real earnings management subsequent to regulation changes (e.g., Cohen et al. 2008; Cohen and Zarowin 2010; Zang 2012; Chan et al. 2014; Kothari, Mizik, and Roychowdhury 2015; Zhang, Perols, Robinson, and Smith 2018). For example, Cohen et al. (2008) document that the significant decline of accrual-based earnings management after the passage of SOX is concurrent with the increasing trend of real earnings management. Chan et al. (2014) examine the impact of the Clawback provisions, which allow for the adjustment of executive compensation after misstating financial reports. Although the provisions are supposed to mitigate executives' earnings management incentive, firms substitute RAM for accrual-based earnings management; thus, the total amount of earnings management does not decrease subsequent to the provision. The main reason for this substitute relationship is that RAM is more difficult to detect. Regulators and auditors scrutinize any accounting practice that may depart from GAAP, but are less concerned about RAM, which deviates from normal business practice but may be recognized as appropriate for accounting purposes (Cohen and Zarowin 2010; Zang 2012; Lopez and Vega 2019).

Nonetheless, similar to accrual-based earnings management, RAM is an opportunistic behavior that alters financial reports to mislead shareholders about the underlying true economic performance of the company (Roychowdhury 2006). Prior studies find that RAM has a negative impact on cash flows and future performance (e.g., Ewert and Wagenhofer 2005; Graham et al. 2005; Cohen et al. 2008; Cohen and Zarowin 2010; Eldenburg et al. 2011; Zang 2012; Kim and Sohn 2013). As such, several studies examine how various monitoring mechanisms affect RAM. For example, Bushee (1998) finds that long-term institutional investors deter myopic R&D investment behavior. Using employment agreements and severance pay agreements as proxies for CEO contractual protection, Chen et al. (2015) find that firms with CEO contractual protection are less likely to engage in real earnings management. Cheng et al. (2016) find that the extent of real earnings management decreases with key subordinate executives' horizon and influence. Kim and Park (2014) argue that auditors are sensitive to the risk related to RAM. Irani and Oesch (2016) find that analyst coverage deters RAM. Overall, these studies, along with the extant literature on accrual-based earnings management, show that effective governance mechanisms deter both real activities-based and accrual-based earnings management.

2.3. Short Selling Threat and Real Activities Manipulation

After Regulation SHO, pilot firms are exposed to more public scrutiny. The recent paper by Fang et al. (2016) finds that pilot firms decrease accrual-based earnings management and are more likely to be caught for fraud when they are in the SHO program period. The authors explain that the SHO program spurs short sellers' interest in pilot firms, increases short sellers' monitoring, and consequently constrains managers' earnings management behavior.

As the most sophisticated investors in the capital market, short sellers have a particular interest in negative information regardless of managers' intent. The negative information can be managerial misconduct, such as accrual earnings management, or abnormal business activities, such as RAM. Short sellers do not need to prove managers' misconduct to the capital market, but can simply reveal any abnormal activities that can negatively affect firm value. The extant literature shows that RAM, which involves inefficient economic activities, has a negative (positive) impact on firms' future operating performance (risk). For example, overproduction leads to inventory build-up, which increases the probability of inventory write-downs. Excessive credit sales result in an increase in receivables, which increases the risk of bad debt (Kim and Park 2014). Prior studies find that overproduction and the cutting of R&D expenditures are costly and reduce the long-term value of the firm (e.g., Graham et al. 2005; Cohen and Zarowin 2010; Eldenburg et al. 2011). Graham et al.'s (2005) survey evidence also shows that RAM could have negative long-term consequences. Cohen and Zarowin (2010) find lower subsequent operating performance for firms that have engaged in RAM around seasoned equity offerings. Using a group of nonprofit hospitals, Eldenburg et al. (2011) produce similar findings.

During the SHO program period, managers are under increased pressure to manage negative information to maintain the stability of stock prices. Short sellers facilitate the flow of unfavorable information into stock prices, leading to relatively low stock prices for pilot firms during the SHO program (Grullon et al. 2015) and more efficient stock prices (e.g., Chang et al. 2007; Karpoff and Lou 2010; Boehmer and Wu 2013). To maintain the current level of stock prices, managers take actions to reduce negative information. Li and Zhang (2015) show that pilot firms reduce the precision of bad news forecasts. We argue that the short selling threat constrains managers' real earnings management during the SHO program, given the severe negative effect of RAM on firm value. Our prediction is consistent with the literature showing that short sellers are proficient at identifying both accrual-based and real-based earnings management and keeping stock prices closer to firm true values (Karpoff and Lou 2010; Park 2017); moreover, various monitoring mechanisms deter real earnings management (e.g., Bushee 1998; Carcello et al. 2006; Roychowdhury 2006; Chen et al. 2015; Irani and Oesch 2016; Cheng et al. 2016).

Alternatively, managers may substitute accrual-based earnings management with RAM. Despite short sellers' monitoring effect, managers still experience pressure to meet earnings expectations. Given the reduced accrual-based earnings management during the SHO program, managers may switch to RAM, which has a less immediate negative impact on stock prices if revealed by short sellers. Accrual earnings management reflects managers' intentional misconduct and has an immediate negative impact on firm value (e.g., Hutton et al. 2009; Massa et al. 2015; Zhu 2016). For example, Palmrose and Scholz (2004) find that firms immediately experience a substantial loss in market value after their financial misconduct is revealed to the market.

Compared to accrual earnings management, RAM is a hidden tool to hold up bad news, deviates from normal business operations, and has a more *delayed* impact on stock prices. For example, according to Khurana et al. (2018), RAM is positively related to one-year-ahead stock price crash risk and predicts up to three-year-ahead crash risk. They argue that RAM allows poorly performing projects, conceals resource diversion, and enables ineffective risk management for extended periods. Similarly, Li (2012) finds that the effect of RAM in the capital market takes about one to three years to be reflected in the stock price. As short sellers are exposed to higher risk and higher trading costs compared to long-term investors, they may prefer to target firms with more accrual-based earnings management over firms with more RAM.

In sum, managers face monitoring pressure from short sellers as well as earnings pressure to meet expectations. In response to the tension between these two kinds of pressure, managers may choose to decrease or increase RAM. As such, we hypothesize that the short selling threat affects RAM, but we do not predict the direction of the impact. In alternative form:

Hypothesis: *Real activity manipulation is affected by an increase in the short selling threat.*

3. Data and Research Design

3.1. Data and Sample Selection

We conduct our tests using the setting of the SEC SHO pilot program, which includes 1,000 firms randomly selected from the Russell 3000 index. We follow the SEC and illustrate the selection procedures in Panel A of Table 1. We start with the 2004 Russell 3000 index firms[4] and identify pilot firms—every third stock as ranked by average daily dollar volume (from June 2003

[4] The initial list excludes stocks that were not previously subject to price tests (i.e., not listed on NYSE, AMEX, or NASDAQ-NM) and stocks that went public or had spin-offs after April 30, 2004.

to May 2004)—selected by the SEC. We merge the dataset of pilot firms and nonpilot firms with the dataset of Compustat, which provides accounting information. Following prior studies using the same setting, we exclude firms in the financial and utilities industries. We include 597 pilot firms and 1,791 nonpilot firms in the sample, which are comparable to prior studies (e.g., Fang et al. 2016; Hope et al. 2017).[5] In most of our tests, to control for the effect of corporate governance on real earnings management, we include institutional ownership as a control variable, which reduces the sample size to 487 pilot firms and 989 nonpilot firms. All continuous variables are winsorized at the 1st and 99th percentiles, and the standard errors in regression models are double clustered by firm-years. Following Fang et al. (2016), we do not include the year 2004, when the SEC was in the process of selecting pilot firms, to eliminate potential confounding effects. Panel B illustrates the year distribution of the final sample. Consistent with Hope et al. (2017), the number of observations peaks in the years before and after the program starting in 2004 (i.e., 2003 and 2005) and the number of decreases after the program begins.

[Insert Table 1 here]

3.2 Real Activity Manipulation Measures

Following Roychowdhury (2006), Cohen et al. (2008), and Francis et al. (2016), we use their RAM models and the method in Chen et al. (2018) to modify the application of these models. Each model is estimated cross-sectionally for industry-years with at least 15 observations.

The first measure of RAM is abnormal cash flow, AB_CFO. Managers can accelerate the timing of sales through increased price discounts or more lenient credit terms. The sales volumes can be temporarily boosted, but they are likely to disappear as managers revert to original prices.

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[5] Compared to prior studies, the difference in the final sample size is attributed to missing values of variables used in the regression.

As a result, the current period earnings will be inflated whereas cash flows in the current period will be lower than normal. CFO is cash flow from operations. The estimated residual captures the abnormal cash flow from operations.

$$\frac{CFO_{it}}{Assets_{i,t-1}} = \alpha_0 + \alpha_1 \frac{1}{Assets_{i,t-1}} + \alpha_2 \frac{Sales_{it}}{Assets_{i,t-1}} + \alpha_3 \frac{\Delta Sales_{it}}{Assets_{i,t-1}} + \varepsilon_{it} \quad (1)$$

The second measure of RAM is abnormal production cost, AB_PROD. One way of increasing earnings is to lower the cost of goods sold through increased production. As more units of products are produced, managers can spread the fixed overhead costs over a larger number of units, thereby lowering the fixed costs per unit. As a result, the reported cost of goods sold can be decreased, leading to higher earnings. Production cost is defined as PROD = COGS + ΔINV, where COGS is cost of goods sold and INV is inventory. The estimated residual captures the abnormal production cost.

$$\frac{Prod_{it}}{Assets_{i,t-1}} = \alpha_0 + \alpha_1 \frac{1}{Assets_{i,t-1}} + \alpha_2 \frac{Sales_{it}}{Assets_{i,t-1}} + \alpha_3 \frac{\Delta Sales_{it}}{Assets_{i,t-1}} + \alpha_4 \frac{\Delta Sales_{i,t-1}}{Assets_{i,t-1}} + \varepsilon_{it} \quad (2)$$

The third measure of RAM is abnormal discretionary expense, AB_DISEXP. Reducing discretionary expenses will boost current period earnings. Discretionary expenses are defined as the summation of advertising expenses, research and development expenses, and SG&A expenses. The estimated residual captures the abnormal discretionary expenses.

$$\frac{DisExp_{it}}{Assets_{i,t-1}} = \alpha_0 + \alpha_1 \frac{1}{Assets_{i,t-1}} + \alpha_2 \frac{Sales_{i,t-1}}{Assets_{i,t-1}} + \varepsilon_{it} \quad (3)$$

Because a higher level of AB_CFO or AB_DISEXP indicates a *lower* level of RAM, while a higher level of AB_PROD indicates a *higher* level of RAM, for ease of exposition, we multiply AB_CFO and AB_DISEXP by –1. Thus, a higher AB_CFO, AB_PROD, or AB_DISEXP indicates a higher level of RAM.

Based on the models above, we use the method in Chen et al. (2018) by including the regressors of RAM measures into the baseline regression. Chen et al. (2018) find that accounting studies using residuals constructed from regression models as a first step can lead to biased coefficients in the second step regressions by including the residuals. The direction of bias can be upward or downward. Chen et al. (2018) propose an alternative model, which includes all the variables from the first step in the second step regression. In other words, the two regression models are combined. The combined regression model also includes industry and year indicators as well as the interaction terms of indicators and first-step regressors. We follow the suggestion in their paper and combine the RAM models with our baseline regression model.

3.3. Empirical Model

Following the recent literature that uses the same setting (e.g., Laksmana and Yang 2014; Fang et al. 2016; Gao et al. 2016; Hope et al. 2017) as well as the method in Chen et al. (2018), we employ a difference-in-differences design in the baseline regressions and estimate the following ordinary least squared (OLS) models:

$$
\begin{aligned}
-CFO = {} & \beta_0 + \beta_1\, DURING * PILOT + \beta_2\, POST * PILOT + \beta_3\, DURING + \beta_4\, POST \\
& + \beta_5\, PILOT + \beta_6\, \frac{1}{AT\_LAG1} + \beta_7\, SALE\_LAG1 + \beta_8\, SALE\_CHG1 + \beta_9\, SOX \\
& + \beta_{10}\, SIZE + \beta_{11}\, MTB + \beta_{12}\, ROA + \beta_{13}\, LEV + \beta_{14} ZSCORE + \beta_{15}\, INS\_OWN \\
& + \beta_{16}\, BIG4 + \beta_{17}\, ANALYST + \beta_{18}\, SEC\_SCRUTINY + Interaction\ Terms \\
& + Industry\ Year\ Fixed\ Effects + \epsilon \qquad (4)
\end{aligned}
$$

$$
\begin{aligned}
&PROD \\
&= \beta_0 + \beta_1\, DURING * PILOT + \beta_2\, POST * PILOT + \beta_3\, DURING + \beta_4\, POST \\
&+ \beta_5\, PILOT + \beta_6\, \frac{1}{AT\_LAG1} + \beta_7\, SALE\_LAG1 + \beta_8\, SALE\_CHG1 + \beta_9\, SALE\_CHG2 + \beta_{10}\, SOX \\
&+ \beta_{11}\, SIZE + \beta_{12}\, MTB + \beta_{13}\, ROA + \beta_{14}\, LEV + \beta_{15} ZSCORE + \beta_{16}\, INS\_OWN + \beta_{17}\, BIG4 \\
&+ \beta_{18}\, ANALYST + \beta_{19}\, SEC\_SCRUTINY + Interaction\, Terms \\
&+ Industry\, Year\, Fixed\, Effects + \epsilon \qquad (5)
\end{aligned}
$$

$$
\begin{aligned}
-DISEXP = {} & \beta_0 + \beta_1\, DURING * PILOT + \beta_2\, POST * PILOT + \beta_3\, DURING + \beta_4\, POST \\
& + \beta_5\, PILOT + \beta_6\, \frac{1}{AT_{LAG1}} + \beta_7\, SALE_{LAG1} + \beta_8\, SOX + \beta_9\, SIZE + \beta_{10}\, MTB \\
& + \beta_{11}\, ROA + \beta_{12}\, LEV + \beta_{13} ZSCORE + \beta_{14}\, INS_{OWN} + \beta_{15}\, BIG4 \\
& + \beta_{16}\, ANALYST + \beta_{17}\, SEC_{SCRUTINY} + Interaction\, Terms \\
& + Industry\, Year\, Fixed\, Effects + \epsilon \qquad (6)
\end{aligned}
$$

We use three individual measures to test the impact of short selling threat on real activity manipulation. PILOT is an indicator variable that takes the value of 1 for all observations of firms selected by the SEC as pilot firms and 0 otherwise. DURING takes the value of 1 for observations from the year 2005 to 2007 and 0 otherwise; POST takes the value of 1 for observations from the year 2008 to 2010 and 0 otherwise. We follow Chen et al. (2018) and include regressors from equations (1) to (3), interaction terms of regressors with fixed effects, and industry year fixed effects. The regression model is OLS with two-way clustering of standard errors by year and firm. Again, for ease of explanation, we multiply CFO and DISEXP by –1 when we run the regressions.

Thus, a positive (negative) sign of the coefficient on DURING* PILOT indicates increases (decreases) of RAM for pilot firms during the program period for all three regression models.

We select control variables following the prior real earning management literature (e.g., Zang 2012). We include SOX (time dummy indicating the years before/after SOX passage), SIZE (firm size), MTB (market-to-book ratio), ROA (return on assets ratio), LEV (leverage), ZSCORE (default risk measure), INS_OWN (institutional ownership), BIG4, ANALYST (number of analyst following), and SEC_SCRUNITY (AAER letters issued by SEC). Cohen et al. (2008) provide evidence that firms switch from accrual-based to real earnings management methods after the passage of SOX. Firm characteristics can also affect real earnings management. Bigger firms have more resources to engage in real earnings management. Undervalued (low MTB), low-profitability (ROA), high-leverage (high LEV) firms have more pressure from the capital market to boost and maintain their earnings. We predict a negative coefficient on MTB, a negative coefficient on ROA, and a positive coefficient on LEV.

Firms with good financial health are more likely to manipulate real activities due to the low associated costs (Zang 2012). We use a modified version of Altman's Z-score (Altman 1968, 2000) to proxy for a firm's financial health: ZSCORE = 3.3*Pre-tax Income/Assets + 0.999*Sales/Assets + 1.4 *Retained Earnings/Assets + 1.2 * (Current Assets - Current Liabilities)/Assets +0.6*Market Equity/Total Liabilities. Higher values of ZSCORE indicate a healthier financial condition. We predict a positive coefficient on ZSCORE.

We also include institutional ownership, which is the proxy for institutions' monitoring effect. Firms are less likely to manipulate real activities under more institutional owners' monitoring. We predict a negative coefficient on INS_OWN. We also control for monitoring effect from auditors, analysts, and the SEC.

3.4. Summary Statistics and Correlation Test

In Panel A of Table 2, we present the summary statistics for the full sample, including pilot firms and nonpilot firms, for the regression analysis of CFO. The summary statistics for the other two models PROD and DISEXP are similar and thus not reported for brevity. The average of dependent variables as well as regressors from equation (1) to (3) are comparable to prior studies (e.g., Roychowdhury 2006).

Approximately 78% of the observations are post-SOX passage. The mean value of SIZE is 7.009, the mean value of MTB is 3.290, the mean value of ROA is 10.3%, and the mean value of LEV is 0.179. The mean value of ZSCORE is 1.394. The mean value of INS_OWN is 0.704. The summary statistics of these firm characteristics are comparable to studies using the SHO setting (e.g., Fang et al. 2016; Hope et al. 2017).

In Panel B of Table 2, we compare pilot firms with nonpilot firms one year before the pilot program (i.e., 2003). The comparison aims to verify that pilot firms are not significantly different from nonpilot firms and thus represent a random draw from the Russell 3000 population. We run *t*-tests on the mean differences between pilot firms and nonpilot firms. For most variables, the t-statistics are not significant, meaning that pilot firms and nonpilot firms are indistinguishable. These results confirm that the pilot program is exogenous to the Russell 3000 firms because the SEC arbitrarily chose pilot firms in 2004.

[Insert Table 2 here]

Panel A of Table 3 reports Pearson correlations among the variables in our analyses. The correlations between paired variables are mostly within the range of -0.3 and 0.3,[6] suggesting that multicollinearity is not a major concern for our regression models.

[Insert Table 3 here]

4. Empirical Results

4.1. Impact of Short Selling Threat on RAM

The baseline regression models (i.e., Equations 4, 5, and 6) are reported in Table 4. In Column (1) of Table 4, the full sample contains 9,362 firm-year observations for the test of abnormal cash flow. As discussed, we multiple CFO by -1 for ease of exposition. The benchmark period consists of the three years before the pilot program period (i.e., 2001 to 2003). In Column (1), we find that the coefficient on the variable of interest DURING*PILOT is -0.014 and significant at the 1% level. This indicates that cash flow is 1.4% higher per dollar of assets for pilot firms than for nonpilot firms during the three-year period of the pilot program compared to the three-year pre-SHO period. The coefficients of most control variables have signs as predicted.[7] Firms can engage in RAM by providing price discounts or more lenient credit terms to boost sales volumes as well as current period earnings, but this results in lower cash flows (or a negative sign for the variable of interest) in the current period. Our finding of higher cash flows (or negative sign

[6] The correlation between ROA and ZSCORE (0.7437) is relatively high, which is consistent with profitable firms that are more financially healthy. To mitigate any concern about multicollinearity, we remove ZSCORE from the baseline regression, and our results hold.

[7] In untabulated results, following Fang et al. (2016), we test the effect using alternative model specification. We include year fixed effects but exclude DURING and POST to avoid multicollinearity. The coefficient of DURING*PILOT is negative and significant at the 10% level. These results support our hypothesis and show that pilot firms reduce RAM in response to the increase in short selling threat. The coefficient of POST*PILOT is negative but not statistically significant, indicating that short sellers' mitigating effect on RAM does not persist after the pilot program ends.

for the variable of interest) indicates that firms may restrict those related economic activities and result in more cash flows.

Using the measure PROD as the dependent variable in Column (2), we find that the coefficient on DURING*PILOT is -0.026 and significant at the 1% level, indicating that abnormal production cost is 2.6% lower per dollar of assets for pilot firms than for nonpilot firms during the three-year period of the pilot program compared to the three-year pre-SHO period. Firms can engage in RAM through overproduction, which increases abnormal production costs but can spread the fixed overhead costs over a larger number of units, thereby lowering fixed costs per unit. This decreases the reported cost of goods sold (COGS) and leads to higher profits. Our finding of a decrease in abnormal production cost (or negative sign for the variable of interest DURING*PILOT) indicates that firms may restrict those abnormal production activities and thus lower the abnormal production costs.

In Column (3), we use DISEXP as the dependent variable. For ease of exposition, we multiple DISEXP by -1. We find that the coefficient on DURING*PILOT is not statistically significant, but the negative sign indicates increased abnormal discretionary expense (or reduced RAM). All of these findings consistently support our hypothesis and show that RAM decreases in response to the increase in the short selling threat. Given the disciplining effect of short selling threat on managers, managers may choose to reduce activities that are difficult to justify when any abnormality occurs. Both abnormal cash flow and abnormal production cost indicate deviations from core business operations and are difficult for managers to justify, whereas abnormal discretionary expenses include R&D and advertising expenses, which managers can use to explore new strategies, and allow for greater high variation over time. As such, we observe the reduction of RAM through abnormal cash flow and abnormal production cost rather than abnormal discretionary expense.

[Insert Table 4 here]

4.2. Relationship to Accrual Earnings Management

Given the substitute relationship between RAM and accrual-based earnings management identified in the extant literature, we run additional tests to examine accrual-based earnings management in our setting of short selling threat.

First, we replicate the test in Fang et al. (2014) to validate the decreased accrual-based earnings management during the SHO program period. We use performance-matched modified discretionary accruals (Dechow, Sloan, and Sweeney 1995; Kothari et al. 2005) as the dependent variable and employ a similar DID model. The result is reported in Column (1) of Table 5. We find that the variable of interest DURING*PILOT has a negative coefficient of -0.014, which is significant at the 1% level. This indicates that pilot firms decrease accrual-based earnings management during the SHO program period. This finding is consistent with Fang et al. (2014).[8]

[Insert Table 5 here]

Second, we include discretionary accruals as an addition control variable into our baseline RAM models. We find that the variable of interest DURING*PILOT is still negative and significant when we use CFO and PROD as dependent variables. These findings indicate that firms reduce both RAM and accrual-based earnings management during the SHO program period. These

[8] In unreported tests, we also use the measure for accrual-based earnings management without performance matching. We have similar findings.

results also suggest that RAM and accrual-based earnings management are not necessarily substituted.

4.3. Impact of Short Selling Threat on RAM: Sub-sample Analysis

The reduction of RAM is likely driven by firms that have the incentive to manage information disclosure. In this section, we examine how financial reporting strategy or financial reporting sentiment affects the relationship between short selling threat and RAM.

4.3.1. Financial Reporting Strategy and RAM

The financial reporting strategy that managers adopt has a significant impact on the capital market. Investors and other market participants have the ability to process information and discern differences in disclosure formats (e.g., in the notes or the financial statements), disclosure quantity (e.g., voluntary disclosure), or disclosure quality. A more transparent disclosure strategy gives investors and other market participants a greater possibility of detecting earnings management (e.g., Hirst and Hopkins 1998).

In our setting, where short sellers increase the stock price efficiency by incorporating unfavorable information, market participants can detect earnings management more easily. Managers can use RAM as an earnings management technique, which can be well hidden in the financial statements, especially when managers have an overall opaque reporting strategy (Kothari et al. 2015). Meanwhile, firms with a transparent reporting strategy disclose more information about firm performance and may easily release negative news that short sellers are seeking. We expect firms with a transparent reporting strategy to be more sensitive to short sellers' monitoring and have more pressure to change their opportunistic behavior such as RAM. Therefore, we predict that firms with a transparent reporting strategy will decrease RAM more than firms with an opaque reporting strategy.

We use a novel measure—namely, the number of voluntary 8-K items—to proxy for the level of financial reporting transparency. The SEC mandates the disclosure of material corporate information using current reports on Form 8-Ks. The current reports cover broad aspects about public companies, ranging from financial information and business operations to corporate governance issues. Although material events should be disclosed, managers have the discretion of determining the threshold of materiality and what events to report. We follow the line of studies on 8-K reports (Zhao 2016; Cooper et al. 2018) and define items 2.02, 7.01, and 8.01 as voluntarily disclosed items. We aggregate the number of voluntary items[9] reported for each firm-year to determine the extent of financial reporting transparency. We divide firms into two groups based on the number of voluntary 8-K items in the year 2004, which is before the pilot program. If the number of voluntary 8-K items is above the median of the sample, the firm is marked as transparent for all firm-years; otherwise, the firm is marked as opaque for all firm-years. In each subsample, we run the baseline regression using the composite measure of RAM as well as the three individual measures of RAM as the dependent variables.

The results in Panel A of Table 6 demonstrate that the variable of interest DURING*PILOT has a coefficient of -0.017 (t-statistic -2.433) for the subsample of reporting transparency, with the measure CFO as the dependent variable. The variable of interest DURING*PILOT has a coefficient of -0.019 (t-statistic -1.670) for the subsample of reporting transparency with PROD as the dependent variable, while DURING*PILOT is not statistically significant for the subsample of reporting opacity. These findings suggest that firms with a higher level of reporting transparency

[9] We obtain data using the SEC database search software DirectEdgar https://www.directedgar.com/.

strategy respond to short selling threat by reducing RAM whereas firms with a lower level of reporting transparency strategy do not significantly change RAM in response to the increased short selling threat. The reduction of RAM occurs by increasing abnormal cash flow and decreasing abnormal production cost, consistent with our findings in the baseline regression.

[Insert Table 6 here]

4.3.2. Financial Reporting Sentiment and RAM

The financial reporting sentiment may also affect managers' choice of accounting practices. During the SHO program, the pilot firms are sensitive to negative information, which is favored by short sellers for profitable arbitrage. To stabilize stock prices, managers of pilot firms may increase the uncertainty in financial information (Li and Zhang 2015) or reduce abnormal activities that produce negative information to the capital market. We argue that managers of firms with more negative sentiment in financial reports before the SHO program have a greater incentive to reduce abnormal activities, such as RAM. Investors of pilot firms with negative sentiment in financial reports are more sensitive to any additional negative information, giving more pressure to managers to reduce activities with a negative impact on stock prices. Therefore, we predict that firms with a more negative financial reporting sentiment prior to the SHO program decrease RAM during the SHO program more than firms with a less negative financial reporting sentiment.

We use the percentage of negative words in 10-K reports to measure the negative sentiment. Loughran and McDonald (2014) use textual analysis and a financial dictionary to count the number of sentiment words. We use the percentage of negative words, which is the number of negative words divided by the total number of words, as a measure of negative sentiment. We divide firms into two groups based on the percentage of negative words in the year 2004, which is before the pilot program. If the percentage of negative words is above the median of the sample, the firm is marked as having a high negative sentiment for all firm-years; otherwise, the firm is marked as having a low negative sentiment for all firm-years. In each subsample, we run the baseline regression using the three individual measures of RAM as the dependent variables.

The results are in Panel B of Table 6. The variable of interest DURING*PILOT has a coefficient of -0.017 (t-statistic -2.202) for the subsample of high negative sentiment with the measure CFO as the dependent variable. However, DURING*PILOT is not statistically significant (t-statistic -0.923) for the subsample of low negative sentiment. The variable of interest DURING*PILOT has a coefficient of -0.028 (t-statistic -2.026) for the subsample of high negative sentiment with PROD as the dependent variable, but it is not statistically significant for the subsample of low negative sentiment. These findings suggest that firms with a high level of negative sentiment respond to the short selling threat by reducing RAM whereas firms with a lower level of negative sentiment do not significantly change RAM in response to the increased short selling threat. The reduction of RAM occurs by increasing abnormal cash flow and decreasing abnormal production cost, which is consistent with our findings in the baseline regression.

4.3.3. Bad News and RAM

Similar to the effect of negative sentiment, we argue that bad news may also affect our baseline findings. Managers of firms with capital market bad news have a greater incentive to reduce abnormal activities, such as RAM. Investors of pilot firms with bad news are more sensitive to any additional negative information, giving more pressure to managers to reduce activities that have a negative impact on stock prices. Therefore, we predict that firms with bad news decrease RAM during the SHO program more than firms with good news.

We use the industry median of changes in market value (changes of market value from previous fiscal year to current fiscal year) to split firm-years. If the change in market value is above the industry-year median, firm-years are grouped in the subsample of good news. Otherwise, firm-years are grouped in the subsample of bad news. In each subsample, we rerun the three baseline models.

As the results in Panel C of Table 6 indicate, the variable of interest DURING*PILOT has a coefficient of -0.018 (t-statistic -2.655) for the subsample of bad news, with CFO as the dependent variable, whereas DURING*PILOT is not statistically significant (t-statistic -0.629) for the subsample of good news. The variable of interest DURING*PILOT has a coefficient of -0.050 (t-statistic -3.735) for the subsample of bad news, with PROD as the dependent variable, whereas DURING*PILOT is not statistically significant for the subsample of good news. These findings suggest that firms with bad news respond to the short selling threat by reducing RAM whereas firms with good news do not significantly change RAM in response to the increased short selling threat. The reduction of RAM occurs by increasing abnormal cash flow and decreasing abnormal production cost, consistent with our findings in the baseline regression.

4.4 Robustness Tests

4.4.1 R-squared Test

We examine the economic significance of our findings. In their working paper, Johannesson, Ohlson, and Zhai (2020) provide several diagnostic techniques to evaluate the explanatory power of the variable of interest. Johannesson et al. (2020) explain that the magnitude of a t-statistic and the resulting interpreted level of significance is a function of the number of observations; they thus suggest the formula t-statistic/sqrt(N)>0.03 to check whether the variable of interest has any incremental explanatory power with respect to the dependent variable. In our main findings, we find that our t-statistic/sqrt(N) is above 0.03 (columns 1 and 2 in Table 4). To further explore the economic meaningfulness of the short selling threat on RAM, we compare the R-squared between the model with and without the explanatory variable. We report the results in Table 7. As we can see, R-squared increases by adding the variable of interest DURING*PILOT for tests of each measure. For the test of CFO, R-squared increases by 2.1%, from 67.7% to 69.8%; for the test of PROD, R-squared increases by 0.8%, from 84.8% to 85.6%. Thus, we could conclude that the variable of interest, DURING*PILOT, has an incremental explanatory power with respect to RAM, showing the potential contribution of the setting to the literature.

[Insert Table 7 here]

4.4.2 Alternative Model Specification

We follow most prior RAM studies (e.g. Roychowdhury 2006; Cohen et al. 2008; Francis et al. 2016) and estimate RAM as the residuals from equations (1) to (3). We use these RAM measures AB_CFO, AB_PROD, and AB_DISEXP for further univariate and multivariate analysis. First, we report in Panel A of Table 8 the univariate test between pilot and nonpilot firms for three periods: pre-, during, and post-SHO program. We conduct both *t*-tests and Wilcoxon tests for mean differences and median differences between pilot and nonpilot RAM for each period. We do not find significant differences between pilot and nonpilot firms pre- and post-SHO program for all RAM measures, meaning that pilot firms do not significantly change their behavior in these two periods. However, during the SHO program, we find significant differences among some tests of AB_CFO and AB_PROD. For example, for the measure of AB_PROD, both mean and median are significantly different between pilot and nonpilot firms. This univariate test provides a preliminary result for the changed RAM behavior during the SHO program.

[Insert Table 8 here]

Second, we also report the correlation test between RAM and PILOT for different periods in Panel B of Table 8. We find that the correlation between each measure of RAM and PILOT is stronger (more positive or more negative) during the pilot period than for other periods. For example, the correlation between AB_PROD and PILOT during the pilot program (2005–2007) is -0.0463, the absolute value of which is greater than the absolute value of -0.0020 for the pre-SHO period and the absolute value of -0.0197 for the post-SHO period.

Lastly, the regression model is reported in Panel C of Table 8. In Column (1), when we use abnormal cash flow AB_CFO as the dependent variable, we find that the coefficient of DURING*PILOT is -0.014 and significant at the 5% level, indicating that abnormal cash flow is 1.4% higher per dollar of assets for pilot firms than for nonpilot firms during the three-year period of the pilot program compared to the three-year pre-SHO period. Firms can engage in RAM by providing price discounts or more lenient credit terms to boost sales volumes as well as current period earnings, but this results in lower cash flows (or a positive sign for the variable of interest) in the current period. Our finding of negative sign for the variable of interest (or higher abnormal cash flows) indicates that firms may restrict those related economic activities and result in more cash flows.

Using the measure AB_PROD as the dependent variable in Column (2), we find that the coefficient of DURING*PILOT is -0.021 and significant at the 1% level, indicating that abnormal production cost is 2.1% lower per dollar of assets for pilot firms than for nonpilot firms during the three-year period of the pilot program compared to the three-year pre-SHO period. Firms can engage in RAM through overproduction, which increases abnormal production costs but can spread the fixed overhead costs over a larger number of units, thereby lowering fixed costs per unit. This decreases the reported cost of goods sold (COGS) and leads to higher profits. Our finding of a decrease in abnormal production cost (or negative sign for the variable of interest DURING*PILOT) indicates that firms may restrict those abnormal production activities and thus lower the abnormal production costs.

In Column (3) when we use AB_DISEXP as the dependent variable, we find that the coefficient of DURING*PILOT is not statistically significant, but the negative sign indicates a reduced abnormal discretionary expense. All of these findings consistently support our hypothesis and show that RAM decreases in response to the increase in the short selling threat. Given the disciplining effect of short selling threat on managers, managers may choose to reduce activities that are difficult to justify when any abnormality occurs. Both abnormal cash flow and abnormal production cost indicate deviations from core business operations and are difficult for managers to justify, whereas abnormal discretionary expenses include R&D and advertising expenses, which managers can use to explore new strategies, and allow for greater high variation over time. As such, we observe the reduction of RAM through abnormal cash flow and abnormal production cost rather than abnormal discretionary expense.

4.4.3 Fama-MacBeth Regressions

We run Fama-MacBeth regressions by industry-year. To better report the effect for each period of pre-, during, and post-SHO program, we run the industry-year regression $Y = \beta_0 + \beta_1$ *PILOT* + *Controls* for each of these three periods. We do not use the modified method in Chen et al. (2018) since the regression is industry-year and has limited degree of freedom for each period of SHO. The *t*-stats of estimated coefficients, average coefficients, and average R-squared are reported (Fama and MacBeth 1973) in Table 9.

For both AB_CFO and AB_PROD, the results for the during period are consistent with baseline findings. Pilot firms have significantly lower AB_CFO and significantly lower AB_PROD during the program. For other periods, pilot firms are mostly not significantly different than nonpilot firms. Moreover, we compare the coefficients among different periods and estimate the frequencies of coefficients during the SHO program as being greater (or less) than other periods. We find that, for each individual measure of RAM, the number of coefficients indicating less RAM during the SHO program is greater than those in other periods.

We further run t tests to compare the differences between coefficients in each period and report the p-values in Table 9. We find that for AB_CFO and AB_CFO, RAM during SHO program is significantly different than pre-SHO program or than post-SHO program, confirming the significant reductions of RAM during the SHO program period compared to other periods.

[Insert Table 9 here]

5. Conclusion

In this paper, we investigate whether and how the short selling threat mitigates real activity manipulation. We test the research question in a unique setting where the SEC randomly selects a group of firms to participate in Regulation SHO, which removes short selling constraints from pilot firms, thereby increasing the short selling threat in these firms.

Using difference-in-differences tests around the pilot program, we find that real activity manipulation is significantly reduced for pilot firms during the program period. Pilot firms have significantly higher abnormal cash flows and lower abnormal production activities. The reduction effect is stronger for firms with a transparent financial reporting strategy, firms with a high level of negative sentiment, and firms with bad news. These firms have higher abnormal cash flows and lower abnormal production costs.

Our findings have several implications. First, prior literature generally finds that firms switch to RAM from accrual-based earnings management after regulation shocks. Our paper presents an interesting finding that RAM is also reduced in response to the short selling threat during the SHO program period. Our result suggests that RAM and accrual earnings management are not necessarily substituted. Second, our finding complements Fang et al.'s (2016) work in that it further advances our understanding of how the short selling threat affects overall earnings management. Third, unlike some other market participants, such as auditors and regulators, who focus more on accrual-based earnings management than RAM, our finding indicates that short sellers are effective monitors in that they deter both RAM and accrual-based earnings management. Finally, our paper supports the notion that the SEC's inclusion of short sellers in the capital market enhances market integrity.

References

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

Boehmer, E., and Wu, J. (2013). Short selling and the price discovery process, *Review of Financial Studies,* 26(2), 287–322.

Bushee, B. J. (1998). The influence of institutional investors on myopic R&D investment behavior. *The Accounting Review,* 73, 305–333.

Carcello, J. V., Hollingsworth, C. W., Klein, A., and Neal, T. L. (2006). Audit Committee Financial Expertise, Competing Corporate Governance Mechanisms, and Earnings Management. *Working paper*, The University of Tennessee and New York University.

Chan, L. H., Chen, K. C., Chen, T. Y., and Yu, Y. (2014). Substitution between real and accrual-based earnings management after voluntary adoption of compensation clawback provisions. *The Accounting Review,* 90(1), 147-174.

Chang, E., Cheng, J., and Yu, Y. (2007). Short-sales constraints and price discovery: Evidence from the Hong Kong market, *Journal of Finance,* 62(5), 2097–2121.

Chen, X., Cheng, Q., Lo, A., and Wang, X. (2015). CEO contractual protection and managerial short-termism. *The Accounting Review,* 90 (5), 1871–1906.

Chen, W., Hribar, P., & Melessa, S. (2018). Incorrect Inferences When Using Residuals as Dependent Variables. *Journal of Accounting Research,* 56(3), 751-796.

Cheng, Q., J., Lee, and Shevlin, T., (2016). Internal Governance and Real Earnings Management. *The Accounting Review,* 91(4), 1051-1085.

Cohen, D. A., Dey, A., and Lys, T. Z. (2008). Real and accrual-based earnings management in the pre-and post-Sarbanes-Oxley periods. *The Accounting Review,* 83(3), 757-787.

Cohen, D. A., and Zarowin, P. (2010). Accrual-based and real earnings management activities around seasoned equity offerings. *Journal of Accounting and Economics*, 50(1), 2-19.

Cooper, M. J., He, J., and Plumlee, M. A. (2018), Measuring Disclosure Using 8K Filings Available at SSRN: https://ssrn.com/abstract=2640722

Dechow, P. M., Hutton, A. P., Meulbroek, L., and Sloan, R. G. (2001). Short-sellers, fundamental analysis, and stock returns. *Journal of Financial Economics,* 61(1), 77-106.

Dechow, P. M., Sloan, R. G., and Sweeney, A. P. (1995). Detecting earnings management. *The Accounting review*, 70(2), 193-225.

Desai, H., Krishnamurthy, S., and Venkataraman, K. (2006). Do short sellers target firms with poor earnings quality? Evidence from earnings restatements. *Review of Accounting Studies*, 11(1), 71-90.

Diamond, D. W., and Verrecchia. R. E. (1987). Constraints on short-selling and asset price adjustment to private information. *Journal of Financial Economics*, 18(2), 277–311.

Duffie, D., Garleanu, N., and Pedersen, L. H. 2002. Securities lending, shorting, and pricing. *Journal of Financial Economics*, 66(2-3), 307–39.

Eldenburg, L. G., Gunny, K. A., Hee, K. W., and Soderstrom, N. (2011). Earnings management using real activities: Evidence from nonprofit hospitals. *The Accounting Review*, 86(5), 1605-1630.

Ewert, R., and Wagenhofer, A. (2005). Economic effects of tightening accounting standards to restrict earnings management. *The Accounting Review,* 80(4), 1101–1124.

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3), 607-636.

Fang, V. W., Huang, A. H., and Karpoff, J. M. (2016). Short selling and earnings management: A controlled experiment. *The Journal of Finance,* 71(3), 1251-1294.

Francis, B., I. Hasan, and L. Li. (2016). A cross-country study of the legal system strength and real earnings management. *Journal of Accounting and Public Policy,* 35(5), 477-512.

Gao, L., He, J., and Wu, J. J. (2016). Standing out from the Crowd via Corporate Goodness: Evidence from a Natural Experiment. Available at SSRN: https://ssrn.com/abstract=2830742

Graham, J., Harvey, C., and Rajgopal., S. (2005). "The Economic Implications of Corporate Financial Reporting." *Journal of Accounting and Economics*, 40 (1-3), 3–73.

Grullon, G., Michenaud, S., and Weston, J. P. (2015). The real effects of short-selling constraints. *Review of Financial Studies,* 28(6), 1737-1767.

Healy, P.M., Wahlen, J.M., (1999). A review of the earnings management literature and its implications for standard setting. *Accounting Horizons,* 13(4), 365–383.

Hirst, D. E., and Hopkins, P. E. (1998). Comprehensive income reporting and analysts' valuation judgments. *Journal of Accounting Research,* 36, 47–75.

Hope, O. K., Hu, D., and Zhao, W. (2017). Third-party consequences of short-selling threats: The case of auditor behavior. *Journal of Accounting and Economics,* 63(2), 479-498.

Hong, H., and J. Stein. (2003). Differences of opinion, short-sales constraints, and market crashes. *Review of Financial Studies,* 16(2), 487–525

Hutton, A. P., Marcus, A. J., & Tehranian, H. (2009). Opaque financial reports, R2, and crash risk. *Journal of Financial Economics*, 94(1), 67-86.

Irani, R. M., and Oesch, D. (2016). Analyst coverage and real earnings management: Quasi-experimental evidence. *Journal of Financial and Quantitative Analysis*, 51(2), 589-627.

Johannesson, E., Ohlson, J. A., & Zhai, W. (2020). The Explanatory Power of Explanatory Variables. Available at https://ssrn.com/abstract=3622743

Jones, J. J. (1991). Earnings management during import relief investigations. *Journal of Accounting Research*, 29(2), 193-228.

Karpoff, J. M., and Lou, X. (2010). Short sellers and financial misconduct, *Journal of Finance*, 65(5), 1879–1913.

Khurana, I. K., Pereira, R., and Zhang, E. (2018). Is real earnings smoothing harmful? Evidence from firm-specific stock price crash risk. *Contemporary Accounting Research*, 35(1), 558-587.

Kim, J.-B., and Sohn, B. C. (2013). Real earnings management and cost of capital, *Journal of Accounting and Public Policy*, 32(6), 518–543.

Kim, Y., and Park, M.S. (2014). Real activities manipulation and auditors' client retention decisions. *The Accounting Review,* 89(1), 367-401.

Kothari, S. P., Mizik, N., and Roychowdhury, S. (2015). Managing for the moment: The role of earnings management via real activities versus accruals in SEO valuation. *The Accounting Review,* 91(2), 559-586.

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

Laksmana, I., and Yang, Y. W. (2014). Product market competition and earnings management: Evidence from discretionary accruals and real activity manipulation. *Advances in Accounting*, 30(2), 263-275.

Li, X. (2012). Real earnings management and subsequent stock returns, *Working Paper*, Hong Kong University of Science & Technology.

Li, Y., and Zhang, L. (2015). Short selling pressure, stock price behavior, and management forecast precision: Evidence from a natural experiment. *Journal of Accounting Research*, 53(1), 79-117.

Lopez, D. M., & Vega, J. J. (2019). Evaluating the effect of industry specialist duration on earnings management. *Advances in Accounting*, 45, 100412.

Loughran, T., and McDonald, B. (2014). Measuring readability in financial disclosures. *The Journal of Finance*, 69(4), 1643-1671.

Matthew J. Belvedere. (2020). SEC chair: We shouldn't ban short selling — it's needed for properly functioning market. https://www.cnbc.com/2020/03/30/sec-chairman-jay-clayton-short-selling-should-not-be-banned.html

Massa, M., Zhang, B., and Zhang, H. (2015). The invisible hand of short selling: does short selling discipline earnings management?. *The Review of Financial Studies*, 28(6), 1701-1736.

Miles, R. E., and Snow, C. C. (1978). Organizational strategy, structure and process. New York: McGraw-Hill.

Miles, R. E., and Snow, C. C. (2003). Organizational strategy, structure, and process. Stanford, CA: Stanford University Press.

Palmrose, Z. V., and S. Scholz. (2004). The circumstances and legal consequences of on-GAAP reporting: Evidence from restatements. *Contemporary Accounting Research,* 21(1), 139–180.

Park, K. (2017) Earnings quality and short selling: Evidence from real earnings management in the United States. *Journal of Business Finance and Accounting,* 44(9-10), 1214-1240.

Roychowdhury, S. (2006). Earnings management through real activities manipulation. *Journal of Accounting and Economics,* 42(3), 335–370.

Saffi, P., and Sigurdsson, K. (2011). Price efficiency and short selling. *Review of Financial Studies,* 24(3), 821–52.

The Securities and Exchange Commission (SEC). (2005). Regulation SHO — Pilot Program. Retrieved from: https://www.sec.gov/spotlight/shopilot.htm

Vorst, P. (2016). Real earnings management and long-term operating performance: The role of reversals in discretionary investment cuts. *The Accounting Review,* 91(4), 1219-1256.

Zang, A. Y. (2012). Evidence on the trade-off between real activities manipulation and accrual-based earnings management. *The Accounting Review,* 87(2), 675-703.

Zhang, Y., Perols, J., Robinson, D., and Smith, T. (2018). Earnings management strategies to maintain a string of meeting or beating analyst expectations. *Advances in Accounting*, 43, 46-55.

Zhao, X. (2016). Does information intensity matter for stock returns? Evidence from form 8-K filings. *Management Science,* 63(5), 1382-1404.

Zhu, W. (2016). Accruals and price crashes. *Review of Accounting Studies*, 21(2), 349-399.

Table 1 Sample

Panel A: Sample-Selection Steps

	Pilot Firms	Nonpilot Firms	Total
Russell 3000 companies on June 30, 2004	986	2012	2998
Merged with Compustat	809	1637	2446
Excluding financial and utilities firms	597	1791	2388
Merged with Institutional ownership and analyst data	487	989	1476

Panel B: Sample Distribution by Year

Year	Nonpilot Firms	Pilot Firms	Firm-Years	Yearly Percentage of Firm-Years
2001	604	306	910	9.72%
2002	728	381	1,109	11.85%
2003	753	387	1,140	12.18%
2005	754	382	1,136	12.13%
2006	725	373	1,098	11.73%
2007	684	358	1,042	11.13%
2008	634	338	972	10.38%
2009	644	339	983	10.50%
2010	641	331	972	10.38%
Total			9,362	100.00%

Table 2 Summary Statistics

Panel A: Full Sample Summary Statistics

VARIABLE	N	Mean	SD	P25	P50	P75
CFO	9362	-0.096	0.157	-0.053	-0.106	-0.164
PROD	8383	0.701	0.578	0.287	0.555	0.942
DISEXP	9447	-0.344	0.278	-0.149	-0.284	-0.465
1/AT_LAG1	9362	0.004	0.007	0.000	0.001	0.004
SALE_LAG1	9362	1.137	0.744	0.626	0.990	1.452
SALE_CHG1	9362	0.056	0.195	-0.015	0.059	0.144
SOX	9362	0.784	0.411	1.000	1.000	1.000
SIZE	9362	7.009	1.647	5.898	6.836	7.975
MTB	9362	3.290	3.637	1.501	2.320	3.753
ROA	9362	0.103	0.158	0.071	0.126	0.179
LEV	9362	0.179	0.233	0.000	0.126	0.270
ZSCORE	9362	1.394	2.709	1.012	1.874	2.629
INS_OWN	9362	0.704	0.242	0.565	0.751	0.876
BIG4	9362	0.905	0.294	1.000	1.000	1.000
ANALYST	9362	8.360	6.830	3.000	6.000	12.000
SEC SCRUTINY	9362	0.015	0.121	0.000	0.000	0.000

Panel B: Comparison between Pilot vs. Non-Pilot firms before the Pilot Program – Year 2003

	Pilot Firms		Non-Pilot Firms			
VARIABLE	N	Mean	N	Mean	Difference	t-stat
CFO	387	-0.086	753	-0.085	0.001	0.14
PROD	387	0.684	752	0.686	-0.002	-0.48
DISEXP	389	-0.364	760	-0.361	0.003	0.10
1/AT_LAG1	387	0.005	753	0.005	0.000	0.02
SALE_LAG1	387	1.147	753	1.150	-0.003	-0.07
SALE_CHG1	387	0.090	753	0.095	-0.005	-0.53
SIZE	387	6.967	753	6.842	0.125	1.34
MTB	387	4.033	753	3.602	0.431	1.76
ROA	387	0.104	753	0.097	0.007	0.72
LEV	387	0.187	753	0.177	0.01	0.69
ZSCORE	387	1.494	753	1.325	0.169	1.16
INS_OWN	387	0.614	753	0.613	0.001	0.08
BIG4	387	0.948	753	0.956	-0.008	-0.60
ANALYST	387	8.189	753	8.046	0.143	0.32
SEC SCRUTINY	387	0.026	753	0.024	0.002	0.20

Table 3 Pearson Correlation

	CFO	*PROD*	*DISEXP*	*1/AT_ LAG1*	*SALE_ LAG1*	*SALE_ CHG1*	*SALE_ CHG2*	*SIZE*	*MTB*	*ROA*	*LEV*	*ZSCORE*	*INS_OWN*	*BIG4*	*ANALYST*	*SEC SCRUTINY*
CFO	1															
PROD	-0.0384*	1														
DISEXP	-0.1988*	0.0195*	1													
1/AT_LAG1	0.3662*	-0.0418*	-0.5140*	1												
SALE_LAG1	-0.2689*	0.7665*	-0.2553*	-0.0320*	1											
SALE_CHG1	-0.1468*	0.2006*	-0.2246*	0.1342*	0.4439*	1										
SOX	-0.0258*	-0.0151	0.0457*	-0.1069*	-0.0214*	0.0079	1									
SIZE	-0.2775*	0.015	0.4516*	-0.6561*	0.0306*	-0.0514*	0.1305*	1								
MTB	-0.0544*	-0.0114	-0.1751*	0.1221*	0.0703*	0.1409*	0.0023	-0.0407*	1							
ROA	-0.6531*	0.1175*	0.2389*	-0.4402*	0.4088*	0.2170*	0.0463*	0.4112*	0.0577*	1						
LEV	-0.0104	-0.0134	0.1667*	-0.1451*	-0.0641*	-0.0481*	0.0039	0.2533*	-0.0976*	0.0598*	1					
ZSCORE	-0.4968*	0.2692*	0.2092*	-0.4726*	0.4673*	0.1351*	0.0088	0.3798*	0.0278*	0.7437*	-0.0844*	1				
INS_OWN	-0.1936*	0.0321*	0.0992*	-0.3874*	0.0722*	0.0382*	0.2596*	0.2935*	0.0126	0.2256*	0.0311*	0.2457*	1			
BIG4	-0.0312*	-0.0092	0.0830*	-0.2111*	-0.0249*	-0.0272*	-0.0921*	0.2447*	0.0290*	0.0276*	0.0678*	0.0570*	0.1209*	1		
ANALYST	-0.1934*	-0.0731*	0.1166*	-0.2975*	-0.0045	0.0495*	0.0994*	0.5601*	0.1079*	0.2463*	0.016	0.1754*	0.3035*	0.1725*	1	
SEC SCRUTINY	0.0357*	-0.0257*	0.0154	-0.0064	-0.0454*	-0.0095	-0.0423*	0.0385*	-0.0089	-0.0506*	0.0404*	-0.0499*	0.0045	0.0297*	0.0099	1

Table 4 The Effect of Short Selling Threat on RAM

This table reports the results of the OLS regression model, following model specification in Chen et al. (2018). In column (1), the dependent variable CFO is cash flow from operating activities scaled by lagged total asset and multiplied by negative one. In column (2), PROD is production cost, including cost of goods sold (COGS) and changes in inventory (INVT), scaled by lagged total asset. In column (3), DISEXP is discretionary expenses, including research and development expense (XRD), advertising expense (XAD), and selling, general and administrative expense (XSGA), scaled by lagged total asset and multiplied by negative one. The variable of interest is DURING*PILOT. The p-values are based on two-way clustering of standard errors by year and firm. The detailed definitions of all variables are provided in the Appendix A.

VARIABLES	(1) CFO	(2) PROD	(3) DISEXP
DURING*PILOT	-0.014***	-0.026***	-0.009
	(-2.960)	(-2.940)	(-0.908)
POST*PILOT	-0.011**	-0.030**	-0.003
	(-2.191)	(-2.528)	(-0.253)
DURING	-0.048**	0.010	-0.010
	(-2.278)	(0.566)	(-0.712)
POST	-0.068***	0.021	-0.006
	(-4.048)	(1.082)	(-0.356)
PILOT	0.008**	0.019	0.017
	(2.301)	(1.611)	(1.364)
1/AT_LAG1	2.323***	-1.865	-12.006***
	(3.842)	(-1.004)	(-9.388)
SALE_LAG1	-0.026***	0.701***	-0.134***
	(-5.481)	(11.988)	(-5.524)
SALE_CHG1	0.026	0.417***	
	(1.315)	(5.496)	
SALE_CHG2		0.069	
		(1.319)	
SOX	0.010	-0.003	-0.008
	(1.126)	(-0.130)	(-0.616)
SIZE	0.009***	0.031***	0.037***
	(6.479)	(5.865)	(7.576)
MTB	-0.003***	-0.005***	-0.004***
	(-4.686)	(-3.302)	(-4.388)
ROA	-0.721***	-0.800***	0.065
	(-35.506)	(-10.827)	(1.248)
LEV	0.007	0.021	0.018
	(0.777)	(0.692)	(0.635)
ZSCORE	0.000	0.017***	0.008*
	(0.356)	(3.068)	(1.917)
INS_OWN	-0.000	0.020	-0.030
	(-0.052)	(0.877)	(-1.270)
BIG4	0.010**	-0.017	-0.054***
	(2.383)	(-0.981)	(-2.948)
ANALYST	-0.002***	-0.005***	-0.007***
	(-7.873)	(-5.889)	(-8.737)
SEC SCRUTINY	0.007	-0.008	0.022
	(1.254)	(-0.238)	(0.808)
Constant	-0.032**	-0.155**	-0.212***
	(-2.273)	(-2.015)	(-2.950)

Observations	9,362	8,383	9,447
Adj. R-squared	0.683	0.856	0.505
Interaction Terms	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes

Table 5 Relation with Accrual Earnings Management

This table reports the results of the OLS regression model. The dependent variable in column (1) is the modified discretionary accruals. The dependent variable CFO in column (2) is cash flow from operating activities scaled by lagged total asset and multiplied by negative one. In column (3), PROD is production cost, while in column (3) DISEXP is discretionary expenses, multiplied by negative one. The variable of interest is DURING*PILOT. The p-values are based on two-way clustering of standard errors by year and firm. The detailed definitions of all variables are provided in the Appendix A.

	(1)	(2)	(3)	(4)
VARIABLES	EM_KOTHARI	CFO	PROD	DISEXP
DURING*PILOT	-0.014***	-0.026***	-0.026***	-0.007
	(-2.989)	(-2.871)	(-2.871)	(-0.729)
POST*PILOT	-0.011**	-0.030**	-0.030**	-0.003
	(-2.180)	(-2.513)	(-2.513)	(-0.241)
DURING	-0.048**	0.009	0.009	-0.009
	(-2.301)	(0.500)	(0.500)	(-0.674)
POST	-0.068***	0.021	0.021	-0.005
	(-4.047)	(1.051)	(1.051)	(-0.298)
PILOT	0.008**	0.019	0.019	0.016
	(2.278)	(1.561)	(1.561)	(1.357)
EM_KOTHARI	0.001	0.001	0.001	0.002
	(0.526)	(0.370)	(0.370)	(0.853)
1/AT_LAG1		2.305***	-2.191	-10.990***
		(3.794)	(-1.144)	(-9.209)
SALE_LAG1		-0.026***	0.703***	-0.130***
		(-5.440)	(11.948)	(-5.714)
SALE_CHG1		0.026	0.413***	
		(1.344)	(5.432)	
SALE_CHG2			0.068	
			(1.307)	
SOX	-0.175***	0.010	-0.003	-0.007
	(-6.050)	(1.119)	(-0.125)	(-0.524)
SIZE	-0.034*	0.009***	0.031***	0.042***
	(-1.845)	(6.400)	(5.862)	(8.947)
MTB	-0.003	-0.003***	-0.003***	-0.004***
	(-0.401)	(-4.575)	(-2.949)	(-4.646)
ROA	-0.243	-0.720***	-0.809***	0.064
	(-0.616)	(-35.311)	(-10.804)	(1.325)
LEV	0.101	0.008	0.009	0.023
	(0.672)	(0.802)	(0.295)	(0.856)
ZSCORE	-0.008	0.000	0.017***	0.008*
	(-0.280)	(0.334)	(3.138)	(1.959)
INS_OWN	0.020	-0.001	0.019	-0.042*
	(0.187)	(-0.094)	(0.800)	(-1.785)
BIG4		0.010**	-0.017	-0.053***
		(2.433)	(-1.014)	(-2.934)
ANALYST		-0.002***	-0.005***	-0.006***
		(-7.748)	(-6.192)	(-8.501)
SEC SCRUTINY		0.007	-0.006	0.024
		(1.191)	(-0.176)	(0.871)
Constant	0.439***	-0.032**	-0.156**	0.247***
	(3.110)	(-2.233)	(-2.021)	(3.355)
Observations	12,312	9,320	8,346	9,402

R-squared	0.039	0.682	0.855	0.511
Interaction Terms		Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes

Table 6 Subsample Analysis

Panel A The Impact of Financial Reporting Strategy

This table reports subsample analysis on how financial reporting strategy affects the relation between short selling threat and RAM. The dependent variables are from the models for individual measures of RAM. The variable of interest is DURING*PILOT. The p-values are based on two-way clustering of standard errors by year and firm. The detailed definitions of all variables are provided in the Appendix A.

	Reporting Transparency	Reporting Opacity	Reporting Transparency	Reporting Opacity	Reporting Transparency	Reporting Opacity
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	CFO	CFO	PROD	PROD	DISEXP	DISEXP
DURING*PILOT	-0.017**	-0.000	-0.019*	-0.016	-0.012	0.008
	(-2.433)	(-0.073)	(-1.670)	(-1.112)	(0.984)	(-0.555)
POST*PILOT	-0.015**	0.001	-0.040**	-0.014	0.008	-0.005
	(-1.997)	(0.206)	(-2.445)	(-0.776)	(0.551)	(-0.326)
DURING	0.026	-0.103***	-0.000	0.033	0.020	-0.036
	(1.141)	(-3.583)	(-0.007)	(0.349)	(1.298)	(-1.039)
POST	-0.007	-0.102***	0.021	0.034	0.018	-0.042
	(-0.361)	(-3.456)	(0.914)	(0.362)	(0.997)	(-1.156)
PILOT	0.011**	-0.002	0.017	0.028	-0.019	-0.018
	(2.050)	(-0.443)	(1.064)	(1.526)	(-1.176)	(-0.911)
1/AT_LAG1	5.347***	0.186	0.583	-5.884***	12.606***	10.863***
	(3.565)	(0.222)	(0.175)	(-2.836)	(5.021)	(5.964)
SALE_LAG1	-0.020**	-0.030***	0.693***	0.719***	0.139***	0.095***
	(-2.507)	(-4.590)	(10.085)	(6.743)	(5.028)	(2.616)
SALE_CHG1	0.033*	0.069***	0.385***	0.442***		
	(1.810)	(2.882)	(5.585)	(4.926)		
SALE_CHG2			0.039	0.142		
			(0.583)	(1.545)		
SOX	0.013	-0.011	0.005	-0.030	0.003	0.040
	(1.183)	(-0.454)	(0.240)	(-0.365)	(0.189)	(1.180)
SIZE	0.010***	0.006***	0.031***	0.031***	-0.044***	-0.043***
	(5.294)	(2.625)	(4.270)	(3.260)	(-6.656)	(-5.868)
MTB	-0.002***	-0.002***	-0.002	-0.012***	0.004***	0.005***
	(-3.633)	(-2.712)	(-0.998)	(-4.522)	(3.317)	(3.212)
ROA	-0.735***	-0.681***	-0.851***	-0.815***	-0.037	-0.052
	(-25.843)	(-25.726)	(-9.818)	(-5.399)	(-0.660)	(-0.527)
LEV	0.007	0.016	0.066	0.040	-0.046	-0.009

	(0.453)	(1.595)	(1.495)	(0.972)	(-1.277)	(-0.212)
ZSCORE	-0.000	0.000	0.031***	-0.001	-0.011***	-0.001
	(-0.055)	(0.368)	(4.874)	(-0.108)	(-2.783)	(-0.128)
INS_OWN	-0.008	-0.003	0.036	-0.047	0.033	0.108***
	(-1.016)	(-0.407)	(1.100)	(-1.099)	(1.002)	(2.826)
BIG4	0.014**	0.006	-0.011	-0.015	0.044	0.048*
	(2.496)	(1.016)	(-0.368)	(-0.668)	(1.555)	(1.771)
ANALYST	-0.002***	-0.001***	-0.005***	-0.004***	0.007***	0.006***
	(-7.186)	(-3.382)	(-4.613)	(-3.080)	(6.645)	(4.842)
SEC SCRUTINY	0.006	0.004	-0.048	0.012	-0.034*	-0.006
	(0.640)	(0.522)	(-1.257)	(0.235)	(-1.759)	(-0.114)
Constant	-0.078***	-0.003	-0.133	-0.070	0.172***	0.243***
	(-3.840)	(-0.164)	(-1.563)	(-0.655)	(2.758)	(2.745)
Observations	5,102	3,634	4,566	3,190	5,156	3,664
R-squared	0.694	0.711	0.841	0.899	0.530	0.527
Interaction Terms	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B The Impact of Negative Sentiment

This table reports subsample analysis on how financial reporting sentiment affects the relation between short selling threat and RAM. The dependent variables are from the models for individual measures of RAM. The variable of interest is DURING*PILOT. The p-values are based on two-way clustering of standard errors by year and firm. The detailed definitions of all variables are provided in the Appendix A.

	High Negative Sentiment	Low Negative Sentiment	High Negative Sentiment	Low Negative Sentiment	High Negative Sentiment	Low Negative Sentiment
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	CFO	CFO	PROD	PROD	DISEXP	DISEXP
DURING*PILOT	-0.017**	-0.006	-0.028**	-0.010	-0.002	0.011
	(-2.202)	(-0.923)	(-2.026)	(-0.867)	(-0.115)	(1.068)
POST*PILOT	-0.011	-0.009	-0.043**	-0.009	0.003	0.009
	(-1.253)	(-1.509)	(-2.324)	(-0.637)	(0.154)	(0.769)
DURING	-0.058***	-0.034	0.016	-0.001	0.022	0.005
	(-3.030)	(-1.154)	(0.613)	(-0.051)	(1.001)	(0.277)
POST	-0.077***	-0.075***	0.039	0.000	0.017	0.004
	(-4.041)	(-3.043)	(1.406)	(0.013)	(0.690)	(0.228)
PILOT	0.008	0.006	0.025	0.006	-0.011	-0.012
	(1.320)	(1.281)	(1.365)	(0.357)	(-0.578)	(-0.724)
1/AT_LAG1	3.487***	2.395**	2.095	-3.828*	10.310***	9.243***
	(2.588)	(2.494)	(0.531)	(-1.701)	(5.110)	(4.571)
SALE_LAG1	-0.037***	-0.013**	0.691***	0.730***	0.132***	0.116***
	(-3.283)	(-2.570)	(8.702)	(8.200)	(4.816)	(3.222)
SALE_CHG1	0.086***	-0.031***	0.409***	0.340***		
	(3.159)	(-2.785)	(5.249)	(4.116)		
SALE_CHG2			0.077	0.073		
			(1.052)	(0.833)		
SOX	0.016	0.000	0.008	-0.014	0.004	0.002
	(1.122)	(0.020)	(0.313)	(-0.503)	(0.194)	(0.124)
SIZE	0.006***	0.010***	0.035***	0.034***	-0.045***	-0.037***
	(2.689)	(5.080)	(4.025)	(4.047)	(-7.012)	(-5.073)
MTB	-0.003***	0.000	-0.003*	-0.008***	0.005***	0.002*
	(-3.243)	(0.141)	(-1.725)	(-3.432)	(3.792)	(1.796)
ROA	-0.702***	-0.780***	-0.824***	-0.882***	-0.151**	0.153**
	(-25.704)	(-22.314)	(-7.539)	(-4.875)	(-2.198)	(2.099)
LEV	0.021	-0.013	0.049	0.033	0.018	-0.144***
	(1.359)	(-1.345)	(1.226)	(0.566)	(0.501)	(-3.687)
ZSCORE	-0.001	-0.000	0.021***	0.022	-0.001	-0.035***

	(-0.490)	(-0.016)	(2.677)	(1.425)	(-0.175)	(-3.302)
INS_OWN	0.001	-0.008	0.018	-0.010	0.060*	0.057
	(0.107)	(-0.920)	(0.470)	(-0.291)	(1.780)	(1.626)
BIG4	0.009	0.014**	0.008	-0.036	0.044*	0.065**
	(1.402)	(2.539)	(0.382)	(-1.376)	(1.730)	(2.242)
ANALYST	-0.002***	-0.001***	-0.006***	-0.003**	0.008***	0.003***
	(-6.132)	(-3.049)	(-4.387)	(-2.201)	(7.509)	(2.907)
SEC SCRUTINY	-0.000	0.016**	0.061	-0.068	-0.024	-0.026
	(-0.003)	(2.107)	(1.537)	(-1.635)	(-0.657)	(-0.677)
Constant	0.008	-0.049***	-0.230*	-0.117*	0.273***	0.202***
	(0.407)	(-2.626)	(-1.958)	(-1.818)	(2.883)	(4.112)
Observations	4,251	4,485	3,803	3,953	4,286	4,534
R-squared	0.672	0.720	0.843	0.878	0.518	0.546
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel C The Impact of Bad News

This table reports subsample analysis on how capital market news affects the relation between short selling threat and RAM. The dependent variables are from the models for individual measures of RAM. The variable of interest is DURING*PILOT. We split the sample based on the industry-year median change of market value. Firm-years with change of market value above industry-year median are grouped in the subsample of good news. Otherwise firm-years are grouped in the subsample of bad news. The p-values are based on two-way clustering of standard errors by year and firm. The detailed definitions of all variables are provided in the Appendix A.

	Bad News	Good News	Bad News	Good News	Bad News	Good News
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	CFO	CFO	PROD	PROD	DISEXP	DISEXP
DURING*PILOT	-0.018***	-0.004	-0.050***	-0.008	0.000	-0.008
	(-2.655)	(-0.629)	(-3.735)	(-0.409)	(0.022)	(-0.473)
POST*PILOT	-0.016**	0.000	-0.046**	-0.015	0.009	-0.006
	(-2.068)	(0.025)	(-2.289)	(-0.716)	(0.488)	(-0.384)
DURING	-0.026	-0.016	0.036	-0.019	-0.046***	-0.011
	(-0.562)	(-0.444)	(1.266)	(-0.755)	(-6.077)	(-0.195)
POST	-0.045	-0.029	0.037	-0.014	-0.053***	-0.013
	(-0.978)	(-0.953)	(1.300)	(-0.543)	(-7.564)	(-0.239)
PILOT	0.011**	-0.001	0.022*	0.014	0.007	0.026**
	(2.325)	(-0.113)	(1.727)	(0.736)	(0.513)	(2.031)
1/AT_LAG1	3.465***	2.761***	1.417	-1.463	-15.740***	-2.422**
	(2.751)	(3.217)	(0.572)	(-0.746)	(-3.475)	(-2.046)
SALE_LAG1	-0.040***	-0.002	0.739***	0.646***	-0.156***	-0.196***
	(-5.795)	(-0.228)	(11.866)	(9.897)	(-4.674)	(-7.981)
SALE_CHG1	0.071***	0.021*	0.468***	0.429***		
	(2.934)	(1.937)	(6.321)	(3.515)		
SALE_CHG2			0.099*	0.041		
			(1.807)	(0.480)		
SOX	-0.021	0.006	0.004	-0.021	-0.107	0.086
	(-0.464)	(0.892)	(0.144)	(-0.865)	(-1.138)	(0.934)
SIZE	0.010***	0.009***	0.029***	0.034***	0.036***	0.052***
	(5.155)	(4.720)	(5.234)	(5.333)	(7.388)	(12.488)
MTB	-0.002***	-0.003***	-0.004***	-0.006**	-0.004***	-0.002*
	(-2.726)	(-3.224)	(-2.762)	(-2.535)	(-2.844)	(-1.897)
ROA	-0.802***	-0.671***	-0.957***	-0.690***	0.119*	0.146***
	(-26.441)	(-24.613)	(-10.410)	(-8.486)	(1.777)	(3.436)
LEV	-0.014	0.036**	0.054*	0.004	0.032	-0.032
	(-1.110)	(2.508)	(1.794)	(0.115)	(0.687)	(-0.847)

ZSCORE	0.002	-0.001	0.027***	0.009*	0.007	0.005*
	(0.869)	(-1.160)	(3.483)	(1.931)	(1.541)	(1.947)
INS_OWN	-0.005	0.005	0.006	0.029	-0.045**	-0.013
	(-0.585)	(0.542)	(0.254)	(0.984)	(-2.260)	(-0.717)
BIG4	0.010*	0.003	-0.014	-0.023	-0.049**	-0.065***
	(1.667)	(0.499)	(-0.532)	(-1.369)	(-2.391)	(-5.293)
ANALYST	-0.002***	-0.001***	-0.005***	-0.005***	-0.006***	-0.008***
	(-6.740)	(-4.279)	(-4.999)	(-5.239)	(-8.593)	(-11.250)
SEC SCRUTINY	0.017**	-0.003	0.029	-0.028	0.052**	-0.007
	(1.976)	(-0.410)	(0.762)	(-0.774)	(2.056)	(-0.344)
Constant	-0.025	-0.066**	-0.208***	-0.036	-0.174*	-0.306***
	(-1.265)	(-2.193)	(-2.837)	(-0.357)	(-1.718)	(-3.482)
Observations	4,861	4,501	4,567	3,816	4,919	4,528
R-squared	0.649	0.724	0.849	0.873	0.466	0.944
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7 R-squared Test

This table reports the results of the OLS regression model. The dependent variables are from the models for individual measures of RAM. We report R-squared rather than adjusted R-squared. The p-values are based on two-way clustering of standard errors by year and firm. The detailed definitions of all variables are in the Appendix A.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	CFO	CFO	PROD	PROD	DISEXP	DISEXP
DURING*PILOT		-0.014***		-0.026***		-0.009
		(-2.960)		(-2.940)		(-0.908)
POST*PILOT	0.002	-0.011**	-0.012	-0.030**	-0.006	-0.003
	(0.562)	(-2.191)	(-1.418)	(-2.528)	(-0.682)	(-0.253)
DURING	0.062**	-0.048**	-0.017	0.010	0.011	-0.010
	(2.320)	(-2.278)	(-1.002)	(0.566)	(0.827)	(-0.712)
POST	0.066***	-0.068***	0.008	0.021	0.009	-0.006
	(3.311)	(-4.048)	(0.397)	(1.082)	(0.610)	(-0.356)
PILOT	-0.002	0.008**	0.002	0.019	-0.012	0.017
	(-0.535)	(2.301)	(0.195)	(1.611)	(-1.117)	(1.364)
1/AT_LAG1	-2.149***	2.323***	-4.293**	-1.865	0.547	-12.006***
	(-3.103)	(3.842)	(-2.073)	(-1.004)	(0.258)	(-9.388)
SALE_LAG1	0.036***	-0.026***	0.718***	0.701***	0.164***	-0.134***
	(3.686)	(-5.481)	(12.963)	(11.988)	(7.431)	(-5.524)
SALE_CHG1	-0.011	0.026	0.359***	0.417***		
	(-0.615)	(1.315)	(4.902)	(5.496)		
SALE_CHG2			0.068	0.069		
			(1.432)	(1.319)		
SOX	-0.011	0.010	0.021	-0.003	0.008	-0.008
	(-1.160)	(1.126)	(0.936)	(-0.130)	(0.570)	(-0.616)
SIZE	-0.004***	0.009***	0.028***	0.031***	-0.068***	0.037***
	(-2.705)	(6.479)	(5.045)	(5.865)	(-14.884)	(7.576)
MTB	-0.000*	-0.003***	-0.000	-0.005***	0.005***	-0.004***
	(-1.655)	(-4.686)	(-0.725)	(-3.302)	(5.477)	(-4.388)
ROA	0.612***	-0.721***	-0.614***	-0.800***	-0.069	0.065
	(20.936)	(-35.506)	(-5.566)	(-10.827)	(-1.264)	(1.248)
LEV	-0.007	0.007	-0.024	0.021	-0.038	0.018
	(-0.788)	-0.777)	(-0.876)	(0.692)	(-1.397)	(0.635)
ZSCORE	-0.000	0.000	-0.000	0.017***	-0.016***	0.008*
	(-0.294)	(0.356)	(-0.311)	(3.068)	(-3.578)	(1.917)
INS_OWN	0.006	-0.000	0.028	0.020	-0.017	-0.030
	(0.671)	(-0.052)	(1.197)	(0.877)	(-0.717)	(-1.270)

BIG4	-0.010**	0.010**	-0.019	-0.017	0.039**	-0.054***
	(-2.044)	(2.383)	(-1.084)	(-0.981)	(2.121)	(-2.948)
ANALYST	0.002***	-0.002***	-0.005***	-0.005***	0.008***	-0.007***
	(5.627)	(-7.873)	(-6.276)	(-5.889)	(10.253)	(-8.737)
SEC SCRUTINY	-0.011	0.007	-0.005	-0.008	-0.022	0.022
	(-1.558)	(1.254)	(-0.142)	(-0.238)	(-0.820)	(0.808)
Constant	0.010	-0.032**	-0.144*	-0.155**	0.482***	-0.212***
	(0.617)	(-2.273)	(-1.779)	(-2.015)	(5.690)	(-2.950)
Observations	9,362	9,362	8,383	8,383	9,447	9,447
R-squared	0.677	0.698	0.848	0.856	0.484	0.505
Interaction Terms	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 8 Alternative Model Specification

Panel A: Comparison between Pilot and Non-Pilot firms pre-, during, and post-SHO program

	Pilot Firms		Non-Pilot Firms					
VARIABLE	Mean	Median	Mean	Median	Mean Difference	t-stat	Median Difference	Wilcoxon stat
Pre-SHO program:								
AB_CFO	-0.114	-0.108	-0.119	-0.112	-0.005	-0.92	-0.001	-0.80
AB_PROD	-0.071	-0.065	-0.071	-0.059	0.000	0.10	0.006	1.05
AB_DISEXP	0.086	0.088	0.086	0.085	-0.000	-0.03	-0.003	-0.07
During SHO program:								
AB_CFO	-0.135	-0.130	-0.129	-0.118	0.006*	1.84	0.012	1.05
AB_PROD	-0.074	-0.078	-0.060	-0.056	0.014*	1.90	0.021***	3.11
AB_DISEXP	0.116	0.098	0.108	0.104	-0.008	-0.43	0.005	0.11
Post-SHO program:								
AB_CFO	-0.102	-0.089	-0.098	-0.087	0.004	0.64	0.002	0.423
AB_PROD	-0.051	-0.043	-0.044	-0.031	0.007	0.98	0.012	1.36
AB_DISEXP	0.087	0.071	0.085	0.067	-0.002	-0.09	-0.004	-0.195

Panel B: Correlation Tests during Different Periods

Pre-SHO Program:	AB_CFO	AB_PROD	AB_DISEXP	PILOT
AB_CFO	1			
AB_PROD	0.4397*	1		
AB_DISEXP	-0.1662*	0.2531*	1	
PILOT	0.0167	-0.002	0.0003	1

During-pilot Program:	AB_CFO	AB_PROD	AB_DISEXP	PILOT
AB_CFO	1			
AB_PROD	0.4254*	1		
AB_DISEXP	-0.2407*	0.0850*	1	
PILOT	-0.0290	-0.0463*	0.0057	1

Post-SHO Program:	AB_CFO	AB_PROD	AB_DISEXP	PILOT
AB_CFO	1			
AB_PROD	0.4485*	1		
AB_DISEXP	-0.2728*	0.1148*	1	
PILOT	-0.0089	-0.0197	0.0023	1

Panel C: Alternative Model Regression

This table reports the results of the OLS regression model. The dependent variables are the individual measures of RAM, estimated as the residuals from regression models in Roychowdhury (2006). AB_CFO and AB_DISEXP are multiplied by negative one. The variable of interest is DURING*PILOT. The p-values are based on two-way clustering of standard errors by year and firm. The detailed definitions of all variables are provided in the Appendix A.

	(1)	(2)	(3)
VARIABLES	AB_CFO	AB_PROD	AB_DISEXP
DURING*PILOT	-0.014**	-0.021***	-0.002
	-(3.119)	(-2.708)	(-0.062)
POST*PILOT	-0.012**	-0.014	-0.002
	(-2.779)	(-1.454)	(-0.074)
DURING	0.000	0.014**	-0.006
	(0.041)	(2.295)	(-0.360)
POST	0.027***	0.020***	-0.049***
	(7.869)	(2.730)	(-2.646)
PILOT	0.007	0.006	0.009
	(1.722)	(0.635)	(0.419)
SOX	0.007***	0.006	-0.013
	(4.592)	(1.293)	(-0.854)
SIZE	0.005**	0.035***	0.066***
	(2.397)	(9.265)	(8.924)
MTB	0.000**	-0.003***	-0.012***
	(2.459)	(-3.783)	(-5.658)
ROA	-0.520***	-0.667***	0.114
	(-13.423)	(-14.638)	(1.562)
LEV	0.004	0.007	-0.094**
	(0.563)	(0.403)	(-2.461)
ZSCORE	0.004**	0.018***	-0.000
	(2.592)	(5.509)	(-0.044)
INS_OWN	-0.027**	-0.005	0.077*
	(-2.439)	(-0.249)	(1.953)
BIG4	-0.004	-0.006	-0.047*
	(-0.544)	(-0.347)	(-1.693)
ANALYST	-0.004***	-0.007***	-0.006***
	(-7.903)	(-10.592)	(-4.644)
SEC SCRUTINY	0.004	0.017	0.024
	(0.402)	(0.727)	(0.577)
Constant	0.026**	-0.252***	-0.452***
	(2.458)	(-6.527)	(-4.645)
Observations	9,348	9,348	9,348
R-squared	0.456	0.227	0.080
Industry FE	Yes	Yes	Yes

Table 9 Fama-MacBeth Regressions

This table reports the results of the Fama-McBeth regression model. The dependent variables are the individual measures of RAM, estimated as the residuals from regression models in Roychowdhury (2006). AB_CFO and AB_DISEXP are multiplied by negative one. The variable of interest is PILOT. We report regressions for each period – pre-SHO, during SHO, and post-SHO. The p-values are based on two-way clustering of standard errors by year and firm. The detailed definitions of all variables are provided in Appendix A.

	Pre-SHO	During SHO	Post-SHO	Pre-SHO	During SHO	Post-SHO	Pre-SHO	During SHO	Post-SHO
	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	AB_CFO	AB_CFO	AB_CFO	AB_PROD	AB_PROD	AB_PROD	AB_DISEXP	AB_DISEXP	AB_DISEXP
PILOT	0.007**	**-0.010***	-0.008	-0.002	**-0.021****	-0.010	-0.007	0.012	0.005
	(4.484)	**(-3.218)**	(-2.074)	(-0.998)	**(-7.110)**	(-2.851)	(-1.500)	(0.557)	(0.243)
SIZE	0.009**	0.014**	0.008*	0.036**	0.031***	0.024***	0.053**	0.045*	0.061***
	(8.680)	(7.948)	(4.235)	(6.493)	(11.300)	(16.009)	(5.708)	(3.374)	(9.981)
MTB	-0.002	-0.001	-0.000	0.000	-0.002	-0.001*	-0.011***	-0.009**	-0.005
	(-2.165)	(-2.476)	(-0.548)	(1.268)	(-2.121)	(-3.008)	(-11.451)	(-6.830)	(-2.843)
ROA	-0.354**	-0.331**	-0.411*	-0.594***	-0.492**	-0.613***	-0.174	0.081	0.342***
	(-7.751)	(-7.125)	(-4.044)	(-15.054)	(-9.643)	(-12.378)	(-0.645)	(1.218)	(15.933)
LEV	0.027	0.010	0.014	0.005	-0.017	0.039	-0.030	-0.116*	-0.113
	(1.821)	(2.618)	(1.381)	(0.503)	(-0.783)	(1.765)	(-0.305)	(-4.187)	(-1.470)
ZSCORE	0.005	0.013***	0.011*	0.021**	0.019***	0.019**	0.013	-0.030*	-0.012
	(1.894)	(36.360)	(3.810)	(4.375)	(10.951)	(6.084)	(0.543)	(-3.408)	(-2.152)
INS_OWN	-0.035**	-0.038*	-0.058	-0.019	-0.002	-0.010	0.083*	0.072*	0.048
	(-7.304)	(-4.188)	(-2.915)	(-2.272)	(-0.243)	(-0.428)	(3.314)	(3.832)	(0.612)
BIG4	0.002	-0.006	0.003	-0.036	-0.007**	0.010	0.027	-0.075	-0.078**
	(0.140)	(-1.379)	(0.688)	(-1.528)	(-6.262)	(1.573)	(0.464)	(-1.961)	(-5.928)
ANALYST	-0.004**	-0.005***	-0.004**	-0.007**	-0.008***	-0.006***	-0.004	-0.001	-0.006
	(-6.820)	(-21.404)	(-6.056)	(-7.205)	(-17.663)	(-11.832)	(-2.108)	(-0.463)	(-2.747)
SEC SCRUTINY	0.016	0.026	0.026	0.047	0.027	-0.060**	-0.017	0.058	0.014
	(0.828)	(1.172)	(1.678)	(2.262)	(2.622)	(-5.630)	(-0.426)	(1.322)	(0.224)
Constant	-0.132**	-0.124**	-0.092***	-0.178***	-0.164***	-0.129**	-0.273**	-0.096	-0.241
	(-7.131)	(-8.987)	(-13.799)	(-10.890)	(-14.133)	(-6.844)	(-7.572)	(-0.969)	(-2.401)
t test (p-value) of coefficient difference:									
Pre vs. During (p-value):	**0.012**			**0.014**			0.265		
During vs. Post (p-value):		**0.026**			**0.097**			0.360	
Observations	3,105	3,283	2,803	3,101	3,283	2,803	3,101	3,283	2,803
R-squared	0.183	0.112	0.162	0.153	0.124	0.168	0.065	0.035	0.046

Appendix A Variable Descriptions

Variable Name	Data Source	Description
Dependent Variables		
CFO	Compustat	Cash flow from operations (OANCF) scaled by total assets (AT), multiplied by -1.
PROD	Compustat	PROD is production cost, including cost of goods sold (COGS) and changes in inventory (INVT), scaled by total assets (AT).
DISEXP	Compustat	Discretionary expenses include research and development expense (XRD), advertising expense (XAD), and selling, general and administrative expense (XSGA). As long as XSGA is available, XRD and XAD are set to zero if they are missing. For ease of explanation, we scaled discretionary expenses by total assets (AT) and multiplied it by -1.
AB_CFO	Compustat	$\frac{CFO_{it}}{Assets_{i,t-1}} = \alpha_0 + \alpha_1 \frac{1}{Assets_{i,t-1}} + \alpha_2 \frac{Sales_{it}}{Assets_{i,t-1}} + \alpha_3 \frac{\Delta Sales_{it}}{Assets_{i,t-1}} + \varepsilon_{it}$ CFO is Cash flow from operations (OANCF). We multiply the residual from the regression by -1.
AB_PROD	Compustat	$\frac{Prod_{it}}{Assets_{i,t-1}} = \alpha_0 + \alpha_1 \frac{1}{Assets_{i,t-1}} + \alpha_2 \frac{Sales_{it}}{Assets_{i,t-1}} + \alpha_3 \frac{\Delta Sales_{it}}{Assets_{i,t-1}} + \alpha_4 \frac{\Delta Sales_{i,t-1}}{Assets_{i,t-1}} + \varepsilon_{it}$ PROD is production cost, including cost of goods sold (COGS) and changes in inventory (INVT).
AB_DISEXP	Compustat	$\frac{DisExp_{it}}{Assets_{i,t-1}} = \alpha_0 + \alpha_1 \frac{1}{Assets_{i,t-1}} + \alpha_2 \frac{Sales_{i,t-1}}{Assets_{i,t-1}} + \varepsilon_{it}$ DisExp is discretionary expenses, including research and development expense (XRD), advertising expense (XAD), and selling, general and administrative expense (XSGA). As long as XSGA is available, XRD and XAD are set to zero if they are missing. We multiply the residual from the regression by -1.
EM_KOTHARI	Compustat	Discretionary Accruals is estimated following Dechow et al. (1995), who modify Jones' model (1991) as follows: $\frac{TA_t}{AT_{t-1}} = \frac{1}{AT_{t-1}} + \frac{(REV_t - REV_{t-1}) - (REC_t - REC_{t-1})}{AT_{t-1}} + \frac{PPE_t}{AT_{t-1}} + \epsilon_t$

		Total accruals TA is the earnings before extraordinary items and discontinued operations minus the operating cash flows reported in the statement of cash flows. Revenue REV is net sales. REC is receivables. PPE is the gross property, plant and equipment. We obtain the residual from the model above as discretionary accruals and adjust it by matching each sample firm with the firm of closest return on asset in the same fiscal year and industry.
Variables of Interest		
*DURING*PILOT*	Compustat	Interaction term of DURING and PILOT.
*POST*PILOT*	Compustat	Interaction term of POST and PILOT.
DURING	Compustat	DURING is an indicator variable that takes the value of 1 for observations from year 2005 to 2007, and 0 otherwise.
POST	Compustat	POST is an indicator variable that takes the value of 1 for observations from year 2008 to 2010, and 0 otherwise.
PILOT	Compustat	PILOT is an indicator variable that takes the value of 1 for all observations of firms that were selected by the SEC as pilot firms, and 0 otherwise.
Control Variables		
1/AT_LAG1	Compustat	The inverse of total assets (AT).
SALE_LAG1	Compustat	Sales (SALE) in the previous year, scaled by previous year total asset (AT)
SALE_CHG1	Compustat	Changes in sales from the previous year to current year, scaled by previous year total asset (AT)
SOX	Compustat	A dummy variable that takes the value of 1 if it's the year of or after 2002, when Sarbanes-Oxley Act was passed.
SIZE	Compustat	Firm size = natural logarithm of total assets;
MTB	Compustat	Market to Book ratio: (PRCC_F*CSHO)/ CEQ
ROA	Compustat	Return on total assets = operating income divided by total assets: OIBDP/AT;
LEV	Compustat	Leverage = Long-term debt divided by total asset: DLTT/AT;
ZSCORE	Compustat	Modified Altman Z score. ZSCORE = 3.3*Pre-tax Income/Assets + 0.999*Sales/Assets + 1.4 *Retained Earnings/Assets + 1.2 * (Current Assets - Current Liabilities)/Assets +0.6*Market Equity/Total Liabilities.
INS_OWN	DirectEdgar[10]	Institutional ownership. The proportion of shares held by institutions.
BIG4	Compustat	An indicator variable that takes the value of 1 if the auditor is a Big 4 CPA firm, and 0 otherwise;
ANALYST	Capital IQ	The number of analysts' estimates.

[10] For the SEC database search software DirectEdgar, please refer to: https://www.directedgar.com/.

SEC SCRUTINY	UC Berkeley[11]	An indicator variable that takes the value of 1 if a firm has been issued an AAER (Accounting and Auditing Enforcement Release) letter by SEC during the current year or in the previous year, and 0 otherwise.
Other Variables		
Reporting Transparency/ Opacity	DirectEdgar	We divide firms into two groups based on the number of items voluntarily disclosed (item 2.02, item 7.01, and item 8.01) in 8-K reports in the year of 2004, which is before the pilot program. If the number of items is above the median of the sample, the firm is marked as transparent for all firm-years; otherwise the firm is marked as opaque for all firm-years. The subsample of Reporting Transparency consists of transparent firm-years; the subsample of Reporting Opacity consists of opaque firm-years.
High Negative Sentiment/Low Negative Sentiment	Loughran & McDonald Website	We divide firms into two groups based on the percentage of negative words in 10-K reports in the year of 2004, which is before the pilot program. If the percentage of negative words is above the median of the sample, the firm is marked as high negative sentiment for all firm-years; otherwise the firm is marked as low negative sentiment for all firm-years.
Bad News/Good News	Compustat	We divide firm-years into two groups based on the change of market value comparing with industry-year median. If the change of market value is above industry-year median, the firm-year is grouped in the subsample of good news; otherwise the firm-year is grouped in the subsample of bad news.

[11] The AAER letters are provided by Center for Financial Reporting and Management at UC Berkeley. Please refer to: https://haas.berkeley.edu/accounting/