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Abnormal real operations, real earnings management, and subsequent crashes in stock prices

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19 • 2014

Abnormal real operations, real earnings management, and subsequent crashes in stock prices

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Abstract

We study the impact of firms' abnormal business operations on their future crash risk in stock prices. Computed based on real earnings management (REM) models, firms' deviation in real operations from industry norms (DRO) is shown to be positively associated with their future crash risk. This association is incremental to that between discretionary accruals (DA) and crash risk found by prior studies. Moreover, after Sarbanes-Oxley Act (SOX) of 2002, DRO's predictive power for crash risk strengthens substantially, while DA's predictive power essentially dissipates. These results are consistent with the prior finding that managers shift from accrual earnings management (AEM) to REM after SOX. We further develop a suspect-firm approach to capture firms' use of DRO for REM purposes. This analysis shows that REM-firms experience a significant increase in crash risk in the following year. These findings suggest that the impact of DRO on crash risk is at least partially through REM.

Keywords: crash risk; deviation in real operations; earnings management; real earnings management; Sarbanes-Oxley.

JEL Classification:

D89; G19; M10; M41

*Corresponding author. We are thankful to the discussants and participants at the concurrent sessions at the 2012 AAA annual meeting in D.C. and 2012 FMA annual meeting in Atlanta, GA. Usual caveats apply. This research has begun as Chapter 2 of Lingxiang Li's dissertation submitted in partial fulfillment of the requirements for a Ph.D. at Rensselaer Polytechnic Institute.

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Abstract

We study the impact of firms' abnormal business operations on their future crash risk in stock prices. Computed based on real earnings management (REM) models, firms' deviation in real operations from industry norms (DRO) is shown to be positively associated with their future crash risk. This association is incremental to that between discretionary accruals (DA) and crash risk found by prior studies. Moreover, after Sarbanes-Oxley Act (SOX) of 2002, DRO's predictive power for crash risk strengthens substantially, while DA's predictive power essentially dissipates. These results are consistent with the prior finding that managers shift from accrual earnings management (AEM) to REM after SOX. We further develop a suspect-firm approach to capture firms' use of DRO for REM purposes. This analysis shows that REM-firms experience a significant increase in crash risk in the following year. These findings suggest that the impact of DRO on crash risk is at least partially through REM.

1. Introduction

Hutton et al. (2009) have documented that firms' *discretionary accruals* (*DA*) can serve as a strong predictor of firm-level stock price crashes. They attribute this association to firms' use of *DA* to hoard negative information. Our primary task in this study is to examine whether firms' deviation in real operations (DRO) from industry norms is associated with their crash risk. Similar to accruals, real operations can be used to hide bad news about performance and prospects. The reversal of this manipulation can cause stock price crashes; but different from accruals manipulation, operation manipulation comes with real economic consequences. The realization of the negative consequences can also contribute to price crashes. Moreover, DRO also reflects firms' uncommon business models, which obstruct the market's timely understanding of firm information. We expect that this mechanism also contribute to the association between DRO and crash risk.

An important contributor to crash risk is managerial intentional manipulation of information. Jin and Myers (2006) predict that the hoarding of negative information by insiders leads to later stock price crashes. Specifically, as the accumulation of negative information reaches a tipping point, managers may have to dump all the hidden information on the market at once, resulting in a large negative return. Using several measures of country-level opaqueness, their study has produced supporting results in an international context. In a firm-level analysis, Hutton et al. (2009) have documented that information opacity, measured as *DA*, is positively associated with future crash risk. The notion that negative information hiding leads to price crashes is also consistent with findings in other important crash risk studies (e.g. Kim et al. 2011a 2011b, Kim and Zhang, 2013). In the above arguments, DRO causes crashes through several mechanisms, one of which is DRO being used for earnings management purposes.

Our motivation for this study originates from the growing research interest in real-activities earnings management (REM). This growing interest is a response to the literature's long-time focus on accrual-based EM (AEM), whereas survey results suggest that managers actually prefer real activities over accruals to manage earnings (Graham et al. 2005). Our analysis of the relationship between DRO and crash risk is also timely in the sense that there is a decline of earnings-increasing DA and a rise of earnings-increasing DRO following the passage of SOX 2002 (Cohen et al. 2008). Consistent with the decline of DA, Hutton et al. (2009) find that DA's predictive power for crash risk seems to have weakened after SOX. Considering the above findings, we wonder whether DRO gains strength in its predictive power after SOX.

To implement our analyses, we first compute DRO measures as the prior three years' moving sum of the abnormal amounts in discretionary expenses, production cost, cash flows, and their aggregates. The use of moving sum follows Hutton et al. (2009). The abnormal values are residuals from several REM models provided in the literature. Using a large sample of U.S. firms for the period 1994-2009, we find a strong positive association between DRO and crash likelihood in the next period. The relationship is shown to be concave and robust to firm-fixed effects and alternative crash likelihood measures.

It is worth noting that we take a conservative stance in the use of the term REM throughout this paper: Instead of directly equating our DRO measures with REM, we refer to them as REM only in our suspect-firm analysis in which managers' incentives of manipulating earnings are present.[1] The underlying reason for this approach is that DRO may largely capture non-EM behaviors, especially when researchers do not consider firms' incentives to manage earnings (see Cohen et al. 2013; Gunny 2010). Therefore, factors including, but not necessarily limited to, REM can all contribute to DRO's strong power to predict crash risk. In our main hypothesis construction, we intentionally acknowledge the non-REM mechanisms through which DRO causes crashes. Our further analyses strive to show that at least one of those contributing factors is REM. To identify REM-induced DRO, the presence of DRO is necessary but not sufficient. We use a sub-sample suspect-firm analysis to more precisely identify REM with DRO (see Gunny 2010; Zang 2012; and Zhao et al. 2011). The results from this analysis confirm our conjecture. Specifically, suspect firms that have large earnings-inflating DRO (REM firms) are about 30% more likely to experience a crash in the following year than non-REM firms are.[2]

The intuition and prior empirical finding suggest that managers substitute real operations for accruals to manage earnings following SOX (Cohen et al. 2008).[3] To support the argument that the association between DRO and future crash risk is, at least partially, due to REM's role, we separately examine the association in the pre-SOX and post-SOX periods. Accordingly, we expect a stronger (weaker) association between the DRO (DA) and crash risk following the passage of SOX. In our results, DRO's predictive power experiences a three-fold jump following SOX; DA's impact drops by about half and becomes insignificant statistically, consistent with Hutton et al. (2009).

[1] This is less of a concern when DRO is used as the dependent variable, which is the case in most prior REM studies.
[2] Suspect firms are those that report earnings that are just above zero or just above last years'.
[3] Substitution effect between REM and AEM is also evident in Zang (2012).

REM and AEM have timing difference: REM implemented during the accounting period (it takes time to implement a real operation); AEM is placed at the end before financial reporting (Zang 2012). Therefore, when managers can no longer withhold negative information and decide to release it through reversions of REM and AEM, market participants can observe REM's reversion during the period, but not AEM's until the release of financial statements. Following this rationale, we further explore whether this timing difference has any implications on DA/DRO's impact on crash risks. To examine this issue, we divide crashes into two groups: About one third of crashes happen within the [0, +5 days] window relative to quarterly earnings announcement date. We assume that those crashes are triggered by financial reporting, and thus referred to them as EA crashes in our study. The rest two thirds are referred to as non-EA crashes. In comparison with DRO's impact on crash risk, we find that DA's impact is more concentrated on EA crashes. This result reflects the timing difference between REM and AEM.

Our study enhances the understanding of REM. The empirical literature repeatedly finds firms' opportunistic DRO for earnings management purposes (e.g., Bushee 1998. Cohen and Zarowin 2010; Cohen et al. 2010; Ertan 2013; Gunny 2010; Roychowdhury 2006; Zang 2012; Zhao 2011). Outsiders have limited ability to distinguish opportunistic operating decisions from legitimate ones made in good faith. This information asymmetry provides managers with the opportunities to hide negative news with DRO. However, it is likely to jeopardize the firm value in future. In contrast with the pervasive evidence for the existence of EM-induced DRO, there exists limited evidence for the real consequences following DRO: Cohen and Zarowin (2010) show that pre-SEO DRO leads to a more sever post-SEO performance decline than pre-SEO DA. The result is consistent with the commonly held belief that real activities are more costly than accruals to manage earnings. On the other hand, Gunny (2010) finds that firms that use DRO to meet earnings benchmarks display better subsequent performance than those that do not use DRO.[4] Our paper does not directly address DRO's impact on firm operating performance. Instead, we shed light on the consequences of DRO from the perspective of stock price behaviors.

We broaden the crash risk literature by showing that firms' DRO leads to price crashes and thus serves as a good predictor for this tail event. The predictive power is even stronger after the passage of SOX period and for non-EA crashes. As pointed out by Hutton et al. (2009), crash incidence is of great importance for risk management and option pricing. From this perspective, our results are especially useful to investors or fund managers who focus on

[4] While not directly analyzing the consequence of REM on operating performance, Kim and Sohn (2013) and Ge and Kim (2013) find that DRO increases the cost of capital.

those tail events. In addition, since firms' extreme stock performance affects top management turnover (Warner and Watts, 1988, Kang and Shivdasani 1995), our results may raise managers' concerns about their decision to engage in abnormal real operations.

The rest of our paper is structured as follows: We develop and provide our three hypotheses in Section 2. In section 3, we discuss the measurements of *DRO, REM,* and *crash risk*. Section 4 shows our regression analyses and the corresponding results in support of the three hypotheses. The first part of this section (4.1) deals with our main hypothesis (H1) (association between *DRO* and *crash*). In Section 4.2, we provide robustness tests for H1: (I) non-linearity; (II) alternative measurements of crash likelihood; and (III) firm-fixed effects; Section 4.3 and 4.5 tests H2 (association between *REM* and *crash*) and H3 (the impact of SOX), respectively. Section 5 deals with the issue of crash timing and other robustness checks. Section 6 summarizes our findings and concludes.

2. Literature and Hypotheses Development

Empirical studies of earnings management typically focus on discretionary accruals (DA). Roychowdhury (2006) uses the term *real earnings management* to refer to firms' deviations in real operating activities from normal practices (DRO), undertaken to achieve earnings targets. While his study popularizes the models to estimate REM, several prior empirical studies have documented the use of real activities, such as R&D spending and sales of assets, to manipulate earnings information (see Baber et al. 1991; Bartov 1993; Bens et al. 2002; Bushee 1998; Butler and Newman 1989; Dechow and Sloan 1991; Murphy and Zimmerman 1993). The survey by Bruns and Merchant (1990) reports that managers prefer DRO over DA to manage earnings. A more widely noticed survey by Graham (2005) again shows the prevalence of abnormal real activities as EM tools, even though the surveyed CFOs are aware of the long-term detrimental effects of such manipulations.

The study by Cohen et al. (2008) finds an increasing magnitude of earnings-inflating DRO after SOX 2002, a likely result of SOX's extra requirements on financial reporting and internal control. Evidence about the substitution between AEM and REM is also evident in Zang (2012). Ge and Kim (2013) further show that the substitution effects are stronger in firms with better board governance.

The literature provides mixed evidence in the real economic consequences of DRO. For example, the results in Cohen and Zarowin (2010) suggest that earnings-inflating DRO before seasoned equity offerings (SEO) takes its toll on post-SEO performance. Consistently, Bhojraj et al. (2009) find that firms that use DRO to beat analysts' forecasts underperform those that do not use DRO but miss the targets. On the other hand, Gunny (2010) finds that firms that use DRO to meet earnings benchmarks actually perform better in the subsequent period than those that do not use DRO. She gives two reasons for this counter-intuitive observation: First, achieving earnings targets helps firms to keep or enhance credibility and reputation with stakeholders (e.g. suppliers and creditors); second, managers resort to earnings-inflating DRO simply to signal positive prospects. In this case, DRO is employed to reveal rather than hide information. A similar signaling theory with respect to DA is frequently argued and supported in the empirical literature (e.g., Chaney and Lewis 1995; Linck et al. 2013; Louis and Robinson 2005; Subramanyam 1996; Wu and Robin 2014).

Jin and Myer (2006) demonstrate in a model that the less transparent a firm is, the larger amount of firm-specific negative information managers can hide. When the accumulation of negative information reaches the maximum amount that insiders are willing or able to hide, they may choose to dump all the hidden news on the public at once, leading to a crash in the form of a large negative return. Hutton et al. (2009) provide the first firm-level empirical evidence as a support of this argument. Following this view that managers' hoarding of negative information leads to price crashes, subsequent studies have discovered some other predictors of crashes, such as tax avoidance levels, CFO option holdings, accounting conservatism, corporate location, etc. (Kim et al.2011a, 2011b; Kim and Zhang 2013; Callen and Fang 2013).

Evidenced in the prior REM studies (e.g. Roychowdhury 2006; Gunny 2010; Cohen et al. 2010) managers can engage in DRO to reach earnings targets. Therefore, we expect DRO to be able to cause future crashes at least through the EM mechanism. DA causes crashes through this same mechanism, as discussed above. Different from DA, ill intentioned and sub-optimal DRO is potentially followed by negative real economic effects. The actual materialization of those negative effects may become the last straw, forcing managers to give up on hiding negative information. When market participants suddenly observe, at the same time, (I) the release of previously hidden negative information and (II) the negative real economic consequences, the stock price is more likely to experience a deep drop than in the case when they observe only (I).

From a non-EM perspective, managers can engage in DRO to manipulate investors' beliefs about the growth prospects. For example, Benmelech et al. (2010), Kedia and Philippon (2009), McNichols and Stubben

(2008), among others, show that firms may invest and hire excessively to fabricate robust outlook for growth opportunities.[5] The hiding of true growth prospects can cause price crashes in future when the true information is ultimately released. Furthermore, as argued by Bleck and Liu (2007) and Kim et al. (2011b), hiding negative growth prospects prevents investors and board of directors from discovering, and then forcing abandonment of, negative NPV projects in a timely manner. The long-lasting inefficient allocation of resources can increase the likelihood of stock price crashes.

The arguments above hinge on DRO's ability to capture opportunistic behaviors. We acknowledge that non-opportunistic DRO can also cause drastic price adjustments (not necessarily downward though)[6]: To strategically differentiate itself from its industry peers, a firm may adopt a unique business model, which mechanically creates DRO. Although not intended for information manipulation, this kind of DRO may cause drastic price adjustments in stock prices. This is the case because the market has limited ability to timely understand the unique business moves (lack of comparisons in the same industry). For example, firms' intensive innovation compared to their industry peers can create information asymmetry (Aboody and Lev 2000). When more definite information finally comes to resolve the uncertainty, the market experiences a drastic value adjustment (e.g. crash);

The above discussions lead to our main hypothesis:

H1. Firms' deviation in real operations (DRO) from industry norms is positively related to their stock price crash risk in future.

H1 speaks to the relation between *REM* and *crash risk* only to the extent of DRO's ability to capture REM. Throughout this study, we use the term REM in a cautious way to avoid over-generalizing our results. To further investigate the relationship between REM and crash risk, we analyze a sub-sample of firm-years observations that report earnings that are just above zero or last years' earnings. Because prior studies have documented that those firms, on average, are likely to have managed up earnings using DRO, We believe DRO can better capture firms'

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[5] In their dynamic rational expectations model, Benmelech et al. (2010) show that equity incentives may induce managers to conceal bad news about future growth options through investment policies. Those suboptimal real activities are implemented to support the pretense; Kedia and Philippon (2007) predict and find firm-level evidence that, in equilibrium, low-productivity firms need to hire and invest excessively in order to appear as high productivity firms. Consistent evidence is also found in the results by McNichols and Stubben (2008).

[6] The impact of DRO on stock prices may also depends on firm characteristics. For example, Chen et al. (2012) shows that increases in R&D are associated with much more upward movements in stock prices for firms that have "focus" strategy as opposed to those with "diversification" strategy.

REM activities in such a setting than in a broad sample. As a result, our second hypothesis (H2) is based on our main hypothesis (H1) and is stated as follows:

H2. Firms with earnings-inflating REM are more likely to experience crashes in future than other firms.

The substantial influence of the Sarbanes-Oxley Act of 2002 (SOX) on accounting practices has been well documented in the literature. Cohen et al. (2008) find that managers' reliance on accruals to manage earnings waned down after SOX. At the same time, REM gained momentum. This substitution is presumably managers' response to the increased cost of AEM due to SOX. Drawing on those findings, we expect to see an increase in the ability of DRO and a decrease in the ability of DA to predict crashes after SOX. This finding also helps us to show that REM contributes to the predictive power of DRO for crashes. Hutton et al. (2009) has already provided initial evidence of the decrease in DA's predictive power after SOX. Besides the additional interest placed on DRO, out analysis includes a longer post-SOX period than Hutton's and thus allows us to better examine the issue in the post-SOX period.[7]

H3. DRO's predictive power for future crashes is stronger in the post-SOX period than in the pre-SOX period.

3. Measurements and Sample Statistics

3.1 Measuring the deviation in real operations (DRO)

Following Roychowdhury (2006), we use three models to detect abnormal real activities. The first one detects abnormal discretionary expenses. Discretionary expenses are the sum of *selling, general and administrative expenses (SG&A)*, *research and development expenses* (*R&D*), and *advertising expenses*. A one-dollar manipulation of those expenses generates one-dollar opposite change in financial earnings before taxes, assuming that the manipulation does not immediately affect actual firm performance in the current period. To estimate the normal

[7] The technical reason for this conjecture is well explained in Hutton et al. (2009). Our DA and DRO measures are residuals from equations (1) (2) (3) (5). Those measures include both intentional earnings management (REM and AEM) and errors due to problems in model fitness. If SOX reduces AEM (increases REM), then in the post-SOX period, the DA measure should be composed of more model errors (DRO measure should be composed of less model errors). Assuming that those errors due to fitness problems are random and not correlated with crash variables, we should see a decrease in DA's power (an increase in DRO's) to predict crash.

levels of discretionary expenses, Roychowdhury uses *lagged sales scaled by lagged total assets* (S_{t-1} / A_{t-1}) and controls for the common scaling factor: *lagged total assets* (1 / A_{t-1}). We augment this model with additional variables used by Gunny (2010) in estimating *SG&A* expenses: (1) natural log of *market value* (*MV*), which proxies for firm size; (2) *Tobins Q* (*Q*), which measures the marginal benefit to cost for each unit of new investment; (3) *internal funds (INT),* which controls for the funds available for investment that are generated from within the firm; and (4) *change in sales* (ΔS_t / A_{t-1}), which controls for the impact of *trends in sales* on *discretionary expenses*. Considering the "sticky" cost behavior (see Anderson et al. 2003), Gunny (2010) interacts *change in sales* (ΔS_t) with an indicator variable (*DD*) that is equal to one when *total sales* decrease from the prior year and zero if not. As a result, the impact of positive ΔS_t on normal levels of *discretionary expenses* is not constrained by this model to be the same as that of negative ΔS_t.[8]

$$\frac{DISX_t}{A_{t-1}} = \alpha_1(\frac{1}{A_{t-1}}) + \beta_1(\frac{S_t}{A_{t-1}}) + \beta_2(MV_t) + \beta_3(Q_t) + \beta_4(\frac{INT_t}{A_{t-1}}) + \beta_5(\frac{\Delta S_t}{A_{t-1}}) + \beta_6(\frac{\Delta S_t}{A_{t-1}} \times DD) + \varepsilon_t \quad (1)$$

The second model detects abnormal *production cost* (*PROD*). *PROD* is the sum of *cost of goods sold (COGS)* and *change in inventory* (Δ*Inventory*). Variables *sales* (S_{t-1} / A_{t-1}), *change in sales* (ΔS_{t-1} / A_{t-1}), and *lagged change in sales* have been employed to estimate the normal levels of production costs in other studies. In addition, we augment the model with *Tobins Q* (Q_t) and *market value* (MV_t) following Gunny (2010). This proxy potentially captures the outcome of two REM activities. First, it measures managers' manipulation of production to change *COGS*. The more units a firm produces during an accounting period, the less fixed manufacturing overhead each unit shares, and vice versa. Second, it captures manipulation of products' selling prices for the following reason: The variable *sales* (S) used in Eq. (2) is the sales amount reported by companies in their financial statements. Following GAAP, this amount is already net of sales discounts. Therefore, deep discounts will show up as positive abnormal *PROD* from Eq. (2).

$$\frac{PROD_t}{A_{t-1}} = \alpha_1(\frac{1}{A_{t-1}}) + \beta_1(MV_t) + \beta_2(Q_t) + \beta_3(\frac{S_t}{A_{t-1}}) + \beta_4(\frac{\Delta S_t}{A_{t-1}}) + \beta_5(\frac{\Delta S_{t-1}}{A_{t-1}}) + \varepsilon_t \quad (2)$$

The third model detects manipulation of sales through lenient credit terms. This model identifies the offering of lenient credits with negative abnormal *cash flows from operations* (*CFO*). As Roychowdhury (2006)

[8] The *R&D* and *advertising expenses* are set to zero if they are not available in COMPUSTAT.

points out, this proxy is ambiguous to interpret by itself. This is because other REM activities also lead to abnormal *CFO*, but in different directions. For example, cutting discretionary expenses to inflate earnings causes positive abnormal *CFO*, while overproducing to inflate earnings leads to negative abnormal *CFO*. Since all REM activities have cash flow effects, the ambiguity of this CFO-based REM measure is not limited to the two types of REM activities indentified above. Therefore, caution should be used when interpreting results based on this proxy.

After adding the two extra variables from (1) and (2) (*MV* and *Q*) into Roychowdhury's model, we arrive at the following model to estimate the normal level of *CFO*:

$$\frac{CFO_t}{A_{t-1}} = \alpha_1\left(\frac{1}{A_{t-1}}\right) + \beta_1(MV_t) + \beta_2(Q_t) + \beta_3\left(\frac{S_t}{A_{t-1}}\right) + \beta_4\left(\frac{\Delta S_t}{A_{t-1}}\right) + \varepsilon_t \tag{3}$$

We run regressions based on (1), (2), and (3) in each Fama and French industry-year if there are at least 15 observations that have the required data available. We measure *DRO* as deviations of dependent variables' actual values in (1) (2) (3) from their predicted ones. Three initial proxies come from this process: abnormal discretionary expenses (*Residual_DISX*), abnormal production cost (*Residual_PROD*), and abnormal cash flows (*Residual_CFO*). For convenience, *Residual_DISX* and *Residual_CFO* have already been multiplied by negative one, so, like *Residual_PROD*, the signed values of those proxies are positively related to their effects on earnings. Following Cohen and Zarowin (2010), we generate two aggregate measures: *Residual_1* is the sum of *Residual_DISX* and *Residual_CFO*; *Residual_2* is the sum of *Residual_DISX* and *Residual_PROD*. One may note that we do not have a measure that combines *Residual_CFO* and *Residual_PROD*. This practice follows Cohen and Zarowin (2010). They explain that overproduction automatically leads to abnormally low *CFO*. Adding up these two measures may double-count REM. Despite this concern, we create *Residual_3*, computed as the aggregate of the three proxies, for robustness purposes.

Following the modified Jones model (Dechow et al. 1995), we estimate the cross-sectional Eq. (4) in each Fama and French industry-year:

$$\frac{Accruals_t}{A_{t-1}} = \alpha_1\left(\frac{1}{A_{t-1}}\right) + \beta_1\left(\frac{\Delta S_t}{A_{t-1}}\right) + \beta_2\left(\frac{PPE_{t-1}}{A_{t-1}}\right) + \varepsilon_t \tag{4}$$

In the above equation, *Accruals* are the total accruals, calculated as the difference between *CFO* and *net income before extraordinary items* (*income*). *PPE* is *gross property, plants and equipment.* Equation (5) shows our computation of *Discretionary accruals* (DA) for each observation. The coefficients in (5) are from the estimates in Equation (4). Δ *AR* is the change in accounts receivable.

$$Discretionary\ Accruals_t = \frac{Accruals_t}{A_{t-1}} - \left[\widehat{\alpha_1}(\frac{1}{A_{t-1}}) + \widehat{\beta_1}(\frac{\Delta S_t - \Delta AR_t}{A_{t-1}}) + \widehat{\beta_2}(\frac{PPE_{t-1}}{A_{t-1}})\right] \qquad (5)$$

Following the lead of Hutton et al. (2009), we measure the Discretionary Accruals as the moving sum of the absolute values of discretionary accruals in the prior three years:

$$DA_t = |Discretionary\ Accruals_{t-1}| + |Discretionary\ Accruals_{t-2}| + |Discretionary\ Accruals_{t-3}| \quad (6)$$

In the same way, we construct our final measurements of *DRO* following Equation (7).

$$DRO\_Item = |Residual\_Item_{t-1}| + |Residual\_Item_{t-2}| + |Residual\_Item_{t-3}| \qquad (7)$$

Item stands for each of the following six proxies: the three individual residuals (*Residual_DISX*, *Residual_PROD*, and *Residual_CFO)* and the three aggregate residuals (*Residual_1*, *Residual_2*, and *Residual_3*). The six *DRO_Items* are labeled as *DRO_DISX*, *DRO_PROD, DRO_CFO*, *DRO_1*, *DRO_2, and DRO_3*.

Our measurements of *DRO* and *DA* are based on the absolute values of residuals from REM and AEM models.[9] These models do not consider managers' incentives to manage earnings. As a result, we hold the view that we should not directly label those DRO proxies as REM or AEM, because they are likely to capture non-EM factors.[10] In addition, when we construct H1, we argue that non-REM DRO could also lead to crash risk. We do not intend to (neither can we) show that the impact of DRO on crash risk, as predicted in H1, is exclusively due to REM. However, in an attempt to better capture REM and AEM with DRO and DA, we use context-based directional DRO and DA as explained in Section 3.2.

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[9] In the study by Ascioglu et al. (2012), both signed and unsigned REM proxies are used.

[10] Even though we do not think DRO is a direct measure of REM, it captures both earnings-inflating and earnings-deflating REM. Special corporate events, such as stock repurchases or management buyouts, may be surrounded by income-decreasing activities since mangers benefit from lowered reacquisition prices. Existing literature has already provided such evidence for AEM (see Jones 1991; Perry and Williams 1994; DeFond and Subramanyam 1998; Baker et al. 2003; Guan et al. 2005; Gong et al. 2008). The evidence about downward REM is scarce in this relatively young literature. The working papers by Mao and Renneboog (2013) and Hasan et al. (2014) have provided some supporting empirical evidence.

Using the absolute value of DA is a common practice in accounting and finance research. The rationale is that accruals reverse over time and can be used to both increase and decrease earnings. Our use of absolute values of DRO measures is justified by the same rationale.[11] Moreover, absolute values of DRO better captures abnormal business models, which we expect to increase crash risk as well.

3.2 Measuring REM

The literature criticizes the use of those model-estimated proxies as direct measures of earnings management (Gunny 2010); without considering managers' incentives, those proxies may largely capture other behaviors than intentional earnings manipulation. To address this problem, our identification of REM is context-based. We zero in on those suspect firm-year observations with reported earnings that are just above zero ($0<ROA<0.01$) or just above last year's earnings ($0<\Delta ROA<0.01$). They are called *suspect* firms because prior studies find that, on average, they use earnings-inflating real activities to reach those targets (e.g., Roychowdhury 2006; Gunny 2010).

In Gunny (2010), firms with low levels of abnormal *R&D* and abnormal S*G&A expenses* (lowest quintile) and high levels of abnormal *production cost* (highest quintile) are identified as *REM firms*. We follow her approach and sort our total suspect-firm sample separately by quintiles of signed *Residual_DISX* and *Residual_PROD*.[12]

We set an indicator variable *REM_1_SUSPECT* to one for expense-related REM observations (Quintile 5) and zero for others (Quintiles 1-4). *REM_2_SUSPECT* is a similar indicator of production-cost-related REM observations. In addition, we construct an even stricter REM indicator *REM_3_SUSPECT,* which is equal to one if the firm-year observation is both an expense-related and a production-related REM observation.[13] Similarly, we construct *Accrual_Suspect* indicator based on the quintiles of signed DA. The final sample we use to test H2 includes only suspect firm-year observations (lagged ROA<0.01 or lagged ΔROA<0.01). To support H2, suspect

[11] However, one difference between the reversion of DRO and DA is that the latter is a mechanic reversion.
[12] RM_CFO is not used here because of the aforementioned ambiguity problem and also the inconsistent results for this measure shown in Table 4; our measure of discretionary expenses (DISX) already includes R&D expenses, so it represents general expense-related real earnings management.
[13] For expense-related REM proxies, Gunny (2010) actually identifies the lowest quintile as REM firms (firms that cut expenses to boost earnings). However, for convenience, our *REM_DISX* has already been multiplied by negative one so positive/negative values have upward/downward effects on earnings. As a result, we identify as REM firms those in the highest quintile. *REM_CFO* is not used to identify REM firms because, first, it is an ambiguous measure of REM for the aforementioned reasons, and, second, our results in Table 4 indicate that it does not significantly predict crashes, potentially due to the first reason.

firms with large upward REM should be more prone to price crashes in the following year than those without large upward REM.

3.3 Measuring crash risk

Following Hutton et al. (2009), we obtain residual returns and R squares from the following model:

$$r_{j,t} = \alpha_j + \beta_{1,j} r_{m,t-1} + \beta_{2,j} r_{i,t-1} \beta_{3,j} r_{m,t} + \beta_{4,j} r_{i,t} + \beta_{5,j} r_{m,t+1} + \beta_{6,j} r_{i,t+1} + \varepsilon_{j,t} \quad (8)$$

In this model, $r_{j,t}$ is the return of stock j in week t, $r_{m,t}$ is value-weighted market index from CRSP, and $r_{i,t}$ is Fama and French value-weighted industry index. Firm-specific returns, denoted by r_{fs} is the log of one plus the residual from Eq. (8). *Crashes* and *jumps* are identified as firm-specific returns that are 3.09 standard deviations below and above their means in the firm's fiscal year. Standard deviation is computed for each firm-year. Using a uniform standard deviation instead of firm-year ones would mechanically identify high-volatility firms with more crashes and jumps. Indicator variable *crash*/*jump* is equal to one if a stock experiences at least one crash/jump during the fiscal year and zero if not. In our additional tests, we use two other crash likelihood measures from Chen et al. (2000) for robustness purposes: *negative skewness (NCSKEW)* and *down-to-up volatility* (*DUVOL)* of r_{fs}.[14]

$$NCSKEW_{ji} = -\frac{n(n-1)^{3/2} \sum \left(r_{fs,jt} - \bar{r}_{fs,jt}\right)^3}{(n-1)(n-2)\left[\sum (r_{fs,jt} - \bar{r}_{fs,jt})^2\right]^{3/2}} \quad (9)$$

$$DUVOL_{j,t} = \; log\left[\frac{(n_{up}-1)\sum_{down}(r_{fs,jt} - \bar{r}_{fs,jt})^2}{(n_{down}-1)\sum_{up}(r_{fs,jt} - \bar{r}_{fs,jt})^2}\right] \quad (10)$$

$\bar{r}_{fs,jt}$ is the mean of firm-specific stock return for stock j in year i. n_{up} and n_{down} are respectively the number of times with demeaned r_{fs} that is positive and negative. For both *NCSKEW* and *DUVOL*, a higher value indicates that the firm is more prone to stock price crashes. In comparison, the dummy variable *crash* identifies each crash occurrence based on an arbitrary threshold, while the other two alternative crash risk measures are continuous

[14] To avoid confusion, we use the following terminologies in a consistent manner throughout this paper: (1) we use "probability to observe crash during a full year", "average crash probability", etc. to refer to the average number of firm-year observations that have at least one crash during a fiscal year; (2) we use "marginal impact on crash risk", "change in crash risk", etc. (instead of crash likelihood) to refer to the results from logistic regressions, in which the dummy *Crash* is the dependent variable; (3) we use "crash likelihood" when the dependent variables are our two continuous variables that measure how crash-prone a firm is: *NCSKEW* and *DUVOL*.

variables and based on the distribution of stock returns. Further, *DUVOL* is less influenced by extreme values than *NCSKEW* is.

3.4 Sample selection and descriptive statistics

Firms' weekly return data is from CRSP; annual financial data is from COMPUSTAT. We merge the two datasets based on fiscal years. Financial data is from fiscal year 1989 to 2009. The estimate of the proxy *Residual_PROD* includes the variable s*ales* lagged for two periods. In addition, our measures of DRO are the sums of the prior three years' levels. As a result, our final sample is from 1994 to 2009. Our sample includes firm-year observations that meet the following requirements: (1) yearly average stock prices are above 2.5; (2) having at least 26 weeks of stock-return data are excluded; (3) not in banking or utilities industries; (4) having control variables available; (5) having at least one DRO available. Table 1 reports the number of observations of our final sample for each fiscal year. As shown in the table, the number of observations is generally comparable across years. Since some observations do not have all the three DROs available, we report the number of observations that have each of the three available. We do not find substantial differences among the three samples (40,037 for *DISX*, 42,404 for *PROD*, 44,731 for *CFO*). Actual sample size in each estimation depends on which DRO we use in the model.

Table 2 reports descriptive statistics of our main variables. Similar to those reported by Hutton et al. (2009), *DA* is equal to 23% of lagged total assets. Abnormal real activities (*DRO_DISX*, *DRO_PROD*, and *DRO_CFO*) generally have larger magnitudes and variances than DA. This is consistent with the notion that REM is likely to be more prevalent than AEM. However, different levels of model fitness may also contribute to the above differences because our measures are based on unsigned residuals from Models (1) (2) (3) and (5). Models with poorer fitness leave a larger part of dependent variables' variation in residuals. As a result, we interpret and compare the economic significance of our results based on one standard deviation change in our variables of interest.

Hribar and Nichols (2007) have shown that unsigned DA is correlated with firms' operating volatility. Since the construction of DRO is similar to that of unsigned DA, we control for operating volatility in our analyses. To comprehensively control for operating volatility, we compute three volatility measures for each firm-year: earnings volatility, cash flow volatility, and sales volatility. We compute those volatility measures for each firm year based on quarterly financials in a four-year period (previous three years and the current year). Similar to the sample by Hutton, an average of 19.5% and 23.1% of our firm-year observations have at least one *crash* and *jump* during a fiscal year. The correlation coefficients between our variables of interest are presented in Table 3. The correlations among DROs and DA are positive and significant. The observed correlations may be driven by (I) earnings management and/or (II) model specification and/or (III) operating volatility.

(I) *Earnings management*: when managers intend to manipulate a non-trivial amount of earnings, they may need to resort to several methods simultaneously, which mechanically creates positive correlations among those DRO measures. Here are several possible reasons. First, each EM technique has its own theoretical or practical upper limit; second, the marginal cost of an EM technique may increase with the magnitude (Zang 2012); third, an abnormal activity at an excessive level easily invites suspicion. To avoid that, managers engage in several DRO activities but at moderate levels. (II) *Model specification*: The significant correlations are also very likely to be driven by some common variables used in Eq. (1) to (5). (III) Operating volatility: We find that there are strong and positive correlations between all DA/DRO measures and operating volatility variables. Therefore, the high correlations among DA and DRO variables are partially driven by those measures' ability to pick up the same operating volatility factor. This also highlights the importance for us to control for those volatility variables in testing our hypotheses.

We find positive correlations between *crash* and each DRO, producing initial support for our Hypothesis 1. However, the other two alternative crash likelihood measures *NCSKEW* and *DUVOL* are not consistently related to DRO measures. Since firm-characteristics greatly affect crash risk (see Hutton et al. 2009; Kim et a. 2011a and 2011b), we rely on multivariate analyses to test our hypotheses.

3.5 Other data sources

We extract our extra control variables from the following databases: Bond issuance and seasoned equity offerings are from *Thomson SDC.* Analysts' coverage and forecast consensus are from I/B/E/S summary files. The raw information about institutional investors' holdings is from *Spectrum*.

4. Multivariate Analyses

4.1 The impacts of DRO on crashes (Testing of Hypothesis 1)

We use the following logistic regression model to explain crash risk.

$$Crash_t = \alpha_0 + \beta_1 DRO_{t-4\sim t-1} + \sum_{i=2}^{n} \beta_i \, Control_i + \varepsilon_t \tag{11}$$

Crash is an indicator variable. It is equal to one if a firm's firm-specific weekly returns rise above 3.09 standard deviations from the fiscal-year mean for at least once in a year. Following prior studies, we control for the following firm characteristics: size of the firm (*size*), capital structure (*leverage*), growth opportunities (*MTB*), firm performance (*ROA*), net operating assets (*NOA*), and *auditor* (*BIG5*) dummy. To be consistent with the literature, we use the current-year values for firm performance and auditor, and lagged values for the other variables. We also control for firms' stock-return characteristics (lagged by one period) in the full model. These characteristics include *negative skewness* (*NCSKEW)* of returns, *standard deviation* (*Stock_std*) of returns, and average *firm-specific return* (*RET*). Following the guidance by Hribar and Nichols (2007), we control for firm-level volatility in earnings, cash flows, and sales. In addition, we include the main variable of interest in Hutton et al. (2009): the prior three-year sum of discretionary accruals (*DA*). This variable has been shown by Hutton and the following studies to affect crash risk. Since DA is also correlated with our *DRO* measures, we control for it in our model to assess the incremental predictive power of DRO for crash risk.

Table 4 summarizes the results of our estimations using each of the three specific DRO measurements. We control for year dummies in all the logistic regressions. Z-statistics reported below coefficient estimates are based on robust standard errors corrected for firm-level clustering. Columns (1), (4), and (7) report results without return controls and volatility controls. All three specific DROs are positively related to future crash risk, even though the one for *CFO* is not statistically significant. Then we progressively control for stock-return characteristics and volatility measures. The predictive power for crashes is still positive and significant for *DRO_DISX* and *DRO_PROD*, with p-values smaller than 0.001.[15] *DRO_CFO*'s impact remains insignificant statistically. As mentioned in the literature (see Roychowdhury 2006; and Cohen and Zarowin 2010) and in Section 3, abnormal *CFO* is an ambiguous proxy due to other REM activities' different effects on it.[16]

[15] The coefficients of DRO in Columns (3) (6) (9) are all smaller than those in (2) (5) (8), suggesting the importance of controlling for operating volatility measures.

[16] Our robustness analysis shows that DRO_CFO's impact on crash risk becomes significant when we consider the non-linearity in the relationship.

We then turn to the use of the three aggregate measurements of DRO: *DRO_1, DRO_2, and DRO_3*. Estimation results of logistic regressions based on those aggregate measures are reported in Table 5. In support of H1, all three of our aggregate DROs are shown to significantly increase crash occurrences. The coefficient estimates for our firm characteristics are generally consistent with Hutton et al. (2009). Consistent with Kim et al. (2010), lagged *negative skewness* of stock returns (*NCSKEW*) is positively and significantly related to crash risk. This is not a surprise, since *NCSKEW* is simply another measure of crash tendency. We thus interpret this result simply as evidence of serial correlation in firms' crash risk: a firm that had high crash likelihood in the last period is more likely to experience a crash in this period.

To show the economic significance of our results, we compute the marginal impacts on crash risk based on one standard deviation (s.d.) change in DRO. Results are summarized in Table 5 Panel B. Specifically, the change in DRO is from 0.5 s.d. left of the mean to 0.5 s.d. right of the mean, while other variables are kept to their means. Since year controls are categorical variables, we cannot set them to their mean values. Instead, to account for year effect, we re-run the above procedure for 16 times (set one year dummy equal to one each time), and the impacts presented in the table are averages of 16 estimations. We set the Big5 dummy equal to one since almost 90% of firm-years in our sample have *Big 5* auditors.

The column numbers (1) - (9) in Panel B correspond to those in Panel A of Table 5. We find that *DRO_3*, which aggregates the three activities, outperforms the other two DRO aggregates, in terms of impacts on crash risk. One interpretation of this result is that crash occurrence is more affected by the total amount of abnormal activities than by a specific one.

One standard deviation change around the mean of *DRO_3* increases crash likelihood by 0.94 percent, a magnitude that seems small economically. However, given that the unconditional probability to observe a crash during a full year is about 19%, DRO accounts for about 5% of the variation (0.94% divided by 19.52%). Therefore, we think it is still economically significant, especially for investors who focus on tail events. Moreover, the definition of *crash* hinges on the standard deviation of firm-specific stock returns. Those deviations may systematically vary with firms' magnitudes of abnormal real operations. To investigate this issue, we divide firms into four groups according to the magnitudes of their DRO. We find that groups with higher DRO display larger standard deviations in their firm-specific returns. On average, the standard deviation of the highest-DRO group is about 30% larger than that of the lowest-DRO group. This means that the economic significance of our result is even larger than it seems. In other words, firms with more DRO are associated with more crashes, and, more importantly, their crashes come with deeper declines in stock prices than their counterparts' crashes. In addition, we find much larger economic impacts from DRO when non-linearity is considered (section 4.2.1), in our suspect-firm analysis (section 4.3), in the post-SOX period (section 4.4), and in the non-EA window (section 5.1).

4.2 Robustness Tests for H1

We implement the following three analyses to build up the robustness of our results: (1) analyses of non-linearity; (2) alternative measures of crash likelihood; (3) firm-fixed effects.

4.2.1 Analyses of non-linearity

The relationship between *DRO* and crash risk could be non-linear, either convex or concave: *DRO* may need to be relatively aggressive to affect information flow, resulting in the convexity of the relationship; alternatively, DRO may have diminishing marginal effect on information hiding. Moreover, there could be thresholds beyond which DRO may incur suspicion from market participants. This alternative mechanism leads to concavity in the relationship between DRO and crash risk. To empirically test the existence of non-linearity, we include DRO^2 in our model and re-run our estimations. In addition, the results in Hutton et al. (2009) strongly suggest the concavity in the relationship between DA and crash risk, so we include DA^2 into the model as well.

We report the regression results from our full model in Table 6.1 A. For brevity, all the control variables are omitted from the table. The consistent negative signs before DRO/DA suggest that the relationship is concave. Recall that, in quadratic models, the total impact of DRO on crash is obtained through two terms, *DRO* and DRO^2, *on* the right-hand side of the equation. However, this total impact is not simply the arithmetic sum of the individual impact.[17] Instead, we use the following procedures to compute it: (1) we set DRO to its mean - 1/2 s.d.; (2) we set the term DRO^2 equal to the square of DRO value set in (1).[18] (3) We predict the crash probability Pr_1 with all other continuous variables set to their mean values. (4) We then set DRO = mean + 1/2 s.d. and go through Step (1) - (3)

[17] This is the case because those results are from logistic regressions.
[18] Setting DRO^2 equal to its own mean-1/2 s.d. overstates the impact from the square term, because DRO^2 is much more dispersed in value than DRO.

again to obtain the corresponding Pr_2. (5) The difference between Pr_2 and Pr_1 is the marginal effect we report in Table 6.1 (B). Please refer to the above section for our value setting for categorical variables.

The magnitudes of the impacts are even larger here than in Table 5 (B). The changes in crash risk (%) with one s.d. change in our three aggregate DRO measures (alone with the corresponding changes in DRO^2) are 1.21, 1.20, and 1.37. In comparison, those impacts are 0.79, 0.79, and 0.94 in our earlier analyses without those square terms. We further analyze to what extent is H1 supported by these results. While the relationship is concave, crash probability monotonically increases with DRO and DA within each one's relevant value range: 1st percentile to 99th percentile.[19] Therefore, H1 is strongly and widely supported.

4.2.2 Alternative measurements of crash likelihood

In this section, we re-run the above analyses in OLS regressions with two alternative crash likelihood measures: *negative skewness* (*NCSKEW*) and *down-to-up volatility* (*DUVOL*). They measure how crash-prone each stock is based on its return distribution. Since it does not involve third moments, *DUVOL* is less affected by extreme values than *NCSKEW*. That means results based on *DUVOL* is less important to those who care more about extreme crashes than moderate ones.

In our OLS regressions, we use the same control variables (financials, stock-return characteristics, and operating volatilities) as in Section 4.1. We report the results in Table 6.2 (A). The three measurements of *DRO* are all shown to be positively associated with both crash likelihood measures, with p-values smaller than 0.01. While the positive relation is still significant between DA and *NCSKEW*, it is interesting that DA does not seem to be related to *DUVOL* (Column (4) to (6)). Since *NCSKEW* gives more weight to extreme values than *DUVOL*, the results imply that *DA* better predicts those extremely negative returns than it predicts the general asymmetry of positive and negative stock returns.

Consistent with the literature (Kim et al. 2011a and 2011b), we find relatively low R^2 within those estimations (between 4% and 6%). Again, this is consistent with the well-known empirical fact that extreme events

[19] Our DRO and DA measures have been winsorized on 1% level on both ends.

are difficult to predict (Marsh and Pfleiderer 2012).[20] We further include the square terms in the analyses and find evidence of concavity in DRO's impacts on crashes. Results are reported in Table 6.2 (B). Again, we find the DRO/DA's impacts on crash likelihood appear larger in a quadratic model than in our baseline model.

4.2.3 Firm-fixed effects

We further control for firm-level fixed effects into our baseline model. By controlling for firm-fixed effects, we address the concern that our earlier results may have been driven by some unobserved firm-level characteristics that simultaneously affect both firms' DRO and future crash risk. We replace our original logistic regressions with conditional logistic regressions on firm level. For the estimations of *NCSKEW* and *DUVOL*, we now absorb firm dummies when running OLS regressions. About one fourth of firms are dropped from logistic estimations, either because those firms do not have any crashes in our sample period, or because they have (a) crash(es) in every single year of the period. Therefore, the numbers of observations in the logistic regressions are smaller than those in the OLS regressions. Results are summarized in Table 6.3. Our three DRO aggregates consistently show positive association with crash occurrences (*crash*) and crash likelihood (*NCSKEW* and *DUVOL)* in all of those analyses. However, the significance of the coefficient before DA only marginally holds in predicting *crash* and fails to hold in predicting the other two "crash-prone" measures. Once again, DRO outperforms DA in predicting crash risk. Results for all other control variables are generally consistent with those in our earlier analyses.

4.3 Suspect-Firm Analysis of REM (Testing of Hypothesis 2)

In a before-and-after structure, Figure 1 presents average probability for suspect firms to experience crash in Year T and Year T+1. Suspect firms are sorted into groups based on the signed DRO quintiles. This approach allows us to see how REM is associated with (1) the crash probability following suspect year (Year T+1) and (2) the change in crash probability from Year T to Year T+1.

As expected, Group 5 (the group with the largest upward REM) is found to have the highest crash probability in year T+1 (the year after the suspect year). In Panel A (*REM_DISX* quintiles), this group's average crash probability is as high as 22.03% compared with an average of 18.51% for the other four groups. In Panel B

[20] The Pseudo R squares reported for the logistic regressions in the previous section, being around 1%, are McFadden's Pseudo R Square. Like many other varieties of Pseudo R square, it is not directly comparable to the adjusted R square from OLS.

(*RM_PROD*), Group 5 has an average crash probability of 21.74%, 3.48% higher than the average of the other four. We find that the economic significance here is much stronger than from our earlier results. We also notice that Group 5's average crash probability in Year T is similar to other groups in Year T. This suggests that our finding cannot be simply explained by unobservable firm characteristics. Instead, the crash probability surge in Year T+1 is likely the aftermath of the Year T's use of REM to hide negative information.

Given that these are just univariate results and may suffer from omitted variable biases, we turn to regressions controlling for certain firm characteristics. Results are summarized in Table 7 (A). Columns (1) to (3) report results from our logistic regression models. As expected, REM firms have a significantly higher likelihood of experiencing price crash in the next period than non-REM firms. On the other hand, *AEM* firms do not display higher crash likelihood. These results are consistent with the notion and the survey evidence that suspect firms use much less earnings-inflating DA than earnings-inflating DRO. Economic impacts of both *REM* and *AEM* are presented in Panel B. We see an incremental crash risk of 3.66% for expense-related *REM* firms, 3.1% for production-related *REM* firms, and as large as 5.80% for firms that are both expense- and production-related *REM* firms.[21] Considering the fact that the probability to observe a crash in a firm-year is only 18.9% for our suspect firms, the relative impact we observe here is as large as 30.6% (5.80% divided by 18.9%) of the sample average.

Using the two alternative "crash-prone" measures, we also find strong support for H2. The results in Table 7 are generally stronger than those in Table 5 in terms of magnitudes.[22] This indicates that *DRO* in a suspect-firm setting better captures REM than in a broad sample.

4.4 Before and after the Sarbanes-Oxley (SOX) Act (Testing of Hypothesis 3)

Since our *DA* and *DRO* measures are based on the moving sum of the previous three years' values, our post-SOX observation year starts from the year 2005. The observations in the years 2003 and 2004 are excluded because their three-year period spans across both the pre- and post-SOX periods. We split the sample into the two sub-samples and run logistic regressions in each sample. This allows us to directly compare the impacts of earnings management on crash in the two periods, without imposing the same coefficients on control variables. To examine

[21] The values in Panel B are based on one standard deviation change around the mean of earnings management (mean-0.5 s.d. to mean+0.5 s.d.).
[22] This comparison is made based on one standard deviation change in DRO, as shown in Table 5 (B).

the statistical significance of the differences, we also interact each one of our DRO/DA and control variables with the SOX dummy and then include all the interactions in our regressions. Results are summarized in Table 8 Panel A. Each number in Column 3,6,9 is actually the coefficient before the interaction term. For example, 0.097 in column (3) represents the coefficient before *DRO_1* SOX* instead of the coefficient before *DRO_1*. Similarly, -0.069 in column (6) represents the coefficient before *Size* SOX* instead of the one before *Size.*

Comparing the results in the two periods, we have two observations. The first observation is consistent with Hutton et al. (2009): DA displays a strong power to predict crash before SOX, but this no longer holds after SOX. Second, while DRO is significantly associated with crash both before and after SOX, the impact is much larger in the post-SOX period. The results for *DRO_1*, *DRO_2*, and *DRO_3* consistently support Hypothesis 3. Based on models with interaction terms (Column (3), (6), and (9)), only DRO_3's Δimpact is shown to be significant at the 10% level. A further investigation shows that, in a simpler model without interacting SOX with each control variables in (3) (6) (9), the coefficients before the other two interactions, SOX*DRO_1 and SOX*DRO_2, all become significant at the 10% level. We do not find any of the coefficients before *SOX * DA* statistically significant at the 10% level in Table 8. However, our later analyses suggest that this is likely due to DA's nonlinear impact on crash risk (Panel C).

In spite of the weak statistical significance, the above differences between pre-SOX and post-SOX periods are large in terms of crash probability. To quantify them, we present in Panel B the marginal impacts based on one s.d. changes in DA and DRO measures. We find economically meaningful differences in the predictive power of DA/DRO between the two periods. For example, one s.d. increase in the aggregate measure *DRO_3* is associated with only a 0.60 percent increase in crash likelihood before SOX but with a 1.73 percent increase after SOX (Δmarginal impact = 1.13). Put in perspective, this marginal impact in the post-SOX period is about 9% of the average crash risk (1.73% divided by 19.52%).[23] On the other hand, in all three models, the impact of DA on crashes drops by nearly one half after SOX (Δmarginal impact = -0.50).

Once we include the DRO^2 and DA^2 terms into the regression models, the two-period difference in DRO's predictive power is even larger than shown in the above results (Δmarginal impact = 1.70 vs. 1.13). This difference

[23] Comparison is made based on DRO_3's impact.

is also larger for DA (Δmarginal impact = -1.40 vs. -0.50). The results are reported in Panel C and D. Further analyses using alternative crash likelihood measures also provide results in support of H3 (Panel E).

5. Other issues and robustness checks

5.1 Timing difference between DRO and DA: Crashes following earnings announcement

When using DRO and DA to manipulate information, a manager can only implement the former during an accounting period, whereas the latter can be performed at the end of the period (Zang 2012).[24] Considering this timing difference between DRO and DA, we classify crashes into two types: those that happen in the earnings announcement (EA) window (*EA crashes*), and those in the non-EA window (*non-EA crashes*). The EA-crashes are likely triggered by the information released on the financial reporting date; the non-EA crashes are likely triggered by negative information released during the year.

Both managers' intentional reversion and market participants' detection of information-manipulating DRO/DA can both cause drastic downward movements in stock prices. The reversion and detection of DA rely on financial reporting and thus become observable right after earnings announcement; By contrast, DRO involves real activities and takes time to implement. Therefore, its reversion or detection happen throughout the accounting period. Therefore, we expect DA's crash-predicting ability to be more towards the EA window than is DRO's.

To test the above conjecture, we need to decompose the impact of DRO (DA) on crash into its impact on EA crash and its impact on non-EA crash. Then we compute the *impact ratio* = non-*EA crash impact/EA crash impact* separately for DRO and DA. To support our conjecture, this ratio should be higher for DRO than for DA.

Recall that we use weekly returns to identify a crash. As long as the last day of the week falls into the [0, +5 Day] window relative to the quarterly EA date, it is classified as an EA crash. We also identify EA jumps in the same fashion for comparison. Figure 2 shows the distribution of crashes and jumps in the 100-day window following quarterly EAs. A large portion of jumps and crashes are in the EA [0, 5] window. This does not come as a

[24] This is the case because real activities take time to carry out, while accruals manipulation can be done at the last minute. Also, technically speaking, DA can be done even after the end of the fiscal period end, as long as it is before the statements issuance date.

surprise and indicates that many of the crashes and jumps are market's reactions to information contained in quarterly reports.

To obtain the impact of DRO (DA) on EA and non-EA crash, we run our baseline model with the dependent variable Y=*Dummy EA Crash* and Y=*Dummy Non-EA Crash* separately. Results of our regression analyses are summarized in Table 9 Panel A. Based on those results, we compute and present in Panel B the marginal impacts of both DRO and DA on the two types of crashes. The impact ratios are substantially higher for DRO than for DA. For example, in the model that has both DRO_3 and DA on the right-hand side of the regression, the impact ratio is 3.17 for DRO but only 1.85 for DA. The results corroborate our conjecture that DA's predictive power for crashes is more concentrated on EA crash than is DRO's predictive power.[25]

5.2 Winsorizations, additional controls, and other robustness tests

All the financial variables and measurements of DRO and DA (except categorical variables) have been winsorized at the 1% level (both ends) to avoid outlier effects. Winsorizing at 0.5%, 2%, and 5% levels do not qualitatively change the results in our main analyses reported in Table 5 (H1), Table 7 (H2), and Table 8 (H3). Eq. (1) (2) (3) are based on models from Roychowdhury (2006) with additional controls used by Gunny (2010). The more variables we include in a cross-sectional model the less degree of freedom do we have in each industry-year estimation. This is a concern for industry-years that have small number of observations. Therefore, we re-estimate the proxies using Roychowdhury's models without the additional controls. Using those proxies, we are able to obtain results that are as strong as those presented in the tables.

The following additional variables are further controlled for: *D_SEO* is a dummy variable that equals one if there is a seasoned equity offering (SEO) announcement in the current or the following year. *D_Bond* is a dummy equal to one for bond issuance in the current or the following year. These two events are previously shown to be accompanied by earnings management. The variable *Analysts* is the log of one plus the number of analysts following the firm. Following Gunny (2011), we construct a variable called *Habitual Target Beater* that is equal to the number of times a firm beats/meets analysts' forecasts consensus in the past four quarters. *Institutional ownership* is the

[25] We also used multinomial logistic regressions to re-examine the issue. Since EA crash and non-EA crash are not mutually exclusive for a given firm-year, we have to drop firm-years that have two or more crashes during the year. The results are extremely close to what we show in Table 9.

percentage of shares outstanding held by the two types of institutional investors: long-term and short-term. Classification of investor horizon is based on how frequently each institutional investor rotates the positions on all of the stocks in his or her portfolio (also called "churn rate"). Our construction of these two institutional variables closely follows the formulas in Gaspar et al. (2005). After we control for these additional variables, the sample size drops by about 30% due to data availability. The association between DRO and crash remains strong after those additional controls. In addition, we consistently find among our analyses that crash risk is smaller before SEO, before bond offering, and for firms that constantly beat their earnings targets.

To provide further support for the suspect-firm analyses (H2), we replace the dummy variable *Suspect_REM* with a continuous signed REM variable and again find positive association between upward-*REM* and crash risk. Furthermore, to show that our suspect-firm sample helps to identify REM, we replicate our suspect-firm analyses in the sample consisting of non-suspect firm-years. If suspect-firm approach does not provide incremental value in our research design, we should observe similar results in the non-suspect-firm analyses. While the results are generally suggesting a positive association between REM and crash risk, the magnitudes drop significantly compared with those in our suspect-firm analyses.

In our suspect-firm analyses, we use two earnings benchmarks: zero loss and last years' earnings. There is another earnings' benchmark, *analysts' forecasts consensus*, which could have been included in our suspect-firm analysis. Gunny (2010) has provided two reasons for not using it in a suspect-firm analysis: first, unlike AEM, REM takes place during the year, long before the analysts' consensus is available; second, the literature suggests that forecast guidance provided by management to analysts may be a more important tool than earnings management in companies' attempts to avoid missing the targets. Nevertheless, we further incorporate in our suspect-firm analysis those firms that beat the consensus (mean) of analysts' forecasts of earnings, obtained from the summary file of I/B/E/S, by 1 penny. The marginal impacts of REM on crash risk are smaller compared with our original results: 2.86% versus 3.66% for REM_1, 1.19% versus 3.10% for REM_2, and 4.28% versus 5.80% for REM_3. Among those results, the impacts from REM_1 and REM_3 are still strongly significant ($P<0.01$).

In their study of price jumps, Hutton et al. (2009) do not find any association between DA and crashes. They explain that information hiding is asymmetric and managers do not have the incentive to hide positive information in an extreme manner. Following their lead, we extend our main analyses to price jumps. In the results, none of our DRO measures is associated with price jumps. These results provide further support for the above view.

In Table 4, *DRO_CFO*'s impact on crash risk is not statistically significant ($\beta=0.082$, $T=1.364$). While we argue that this is likely the result of the measurement issue, further investigation suggests that non-linearity helps to explain the insignificance as well. When we analyze its impact on crash risk in a quadratic model, the coefficients before *DRO_CFO* ($\beta=0.641$, $T=3.880$) and DRO_CFO^2 ($\beta=-0.529$, $T= -3.641$) are both significant. The marginal impact monotonically increases with *DRO* within its relevant value range (up to almost the 99th percentile of *DRO_CFO*).[26] Therefore, H1 is still strongly supported.

6. Conclusion

This study finds strong evidence that firms' abnormal real business operations increase their subsequent crash risk. This supports our conjecture that managers use real operations to hoard negative information and the market cannot timely understand those abnormal business operations. This positive association is robust to firm-fixed effects, alternative crash likelihood measurements, and the controls of firm financial characteristics, return characteristics, institutional holdings, analysts' coverage, and major financial events. As expected, we do not find similar association between abnormal business activities and positive price jumps.

The impacts of DRO and DA on crash risk appear to be concave. This supports the notion that the excessive use of DRO and DA raises suspicion from the market, and, therefore, leads to a timely downward price adjustment before the build-up of crash pressure. This could also be the result of diminishing marginal impacts of DRO and DA on crash risk.

Our further analyses concerning suspect firms and SOX 2002 suggest that the above association between DRO and crash risk, at least to some extent, reflects the role played by REM. Specifically, firms with upward-REM experience a significant crash probability increase in the following year. The impact of abnormal real activities on crash risk is dramatically higher after the passage of SOX. In contrast, discretional accruals' ability to predict crash risk loses its statistical significance in the post-SOX period. This is consistent with the finding in the literature that firms’ reliance on real activities to manipulate earnings increases after SOX, while the accrual-based counterpart

[26] Relevant value range: from 1st percentile to 99th percentile.

becomes less important (Cohen et al. 2008). In line with the timing difference between DA and DRO, DA's predictive power for crashes is more concentrated on EA-induced crashes.

Our results add to the understanding of the consequences of REM. We also contribute to the literature of stock price behaviors by providing a new predictor for crash risk. More importantly, to the extent that DA and DRO capture earnings management, what we find suggest that the impact of EM on crash risk has not dissipated after SOX. The only difference is now REM becomes more important than AEM to predict crashes.

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Table 1 Number of observations for Different Years

To be included in our sample, observations need to have all control variables available and at least one of the three deviation of real operations (DRO) available. Numbers in the Column DISX/PROD/CFO are the No. of Observations that have the corresponding DRO available in a certain year. DISX/PROD/CFO: Discretionary expenses / Production Cost / Cash Flows from Operations.

Fiscal Year Period	DISX	PROD	CFO
1994	2,307	2,360	2,536
1995	2,438	2,460	2,696
1996	2,678	2,630	2,969
1997	2,768	2,826	3,107
1998	2,741	2,778	3,062
1999	2,693	2,657	3,013
2000	2,630	2,866	2,986
2001	2,368	2,660	2,721
2002	2,408	2,646	2,765
2003	2,498	2,815	2,878
2004	2,699	3,036	3,069
2005	2,628	2,892	2,939
2006	2,519	2,742	2,775
2007	2,419	2,576	2,643
2008	2,244	2,371	2,423
2009	1,999	2,089	2,149
Total	40,037	42,404	44,731

Table 2 Descriptive statistics of important variables

Crash is equal to one if firm-specific weekly return (*r_fs*) drops below 3.09 standard deviations from its fiscal-year mean for at least once in the year and equal to 0 if not. Deviation in real operations *DRO_DISX/DRO_PROD/DRO_CFO* is computed as the moving sum of the prior three years' absolute value of the corresponding proxy from Model (1)/(2)/(3). *DA* is the sum of the prior three years' discretionary accruals (absolute value) from Modified Jones Model. *NCSKEW*, the negative skewness of *r_fs*, is a measurement of crash likelihood computed based on Eq. (9). *DUVOL* stand for down-to-up volatility, which is another measure of crash likelihood and computed based on Eq. (10). *Stock_std* and *RET* are the standard deviation and mean of *r_fs* for each firm-year. *Size* is the natural log of *MVE* at the beginning of each fiscal year. *ROA* is net income divided by total assets at the beginning of the year. *MTB* is (*MVE*+book value of equity (*BVE*)) / *BVE*. Year dummies are controlled. *R_Square* for firm-year regressions based on Model (8). Net operating assets *(NOA)* is calculated as total assets minus cash and marketable securities at the beginning of the year, scaled by total assets. *Sales/Earnings/Cash flow volatility* is the standard deviation of the quarterly sales/net income/cash flow computed over a four-year window: [T-3, T].

	Mean	s.d.	Q1	Median	Q3
DRO_DISX	0.401	0.380	0.137	0.275	0.527
DRO_PROD	0.466	0.417	0.174	0.330	0.613
DRO_CFO	0.293	0.249	0.123	0.214	0.371
DA	0.227	0.192	0.097	0.167	0.287
Crash	0.195	0.396	0.000	0.000	0.000
Jump	0.231	0.421	0.000	0.000	0.000
R_Square	0.273	0.175	0.137	0.230	0.374
NCSKEW	-0.072	0.792	-0.516	-0.112	0.298
DUVOL	-0.141	0.505	-0.471	-0.151	0.171
Stock_std	0.061	0.034	0.037	0.054	0.077
Kurtosis	4.410	2.481	2.963	3.639	4.845
TobinsQ	1.742	1.973	0.845	1.212	1.938
Internal Funds/TA	0.113	0.163	0.051	0.112	0.182
NOA	0.549	0.797	1.239	1.160	1.219
Sales Volatility	0.028	0.048	0.081	0.065	0.059
Earnings Volatility	0.010	0.019	0.040	0.032	0.037
Cash flow Volatility	0.020	0.031	0.050	0.041	0.032
Size	5.863	2.043	4.367	5.770	7.192
ROA	0.011	0.161	-0.017	0.041	0.090
MTB	3.025	6.814	1.252	2.056	3.520

Table 3 Correlation table

Crash is equal to one if firm-specific weekly return (*r_fs*) drops below 3.09 standard deviations from its fiscal-year mean for at least once in the year and equal to 0 if not. Deviation of real operations *DRO_DISX/DRO_PROD/DRO_CFO* is computed as the moving sum of the prior three years' absolute value of the corresponding proxy from Model (1)/(2)/(3). Discretionary Accruals(*DA*) is the sum of the prior three years' discretionary accruals (absolute value) from Modified Jones Model. *NCSKEW*, the negative skewness of *r_fs*, is a measurement of crash likelihood computed based on Equation (9). *DUVOL* stand for down-to-up volatility, which is another measure of crash likelihood and computed based on Equation (10). *Stock_std* and *RET* are the standard deviation and mean of *r_fs* for each firm-year. *Size* is the natural log of *MVE* at the beginning of each fiscal year. *ROA* is net income divided by total assets at the beginning of the year. *MTB* is (*MVE*+book value of equity (*BVE*)) / *BVE*. Year dummies are controlled. *R_Square* is from model (8) for each firm-year run. Net operating assets (*NOA*) is calculated as total assets minus cash and marketable securities at the beginning of the year, scaled by total assets. *Sales / Earnings / Cash flow volatility* is the standard deviation of the quarterly sales / net income / cash flow computed over a four-year window: [T-3, T].

	DRO_DISX	*DRO_PROD*	*DRO_CFO*	*DA*	*Crash*	*Jump*	*NCSKEW*	*DUVOL*	*R_Square*	*Earnings Volatility*	*Cash flow Volatility*	*Sales Volatility*
DRO_DISX	1											
DRO_PROD	0.753	1										
DRO_CFO	0.293	0.393	1									
DA	0.245	0.242	0.464	1								
Crash	0.016	0.029	0.018	0.015	1							
Jump	0.019	0.017	0.014	0.033	-0.163	1						
NCSKEW	-0.005	0.006	0.002	-0.021	0.632	-0.558	1					
DUVOL	-0.022	-0.013	-0.026	-0.054	0.504	-0.47	0.89	1				
R_Square	-0.128	-0.118	-0.083	-0.132	-0.037	-0.144	0.081	0.125	1			
Earnings Vol.	0.173	0.184	0.379	0.548	0.016	0.047	-0.027	-0.066	-0.120	1		
Cash flow Vol.	0.269	0.29	0.416	0.43	0.002	0.052	-0.041	-0.069	-0.208	0.427	1	
Sales Vol.	0.361	0.329	0.254	0.358	0.018	0.031	-0.009	-0.029	-0.161	0.306	0.51	1

Table 4 Predicting crashes using individual type of Deviation of Real Operation (*DRO*) (Logistic Regression): H1

This table presents results based on logistic regressions with *Crash* being the dependent variable. *Crash* is equal to one if firm-specific weekly return (*r_fs*) drops below 3.09 standard deviations from its fiscal-year mean for at least once in the year and equal to 0 if not. Deviation of real operations *DRO_DISX/DRO_PROD/DRO_CFO* is computed as the moving sum of the prior three years' absolute value of the corresponding proxy from Model (1)/(2)/(3). Discretionary Accruals(*DA*) is the sum of the prior three years' discretionary accruals (absolute value) from Modified Jones Model. *NCSKEW*, the negative skewness of *r_fs*, is a measurement of crash likelihood computed based on Equation (9). *DUVOL* stand for down-to-up volatility, which is another measure of crash likelihood and computed based on Equation (10). *Stock_std* and *RET* are the standard deviation and mean of *r_fs* for each firm-year. *Size* is the natural log of *MVE* at the beginning of each fiscal year. *ROA* is net income divided by total assets at the beginning of the year. *MTB* is (*MVE*+book value of equity (*BVE*)) / *BVE*. Year dummies are controlled. *R_Square* is from model (8) for each firm-year run. Net operating assets *(NOA)* is calculated as total assets minus cash and marketable securities at the beginning of the year, scaled by total assets. *Sales / Earnings / Cash flow volatility* is the standard deviation of the quarterly sales / net income / cash flow computed over a four-year window: [T-3, T]. Z-statistics reported under coefficients estimates are based on robust standard errors clustered on firm level.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Deviation in Real Operation/Accruals					Dependent Variable: Y=Crash				
DRO_DISX	**0.121*** **	**0.123*** **	**0.089** **						
	(3.387)	**(3.488)**	**(2.429)**						
DRO_PROD				**0.193*** **	**0.191*** **	**0.172*** **			
				(6.240)	**(6.259)**	**(5.448)**			
DRO_CFO							**0.090**	**0.094**	**0.082**
							(1.556)	**(1.619)**	**(1.364)**
DA	0.295***	0.324***	0.342***	0.215***	0.240***	0.266***	0.279***	0.293***	0.316***
	(4.039)	(4.226)	(4.027)	(2.975)	(3.187)	(3.178)	(3.789)	(3.896)	(3.830)
Financial Variables									
Income	-0.679***	-0.731***	-0.810***	-0.593***	-0.637***	-0.693***	-0.577***	-0.620***	-0.702***
	(-7.365)	(-7.764)	(-8.150)	(-7.269)	(-7.571)	(-7.883)	(-7.186)	(-7.550)	(-8.110)
Size (Lagged)	0.075***	0.069***	0.068***	0.060***	0.056***	0.054***	0.060***	0.057***	0.056***
	(9.345)	(7.199)	(7.061)	(7.863)	(6.067)	(5.862)	(8.020)	(6.254)	(6.092)
MTB (Lagged)	0.003*	0.004**	0.004**	0.002	0.002	0.003	0.003	0.003**	0.003**
	(1.695)	(2.120)	(2.155)	(1.049)	(1.480)	(1.590)	(1.611)	(2.034)	(2.090)
Leverage (Lagged)	-0.032	-0.028	-0.034	-0.028	-0.026	-0.031	-0.002	-0.000	-0.006
	(-0.514)	(-0.460)	(-0.545)	(-0.494)	(-0.474)	(-0.555)	(-0.040)	(-0.003)	(-0.111)
NOA (Lagged)	0.156*	0.147*	0.114	0.214**	0.211**	0.164*	0.216***	0.213***	0.163**
	(1.761)	(1.667)	(1.264)	(2.567)	(2.544)	(1.943)	(2.630)	(2.627)	(1.977)
Auditor(BIG5)	0.035	0.021	0.024	0.062	0.048	0.050	0.063	0.047	0.050

Table 4 Continued

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	(0.836)	(0.508)	(0.583)	(1.519)	(1.185)	(1.246)	(1.567)	(1.193)	(1.253)
Stock Return Characteristics									
RET (Lagged)		32.937	30.309		37.646	35.414		41.498*	38.273
		(1.339)	(1.249)		(1.543)	(1.467)		(1.747)	(1.632)
Stock_std (Lagged)		1.820	1.544		2.432	2.192		2.837	2.478
		(0.756)	(0.648)		(1.025)	(0.931)		(1.226)	(1.080)
NCSKEW (Lagged)		0.087***	0.086***		0.081***	0.080***		0.084***	0.083***
		(5.603)	(5.524)		(5.354)	(5.291)		(5.743)	(5.652)
Operating Volatility									
Earnings Volatility			-1.063**			-0.598			-0.944**
			(-1.977)			(-1.208)			(-1.963)
Cash flow Volatility			-0.915			-1.351**			-1.327**
			(-1.444)			(-2.247)			(-2.253)
Sales Volatility			1.228***			1.077***			1.306***
			(4.316)			(3.812)			(4.979)
Constant	-2.211***	-2.220***	-2.194***	-2.161***	-2.208***	-2.184***	-2.134***	-2.201***	-2.180***
	(-26.211)	(-15.025)	(-14.821)	(-26.434)	(-15.164)	(-14.983)	(-26.787)	(-15.510)	(-15.363)
Observations	40,037	40,037	40,036	42,404	42,404	42,403	44,731	44,731	44,730
Pseudo R^2	0.0148	0.0162	0.0167	0.0149	0.0162	0.0167	0.0135	0.0150	0.0156

*** p<0.01, ** p<0.05, * p<0.1

Table 5 Predicting crashes using aggregate Deviation in Real Operation (*DRO*) (Logistic): H1

Panel A: This table presents results based on logistic regression with *Crash* being the dependent variable. *Crash* is equal to one if firm-specific weekly return (*r_fs*) drops below 3.09 standard deviations from its fiscal-year mean for at least once in the year and equal to 0 otherwise. The variable *Discretionary Accruals* (*DA*) is computed as the sum of the prior three years' discretionary accruals (absolute value) obtained from Modified Jones Model. *DRO_1/DRO_2/DRO_3* is the moving sum of the absolute values of *REM_1/REM_2/REM_3* in prior three years. Following Cohen and Zarowin (2010), *REM_1* aggregates signed *REM_SGA* and *REM_CFO*. *REM_2* aggregates signed *REM_SGA* and *REM_PROD*. In addition, we construct *REM_3 as* the aggregate of the three REMs. *REM_SGA/REM_PROD/REM_CFO* is estimated from equation (1)/(2)/(3). *NCSKEW*, the negative skewness of *r_fs*, is a measurement of crash likelihood computed based on Equation (9). *Stock_std / RET* is the standard deviation/mean of *r_fs* for each firm-year. *Size* is the natural log of *MVE* at the beginning of each fiscal year. *ROA* is return on assets. *MTB* is (*MVE*+book value of equity (*BVE*))/*BVE*. Year dummies are controlled. Z-statistics reported under coefficients estimates are based on robust standard errors clustered on firm level. Net operating assets *(NOA)* is calculated as total assets minus cash and marketable securities at the beginning of the year, scaled by total assets. *Sales/Earnings/Cash flow volatility* is the standard deviation of the quarterly sales/net income/cash flow computed over the four-year window: [T-3, T].

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Deviation in Real Operation/Accruals	Dependent Variable: Y=Crash								
DRO_1	**0.158*** **	**0.157*** **	**0.125*** **						
	(4.578)	**(4.598)**	**(3.491)**						
DRO_2				**0.086*** **	**0.085*** **	**0.069*** **			
				(4.532)	**(4.567)**	**(3.566)**			
DRO_3							**0.093*** **	**0.092*** **	**0.078*** **
							(5.210)	**(5.217)**	**(4.226)**
DA	0.246***	0.277***	0.305***	0.258***	0.289***	0.305***	0.230***	0.264***	0.282***
	(3.309)	(3.554)	(3.550)	(3.323)	(3.554)	(3.381)	(2.942)	(3.217)	(3.110)
Financial Variables									
Income	-0.712***	-0.763***	-0.828***	-0.707***	-0.754***	-0.813***	-0.728***	-0.775***	-0.828***
	(-7.719)	(-8.099)	(-8.353)	(-7.375)	(-7.693)	(-7.938)	(-7.593)	(-7.906)	(-8.089)
Size (Lagged)	0.076***	0.070***	0.068***	0.073***	0.067***	0.066***	0.072***	0.066***	0.065***
	(9.432)	(7.258)	(7.088)	(8.863)	(6.822)	(6.666)	(8.820)	(6.752)	(6.605)
MTB (Lagged)	0.003*	0.004**	0.004**	0.003	0.003*	0.003*	0.003	0.003*	0.003*
	(1.698)	(2.132)	(2.157)	(1.449)	(1.848)	(1.872)	(1.400)	(1.802)	(1.829)
Leverage (Lagged)	-0.038	-0.034	-0.038	-0.044	-0.040	-0.047	-0.044	-0.040	-0.047
	(-0.617)	(-0.562)	(-0.614)	(-0.685)	(-0.632)	(-0.737)	(-0.679)	(-0.625)	(-0.730)
NOA (Lagged)	0.163*	0.154*	0.118	0.154*	0.147	0.115	0.158*	0.150*	0.118
	(1.838)	(1.746)	(1.309)	(1.681)	(1.614)	(1.238)	(1.725)	(1.656)	(1.270)
Auditor(BIG5)	0.035	0.021	0.024	0.032	0.019	0.023	0.033	0.021	0.024
	(0.831)	(0.505)	(0.572)	(0.741)	(0.448)	(0.535)	(0.779)	(0.487)	(0.564)
Stock Return Characteristics									
RET (Lagged)		32.368	29.915		31.307	28.990		30.652	28.470
		(1.323)	(1.238)		(1.226)	(1.150)		(1.205)	(1.133)
Stock_std (Lagged)		1.769	1.506		1.758	1.505		1.678	1.439
		(0.738)	(0.634)		(0.705)	(0.610)		(0.676)	(0.585)
NCSKEW (Lagged)		0.086***	0.086***		0.083***	0.082***		0.082***	0.082***
		(5.571)	(5.503)		(5.176)	(5.127)		(5.161)	(5.117)
Operating Volatility									
Earnings Volatility			-0.969*			-0.846			-0.790
			(-1.802)			(-1.522)			(-1.421)

Table 5 Panel A Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Cash flow Volatility			-0.985			-0.987			-1.005
			(-1.551)			(-1.503)			(-1.529)
Sales Volatility			1.151***			1.184***			1.144***
			(4.015)			(3.934)			(3.792)
Constant	-2.227***	-2.233***	-2.206***	-2.195***	-2.207***	-2.180***	-2.201***	-2.208***	-2.182***
	(-26.419)	(-15.111)	(-14.901)	(-25.511)	(-14.465)	(-14.253)	(-25.636)	(-14.510)	(-14.307)
Observations	40,037	40,037	40,036	38,030	38,030	38,029	38,030	38,030	38,029
Pseudo R^2	0.0150	0.0164	0.0169	0.0155	0.0167	0.0172	0.0157	0.0169	0.0173

*** p<0.01, ** p<0.05, * p<0.1

Panel B: This table presents the marginal impacts of deviation in real operation (DRO) and discretionary accruals (DA) on crash risk based on the estimations presented in Panel A. The impact is computed based on one standard deviation change in our DRO and DA measurements around their means (from mean-1/2 s.d. to mean+1/2 s.d.) while controlling other variables at their mean values. Since year controls are categorical variables, we cannot set them to their mean values. Instead, we re-run the above procedure for 16 times (set one year dummy equal to one each time), and the impact presented in the table is based on the average of those 16 results.

	DRO_1			*DRO_2*			*DRO_3*		
Marginal Effects (%)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DRO	**1.00**	**0.99**	**0.79**	**0.99**	**0.98**	**0.79**	**1.14**	**1.12**	**0.94**
DA	0.73	0.82	0.90	0.74	0.83	0.88	0.66	0.76	0.81

Panel C. Average standard deviation of firm-specific stock return by firms' levels of *DRO*. Four levels of *DRO* are defined using the 25th, 50th, and 75th percentile of *DRO_1*, *DRO_2*, and *DRO_3*: Group (1) has the lowest level of *DRO* and Group (4) the highest level. The means, the differences between means, and the t-statistics of the differences are presented.

	Groups based on *DRO_1*				Groups based on *DRO_2*				Groups based on *DRO_3*			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Mean	0.052	0.059	0.064	0.070	0.053	0.059	0.062	0.067	0.052	0.059	0.063	0.066
Difference		(2)-(1)	(3)-(2)	(4)-(3)		(2)-(1)	(3)-(2)	(4)-(3)		(2)-(1)	(3)-(2)	(4)-(3)
		0.006***	0.005***	0.006***		0.006***	0.004***	0.005***		0.007***	0.004***	0.004***
T-statistics		14.693	10.806	12.359		13.120	7.435	9.869		14.811	7.898	7.364

*** p<0.01, ** p<0.05, * p<0.1

Table 6.1 Analyses of non-linearity (Logistic): H1 (Robustness 1)

Panel A: Results are from our baseline logistic regression models with extra DA and DRO square terms included. For brevity, the controls variables are omitted from this table for brevity. Please refer to Table 5 for those variables and their definitions.

	DRO_1			*DRO_2*			*DRO_3*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DRO	0.292***	0.289***	0.272***	0.154***	0.152***	0.139***	0.164***	0.161***	0.151***
	(2.936)	(2.943)	(2.756)	(2.904)	(2.897)	(2.640)	(3.267)	(3.250)	(3.034)
DRO Square	-0.079	-0.077	-0.086	-0.023	-0.022	-0.023	-0.022	-0.021	-0.023
	(-1.476)	(-1.469)	(-1.631)	(-1.403)	(-1.377)	(-1.438)	(-1.554)	(-1.525)	(-1.618)
DA	0.524**	0.531**	0.535**	0.433**	0.433*	0.426*	0.377*	0.382*	0.380*
	(2.471)	(2.416)	(2.414)	(1.968)	(1.896)	(1.851)	(1.710)	(1.670)	(1.648)
DA Square	-0.344	-0.311	-0.286	-0.223	-0.181	-0.156	-0.191	-0.153	-0.131
	(-1.467)	(-1.308)	(-1.206)	(-0.894)	(-0.717)	(-0.620)	(-0.766)	(-0.603)	(-0.520)
Pseudo R^2	0.0152	0.0165	0.0170	0.0155	0.0168	0.0173	0.0157	0.0170	0.0174
Is crash risk monotonically increasing with DRO within DRO's relevant value range? (Is H1 supported within DRO's relevant value range?)									
	YES	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*

Panel B: This table presents the marginal effects of deviation of real operations (*DRO*) and deviation of accruals (DA) on crash risk based on the estimations presented in Because we use a nonlinear model to predict crash probability, the total impact on change in probability is not equal to the sum of the individual impacts. Instead, we predict the crash likelihood by setting (1) the *DRO* to *mean-1/2 s.d.*and *mean+1/2 sd.*and (2) *DRO2* = Square of *DRO* values set in (1). The difference between the two probability values represents the marginal effect. In this procedure, all the other continuous variables are to their mean values. Since year controls are categorical variables, we cannot set them to their mean values. Instead, we re-run the above procedure for 16 times (set one year dummy equal to one each time), and the impact presented in the table is based on the average of those 16 results. We set the Big4 dummy equal to one since the majority of firm-years have this variable equal to one.

	DRO_1			*DRO_2*			*DRO_3*		
Marginal Effects (%)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DRO	1.39	1.38	1.21	1.39	1.37	1.20	1.55	1.53	1.37
DA	1.12	1.18	1.22	1.00	1.05	1.07	0.88	0.94	0.96

Table 6.2 Predicting crash likelihood (**NCSKEW/DUVOL**) using Deviation in Real Operation (*DRO*) (OLS): H1 (Robustness 2)

Panel A: This table presents results based on OLS regressions. The dependent variable is *NCSKEW* in Column (1) - (3) and *DUVOL* in Column (4)-(6). They are two measurements of how "crash prone" the firm's stock price is. They are computed in Equation (9) and (10) respectively. The variable *Discretionary Accruals* (*DA*) is computed as the sum of the prior three years' discretionary accruals (absolute value) obtained from Modified Jones Model. *DRO_1/DRO_2/DRO_3* is the moving sum of the absolute values of *REM_1/REM_2/REM_3* in prior three years. Following Cohen and Zarowin (2010), REM_1 aggregates signed *REM_SGA* and *REM_PROD*. *REM_2* aggregates signed *REM_SGA* and *REM_CFO*. In addition, we construct *REM_3*, which is the aggregate of the three REMs. *REM_SGA/REM_PROD/REM_CFO* is estimated from equation (1)/(2)/(3). *Stock_std/RET* is the standard deviation/mean of *r_fs* for each firm-year. *Size* is the natural log of *MVE* at the beginning of each fiscal year. *ROA* is return on assets. *MTB* is (*MVE*+book value of equity (*BVE*))/*BVE*. Year dummies are controlled. T-statistics reported under coefficients estimates are based on robust standard errors clustered on firm level. Net operating assets *(NOA)* is calculated as total assets minus cash and marketable securities at the beginning of the year, scaled by total assets. *Sales/Earnings/Cash flow volatility* is the standard deviation of the quarterly sales/net income/ cash flow computed over four years: [T-3, T].

VARIABLES	OLS: Y=*NCSKEW*			OLS: Y=*DUVOL*		
Deviation in Real Operation/Accruals	(1)DRO_1	(2)DRO_2	(3)DRO_3	(4)DRO_1	(5)DRO_2	(6)DRO_3
DRO	**0.029****	**0.016*****	**0.017*****	**0.015****	**0.008***	**0.009****
	(2.570)	**(2.596)**	**(2.856)**	**(2.094)**	**(1.941)**	**(2.308)**
DA	0.068**	0.065**	0.061**	0.009	0.009	0.006
	(2.508)	(2.299)	(2.137)	(0.558)	(0.501)	(0.357)
Financial Variables						
Income	-0.197***	-0.207***	-0.210***	-0.110***	-0.118***	-0.119***
	(-5.879)	(-5.896)	(-5.981)	(-5.250)	(-5.375)	(-5.447)
Size (Lagged)	0.067***	0.067***	0.067***	0.045***	0.045***	0.045***
	(24.055)	(23.394)	(23.362)	(25.843)	(25.136)	(25.124)
MTB (Lagged)	0.002***	0.002**	0.002**	0.001**	0.001**	0.001**
	(2.677)	(2.416)	(2.404)	(2.420)	(2.091)	(2.071)
Leverage (Lagged)	-0.058***	-0.058***	-0.058***	-0.030**	-0.028**	-0.028**
	(-2.680)	(-2.607)	(-2.596)	(-2.354)	(-2.183)	(-2.177)
NOA (Lagged)	-0.020	-0.025	-0.024	-0.007	-0.008	-0.008
	(-0.691)	(-0.844)	(-0.810)	(-0.385)	(-0.444)	(-0.421)
Auditor(BIG5)	-0.011	-0.015	-0.014	-0.010	-0.013	-0.013
	(-0.834)	(-1.083)	(-1.064)	(-1.224)	(-1.477)	(-1.465)
Stock Return Characteristics						
RET (Lagged)	7.019***	7.393***	7.338***	1.086	1.763	1.729
	(2.630)	(2.608)	(2.596)	(0.906)	(1.397)	(1.374)
Stock_std (Lagged)	0.497	0.581*	0.573*	-0.569***	-0.485***	-0.490***
	(1.501)	(1.677)	(1.657)	(-3.353)	(-2.746)	(-2.778)
NCSKEW (Lagged)	0.034***	0.032***	0.032***	0.024***	0.023***	0.023***
	(6.489)	(6.021)	(6.016)	(7.691)	(7.208)	(7.204)
Operating Volatility	Controlled					
Observations	40,036	38,029	38,029	40,036	38,029	38,029
Adj. R^2	0.041	0.041	0.041	0.055	0.055	0.055

Panel B: Predicting Crash Likelihood (**NCSKEW/DUVOL**): Analysis of Non-linearity For brevity, the controls variables are omitted. Please refer to Table 6.1 for those variables and their definitions.

	OLS: Y=*NCSKEW*			OLS: Y=*DUVOL*		
	DRO_1	*DRO_2*	*DRO_3*	*DRO_1*	*DRO_2*	*DRO_3*
	(1)	(2)	(3)	(4)	(5)	(6)
DRO	0.072**	0.048***	0.045***	0.042**	0.021**	0.023**
	(2.390)	(2.863)	(2.867)	(2.242)	(2.053)	(2.298)
DRO Square	-0.026	-0.011**	-0.009*	-0.016	-0.005	-0.004
	(-1.553)	(-2.024)	(-1.949)	(-1.589)	(-1.428)	(-1.557)
DA	0.241***	0.226***	0.217***	0.078*	0.070	0.064
	(3.561)	(3.244)	(3.106)	(1.853)	(1.611)	(1.478)
DA Square	-0.213***	-0.204**	-0.198**	-0.085*	-0.077	-0.074
	(-2.861)	(-2.576)	(-2.502)	(-1.842)	(-1.576)	(-1.506)
Adj. R^2	*0.042*	*0.042*	*0.042*	*0.056*	*0.055*	*0.055*

*** p<0.01, ** p<0.05, * p<0.1

Table 6.3 Application of firm fixed effects (conditional logistic and OLS): H1 (Robustness 3)

Columns (1) to (3) report results of conditional logistic regressions. The dependent variable *Crash* is equal to one if firm-specific weekly return (*r_fs*) drops below 3.09 standard deviations from its fiscal-year mean for at least once in the year and equal to zero if not. Column (4) to (9) report results of OLS regressions with firm-dummies controlled, and the dependent variables for (4) to (6) and (7) to (9) are *NCSKEW* and *DUVOL* respectively. They are two measurements of how "crash prone" the firm's stock price is. They are computed in Equation (9) and (10) respectively. The variable *Discretionary Accruals* (*DA*) is computed as the sum of the prior three years' discretionary accruals (absolute value) obtained from Modified Jones Model. *DRO_1/DRO_2/DRO_3* is the moving sum of the absolute values of *REM_1/REM_2/REM_3* in prior three years. Following Cohen and Zarowin (2010), REM_1 aggregates signed *REM_SGA* and *REM_PROD*. *REM_2* aggregates signed *REM_SGA* and *REM_CFO*. In addition, we construct *REM_3*, which is the aggregate of the three REMs. *REM_SGA/REM_PROD/REM_CFO* is estimated from equation (1)/(2)/(3). *Stock_std* and *RET* is the standard deviation and mean of *r_fs* for each firm-year. *Size* is the natural log of *MVE* at the beginning of each fiscal year. *ROA* is return on assets. *MTB* is computed as (*MVE*+book value of equity (*BVE*))/*BVE*. Year dummies are controlled. Z-statistics / T-statistics reported under coefficients estimates are based on robust standard errors clustered on firm level. Net operating assets (*NOA*) is calculated as total assets minus cash and marketable securities at the beginning of the year, scaled by total assets. *Vol. in Sales/Earnings/Cash flow* is the standard deviation of the quarterly sales/net income/ cash flow computed over four years: [T-3, T].

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Conditional Logistic (Y=*Crash*) *DRO=DRO_1*			OLS (Y=*NCSKEW*) *DRO=DRO_2*			OLS (Y=*DUVOL*) *DRO=DRO_3*		
Deviation in Real Operation/Accruals									
DRO	**0.170****	**0.131*****	**0.127*****	**0.047***	**0.048*****	**0.035****	**0.045*****	**0.038*****	**0.030*****
	(2.082)	**(2.577)**	**(2.854)**	**(1.784)**	**(2.908)**	**(2.434)**	**(2.724)**	**(3.636)**	**(3.312)**
DA	0.126	0.131	0.113	-0.013	-0.016	-0.018	-0.020	-0.019	-0.021
	(0.937)	(0.931)	(0.800)	(-0.302)	(-0.346)	(-0.397)	(-0.742)	(-0.654)	(-0.751)
Observations	31,090	29,554	29,554	40,036	38,029	38,029	40,036	38,029	38,029
Pseudo R^2/Adjusted R^2	0.0464	0.0451	0.0452	0.249	0.248	0.248	0.253	0.252	0.252

*** p<0.01, ** p<0.05, * p<0.1

Table 7 Suspect-firm analysis (H2)

Panel A: The sample is restricted to firms that are identified as "*suspect firms"* (limited to observations in the year following the suspect-year). *Suspect* firm-year observations are those that reported earnings that just beat zero (ROA<0.01) and last years' earnings (ΔROA<0.01). *REM_1_Suspect*/*REM_2_Suspect* /*Accrual_Suspect* is a dummy variable that is equal to one if the suspect firm's signed *REM_DISX / REM_PROD / Discretionary Accrual* is in the highest quintile, and zero otherwise. *REM_3_Suspect* equals to one if suspect firm's *REM_DISX* and *REM_PROD* are both in their highest quintile and zero if not. *REM_DISX* /*REM_PROD* / *Discretionary Accrual*s is the proxy of earnings manipulation through discretionary expenses / production / accruals.

	REM_Suspect=REM_Suspect_1			*REM_Suspect=REM_Suspect_2*			*REM_Suspect=REM_Suspect_3*		
Earnings Management Variables	*(1) Crash*	*(2)NCSKEW*	*(3)DUVOL*	*(4) Crash*	*(5)NCSKEW*	*(6)DUVOL*	*(7) Crash*	*(8)NCSKEW*	*(9)DUVOL*
REM_Suspect	**0.213****	**0.089*****	**0.047*****	**0.185****	**0.061****	**0.038****	**0.329*****	**0.118*****	**0.067*****
	(2.497)	**(3.196)**	**(2.747)**	**(2.241)**	**(2.320)**	**(2.240)**	**(3.291)**	**(3.437)**	**(3.113)**
Accrual_Suspect	-0.005	0.026	0.026	-0.025	0.019	0.023	-0.017	0.020	0.023
	(-0.056)	(0.907)	(1.547)	(-0.274)	(0.697)	(1.394)	(-0.192)	(0.730)	(1.448)
Financial Variables									
Income	-1.689***	-0.655***	-0.424***	-1.663***	-0.566***	-0.342***	-1.725***	-0.589***	-0.354***
	(-4.343)	(-4.824)	(-5.079)	(-4.515)	(-4.434)	(-4.312)	(-4.695)	(-4.604)	(-4.479)
Size (Lagged)	0.033	0.057***	0.036***	0.021	0.055***	0.034***	0.025	0.054***	0.034***
	(1.558)	(7.907)	(8.343)	(1.013)	(7.870)	(8.108)	(1.207)	(7.803)	(8.150)
MTB (Lagged)	0.013**	0.007***	0.005***	0.017***	0.007***	0.004***	0.016***	0.007***	0.005***
	(2.090)	(3.774)	(4.008)	(2.688)	(3.906)	(3.789)	(2.614)	(4.151)	(4.063)
Leverage (Lagged)	0.187	-0.085	-0.036	0.121	-0.081	-0.036	0.119	-0.080	-0.036
	(1.058)	(-1.545)	(-0.961)	(0.702)	(-1.564)	(-1.022)	(0.690)	(-1.535)	(-1.021)
NOA (Lagged)	0.194	-0.068	-0.067	0.298	-0.015	-0.028	0.262	-0.026	-0.032
	(0.727)	(-0.860)	(-1.285)	(1.158)	(-0.201)	(-0.557)	(1.020)	(-0.351)	(-0.655)
Auditor(BIG5)	0.079	-0.020	-0.008	0.161	-0.010	-0.004	0.155	-0.008	-0.003
	(0.684)	(-0.524)	(-0.323)	(1.425)	(-0.283)	(-0.168)	(1.373)	(-0.225)	(-0.127)
Stock Return Characteristics									
RET (Lagged)	-1.079	-0.517	-6.968	4.883	2.698	-6.866	4.235	2.473	-6.835
	(-0.026)	(-0.029)	(-0.695)	(0.117)	(0.149)	(-0.698)	(0.101)	(0.137)	(-0.693)
Stock_std (Lagged)	-0.928	0.030	-1.231	-0.023	0.399	-1.277	-0.122	0.356	-1.287
	(-0.227)	(0.019)	(-1.354)	(-0.006)	(0.251)	(-1.442)	(-0.030)	(0.224)	(-1.452)
NCSKEW (Lagged)	0.098**	0.030**	0.022***	0.092**	0.028**	0.022***	0.097**	0.030**	0.024***
	(2.243)	(2.176)	(2.637)	(2.206)	(2.067)	(2.690)	(2.310)	(2.222)	(2.881)
Operating Volatility									
Earnings Volatility	1.502	-0.203	-0.166	1.187	-0.298	-0.075	1.304	-0.265	-0.052
	(0.903)	(-0.410)	(-0.489)	(0.735)	(-0.636)	(-0.231)	(0.815)	(-0.569)	(-0.161)
Cashflow Volatility	-1.209	0.048	-0.140	-1.881	-0.024	-0.168	-1.726	0.048	-0.130
	(-0.672)	(0.096)	(-0.441)	(-1.081)	(-0.051)	(-0.547)	(-0.997)	(0.100)	(-0.421)
Sales Volatility	1.081	0.325	0.290	1.298	0.371	0.290*	1.158	0.297	0.257
	(1.230)	(1.210)	(1.643)	(1.539)	(1.440)	(1.732)	(1.379)	(1.134)	(1.509)
Constant	-2.008***	-0.468***	-0.336***	-2.020***	-0.214**	-0.182***	-2.063***	-0.207**	-0.181***
	(-6.330)	(-4.745)	(-5.515)	(-6.558)	(-2.391)	(-3.317)	(-6.720)	(-2.336)	(-3.296)
Observations	5,861	5,861	5,861	6,341	6,341	6,341	6,395	6,395	6,395
Pseudo R^2/Adjusted R^2	0.0205	0.044	0.046	0.0191	0.039	0.042	0.0206	0.040	0.043

Table 7

Panel B: Marginal Effects. Results are based on above logistic regressions. See Columns (1) to (3) in Panel A. Overall crash percentages for suspect sample is: 18.9%.

	(1)	(2)	(3)
Incremental Likelihood of *Crash* For RM Firms (%)	3.66***	3.10**	5.80***
Incremental Likelihood of *Crash* For AM Firms (%)	-0.05	-0.37	-0.27

*** p<0.01, ** p<0.05, * p<0.1

Table 8 Before and After SOX: Predicting Crash Using Deviation of Real Operation (*DRO*) (Logistic*)*: H3

Panel A: Column (1) (4) (7) report results of estimations in the pre-SOX sub-sample. Column (2) (5) (8) report results of estimations in post-SOX sub-sample. (3) (6) (9) report our results from the model in which the additional interaction terms are included: coefficients presented in the three columns are those before the interaction terms. *DRO_1/DRO_2/DRO_3* is the moving sum of the absolute values of *REM_1/REM_2/REM_3* in prior three years. Following Cohen and Zarowin (2010), REM_1 aggregates signed *REM_SGA* and *REM_PROD*. *REM_2* aggregates signed *REM_SGA* and *REM_CFO*. In addition, we construct *REM_3*, which is the aggregate of the three. *REM_SGA/REM_PROD/REM_CFO* is estimated from equation (1)/ (2)/ (3). *NCSKEW*, the negative skewness of *r_fs*, is a measurement of crash likelihood computed based on Equation (9). *Stock_std / RET* is the standard deviation/mean of *r_fs* for each firm-year. *Size* is the natural log of *MVE* at the beginning of each fiscal year. *ROA* is return on assets. *MTB* is (*MVE*+book value of equity (*BVE*))/*BVE*. Year dummies are controlled. Z-statistics reported under coefficients estimates are based on robust standard errors clustered on firm level. . Net operating assets *(NOA)* is calculated as total assets minus cash and marketable securities at the beginning of the year, scaled by total assets. *Sales/Earnings/Cash flow volatility* is the standard deviation of the quarterly sales/net income/ cash flow computed over four years: [T-3, T].

Deviation in Real Operation/Accruals	Logistic (Y=*Crash*) *DRO=DRO_1*			Logistic (Y=*Crash*) *DRO=DRO_2*			Logistic (Y=*Crash*) *DRO=DRO_3*		
	(1)Before Baseline	***(2)After Baseline***	***(3) All Interaction***	***(4)Before Baseline***	***(5)After Baseline***	***(6) All Interaction***	***(7)Before Baseline***	***(8)After Baseline***	***(9) All Interaction***
DRO (DRO X SOX in Column 3,6,9)	**0.088***	**0.185*****	**0.097**	**0.047***	**0.105*****	**0.059**	**0.054****	**0.125*****	**0.072***
	(1.844)	**(3.086)**	**(1.266)**	**(1.774)**	**(3.368)**	**(1.455)**	**(2.164)**	**(4.233)**	**(1.867)**
DA (DA X SOX in Column 3,6,9)	0.410***	0.164	-0.245	0.400***	0.220	-0.179	0.384***	0.173	-0.211
	(3.620)	(1.024)	(-1.245)	(3.275)	(1.365)	(-0.886)	(3.130)	(1.066)	(-1.035)
Financial Variables									
Income(Income X SOX in 3,6,9)	-0.787***	-0.972***	-0.186	-0.762***	-0.961***	-0.198	-0.770***	-0.986***	-0.216
	(-6.146)	(-5.439)	(-0.853)	(-5.651)	(-5.320)	(-0.890)	(-5.713)	(-5.478)	(-0.970)
Size (Lagged) (Size X SOX in 3,6,9)	0.106***	0.030**	-0.076***	0.102***	0.033**	-0.069***	0.102***	0.032**	-0.069***
	(9.202)	(1.995)	(-4.048)	(8.589)	(2.186)	(-3.608)	(8.554)	(2.126)	(-3.660)
MTB (Lagged) (MTB X SOX in 3,6,9)	0.003	0.002	-0.001	0.002	0.002	0.000	0.002	0.002	0.000
	(0.927)	(0.713)	(-0.128)	(0.576)	(0.692)	(0.081)	(0.550)	(0.620)	(0.049)
Leverage (Lagged) (Leverage X SOX in 3,6,9)	0.030	-0.092	-0.122	0.019	-0.095	-0.114	0.019	-0.092	-0.111
	(0.375)	(-0.833)	(-0.894)	(0.230)	(-0.839)	(-0.812)	(0.229)	(-0.815)	(-0.791)
NOA (Lagged) (NOA X SOX in 3,6,9)	0.017	0.214	0.197	0.022	0.202	0.181	0.025	0.202	0.177
	(0.137)	(1.450)	(1.022)	(0.161)	(1.357)	(0.908)	(0.189)	(1.358)	(0.890)
Auditor(BIG5) (Auditor X SOX in 3,6,9)	0.059	0.038	-0.021	0.051	0.038	-0.012	0.052	0.040	-0.012
	(0.930)	(0.605)	(-0.240)	(0.769)	(0.605)	(-0.137)	(0.790)	(0.636)	(-0.131)
Stock Return Characteristics									
RET (Lagged) (RET X SOX in 3,6,9)	28.441	9.344	-19.096	29.908	10.643	-19.265	29.471	9.948	-19.523
	(0.819)	(0.543)	(-0.476)	(0.783)	(0.619)	(-0.445)	(0.773)	(0.591)	(-0.453)
Stock_std (Lagged) (Stock_std X SOX in 3,6,9)	2.580	-0.997	-3.576	2.966	-0.705	-3.671	2.909	-0.793	-3.702
	(0.767)	(-0.518)	(-0.900)	(0.811)	(-0.365)	(-0.866)	(0.797)	(-0.416)	(-0.877)
NCSKEW (Lagged) (NCSKEW X SOX in 3,6,9)	0.112***	0.033	-0.079**	0.107***	0.034	-0.073**	0.107***	0.034	-0.073**
	(4.935)	(1.307)	(-2.319)	(4.483)	(1.315)	(-2.096)	(4.479)	(1.304)	(-2.100)
Operating Volatility									
Earnings Volatility (EV X SOX in 3,6,9)	-1.811**	-0.699	1.111	-1.742**	-0.738	1.004	-1.703**	-0.637	1.066
	(-2.538)	(-0.750)	(0.951)	(-2.317)	(-0.784)	(0.837)	(-2.263)	(-0.678)	(0.889)
Cashflow Volatility (CV X SOX in 3,6,9)	-1.020	0.125	1.145	-1.228	0.466	1.694	-1.248	0.471	1.719
	(-1.339)	(0.114)	(0.879)	(-1.541)	(0.422)	(1.279)	(-1.566)	(0.427)	(1.299)
Sales Volatility (SV X SOX in 3,6,9)	1.089***	1.321**	0.233	1.233***	1.148*	-0.086	1.205***	1.044*	-0.162

Table 8 Continued

	(3.145)	(2.279)	(0.345)	(3.344)	(1.947)	(-0.123)	(3.264)	(1.776)	(-0.233)
Constant	-2.430***	-1.379***	1.052***	-2.410***	-1.417***	0.994***	-2.414***	-1.425***	0.989***
	(-14.285)	(-9.487)	(4.627)	(-13.283)	(-9.650)	(4.199)	(-13.339)	(-9.781)	(4.197)
Observations	23,030	11,809	34,839	21,331	11,581	34,839	21,331	11,581	9750
Pseudo R^2	0.0119	0.00506	0.00684	0.0111	0.00507	0.00603	0.0112	0.00558	0.00562

Panel B: This table presents the marginal effects of our measurements of earnings management on crash risk based on the estimations presented in Panel A. The effects are based on one standard deviation change in our RM and AM measurements around their means (from mean-1/2sd to mean+1/2sd) while controlling other variables at their mean values.

Marginal Effects (%)	RM_1_SUM			RM_2_SUM			RM_3_SUM		
	Before	*After*	*Diff*	*Before*	*After*	*Diff*	*Before*	*After*	*Diff*
Real	0.51*	1.31***	0.80	0.49*	1.37***	0.88	0.60***	1.73***	1.13*
Accrual	1.15***	0.50	-0.65	1.07***	0.67	-0.40	1.03***	0.53	-0.50

Panel C: Analyses of Non-linearity. For brevity, the controls variables are omitted. Please refer to Table 8 Panel A for those variables and their definitions.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		DRO_1			DRO_2			DRO_3	
	Before	***After***	***Diff.***	***Before***	***After***	***Diff.***	***Before***	***After***	***Diff.***
DRO	0.146	0.427***	0.281	0.016	0.248***	0.233**	0.082	0.231***	0.149
	(1.102)	(2.650)	(1.367)	(0.218)	(2.910)	(2.120)	(1.200)	(2.893)	(1.425)
DRO_Square	-0.034	-0.145	-0.112	0.010	-0.048*	-0.058*	-0.009	-0.033	-0.024
	(-0.485)	(-1.625)	(-0.989)	(0.466)	(-1.838)	(-1.705)	(-0.464)	(-1.443)	(-0.802)
DA	0.836***	-0.260	-1.095**	0.607*	-0.222	-0.829*	0.566*	-0.295	-0.861*
	(2.816)	(-0.680)	(-2.272)	(1.933)	(-0.578)	(-1.683)	(1.796)	(-0.768)	(-1.742)
DA_Square	-0.495	0.531	1.026*	-0.241	0.554	0.796	-0.219	0.591	0.810
	(-1.596)	(1.209)	(1.915)	(-0.712)	(1.245)	(1.438)	(-0.646)	(1.326)	(1.461)
Pseudo R^2	0.012	0.005	0.015	0.011	0.005	0.015	0.011	0.006	0.015

Table 8 Continued

Panel D: Impact on crash risk in the pre- and post-SOX periods

This table presents the marginal effects of deviation of real operations (DRO) and deviation of accruals (DA) on crash risk based on the estimations presented in Panel C. Because we use a nonlinear model to predict crash probability, the total impact on change in probability is not equal to the sum of the individual impacts. Instead, we predict the crash likelihood by setting (1) the DRO to mean-1/2 s.d. and mean+1/2 s.d. and (2) DRO2 = Square of DRO values set in (1). The difference between the two probability values represents the marginal effect. In this procedure, all the other continuous variables are to their mean values. Since year controls are categorical variables, we cannot set them to their mean values. Instead, we re-run the above procedure for 16 times (set one year dummy eqaul to one each time), and the impact presented in the table is based on the average of those 16 results. We set the Big4 dummy equal to one since the majority of firm-years have this variable equal to one.

Marginal Effects (%)	RM_1_SUM			RM_2_SUM			RM_3_SUM		
	Before	***After***	**Change**	***Before***	***After***	**Change**	***Before***	***After***	**Change**
Real	0.67	2.12	**1.45**	0.33	2.33	**2.01**	0.76	2.46	**1.70**
Accrual	1.73	-0.07	**-1.79**	1.40	0.10	**-1.30**	1.31	-0.10	**-1.40**

Panel E: Impact on crash likelihood (*NCSKEW*) in the pre- and post-SOX periods

Δ Impact on crash likelihood (*NCSKEW*) between pre-SOX and post-SOX periods	RM_1_SUM's			RM_2_SUM			RM_3_SUM		
	Before	***After***	***Change***	***Before***	***After***	***Diff***	***Before***	***After***	***Diff***
Real (Expected Change: Positive)	0.012	0.026	**0.014**	0.016	0.023	**0.007**	0.016	0.034	**0.018**
Accrual (Expected Change: Negative)	0.033	0.004	**-0.029**	0.032	0.005	**-0.027**	0.031	0.001	**-0.030**

Panel F: Impact on crash likelihood (*DUVOL*) in the pre- and post-SOX periods

	RM_1_SUM's			RM_2_SUM			RM_3_SUM		
	Before	***After***	***Change***	***Before***	***After***	***Diff***	***Before***	***After***	***Diff***
Real (Expected Change: Positive)	0.007	0.012	**0.005**	0.007	0.010	**0.004**	0.007	0.017	**0.010**
Accrual (Expected Change: Negative)	0.010	-0.002	**-0.012**	0.010	-0.003	**-0.013**	0.009	-0.005	**-0.014**

Table 9 Crashes in the Earnings Announcement (EA) Period and Non-EA Period (logistic)

Panel A: Logistic Regressions

In (1) (3) (5), the dependent variable is *EA crash* , which is equal to one if there is at least one crash during an earnings announcement (EA) window for the firm-year. In (2) (4) (6), the dependent variable is *non-EA crash*, which is equal to one if there is at least one crash during an non-EA window for the firm-year. The EA window is [0, +5] days around the quarterly earnings announcement date.

Panel A Logistic Regressions	(1) DRO_1	(2) DRO_1	(3) DRO_2	(4) DRO_2	(5) DRO_3	(6)DRO_3
Deviation in Real Operations/Accruals	Y=EA Crash	Y=Non-EA Crash	Y=EA Crash	Y=Non-EA Crash	Y=EA Crash	Y=Non-EA Crash
DRO	0.091*	0.146***	0.051*	0.083***	0.051*	0.091***
	(1.653)	(3.331)	(1.718)	(3.501)	(1.818)	(4.080)
DA	0.249*	0.292***	0.265**	0.280**	0.253*	0.254**
	(1.894)	(2.793)	(1.961)	(2.525)	(1.857)	(2.277)
Financial Variables				Controlled		
Stock Return Characteristics				Controlled		
Volatility Variables				Controlled		
Observations	40,036	40,036	38,029	38,029	38,029	38,029
Pseudo R^2	0.0476	0.0109	0.0480	0.0106	0.0480	0.0108

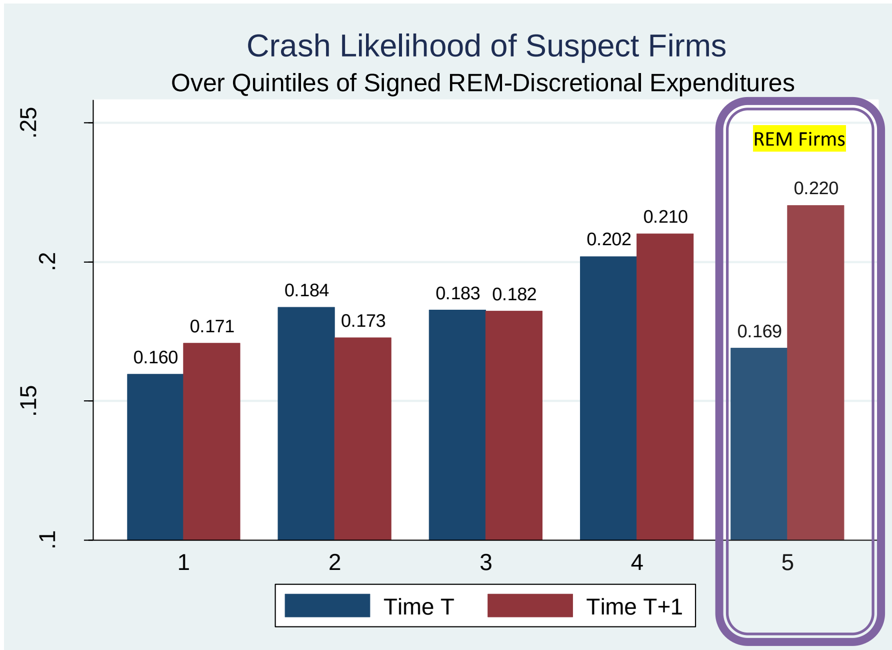
Panel B: Marginal Impact and Impact Ratio

The column number here corresponds to those in Panel A. In addition, we create those Non-EA/EA ratio columns. The higher the ratio, the more impact DRO/DA has on non-EA crash as opposed to EA crash. To test our conjecture about the timing difference between DRO and DA, we compare this ratio between the DRO and DA.

	(1) EA Crash	(2) Non-EA Crash	**Non-EA/EA ratio**	(3) EA Crash	(4) Non-EA Crash	**Non-EA/EA ratio**	(5) EA Crash	(6) Non-EA Crash	**Non-EA/EA ratio**
DRO	0.20	0.61	**3.05**	0.21	0.63	**3.00**	0.23	0.73	**3.17**
DA	0.26	0.57	**2.19**	0.28	0.53	**1.89**	0.26	0.48	**1.85**

Fig. 1 Change in crash likelihood from suspect year to the year after

Suspect firm-year observations are those that reported earnings that just beat zero (ROA<0.01) and last year's earnings (ΔROA<0.01). This suspect-firm sample is sorted into five groups based on the signed value of *REM_DISX* (discretionary expenses) estimated from model (1). *Group 5* consists of those suspect firms that are the most likely to have used discretionary expenditures to upwardly manipulate earnings so as to reach the two earnings benchmarks.



Suspect firm-year observations are those that reported earnings that just beat zero (ROA<0.01) and last year's earnings (ΔROA<0.01). This suspect-firm sample is sorted into five groups based on the signed value of *REM_PROD* (abnormal production cost) estimated from model (1). *Group 5* consists of those suspect firms that are the most likely to have overproduced to upwardly manipulate earnings so as to reach the two earnings benchmarks.

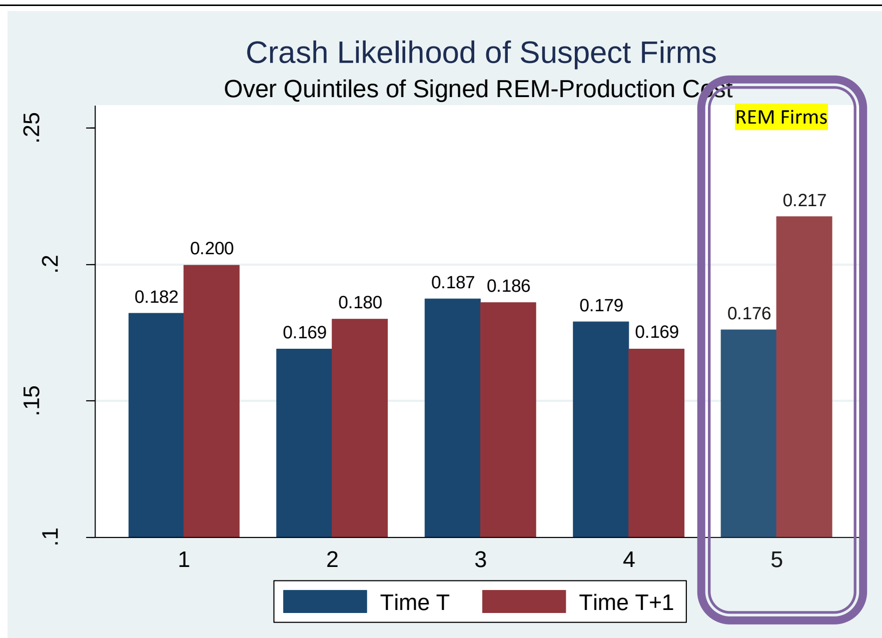
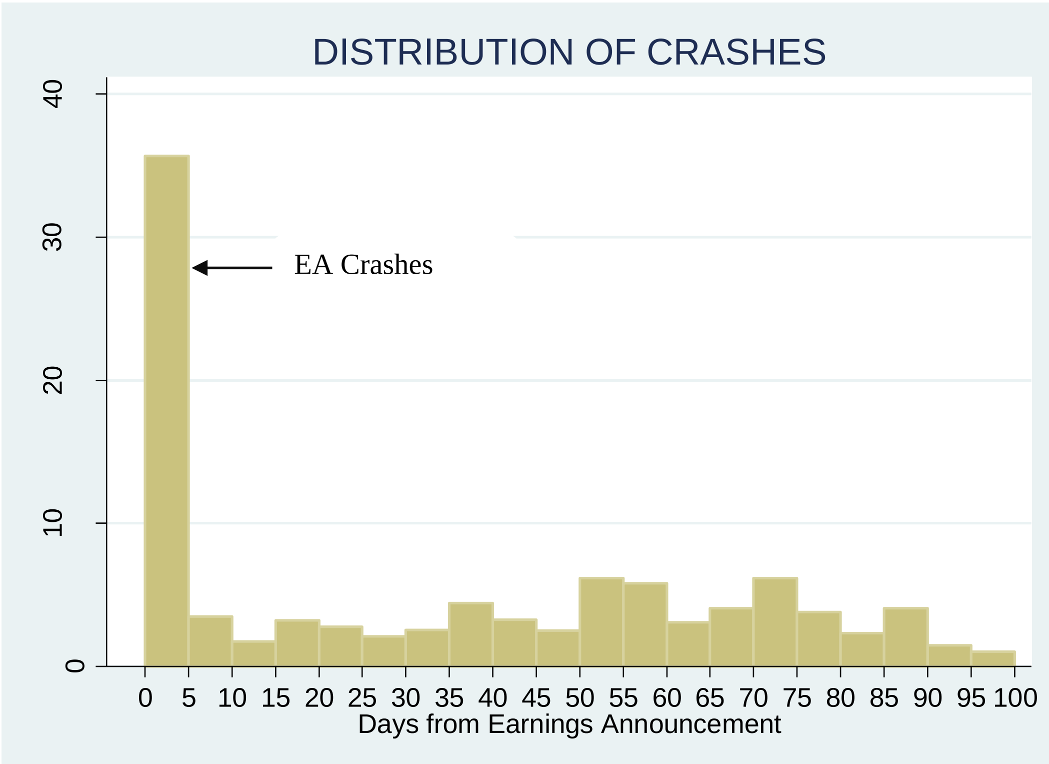
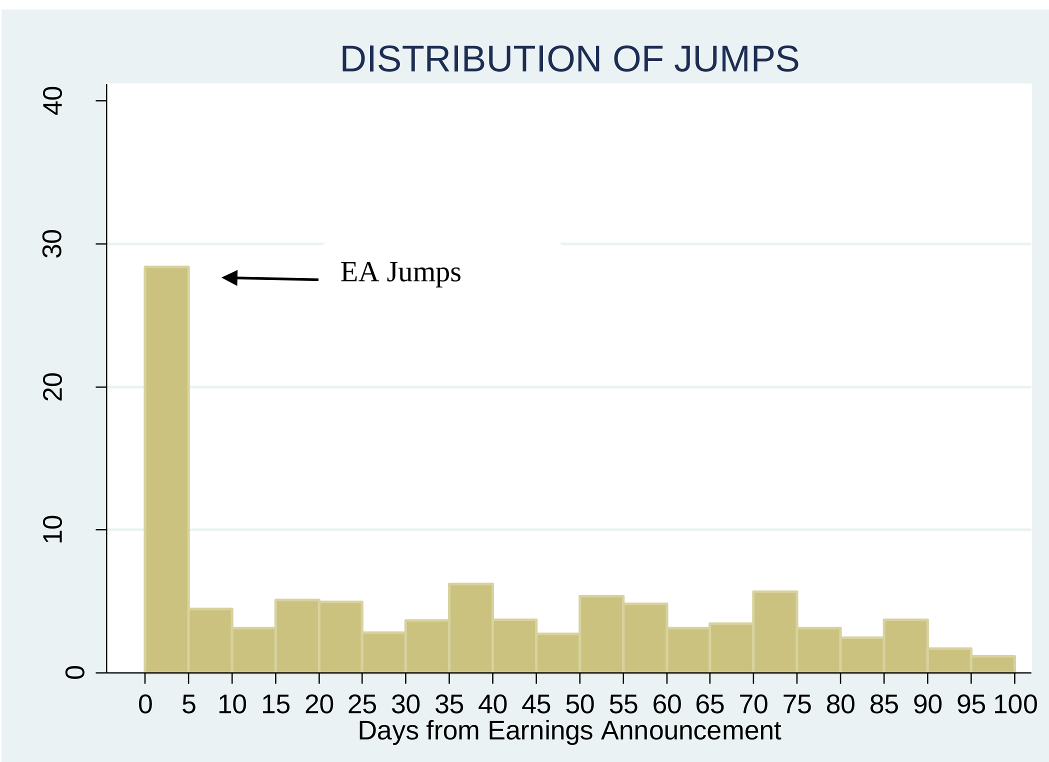


Fig. 2 Distribution of crashes and jumps





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ISBN 978-952-6699-92-9, ISSN 1456-6184, online