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Non-GAAP earnings and stock price crash risk

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Abstract

Prior research concludes that stock price crash risk is primarily attributable to managers' *withholding* of bad news from investors. We extend this literature by investigating whether crash risk can also occur when managers *disclose additional* information via non-GAAP reporting, which downplays reported bad news by re-directing investors' attention to other, more positive aspects of performance. We find that the likelihood of crash risk is higher when managers have reported non-GAAP earnings more frequently during the past year. We also find that managers appear to use non-GAAP reporting as a substitute for the more common reason for crash risk in prior research–withholding bad news. Moreover, we find that the association between non-GAAP disclosure and crash risk increases in periods when managers are likely more aggressive in their non-GAAP reporting. Finally, we use a regulatory shock as a quasi-natural experiment to mitigate endogeneity concerns.

Key words: Non-GAAP earnings, Stock price crash risk, Disclosure, Regulation

JEL: D82, G12, G17, G18, M41

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1. Introduction

We investigate the relation between non-GAAP reporting and stock price crash risk. The extant literature defines a stock price crash as an extreme drop in stock price and finds that these crashes frequently have severe effects on investors. A burgeoning literature has identified several firm and executive characteristics that predict a higher likelihood of stock price crashes, including reporting opacity, less conservative earnings, and CEO overconfidence (Hutton et al., 2009; Kim et al., 2016b; Kim and Zhang, 2016). This literature attributes crashes to managers' ability to exploit their information advantage over investors by withholding bad news about firm performance. We examine whether crashes only occur when managers *withhold* information, or whether crash risk can also occur when managers *disclose additional* information about current performance beyond what is required by GAAP. Specifically, we study whether managers' non-GAAP earnings disclosures influence crash risk.

Non-GAAP earnings are adjusted earnings numbers that exclude certain GAAP-mandated earnings components. Managers can provide these alternative metrics to signal the relative importance of earnings components that managers choose to include, versus exclude, in calculating non-GAAP earnings (Gu and Chen, 2004; Hsu and Kross, 2011). Moreover, prior research indicates that investors find these alternative performance metrics to be more informative than GAAP earnings (e.g., Bradshaw and Sloan, 2002; Bradshaw et al., 2018). However, critics of non-GAAP reporting have long questioned whether managers' primary reason for disclosing adjusted earnings metrics is to refocus investors' attention away from the negative aspects of firm performance. Moreover, prior research finds that managers can use non-GAAP earnings as a substitute for other forms of earnings management (Doyle et al., 2013; Black et al., 2017). As a result, a stock price crash might occur not only when managers withhold bad news, but also when they choose to disclose additional information about performance (through non-GAAP earnings measures) to divert investors' attention from disclosed bad news and to instead focus their attention on other, more positive aspects of performance. This reasoning suggests that non-GAAP metrics could lead investors to discount certain negative aspects of GAAP earnings, over-value the firm, and subsequently experience a stock crash.

Prior research does not offer direct evidence on whether non-GAAP reporting is likely to increase or decrease crash risk. On the one hand, some researchers find that non-GAAP earnings generally provide investors with a better understanding of a firm's underlying economics and aid in valuation (Brown and Sivakumar, 2003; Gu and Chen, 2004). Further, recent research finds that managers' non-GAAP adjustments increase the comparability of earnings metrics across firms (Black et al., 2018a), and that more comparable earnings are associated with lower crash risk (Kim et al., 2016a). On the other hand, prior research also finds that non-GAAP earnings can potentially mislead investors' perceptions of firm performance. For example, (1) non-GAAP earnings tend to exceed their GAAP counterpart (e.g., Bradshaw and Sloan, 2002), (2) non-GAAP earnings increase the likelihood of meeting or beating market expectations (Black and Christensen, 2009; Barth et al., 2012; Doyle et al., 2013), and (3) the items excluded in calculating non-GAAP earnings, which primarily represent expense items, are associated with future operating performance (e.g., Doyle et al., 2003; Kolev et al., 2008). Thus, non-GAAP earnings could optimistically bias investors' perceptions of firm value, and increase the likelihood of a stock price crash when the subsequent performance is not consistent with investors' optimistic expectations.

We investigate the relation between managers' non-GAAP earnings disclosures and crash risk using a large sample of US firms with fiscal years ending between 2003 and 2015. Our non-GAAP disclosure measure focuses on the frequency with which managers disclose non-GAAP earnings to investors, which we measure as the percentage of firm-quarters in the fiscal year in which managers disclose non-GAAP earnings. Since we are interested in whether non-GAAP reporting is associated with higher future crash risk, we examine the relation between the frequency of non-GAAP reporting during a given fiscal year and crash risk in the subsequent year. Following prior research (e.g., Hutton et al., 2009; Kim et al., 2016b), we use four empirical measures to capture crash risk: (1) an indicator for when a firm experiences an extreme negative weekly stock return, (2) the negative skewness of weekly stock returns, (3) the asymmetric volatility of positive and negative stock returns, and (4) a composite measure based on the three individual crash risk measures.

Across all four crash risk measures, we find that crash risk is higher when managers disclose non-GAAP earnings more frequently in the previous year. For example, a one standard deviation increase in the frequency of non-GAAP reporting during the year leads to a 4% increase in the likelihood of an extreme negative weekly return (i.e., a crash) in the subsequent year.[1] To further examine our evidence, we assert that if investors over-estimate a firm's value because of their focus on non-GAAP earnings, our results should be attributable to observations where non-GAAP earnings paint a rosier picture of performance. Consistent with this assertion, the positive association between non-GAAP reporting frequency and future crash risk only exists when non-GAAP earnings exceed GAAP earnings (i.e., the firm makes income-increasing adjustments).

Next, we examine whether non-GAAP reporting serves as a complement or a substitute for what prior research has traditionally viewed to be the primary reason for crash risk—the withholding of bad news through managing earnings. On the one hand, managers could use non-GAAP disclosure to inflate investors' perceptions *in conjunction with* the

[1] We find that the unconditional probability of having a crash in a year is 22%. As a result, the increase in a firm's probability of having a crash due to a one standard deviation increase in the frequency of non-GAAP reporting is approximately 18% (4% divided by 22%) of the unconditional probability of having a crash.

withholding of bad news (complementary role).[2] On the other hand, prior research finds that managers can use non-GAAP reporting to substitute for other forms of earnings management (Doyle et al., 2013; Black et al., 2017), suggesting that managers may prefer to influence investors' perceptions by "backing out" the bad news in GAAP earnings through non-GAAP adjustments (substitutionary role). Consistent with managers using non-GAAP reporting as a substitute for withholding bad news, we find that the relation between non-GAAP reporting frequency and crash risk is concentrated among firms that are less likely to withhold bad news.

Next, we examine whether the relation between non-GAAP reporting and crash risk is the result of managers' aggressive non-GAAP reporting, or simply an artifact of non-GAAP reporting more generally. We begin by examining whether the non-GAAP reporting and crash risk relation is stronger in periods when managers are more likely to be aggressive in their reporting. We first examine this relation in periods of high investor sentiment. Brown et al. (2012) find that managers are more aggressive in their non-GAAP reporting during periods of high investor sentiment, likely because investors scrutinize managers' adjustments less during these periods. We find that the relation between non-GAAP reporting and crash risk is significantly higher in periods of high investor sentiment. Next, we examine another common measure of aggressive non-GAAP reporting, the use of non-GAAP exclusions to meet analysts' quarterly forecasts when GAAP earnings fall short of expectations (e.g., Bradshaw et al., 2018). Again, we find that the relation between non-GAAP reporting and crash risk is higher when non-GAAP earnings more frequently allow firms to report a positive earnings surprise.

We also examine the relation between non-GAAP reporting and crash risk, conditional on managers' incentives to use aggressive non-GAAP reporting to inflate stock

[2] Prior research suggests that managers could use a complementary tool (e.g., manipulate the readability of 10-Ks) in conjunction with the withholding of bad news to inflate investors' perceptions (e.g., Kim et al., 2019).

price. We expect managers to have greater incentives to use aggressive non-GAAP reporting to inflate stock price when they have a higher potential to benefit from their actions. We consider two scenarios where managers are more likely to benefit from an inflated stock price: (1) when their compensation is more sensitive to stock price changes and (2) when they are more likely to engage in opportunistic insider sales. If managers are aggressive in their non-GAAP reporting to inflate stock price, we expect the relation between non-GAAP reporting and crash risk to be more pronounced in these two scenarios. Our results are consistent with this expectation.

We conduct several additional analyses, including a test that examines an exogenous shock to the quality of non-GAAP reporting (i.e., Regulation G).[3] In particular, we examine a difference-in-differences (DiD) research design with propensity score matching between a treatment group and a control group around the enactment of Regulation G. We identify our treatment group as firms where Regulation G is most likely to improve the quality of firms' non-GAAP exclusion choices, and our control group as firms where the regulation is less likely to affect the firms' exclusion choices.[4] As a result, we expect the decline in crash risk to be greater for the treatment group than for the control group after Regulation G. Our empirical results are consistent with this prediction. Our DiD design offers two key advantages. First, it rules out omitted trends that correlate with both non-GAAP reporting and crash risk in the treatment and control groups (e.g., certain omitted firm fundamentals). Second, it strengthens our inferences regarding the influence of non-GAAP reporting on

[3] The SEC implemented Regulation G in early 2003, which mandates firms that publicly disclosures a non-GAAP earnings number to provide a clearly understandable quantitative reconciliation of that number to the most directly comparable GAAP number. Firms must also present non-GAAP earnings in ways that do not mislead investors.

[4] Prior research finds that Regulation G improved the quality of non-GAAP reporting in the years immediately after its implementation (Heflin and Hsu 2008; Kolev et al. 2008). We thus conduct our DiD analysis using a four-year window centered on Regulation G. Using a relatively short-window in our DiD test can help mitigate the potential confounding effects that tend to be larger in a longer-window test (Heflin and Hsu 2008). We provide a detailed discussion of our DiD design in Section 6.

crash risk as we conduct our analysis around an exogenous shock to non-GAAP reporting quality using Regulation G.

Finally, we provide additional insight into whether crashes among non-GAAP reporting firms have longer-run implications for investors. We find that non-GAAP reporting firms with subsequent crashes have a more negative annual stock return during the year of the crash (and more negative two- and three-year returns beginning in the crash year), relative to non-GAAP firms that do not experience a crash. These results indicate that the negative implications of crashes related to non-GAAP reporting are not simply short-term in nature (i.e., a crash is empirically identified based on a one-week price decline) but that these crashes expose investors to more sustained negative implications.

Our analyses contribute to the extant literature in several ways. First, we extend the crash risk literature by identifying a new mechanism that influences crashes–the disclosure of *additional* information to investors that paints an overly optimistic perspective of firm performance. In contrast, researchers in the crash risk literature primarily attribute crashes to managers' tendency to *withhold* bad news from investors. Our results suggest that managers view non-GAAP reporting as a substitute to the withholding of bad news and can use this perception management tool to positively influence investors' assessments of firm performance.

Second, we contribute to the non-GAAP earnings literature by providing evidence that managers' non-GAAP earnings disclosures can expose investors to extreme negative economic outcomes, particularly in settings where managers are more likely to be aggressive in their reporting choices. This result is important for several reasons. First, prior studies provide little evidence on how non-GAAP information negatively affects investors' welfare. The closest evidence indicates that investors under-price exclusions over long return windows (i.e., windows of at least one year) *prior to* Regulation G (e.g., Doyle et al., 2003).

However, more recent research indicates that investors no longer significantly misprice non-GAAP earnings after this regulation (Zhang and Zheng, 2011). Thus, we extend the literature by providing evidence that (1) mispricing resulting from non-GAAP disclosure persists in the current reporting environment in certain scenarios, (2) the negative effects of non-GAAP reporting can occur over a very short time period via a "crash", and (3) crashes related to non-GAAP reporting have a sustained negative consequence over a long-run window.[5] Additionally, prior research highlights the need for alternative methods to assess the quality of non-GAAP metrics and how these metrics inform investors (Black et al., 2018b). We answer this call by examining crash risk, which has not been examined in prior non-GAAP studies.

Finally, our results have implications for regulators, who have long expressed concerns about managers' non-GAAP reporting. For example, the SEC expressed considerable concern about non-GAAP reporting in the early 2000s and implemented Regulation G in 2003 in an effort to protect investors from misleading non-GAAP metrics. The SEC's interest piqued again in the recent decade as non-GAAP metrics became commonplace in capital markets (Bentley et al., 2018; Black et al., 2018b).[6] The extant literature, however, provides little evidence consistent with the SEC's recent apprehension about these metrics. Using a sample spanning from 2003 to 2015 (i.e., post-Regulation G), we provide novel evidence (1) consistent with the SEC's ongoing concern that non-GAAP reporting might mislead investors in certain settings and (2) on the type of exclusions that are,

[5] Our focus on crashes is important because crashes expose investors to major downside losses over a very short period of time, while gradual losses across time allow investors to exit their position without much loss. Further, the first moment of the return distribution (i.e., average returns) (e.g., Doyle et al. 2003) cannot differentiate stocks with large and negative price drops within a short period of time (e.g., one week) from stocks with a steady price decline over a long period of time (e.g., one year or longer). Our results regarding the influence of non-GAAP reporting on crashes, together with the results regarding these crashes' long-run consequences, provide a more complete picture on the effects of non-GAAP reporting on stock returns.

[6] For example, since 2010, the SEC (1) labeled non-GAAP metrics as a "fraud risk factor" (Leone, 2010), (2) formed a taskforce to scrutinize non-GAAP metrics (Rapoport, 2013), and (3) used comment letters and Compliance and Disclosure Interpretations to improve the quality of non-GAAP reporting (Black et al., 2018b; Gomez et al., 2018).

and are not, particularly concerning. These results answer Black et al.'s (2018b) call for evidence that helps reconcile the SEC's concern about non-GAAP earnings potentially misleading investors, and the dearth of evidence in the literature that corroborates this concern in the more recent time period.

2. Background and Hypothesis Development

2.1 Crash Risk

The crash risk literature builds upon agency theory, where corporate insiders maintain an information advantage over corporate stakeholders and use their advantage to hide bad news about the firm (Jin and Myers, 2006; Hutton et al., 2009).[7] Because stakeholders are not aware of the accumulating bad news for an extended period of time, the firm's stock return distribution does not reflect enough negative news and becomes asymmetric. At a certain point, corporate insiders are no longer willing or able to continue withholding bad news (i.e., they hit their abandonment option), and the stockpiled news enters the market all at once, leading to a stock price crash.

Stock crashes have significantly negative consequences for investors, whose exposure to these crashes is only mitigated through screening, as opposed to diversification (Sunder, 2010).[8] Thus, a growing body of research examines the relation between certain accounting properties and stock price crashes. Hutton et al.'s (2009) seminal research indicates that more opaque financial reports, measured by absolute value of discretionary operating accruals, are more likely to induce stock price crashes. Kim and Zhang (2014) provide additional evidence on the relation between financial reporting opacity and crash risk by examining different

[7] Corporate insiders might choose to withhold bad news for a number of reasons, including career concerns, compensation, and litigation risk (Kothari et al., 2009).
[8] Crash risk only relates to investment losses, while risk of return refers to a dispersion of outcomes (i.e., uncertainty) that include both investment gains and losses. Although risk of return can be reduced through diversification, crash risk cannot be diversified away because risk-preferring behavior in the crash risk setting would simply relate to incurring more of a loss, as opposed to expecting a higher future return.

proxies of reporting opacity and expected crash risk. They find evidence consistent with more transparent financial reporting reducing expected crash risk.

Other studies explore how different accounting properties affect stock price crashes. For example, Kim et al. (2011b) find that complex and opaque tax avoidance increases the probability of future stock price crashes, which they attribute to tax avoidance allowing managers to hide bad news. Kim and Zhang (2016) argue that conservatism in financial accounting facilitates the disclosure of bad news, and thus decreases the likelihood of future stock price crashes. Kim et al. (2016b) find that expected crash risk declines with financial statement comparability, consistent with comparable reporting practices reducing managers' bad news hoarding. Finally, DeFond et al. (2015) examine the effects of accounting standards on crash risk, and find that mandatory IFRS adoption leads to a lower likelihood of crash risk for nonfinancial firms.

In addition to examining the properties of financial accounting, other studies have examined how managerial characteristics associate with crash risk. For example, Kim et al. (2011a) find that the sensitivity of a CFO's equity incentives is positively associated with future crash risk, while Kim et al. (2016b) find that firms with overconfident CEOs have a higher likelihood of future crashes. He (2015) finds that CEOs with larger inside debt have lower stock price crash risk. Finally, Hamm et al. (2018) examine how managers' forward-looking earnings guidance affects crash risk. They find a positive relation between optimistic forecasts and crash risk, consistent with managers withholding bad news from their forecasts and optimistically biasing investors' perceptions of future firm performance.[9]

[9] Although managers' forecasts provide additional information to investors, stock crashes still occur from managers *withholding bad news* from these forecasts, in particular, optimistic forecasts (Hamm et al., 2018). Their evidence is consistent with managerial incentives, such as career concerns, motivating managers to issue good news guidance early but to withhold and delay the disclosure of bad news (e.g., Kothari et al., 2009). In contrast, we find that managers do not have to withhold bad news from GAAP earnings for stock crashes to occur. Instead, all investors receive information about firm performance through GAAP earnings and some firms provide additional information about that performance through non-GAAP earnings.

2.2 Non-GAAP Earnings

Managers frequently disclose non-GAAP earnings in their earnings announcements. These alternative performance metrics are not prepared in accordance with GAAP because the non-GAAP metrics exclude certain items that GAAP earnings require. Managers' non-GAAP exclusions primarily consist of certain special item adjustments, such as restructuring charges and impairments of goodwill, or recurring item adjustments, such as amortization of acquired intangible assets and stock-based compensation (Whipple, 2015; Black et al., 2018a).[10]

Managers assert that non-GAAP earnings are informative because they provide investors with a performance metric that better depicts core operations. Several studies provide evidence consistent with this assertion. For example, managers most commonly exclude special items when calculating non-GAAP earnings (Black et al., 2018b), and managers can exclude these items even when the exclusion lowers the non-GAAP metric (Curtis et al., 2014). Managers also appear to vary their non-GAAP calculations over time, and across firms, for informative reasons (Black et al., 2018b), and their non-GAAP metrics can be particularly informative when firms report a GAAP loss (Leung and Veenman, 2018). Finally, investors find non-GAAP metrics to be informative and focus more on these metrics than on their GAAP counterparts (Bradshaw and Sloan, 2002; Bhattacharya et al., 2003; Bradshaw et al., 2018).

Non-GAAP earnings, however, have long faced the criticism that they positively bias investors' perceptions by excluding negative aspects of firm performance. For example, the former SEC Chief Accountant, Lynn Turner, famously characterized early non-GAAP

[10] Both managers and analysts play a role in non-GAAP reporting (Bentley et al., 2018), with (1) analysts forecasting firm performance on a non-GAAP basis and demanding this information from managers, and (2) managers disclosing non-GAAP earnings to provide insight into how they evaluate firm performance, and analysts receiving information about possible non-GAAP adjustments from managers (CAQ, 2018).

reporting practices as "everything but bad stuff" (Dow Jones, 2001). The tenor of this criticism carries into the current reporting environment. Black et al. (2018b) find that, among their sample of S&P 500 firms, nearly 70% of non-GAAP reporters disclose a metric that exceeds GAAP earnings. Prior research also finds that (1) non-GAAP exclusions can map into future firm performance (e.g., Doyle et al., 2003; Kolev et al., 2008), which is inconsistent with the assertion that these items are transitory or non-cash in nature, (2) non-GAAP earnings can allow firms to meet market expectations (e.g., Doyle et al., 2013; Bradshaw et al., 2018), and (3) investors under-priced exclusions prior to Regulation G (e.g., Doyle et al., 2003). However, even though prior research indicates that non-GAAP earnings can be used for non-informative reasons, there is little evidence that these metrics have negative economic consequences in the time period after Regulation G.

Finally, it is important to note that non-GAAP earnings have become commonplace in capital markets. Bradshaw and Sloan (2002) were the first to cast light on the increasing popularity of non-GAAP earnings during the 1990s. This increasing popularity has generally continued since that time.[11] For example, Black et al. (2018b) document that 71% of S&P 500 firms report an annual non-GAAP metric in 2014. The SEC has long expressed concern that managers' non-GAAP metrics could mislead investors, and the SEC enacted Regulation G in 2003 to increase the transparency and quality of non-GAAP earnings numbers. Although non-GAAP earnings became more transparent and less biased after the regulation (e.g., Heflin and Hsu, 2008; Kolev et al., 2008; Zhang and Zheng, 2011), aggressive non-GAAP reporting persists (e.g., Curtis et al., 2014; Bradshaw et al., 2018). More recently, the SEC has used comment letters and Compliance and Disclosure Interpretations in an effort to improve the quality of non-GAAP information (Black et al., 2018b; Gomez et al., 2018). In addition to regulators, the FASB questions whether non-GAAP information sends a signal

[11] The use of non-GAAP earnings declined after Regulation G in 2003 (Heflin and Hsu, 2008), however, the reporting practice has since rebounded (Brown et al., 2012).

about ways to improve the quality of GAAP information (e.g., Linsmeier, 2016; Golden, 2017), while the PCAOB questions the role of auditors in auditing non-GAAP metrics (PCAOB, 2016). Needless to say, regulators and standard setters have expressed a substantial interest in non-GAAP earnings in recent years.

2.3 Hypothesis Development

The crash risk literature primarily views stock price crashes as being the result of managers withholding bad news about firm performance. We examine whether another way that crashes can occur is through investors having access to additional information about current performance that biases their perceptions of the firm. We examine this question using non-GAAP earnings because (1) they are the most commonly used alternative performance metric in capital markets (Audit Analytics, 2018), (2) prior research finds that managers use non-GAAP earnings as a substitute to other forms of earnings management (Doyle et al., 2013; Black et al., 2017), and (3) critics of non-GAAP earnings argue that they positively bias investors' perceptions of firm performance, which aligns with the underlying reason for crash risk. In addition, investors care about non-GAAP earnings and find them more informative than GAAP earnings when pricing firm performance (Bradshaw and Sloan 2002; Bradshaw et al., 2018).

Ex ante, it is unclear whether non-GAAP earnings increase or decrease crash risk. On the one hand, non-GAAP earnings better capture firms' core operations and are more value relevant for investors than GAAP earnings (Brown and Sivakumar, 2003; Gu and Chen, 2004). Moreover, Black et al. (2018a) find that non-GAAP earnings is a more comparable earnings metric across peer firms, and Kim et al. (2016a) find that more comparable earnings are associated with lower crash risk. Thus, non-GAAP earnings might allow investors to more accurately value the firm, and mitigate the chances of a crash. On the other hand, critics of non-GAAP earnings argue that these metrics present an overly optimistic picture of the firm by purging out negative aspects of performance. Consistent with this view, prior research indicates that managers can use non-GAAP reporting for non-informative reasons (e.g., Doyle et al., 2003; Barth et al., 2012). As a result, non-GAAP earnings may create an illusion of good performance for investors, leading them to inflate stock price. However, once investors realize they have overvalued the firm by a large margin, the stock price will likely crash. We state our first hypothesis in alternate form as follows:

> **H1:** *There is a positive relation between non-GAAP reporting frequency and stock price crash risk.*

Next, we examine whether non-GAAP reporting serves as a complement or a substitute to withholding bad news, the traditional method that contributes to crashes. Non-GAAP reporting could play a complementary role if managers use this disclosure practice in addition to withholding bad news to influence investors' perceptions. In contrast, non-GAAP reporting could play a substitutionary role if managers prefer using this disclosure practice over withholding bad news (in mandatorily reported GAAP earnings) to influence investors' perceptions. This substitutionary role is consistent with prior evidence that managers use non-GAAP reporting to substitute for other forms of earnings management in certain scenarios (Doyle et al., 2013; Black et al., 2017). To investigate whether non-GAAP reporting serves as a complement or a substitute to withholding bad news, we examine the relation between non-GAAP reporting and crash risk conditional on the extent to which managers withhold bad news from investors. If non-GAAP reporting is a complement (substitute) for withholding bad news, we expect the non-GAAP reporting and crash risk relation to concentrate among firms with a high (low) level of bad news withholding. We state our second hypothesis in two alternate forms as follows:

> **H2a**: *The relation between non-GAAP reporting and crash risk is higher among firms with a high level of bad news withholding (complementary role).*

> **H2b**: *The relation between non-GAAP reporting and crash risk is higher among firms with a low level of bad news withholding (substitutionary role).*

3. Variable Measurement and Research Design

3.1 Variable Measurement: Crash Risk

Following prior research, we examine four measures of crash risk (e.g., Hutton et al., 2009; Kim et al., 2011a, b). Because all four measures are based on a firm's weekly returns, we first estimate the following model to ensure that our weekly return estimates capture firm-specific factors, as opposed to market-wide factors:

$$r_{j,\omega} = \alpha_j + \beta_{1,j}r_{m,\omega-2} + \beta_{2,j}r_{m,\omega-1} + \beta_{3,j}r_{m,\omega} + \beta_{4,j}r_{m,\omega+1} + \beta_{5,j}r_{m,\omega+2} + \varepsilon_{j,\omega}, \tag{1}$$

where $r_{j,\omega}$ is the return for firm j in week ω, and $r_{m,\omega}$ is the value-weighted CRSP return in week ω. For each firm and fiscal year, we estimate weekly returns throughout a 12-month return window that ends three months after firm *i*'s fiscal year end. We define the firm's specific weekly return ($W_{j,\omega}$) as the natural log of 1 + $\varepsilon_{j,\omega}$.

Our first measure of crash risk (*Crash*) is an indicator variable equal to one if a firm has at least one weekly return falling 3.2 standard deviations or more below the mean firm-specific weekly return in fiscal year t + 1. Similar to prior studies (e.g., Kim et al., 2011a, b), we focus on returns that are at least 3.2 standard deviations below the mean because they identify extreme negative returns, consistent with the notion of a stock crash. Our second crash risk measure is negative return skewness (*NSkewness*), which captures the amount of negative skewness in a firm's weekly stock returns during the year. Our third crash risk measure is the natural logarithm of *DuVol* (*LnDuVol*), which represents the asymmetric volatility of weekly stock returns over the year. We measure *DuVol* using the ratio of the standard deviation of weekly returns ($W_{j,\omega}$) that are below the firm's mean specific weekly return for the year to the standard deviation of weekly returns that are above the firm's mean weekly return for the year. Finally, because the three individual crash risk measures proxy for the construct of crash risk in different ways, they inevitably capture some non-overlapping features of the construct of crash risk. Therefore, we also use a composite measure of crash risk (*Crash Composite*) based on a principal component analysis of the three individual crash risk measures (*Crash*, *NSkewness*, and *LnDuVol*). This composite measure extracts the commonality across the three individual measures and reduces measurement error in the proxy. Across all four crash risk measures, higher values represent greater crash risk.

3.2 Research Design

We test our hypothesis, that there is a positive relation between non-GAAP reporting frequency and stock price crash risk, using the following regression:

$$\begin{aligned} Crash\ Risk_{i,t+1} = \quad & a_0 + a_1 NonGaapFreq_{i,t} + a_2 NSkewness_{i,t} + a_3 Size_{i,t} + a_4 MTB_{i,t} \\ & + a_5 Leverage_{i,t} + a_6 ROA_{i,t+1} + a_7 Return_{i,t} + a_8 Sigma_{i,t} \\ & + a_9 ChgTurnover_{i,t} + a_{10} DisAccurals_{i,t} + a_{11} SqAbAccruals_{i,t} \\ & + \sum \gamma_t Year_t + \sum w_j Ind_j + e_{i,t}. \end{aligned} \qquad (2)$$

As previously discussed, we use four different measures of crash risk (*Crash*, *NSkewness*, *LnDuVol*, and *Crash Composite*). When *Crash* is the dependent variable, we estimate the model using a logistic regression. Otherwise, we estimate the model using ordinary least squares (OLS) regressions. *NonGaapFreq* is the percentage of quarters where managers disclose non-GAAP earnings in their earnings announcement during fiscal year *t*.[12] A significantly positive coefficient for *NonGaapFreq* (a_1) indicates that more frequent non-GAAP earnings disclosure is associated with higher crash risk in the subsequent year. In contrast, an insignificant (significantly negative) coefficient for *NonGaapFreq* indicates that non-GAAP disclosure frequency is not (negatively) associated with crash risk in the subsequent year.

We also control for variables identified in prior research that might affect a firm's future crash risk. In particular, we control for the negative skewness of firm-specific weekly returns in fiscal year *t* (*NSkewness*). We control for firm size (*Size*) (Hutton et al., 2009),

[12] We identify non-GAAP earnings using data available from Bentley et al. (2018). The managerial non-GAAP dataset is publicly available at the following website: https://sites.google.com/view/kurthgee/data.

market-to-book ratio (*MTB*) (Chen et al., 2001), leverage (*Leverage*) (Kim and Zhang, 2016), accounting performance (*ROA*) (Hutton et al., 2009; Kim and Zhang, 2016), and average firm-specific weekly return (*Return*) (Hutton et al., 2009; Kim et al., 2011a, b). We also control for volatility in firm-specific weekly returns (*Sigma*) (Chen et al., 2001), changes in investor belief heterogeneity using stock turnover (*ChgTurnover*) (Chen et al., 2001), and measures of information opaqueness (*DisAccruals* and *SqDisAccruals*) (Hutton et al., 2009). Finally, we include year ($Year_t$) and industry (Ind_j) fixed effects in our model to control for time-invariant and industry-invariant unobservable effects based on the Fama-French 48 industry classification. We estimate the model using robust standard errors, which we cluster by firm. We winsorize all control variables at the top and bottom one percent of the sample.[13]

We also use a cross-sectional analysis to examine a setting where we expect the non-GAAP earnings and crash risk relation to be larger. In particular, if non-GAAP earnings lead to future crashes, we expect these crashes to occur because non-GAAP earnings positively bias investors' perceptions of firm performance. Thus, we expect that investors' optimistic bias is larger when non-GAAP metrics have income increasing adjustments, as opposed to income decreasing adjustments, resulting in a non-GAAP metric that exceeds GAAP earnings. We test this prediction using the following equation:

$$\begin{aligned} Crash\ Risk_{i,t+1} = \quad & a_0 + a_1 NonGaapFreq^{NG>G}{}_{i,t} + a_2 NonGaapFreq^{NG<G}{}_{i,t} \\ & + \sum a_n Controls + \sum \gamma_t Year_t + \sum w_j Ind_j + e_{i,t}, \end{aligned} \tag{3}$$

where Equation 3 is similar to Equation 2, except that we use $NonGaapFreq^{NG>G}$ and $NonGaapFreq^{NG<G}$ to measure non-GAAP reporting frequency. $NonGaapFreq^{NG>G}$ represents the percentage of firm quarters in a fiscal year with a non-GAAP metric that exceeds GAAP earnings (i.e., net non-GAAP adjustments increase income). In contrast, $NonGaapFreq^{NG<G}$ represents the percentage of firm quarters in a fiscal year with a non-

[13] Following prior research, we do not winsorize the crash risk variables because they capture the extreme tails of the return distribution (e.g., Kim et al., 2011a, b). Thus, winsorizing these variables would modify the values that are specifically relevant to our study.

GAAP metric that is less than GAAP earnings (i.e., net non-GAAP adjustments decrease income). To measure total non-GAAP exclusions, we follow prior research (e.g., Bentley et al., 2018) and use the difference between managers' non-GAAP EPS and GAAP EPS.[14] A significantly larger coefficient on $NonGaapFreq^{NG>G}$ (a_1) than $NonGaapFreq^{NG<G}$ (a_2) would be consistent with our expectation that optimistic non-GAAP reporting is more likely to lead to future crashes. *Crash Risk* and *Controls* are as previously defined.

4. Sample Construction and Empirical Results

4.1 Sample Construction and Descriptive Evidence

To construct our sample, we first identify all firms from the Compustat, CRSP, and I/B/E/S universe with fiscal years from 2003 to 2015. We begin our sample in 2003 because it is the first year in which large scale data about managers' non-GAAP reporting begins (Bentley et al., 2018). We obtain accounting data from Compustat Quarterly files, stock price and return data from CRSP daily files, and data about managers' non-GAAP reporting from the publicly available Bentley et al. (2018) dataset. In addition, following prior crash risk studies (e.g., Hutton et al., 2009), we require that (1) total assets and book values of equity for each firm be greater than zero, (2) that a firm must have at least 26 weekly returns for each fiscal year, and (3) that firms are not in financial and utilities industries. Finally, we require non-missing GAAP earnings in Compustat and data on whether managers report non-GAAP earnings. Since we calculate the frequency of non-GAAP earnings disclosure during the fiscal year, we require all firm-quarters during the year to be non-missing. Our final sample consists of 30,336 firm-year observations.

Table 1 presents the descriptive statistics. The mean values of our crash risk measures (*Crash*, *NSkewness*, *LnDuVol*) are consistent with the values found in the extant literature

[14] We define GAAP EPS as Compustat's earnings per share before extraordinary items and discontinued operations.

(Kim and Zhang, 2016; Kim et al., 2019). For example, *Crash* is 0.223, suggesting that just over 22% of firm-years in our sample experience at least one crash week during fiscal year *t*+1.[15] Across the sample, 26.1% of fiscal quarters have a non-GAAP metric during the fiscal year.[16] We find that 21.1% of quarters have a non-GAAP metric greater than GAAP earnings ($NonGaapFreq^{NG>G} > 0$), while 5.0% of quarters have a non-GAAP metric less than GAAP earnings ($NonGaapFreq^{NG<G} > 0$). The control variables are also generally consistent with the extant literature.

Because the overall sample includes firms that only report GAAP earnings, we also examine our variables of interest specifically for firm-years with non-GAAP reporting (i.e., *NonGaapFreq* > 0). The untabulated results indicate that 60% of fiscal quarters for these non-GAAP firms have a non-GAAP metric. In addition, 48% of quarters have non-GAAP earnings greater than GAAP earnings ($NonGaapFreq^{NG>G} > 0$), while 12% of quarters have non-GAAP earnings smaller than GAAP earnings ($NonGaapFreq^{NG<G} > 0$).

Next, we provide descriptive evidence on how *Crash* varies with non-GAAP reporting frequency (*NonGaapFreq*). Panel A of Figure 1 indicates that *Crash* monotonically increases with non-GAAP reporting frequency, which provide descriptive evidence consistent with crash risk increasing as managers more commonly disclose non-GAAP metrics to investors. In Panel B, we partition non-GAAP reporting frequency based on whether a non-GAAP metric is greater than GAAP earnings (i.e., $NonGaapFreq^{NG>G}$) or less than GAAP earnings (i.e., $NonGaapFreq^{NG<G}$). We find that the monotonic increase between *Crash* and non-GAAP reporting frequency only exists for the $NonGaapFreq^{NG>G}$ setting, while there is not a discernible pattern between *Crash* and non-GAAP reporting frequency for the $NonGaapFreq^{NG<G}$ setting.

[15] The untabulated mean (median) weekly return ($r_{j,\omega}$) of firms during their crash weeks is -22.7% (-19.7%).
[16] More specifically, 17,123 observations do not report non-GAAP earnings in any of the four fiscal quarters, while 4,346 (2,620) [2,849] {3,389} observations report non-GAAP earnings in 1 (2) [3] {4} of the fiscal quarters.

4.2 Primary Analyses

4.2.1 H1: Non-GAAP reporting and crash risk

Table 2 presents the results from estimating Equation 2, where the dependent variable is *Crash*, *NSkewness*, *LnDuVol*, and *Crash Composite* across the four columns. In each specification, we find that the coefficient on *NonGaapFreq* is positive and statistically significant, indicating that more frequent non-GAAP reporting is associated with higher future crash risk. These results corroborate our first hypothesis (H1), and formally reject the null hypothesis of no relation between non-GAAP reporting frequency and crash risk. The magnitude of the relation is also significant. For example, column 1 suggests that in a logistic regression estimation, a one-standard-deviation increase in *NonGaapFreq* leads to a 4% increase in the likelihood of an extreme negative return (i.e., a crash) in the subsequent year. Given that Table 1 shows the unconditional probability of having a crash in a year is 22%, the economic effect of a one-standard-deviation increase in *NonGaapFreq* is approximately 18% (4% divided by 22%) of the unconditional probability of having a crash in a year. This effect on crash probability is just below the effect from a one-standard-deviation increase in accrual manipulation (*DisAccruals*; 6%), which is a common measure used in the literature to proxy for managers' opaque disclosures, and one of the most important factors to contribute to crash risk (e.g., Hutton et al., 2009).

We also find that the sign of the coefficients for the control variables and other known determinants of crash risk are largely consistent with prior research. For example, in column 1, our results indicate that crash risk is higher for firms with more negative return skewness (*NSkewness*), larger firms (*Size*), and growth firms (*MTB*), while it is lower for firms with better concurrent operating performance (*ROA*). We also find that firms with larger returns (*Return*), higher change in turnover (*ChgTurnover*), and more opaque disclosure (*DisAccruals*) have greater crash risk. Overall, our results suggest that managers' non-GAAP reporting is a significantly positive predictor of crash risk, even after controlling for other known determinants of crash risk.

Table 3 presents the results of estimating Equation 3, where we categorize non-GAAP reporting frequency based on the percentage of fiscal quarters where the net non-GAAP adjustments result in a non-GAAP metric that either exceeds GAAP earnings ($NonGaapFreq^{NG>G}$) or is less than GAAP earnings ($NonGaapFreq^{NG<G}$). Across all four columns, we find that the coefficient on $NonGaapFreq^{NG>G}$ is significantly positive, consistent with crash risk being larger when non-GAAP earnings are more frequently higher than GAAP earnings throughout the year. An *F*-test between the $NonGaapFreq^{NG>G}$ and $NonGaapFreq^{NG<G}$ coefficients indicates that the relation between non-GAAP reporting frequency and crash risk is more positive when non-GAAP earnings exceed GAAP earnings. These results are consistent with the descriptive evidence presented in Figure 1 and indicate that crash risk is higher when non-GAAP earnings paint a rosier picture of performance than GAAP earnings.[17]

4.2.2 H2: Non-GAAP reporting, crash risk, and withholding bad news

Since we find evidence consistent with managers using non-GAAP earnings to positively influence investors' perceptions, we next examine whether managers view non-GAAP reporting as a complement or substitute to withholding bad news. To examine this question, we re-examine the association between non-GAAP reporting frequency and crash risk using Equation 3, and we partition the sample based on firms that have a high versus low level of bad news withholding. We follow prior research (e.g., Hutton et al., 2009) and use

[17] In untabulated analyses, we further partition the frequency of income increasing non-GAAP reporting (i.e., $NonGaapFreq^{NG>G}$) into the frequency of special item exclusions and the frequency of other item exclusions. Special items are transitory items reported by Compustat. Other items consist of recurring earnings components or transitory items that Compustat does not report as special items. We do not find evidence that the relation between crash risk and non-GAAP reporting statistically differs across these two exclusion categories. This result is perhaps not surprising because (1) other item exclusions became less aggressive after Regulation G (Heflin and Hsu, 2008; Kolev et al., 2008), and (2) special item exclusions became more aggressive after Regulation G (Kolev et al., 2008).

discretionary accruals as a proxy for the extent to which managers withhold bad news from investors. We partition our sample into terciles based on discretionary accruals (*DisAccruals*), and define firms in the lowest (highest) tercile as the firms that have a low (high) level of bad news withholding. If non-GAAP reporting is a substitute (complement) for withholding bad news, we expect the relation between non-GAAP reporting and crash risk to be higher in the subsample with the lowest (highest) discretionary accruals. If managers do not jointly consider non-GAAP reporting and withholding bad news as perception management tools, we expect to find evidence of the relation between non-GAAP reporting and crash risk across both the high and low accrual terciles.

We present our results in Table 4. Across all four crash risk measures, we find that the positive association between income increasing non-GAAP reporting ($NonGaapFreq^{NG>G}$) and future crash risk is concentrated among firms with a low level of bad news withholding. In contrast, we do not find evidence of a relation between these exclusions and crash risk for firms with a high level of bad news withholding. Moreover, we find that the coefficient on $NonGaapFreq^{NG>G}$ is significantly larger for firms with a low level of bad news withholding than for firms with a high level of bad news withholding. These results are consistent with H2b as opposed to H2a. That is, our evidence is consistent with managers viewing non-GAAP reporting as a *substitute* for withholding bad news to optimistically influence investors' perceptions.

5. Managerial Incentives, Aggressive Non-GAAP Reporting, and Crash Risk

We next examine whether the relation between crash risk and the frequency of income increasing exclusions is the result of managers' aggressive non-GAAP reporting, or simply an artifact of non-GAAP reporting more generally (e.g., investors misuse informative non-GAAP disclosures). To explore this question, we conduct two sets of analyses. In the first set of analyses, we examine whether the relation between non-GAAP reporting and crash risk is stronger in time periods when managers are more likely aggressive in their non-GAAP reporting. In the second set of analyses, we examine whether this relation is stronger for managers with greater incentives to inflate stock price, which might motivate them to use aggressive non-GAAP reporting. Similar to our analyses in Table 4, we use Equation 3 and partition the sample for each analysis into terciles based on the estimated level of aggressive reporting or incentive to inflate stock price. We then compare the non-GAAP reporting and crash risk relation across the top and bottom terciles. We present the results for each of the analyses in Table 5, where we provide evidence for our main variable of interest ($NonGaapFreq^{NG>G}$).[18]

5.1 Investor Sentiment and Meeting Analysts' Earnings Forecasts

We first examine the relation between non-GAAP reporting and crash risk across time periods with varying levels of aggressive non-GAAP reporting. Prior research finds that managers are more aggressive in their non-GAAP reporting when sentiment is high (Brown et al., 2012), consistent with investors being less rigorous in their scrutiny of non-GAAP reporting in optimistic periods. Thus, we expect the relation between non-GAAP reporting frequency and crash risk to concentrate in periods of high investor sentiment. To examine this expectation, we obtain the investor sentiment index data from Jeffrey Wurgler's website.[19] We then partition the sample based on the magnitude of the average sentiment over the fiscal year *t* (*MktSent*), and classify observations in the highest (lowest) tercile of the sample distribution as the high (low) sentiment group. In Panel A of Table 5, we find that the coefficient on $NonGaapFreq^{NG>G}$ is significantly positive for the high sentiment group across all four crash risk measures. In contrast, the $NonGaapFreq^{NG>G}$ coefficient is insignificant across the crash risk measures for the low sentiment group. We also find that the differences

[18] To prevent Table 5 from becoming unwieldy, we suppress the other variables in Equation 3.
[19] The data is available at http://people.stern.nyu.edu/jwurgler/.

in the $NonGaapFreq^{NG>G}$ coefficients between the high and low sentiment groups are significant at conventional levels across our crash risk measures. Thus, the relation between non-GAAP reporting frequency and future crash risk is stronger when investor sentiment is high, consistent with our conjecture.

Another common proxy for aggressive non-GAAP reporting is when non-GAAP earnings allow a firm to meet analysts' earnings forecasts, while GAAP earnings fall short of expectations. Following Bradshaw et al. (2018), we identify quarters where managers' non-GAAP earnings meet analysts' street earnings forecasts (I/B/E/S variable *EPS*), while their GAAP earnings miss analysts' GAAP earnings forecasts (I/B/E/S variable *GPS*). We then calculate the percentage of quarters during the year where this scenario occurs (*FreqMBE*) and classify observations in the highest (lowest) tercile of the sample distribution as the high (low) *FreqMBE* group. In Panel B of Table 5, we find that the coefficient on $NonGaapFreq^{NG>G}$ for the high tercile group is at least marginally significant across our crash risk measures. In contrast, $NonGaapFreq^{NG>G}$ is not significant across the crash risk measures for the low tercile group. Moreover, when we compare the coefficients for $NonGaapFreq^{NG>G}$ across the high and low tercile groups, we find marginally significant evidence that the coefficient is greater in the high tercile group than in the low tercile group for each of our crash risk measures.

Overall, the evidence in Panels A and B of Table 5 is consistent with the relation between non-GAAP reporting frequency and crash risk being higher in periods when non-GAAP reporting is likely more aggressive.

5.2 Sensitivity of Compensation to Share Price Changes, and Insider Trading

Next, we examine whether the relation between non-GAAP reporting frequency and crash risk is higher for managers who have a greater incentive to inflate stock price, which provides them with the opportunity to benefit from inflating firm value. In this set of analyses, we consider two settings where managers might have varying incentives to inflate stock prices: (i) managers' compensation sensitivity to changes in stock price, and (ii) insider trading.

In our first setting, we posit that managers with high compensation sensitivity to changes in stock price will have a greater incentive to use aggressive non-GAAP reporting to inflate stock prices. If this is the case, we expect the relation between non-GAAP reporting and crash risk to be stronger for managers with compensation that is more sensitive to changes in stock price. To test this conjecture, we partition our sample into terciles based on the sensitivity of managers' compensation plans to changes in stock price. We measure compensation sensitivity based on *Delta*, measured as the minimum level of the compensation sensitivity (i.e., the dollar increase in an executive's wealth for a 1% increase in stock price) among the executives available in Execucomp database of fiscal year *t*. Consistent with our conjecture, our results in Panel C of Table 5 reveal that this relation for each of the crash risk measures is (1) significant in the high tercile, (2) insignificant in the low tercile, and (3) significantly higher in the high tercile than in the low tercile.

In our second setting, we posit that managers who engage in more opportunistic insider sales have a greater incentive to inflate stock prices through aggressive non-GAAP reporting. Thus, we expect the relation between non-GAAP reporting frequency and crash risk to be stronger when manager engage in more opportunistic insider sales prior to the year experiencing the crash risk. To test this conjecture, we partition our sample into terciles based on the amount of opportunistic insider sales in year *t* (*OpptunSales*). We measure opportunistic insider sales following Cohen et al. (2012), which focuses on the non-routine insider sales transactions made by a firm's executives. In contrast, routine sales likely capture personal liquidity or diversification motives rather than the realization of information advantage leading to negative future stock performance.[20] Consistent with our conjecture, our results in Panel D of Table 5 indicate that this relation for each of the crash risk measures is significant in the high tercile group and insignificant in the low tercile group. Additionally, the coefficient in the high tercile group is significantly greater than in the low tercile group. In total, the results in this subsection are consistent with incentives to inflate stock price exacerbating the non-GAAP reporting and crash risk relation, indicating that this relation concentrates in scenarios when managers have a higher potential to benefit from aggressive non-GAAP reporting.

6. Additional Analyses

6.1 Robustness Checks

6.1.1 Controlling for additional factors that affect crash risk

In untabulated analyses, we also examine the relation between non-GAAP reporting frequency and future crash risk after controlling for several other factors that prior crash risk studies find as affecting crash risk. In particular, we consider accounting conservatism (Kim and Zhang, 2016), corporate tax avoidance (Kim et al., 2011b), CEO overconfidence (Kim et al., 2016b), accounting comparability (Kim et al., 2016a), financial reporting complexity (Kim et al., 2019), product market competition (Li and Zhan, 2018), and frequency of management earnings guidance (Hamm et al., 2018). Consistent with non-GAAP earnings having explanatory power for future crash risk over and above other known factors, we find

[20] Specifically, we follow Cohen et al. (2012) and designate an insider's sales on a stock in a particular month as either opportunistic or routine sales according to the insider's past history of trades. In a given firm-year, the Cohen et al. (2012) method identifies three types of insider sales: routine, opportunistic, and unclassified. Unclassified sales are made by some insiders who fail to sell at least once in each of the three preceding years. We exclude these unclassified sales in our tests.

that the relation between non-GAAP reporting frequency and future crash risk remains significant.[21]

6.1.2 Street earnings and crash risk

As an additional analysis, we re-examine our main analyses using I/B/E/S to identify non-GAAP metrics. As previously discussed, our primary analyses are based on managerial non-GAAP reporting because the SEC is specifically interested in managers' non-GAAP metrics. Additionally, the notion of managers' providing investors with non-GAAP earnings (i.e., addition information) is more symmetric with the traditional argument that crash risk occurs through managers' withholding bad news. However, prior studies on non-GAAP earnings also focus on street earnings provided by analysts (i.e., non-GAAP metrics that analysts use to assess performance), or namely I/B/E/S actual earnings, and use street earnings to proxy for managerial non-GAAP earnings (e.g., Doyle et al., 2003; Heflin and Hsu, 2008). Examining the association between street earnings and crash risk is important for at least two reasons. First, prior research indicates that the market pays particular attention to street earnings (Bhattacharya et al., 2003; Marques, 2006) and that analysts help filter out managers' aggressive non-GAAP reporting (Bentley et al., 2018). Thus, it is interesting to examine whether the relation between non-GAAP reporting and crash risk remains when examining street earnings. Second, using street earnings also allows us to extend our sampling period to the pre-Regulation G period (i.e., before 2003), which allows us to examine the effect of an exogenous shock (i.e., Regulation G) to non-GAAP reporting quality and mitigate concerns regarding endogeneity in our main results.[22]

We begin by examining whether the results from our primary analyses generalize to street earnings. Specifically, we repeat our Table 3 analysis using the analyst-based non-

[21] We do not include these additional variables in our primary analyses because their data requirements overly restrict our sample and lower our overall testing power.
[22] As previously discussed, the managerial non-GAAP reporting data from Bentley et al. (2018) is only available for periods after Regulation G (i.e., 2003 and onward).

GAAP metric (i.e., street earnings). To facilitate comparison with our earlier results, we use the same sample period as in our earlier analyses (i.e., 2003-2015), however, untabulated results indicate that the inferences are similar if we extend our sample period back to 1994.

Columns 1-4 of Table 6 present the results. Consistent with our primary analyses based on managerial data, we find a significantly positive relation between the frequency of analysts' non-GAAP reporting (particularly income-increasing non-GAAP reporting) and future crash risk. Thus, our primary inferences regarding managers' non-GAAP reporting also generalize to analysts' metrics. In untabulated analyses, we also partition the non-GAAP reporting variables based on the extent to which managers and analysts agree and disagree in their non-GAAP reporting because prior research finds that managers' reporting is more aggressive than analysts' reporting (e.g., Barth et al., 2012; Bentley et al., 2018). Our results indicate that the relation between non-GAAP reporting frequency and crash risk holds in scenarios where managers and analysts agree in their non-GAAP reporting, but not when they differ. One potential explanation for these results is that investors are more sceptical of non-GAAP reporting when they receive conflicting signals from managers and analysts, and are therefore less likely to misprice the firm. However, it is important to note that managers and analysts are much more likely to agree in their reporting than disagree, thus, another explanation for our results might be due to the power of our analyses.

6.1.3 Analyses of potential endogeneity

Our primary analyses find evidence of a positive relation between non-GAAP reporting frequency and future crash risk, with this relation being due to non-GAAP earnings with income increasing exclusions. Next, we address the alternative explanation that our results are endogenous and due to unobservable firm characteristics that associate with non-GAAP reporting frequency and future crash risk. We first note, however, that our results from Tables 3-5, where the relation between non-GAAP reporting frequency and crash risk is concentrated in low bad news withholding firms and in scenarios where managers are incentivized to aggressively report non-GAAP earnings, help to mitigate concerns that our documented relation is endogenous since the unobservable firm characteristic would also need to vary across each of these scenarios.

To further address the potential endogeneity concern, we use a difference-in-differences (DiD) research design based on a matched sample and centered on Regulation G. Prior research provides evidence that Regulation G improved the quality of non-GAAP reporting (e.g., Heflin and Hsu, 2008; Kolev et al., 2008), with the regulation specifically improving the quality of "other item" exclusions, and reducing the frequency of these adjustments. Other items consist of earnings components other than those components identified by Compustat as "special items." Thus, we focus our analysis on non-GAAP earnings with income increasing other item exclusions because we are specifically interested in examining how an improvement in non-GAAP reporting affects the relation between non-GAAP earnings and crash risk. We use I/B/E/S actual earnings data (i.e., street earnings) covering both the pre- and post-Regulation G periods to conduct our difference-in-differences analysis.

We focus the analysis on years 2001-2004, which comprises the two years before and after the regulation. We define our treatment group as firms with non-GAAP earnings that more frequently exclude income increasing other items during 2001 and 2002 (based on the median exclusion frequency for these items).[23] By construction, these firms are more likely to have an improvement in the overall quality of their non-GAAP reporting because (1) the

[23] We focus on this subsample with a relatively short window centered on Regulation G for two reasons. First, as Heflin and Hsu (2008) point out, a short-window test can help mitigate the potential confounding effects that tend to be larger in a longer-window test. Second, while Heflin and Hsu (2008) show that the use of non-GAAP earnings declines over the eight quarters after Regulation G, more recent studies show that the use of non-GAAP reporting has since rebounded (e.g., Brown et al., 2012). The frequency of income increasing other item exclusions is the number of fiscal quarters in year *t* where I/B/E/S EPS excludes income increasing other items, divided by the four quarters in fiscal year *t*. We follow Hsu and Kross (2011) and measure other items conditional on the magnitude of total exclusions and the magnitude of the difference between operating income and GAAP earnings.

regulation helped curtail managers' aggressive exclusion of other items (Heflin and Hsu, 2008) and (2) other item exclusions that occur after the regulation are of higher quality, on average, than other item exclusions made before the regulation (Kolev et al., 2008). We define our control group as firms that do not exclude income increasing other items during 2001-2004. We expect the decline in crash risk to be greater for the treatment group than for the control group after the regulation.

Next, we use propensity score matching to identify firms in our control group that are most comparable to our treatment firms. We begin by using a Probit model to examine a firm's likelihood of having more frequent non-GAAP reporting with income increasing other items exclusions (i.e., our treatment group) or not (i.e., our control group). We (1) use the control variables in Equation 2 as the independent variables in the Probit model, and (2) use the predicted probabilities from the Probit model to create our propensity score. We use this propensity score to match our treatment firms to a subsample of control firms so that we use a matched sample with minimal observable differences in firm characteristics.[24] Appendix B illustrates the effectiveness of the propensity score matching process. Although differences between the two groups are significant for many variables *before* matching, most differences are insignificant after the matching, suggesting that our matching process is largely effective.

After identifying our treatment and control firms, we estimate the following difference-in-differences model to examine whether treatment firms experience fewer future crashes after Regulation G than before, as compared with control firms:

$$\begin{aligned} Crash\ Risk_{i,t+1} = \quad & a_0 + a_1 Treatment_i + a_2 Post_{i,t} \times Treatment_i \\ & + a_n Controls + \sum \gamma_t Year_t + \sum w_j Ind_j + e_{i,t}, \end{aligned} \tag{4}$$

where *Post* is equal to one for observations after the implementation of Regulation G (years 2003 and 2004), and zero otherwise. *Treatment* is an indicator variable equal to one for

[24] In particular, we match firms of the treatment and control groups via 1-to-4 nearest neighbor (a caliper width of 0.05) propensity score matching with replacement. We allow for the repeated use of control observations to increase the size of the matched sample and hence the testing power.

observations from our treatment group, and zero otherwise. Control variables are the same as in Equation 2, which we supress for presentation purposes. We present the results from estimating Equation 4 in Table 7. Of particular relevance, we first find that the coefficient on *Treatment* is positively significant, suggesting that the treatment group has a greater incidence of crashes than the control group prior to Regulation G. Hence, our construction of treatment and control groups indeed properly captures the association between non-GAAP reporting and crash risk before Regulation G. More importantly, we also find the coefficient on *Post* x *Treatment* is significant and negative across all four measures of crash risk (columns 1-4), consistent with a greater decline in crash risk for treatment firms than for control firms after Regulation G.

We further partition the difference-in-differences design to identify when the effect of Regulation G affects the relation between non-GAAP reporting frequency and crash risk for treatment firms (columns 5-8). Specifically, we compare the matched sample by year, where *Post +1* is 2004 (one year after Regulation G), *Post 0* is 2003 (the year of Regulation G implementation), and *Post -1* is 2002 (one year prior to Regulation G). The omitted year is 2001, which is two years before the regulation and represents the baseline year for the interaction variables. Consistent with the assertion that the decline in crash risk is greater for the treatment group than for the control group after Regulation G, the interaction between *Post* and *Treatment* is significantly negative only after the implementation of Regulation G (i.e., *Post 0* and *Post +1*), but not before. Importantly, these results corroborate the parallel trend assumption of our difference-in-differences design and further mitigate concerns that some endogenous relation is responsible for the results.

6.2 The Long-term Implications of Crashes for Investors

Finally, we examine the long-term implications for investors holding stock in non-GAAP reporting firms that experience a crash. As previously discussed, *Crash* is an indicator equal to one when a firm has an extreme negative weekly return during year *t*+1. Although a crash has negative return implications for equity holders during the week of the crash, it is unclear how far into the future these negative implications extend. For example, if the stock price rebounds in the weeks following the crash, then crashes expose investors to short term losses, but not longer-term losses. In contrast, if the negative price implications extend far into the future, then investors cannot mitigate the negative crash effects by simply holding the stock for a longer period of time. We conduct our analysis using the following model:

$$\begin{aligned} BHAR_{i,t+1 \text{ to } t+n} = \; & a_0 + a_1 NonGaapFreq_{i,t} + a_2 Crash_{i,t} \\ & + NonGaapFreq_{i,t} \times Crash_{i,t} + \textstyle\sum a_n Controls \\ & + \textstyle\sum \gamma_t Year_t + \sum w_j Ind_j + e_{i,t}, \end{aligned} \tag{5}$$

where $BHAR_{t+1,\, t+n}$ is the size-adjusted buy-and-hold return that starts in the year after the non-GAAP reporting (year *t*+1). We examine three different return windows: one-year ahead, two-years ahead, and three-years ahead. We are particularly interested in the interaction between *NonGaapFreq* and *Crash* because it provides insight into the longer-term implications of crashes induced by non-GAAP reporting. Across all three return windows in Table 8, we find that the coefficient on the *NonGaapFreq* and *Crash* interaction is significantly negative and economically large. Thus, crash firms that frequently promote non-GAAP metrics subject investors to extreme negative returns for up to three years after the non-GAAP reporting period. For example, results in column 1 show that crash firms that report non-GAAP earnings in each fiscal quarter of year *t* experience an on average return of -27% during the year of the crash (i.e., year *t*+1). These results indicate that the negative consequences from non-GAAP reporting crash firms affect not only active investors who hold their investments for short periods of time, but also more passive investors who hold their investments for years.

7. Conclusion

We examine whether managers' non-GAAP disclosures influence a firm's crash risk. We find a positive relation between the frequency of managers' non-GAAP reporting and crash risk. Moreover, this relation is attributable to instances where non-GAAP earnings exceed GAAP earnings. We also find that managers appear to use non-GAAP reporting as a substitute for the more traditional perception management tool examined in the crash risk literature, withholding bad news, as our evidence of an association between non-GAAP reporting frequency and crash risk concentrates among firms with a low level of bad news withholding. Our evidence also indicates that the non-GAAP reporting and crash risk relation concentrates in periods when aggressive non-GAAP reporting is more likely and for managers who are incentivized to inflate stock price. Our additional analyses indicate that our results are robust to an exogenous shock to non-GAAP reporting quality and that these crashes for non-GAAP reporting firms have long-run consequences for investors. In total, these results are consistent with a subset of managers aggressively reporting non-GAAP earnings to positively influencing investors' assessments of firm performance, leading investors to overlook negative aspects of the firm and over-estimate the firm's value.

Our study adds to the prior research that examines the determinants of crash risk. The traditional view in the literature attributes crashes to managers' ability to exploit their information advantage over investors by withholding bad news about firm performance. Our evidence suggests that managers withholding bad news is not necessarily required for crash risk to occur, and that crash risk can also occur through managers disclosing additional information about current performance. Furthermore, managers appear to trade-off between these two perception management tools. Finally, our study extends the literature on non-GAAP reporting by providing evidence that non-GAAP earnings can have real negative impacts for capital markets. We are among the first to provide evidence that non-GAAP earnings can expose investors to extreme negative economic outcomes that cannot be avoided by diversification.

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Appendix A
Variable Definitions

Variables	Definitions
$Crash_{t+1}$	An indicator variable that equals one for a firm-year that experiences one or more crash weeks during fiscal year t+1 and zero otherwise. Crash weeks are defined as those weeks during which the firm experiences W with 3.2 standard deviations below the mean firm-specific weekly return over the entire fiscal year.
$NSkewness_{t+1}$	The negative coefficient of skewness of W over fiscal year t+1.
$LnDuVol_{t+1}$	The natural log value of $DuVol_{t+1}$. $DuVol_{t+1}$ is the ratio of the standard deviation of W for the down weeks to the standard deviation of W for the up weeks, where down and up weeks are those with W below and above, respectively, the mean over the fiscal year t+1.
W	Firm-specific weekly return, defined as the natural logarithm of one plus the residual return from estimating the expanded market model for each firm and each fiscal year: $$r_{j,\omega} = \alpha_j + \beta_{1,j}r_{m,\omega-2} + \beta_{2,j}r_{m,\omega-1} + \beta_{3,j}r_{m,\omega} + \beta_{4,j}r_{m,\omega+1} + \beta_{5,j}r_{m,\omega+2} + \varepsilon_{j,\omega},$$ where $r_{j,\omega}$ is the return for firm j in week ω, $r_{m,\omega}$ is the value-weighted CRSP return in week ω. For each firm and fiscal year, we estimate weekly returns throughout a 12-month return window that ends three months after firm i's fiscal year end. We define the firm's specific weekly return ($W_{j,\omega}$) as the natural log of 1 + $\varepsilon_{j,\omega}$.
$Crash\ Composite_{t+1}$	A composite crash measure based on a principal component analysis on *Crash*, *NSkewness*, and *LnDuVol*.
$NonGaapFreq_t$	The number of non-GAAP earnings reported, divided by the four fiscal quarters in fiscal year t. We identify a firm as reporting non-GAAP earnings if non-GAAP EPS from managers (Bentley et al., 2018) differ from GAAP EPS (i.e., total exclusions are not zero).
$NonGaapFreq^{NG>G}_t$	The number of quarters with net income increasing total exclusions, resulting in non-GAAP EPS exceeding GAAP EPS, divided by the four fiscal quarters in fiscal year t.
$NonGaapFreq^{NG<G}_t$	The number of quarters with net income decreasing total exclusions, resulting in non-GAAP EPS being less than GAAP EPS, divided by the four fiscal quarters in fiscal year t.
MTB_t	The ratio of the market value of equity to the book value of equity at the end of fiscal year t.
$Leverage_t$	Company debt scaled by the book value of total assets at the end of fiscal year t. Company debt is the sum of long-term debt and debt in current liabilities.
ROA_{t+1}	Income before extraordinary items in fiscal year t+1 divided by the book value of asset at the end of fiscal year t.
$Return_t$	The mean of W over fiscal year t.
$Sigma_t$	The standard deviation of W over fiscal year t.
$ChgTurnover_t$	The average monthly share turnover over the fiscal year t minus the average monthly share turnover over the fiscal year t-1, where monthly share turnover is calculated as the monthly trading volume divided by the total number of shares outstanding during the month.

$DisAccruals_t$	Discretionary accruals based on Modified Jones Model (1991) in fiscal year *t*.
$SqDisAccruals_t$	Squared term of $DisAccruals_t$.
$Year_t$	Indicator variables for fiscal years.
Ind_j	Indicator variables for industry membership based on Fama and French (1998) 48 industries.
$MktSent_t$	The averaged value of sentiment index as defined by Baker and Wurgler (2006) over fiscal year *t*.
$FreqMBE_t$	Number of firm-quarters in fiscal year *t* where non-GAAP earnings allow the firm to meet or beat analysts' earnings forecasts, divided by the four fiscal quarters in fiscal year *t*. We identify these meet-or-beat firm-quarters as observations where GAAP EPS < forecasted GAAP EPS (I/B/E/S *GPS*), but non-GAAP EPS (Bentley et al., 2018) ≥ forecasted EPS (I/B/E/S *EPS*).
$Delta_t$	The minimum level of Delta among the executives available in Execucomp database of fiscal year *t*. Delta is the dollar increase in an executive's wealth for a 1% increase in stock price.
$OpptunSales_t$	The averaged dollar value of shares that are opportunistically sold by insiders over four quarters of fiscal year *t*. Opportunistic trades are defined as in Cohen et al. (2012).
Treatment	An indicator variable equal to one for observations from our treatment group, and zero otherwise.
$Post_t$	An indicator variable equal to one for observations after the implementation of Regulation G (years 2003 and 2004), and zero otherwise.
Post x	A set of indicator variables equal to one for the observations of a certain year, and zero otherwise. *Post +1* is 2004 (one year after Regulation G), *Post 0* is 2003 (the year of Regulation G implementation), and *Post -1* is 2002 (one year prior to Regulation G).
$BHAR_{t+1,\, t+n}$	Size-adjusted buy and hold stock return from year *t+1* to year *t+n* (*n*=1, 2, or 3).

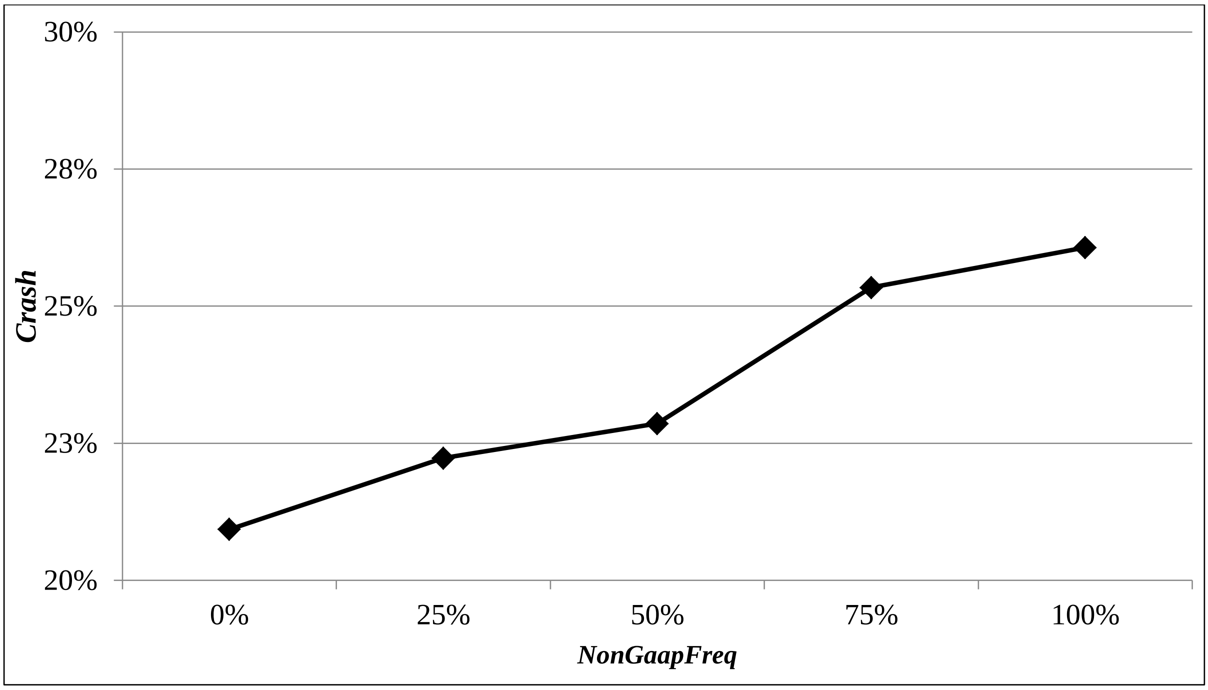
Appendix B
The Effectiveness of PSM in DiD Analysis

	Unmatched			Matched		
	Treatment	Control	Tests of Diff.	Treatment	Control	Tests of Diff.
NSkewness$_t$	0.155	0.080		0.157	0.137	
Size$_t$	7.123	6.281	***	7.109	7.213	
MTB$_t$	3.617	3.515		3.628	4.228	*
Leverage$_t$	0.220	0.180	***	0.221	0.230	
ROA$_{t+1}$	-0.021	0.024	***	-0.016	-0.003	
Return$_t$	0.001	0.004	***	0.002	0.002	*
Sigma$_t$	0.069	0.066		0.068	0.065	*
ChgTurnover$_t$	0.306	0.335		0.308	0.314	
DisAccruals$_t$	0.050	0.094	***	0.053	0.051	
SqDisAccruals$_t$	0.027	0.038	*	0.024	0.024	

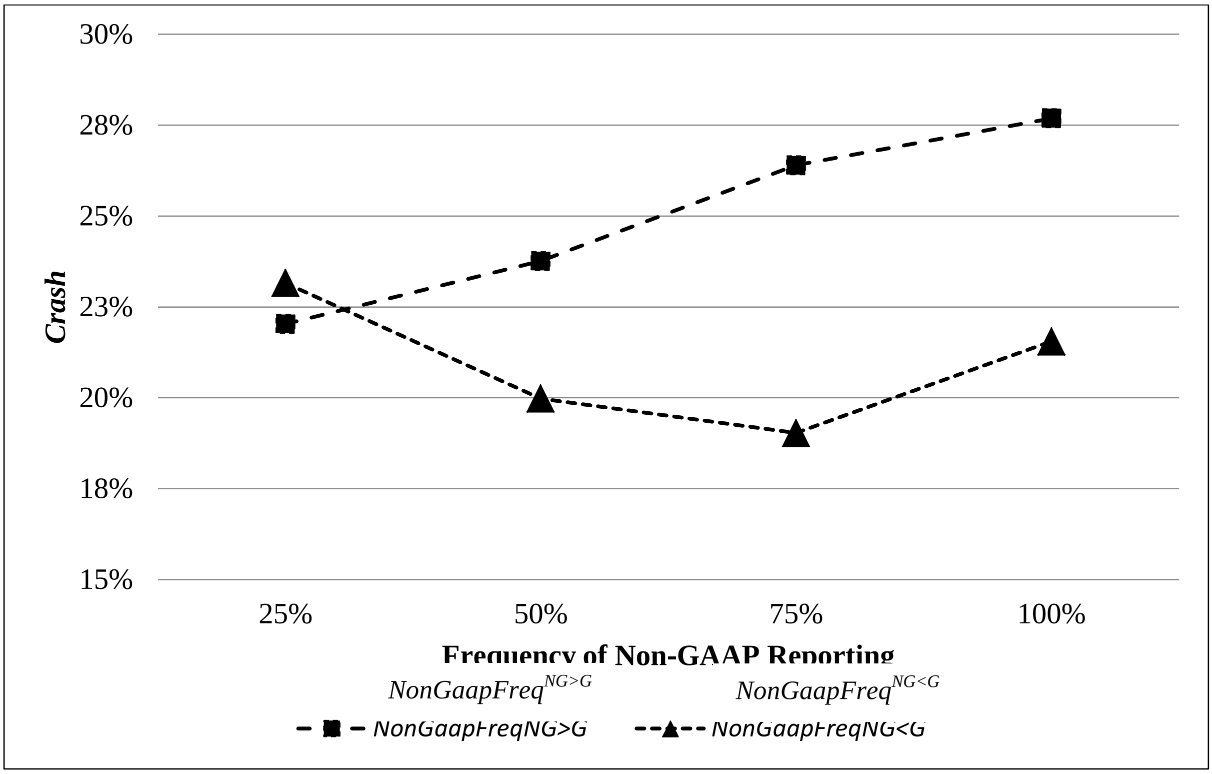
This table compares the mean values for variables in the treatment and control samples before and after PSM. Variable definitions are available in Appendix A. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Figure 1
Non-GAAP Reporting Frequency and Stock Price Crash

Panel A: Stock Price Crash Conditional on Total Non-GAAP Reporting Frequency



Panel B: Stock Price Crash Conditional on Non-GAAP Reporting Frequency by Sign of Exclusions



This figure presents the likelihood of having a crash in year t+1 (*Crash*) conditional on the level of non-GAAP reporting frequency in year t. Non-GAAP reporting frequency is measured as *NonGaapFreq* in Panel A and $NonGaapFreq^{NG>G}$ ($NonGaapFreq^{NG<G}$) in Panel B. Variable definitions are available in Appendix A.

Table 1
Descriptive Statistics (N = 30,336)

	Mean	Std. Dev.	Q1	Median	Q3
Dependent Variables					
$Crash_{t+1}$	0.223	0.416	0.000	0.000	0.000
$NSkewness_{t+1}$	-0.064	1.017	-0.574	-0.106	0.392
$LnDuVol_{t+1}$	-0.052	0.417	-0.315	-0.065	0.198
$Crash\ Composite_{t+1}$	0.000	1.000	-0.609	-0.182	0.427
Variables of Interest					
$NonGaapFreq_t$	0.261	0.356	0.000	0.000	0.500
$NonGaapFreq^{NG>G}_t$	0.211	0.322	0.000	0.000	0.250
$NonGaapFreq^{NG<G}_t$	0.050	0.138	0.000	0.000	0.000
Control Variables					
$NSkewness_t$	-0.047	0.887	-0.542	-0.102	0.370
$Size_t$	6.732	1.853	5.413	6.637	7.947
MTB_t	3.051	3.421	1.328	2.033	3.384
$Leverage_t$	0.185	0.173	0.024	0.152	0.294
ROA_{t+1}	0.010	0.141	0.003	0.031	0.072
$Return_t$	-0.002	0.007	-0.005	-0.001	0.002
$Sigma_t$	0.051	0.027	0.031	0.044	0.063
$ChgTurnover_t$	0.034	1.060	-0.291	0.007	0.325
$DisAccruals_t$	0.069	0.166	-0.011	0.032	0.124
$SqDisAccruals_t$	0.036	0.095	0.000	0.004	0.022

This table reports summary statistics for variables used in our primary analyses. Variable definitions are available in Appendix A.

Table 2
Non-GAAP Earnings and Stock Price Crash Risk

	Dependent Variables			
	(1)	(2)	(3)	(4)
	$Crash_{t+1}$	$NSkewness_{t+1}$	$LnDuVol_{t+1}$	$Crash\ Composite_{t+1}$
$NonGaapFreq_t$	**0.101****	**0.042****	**0.018****	**0.047****
	(0.022)	**(0.024)**	**(0.018)**	**(0.011)**
$NSkewness_t$	0.081***	0.050***	0.022***	0.051***
	(0.000)	(0.000)	(0.000)	(0.000)
$Size_t$	0.024**	0.028***	0.011***	0.024***
	(0.023)	(0.000)	(0.000)	(0.000)
MTB_t	0.009*	0.004**	0.002**	0.005**
	(0.055)	(0.041)	(0.021)	(0.019)
$Leverage_t$	-0.087	-0.084**	-0.039**	-0.080**
	(0.361)	(0.040)	(0.018)	(0.045)
ROA_{t+1}	-0.626***	-0.455***	-0.172***	-0.425***
	(0.000)	(0.000)	(0.000)	(0.000)
$Return_t$	14.157***	14.346***	6.695***	13.573***
	(0.000)	(0.000)	(0.000)	(0.000)
$Sigma_t$	1.337*	-0.782**	-0.447***	-0.517
	(0.082)	(0.018)	(0.001)	(0.104)
$ChgTurnover_t$	0.025*	0.017***	0.007***	0.016***
	(0.054)	(0.003)	(0.004)	(0.004)
$DisAccruals_t$	0.339***	0.077	0.033	0.109**
	(0.004)	(0.147)	(0.109)	(0.032)
$SqDisAccruals_t$	-0.287	-0.156	-0.051	-0.144
	(0.143)	(0.101)	(0.166)	(0.111)
N	30,336	30,336	30,336	30,336
R^2	0.026	0.025	0.030	0.028

This table reports the relation between non-GAAP reporting frequency and stock price crash risk. Variable definitions are available in Appendix A. Constant terms, industry-, and year- fixed effects are included but not reported. We report z(*t*)-statistics based on robust standard errors to heteroscedasticity, which we also cluster at the firm level, in parentheses in column 1 (columns 2-4). ∗∗∗, ∗∗, ∗ denote statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 3
Sign of Exclusions and Stock Price Crash Risk

	Dependent Variables			
	(1)	(2)	(3)	(4)
	$Crash_{t+1}$	$NSkewness_{t+1}$	$LnDuVol_{t+1}$	$Crash\ Composite_{t+1}$
$\boldsymbol{NonGaapFreq^{NG>G}_t}$	**0.145*** **	**0.064*** **	**0.027*** **	**0.071*** **
	(0.003)	**(0.002)**	**(0.001)**	**(0.001)**
$\boldsymbol{NonGaapFreq^{NG<G}_t}$	**-0.140**	**-0.070**	**-0.030***	**-0.075***
	(0.202)	**(0.111)**	**(0.098)**	**(0.086)**
$NSkewness_t$	0.080***	0.050***	0.022***	0.051***
	(0.000)	(0.000)	(0.000)	(0.000)
$Size_t$	0.024**	0.028***	0.011***	0.024***
	(0.022)	(0.000)	(0.000)	(0.000)
MTB_t	0.009*	0.004**	0.002**	0.005**
	(0.058)	(0.043)	(0.022)	(0.020)
$Leverage_t$	-0.089	-0.084**	-0.039**	-0.081**
	(0.351)	(0.038)	(0.017)	(0.043)
ROA_{t+1}	-0.626***	-0.455***	-0.172***	-0.425***
	(0.000)	(0.000)	(0.000)	(0.000)
$Return_t$	14.272***	14.403***	6.719***	13.635***
	(0.000)	(0.000)	(0.000)	(0.000)
$Sigma_t$	1.314*	-0.791**	-0.451***	-0.527*
	(0.087)	(0.017)	(0.001)	(0.098)
$ChgTurnover_t$	0.026*	0.018***	0.007***	0.016***
	(0.050)	(0.002)	(0.004)	(0.004)
$DisAccruals_t$	0.353***	0.083	0.036*	0.116**
	(0.003)	(0.116)	(0.083)	(0.022)
$SqDisAccruals_t$	-0.294	-0.159*	-0.053	-0.148
	(0.134)	(0.094)	(0.154)	(0.102)
N	30,336	30,336	30,336	30,336
R^2	0.026	0.026	0.030	0.028
F-tests (Chi-squared):				
$NonGaapFreq^{NG>G} = NonGaapFreq^{NG<G}$				
	5.62**	7.26***	7.93***	8.77***

This table reports the relation between non-GAAP reporting frequency and stock price crash risk conditional on the sign of net total exclusions. Variable definitions are available in Appendix A. Constant terms, industry-, and year- fixed effects are included but not reported. We report z(*t*)-statistics based on robust standard errors to heteroscedasticity, which we also cluster at the firm level, in parentheses in column 1 (columns 2-4). ***, **, * denote statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 4
Non-GAAP Reporting and Bad News Withholding

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Crash$_{t+1}$		*NSkewness*$_{t+1}$		*LnDuVol*$_{t+1}$		*Crash Composite*$_{t+1}$	
Par. Var. = *DisAccruals*$_t$	High	Low	High	Low	High	Low	High	Low
NonGaapFreq$^{NG>G}_t$	**0.004**	**0.165****	**0.001**	**0.108*****	**-0.002**	**0.044*****	**-0.001**	**0.106*****
	(0.962)	**(0.045)**	**(0.972)**	**(0.002)**	**(0.912)**	**(0.002)**	**(0.989)**	**(0.002)**
NonGaapFreq$^{NG<G}_t$	0.163	-0.266	0.003	-0.194**	0.007	-0.077**	0.030	-0.182**
	(0.352)	(0.194)	(0.967)	(0.012)	(0.827)	(0.020)	(0.710)	(0.017)
NSkewness$_t$	0.094***	0.065**	0.061***	0.034***	0.026***	0.017***	0.060***	0.037***
	(0.001)	(0.027)	(0.000)	(0.007)	(0.000)	(0.001)	(0.000)	(0.003)
Size$_t$	0.009	0.031*	0.029***	0.027***	0.011***	0.012***	0.023***	0.026***
	(0.590)	(0.079)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)
MTB$_t$	0.012*	0.015**	0.005	0.004	0.002	0.002	0.005*	0.006*
	(0.089)	(0.035)	(0.150)	(0.272)	(0.162)	(0.141)	(0.095)	(0.092)
Leverage$_t$	-0.223	-0.086	-0.160**	-0.045	-0.072**	-0.023	-0.160**	-0.048
	(0.152)	(0.594)	(0.020)	(0.495)	(0.011)	(0.394)	(0.018)	(0.456)
ROA$_{t+1}$	-0.647***	-0.448**	-0.447***	-0.354***	-0.167***	-0.136***	-0.424***	-0.325***
	(0.001)	(0.015)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Return$_t$	16.740***	11.572***	14.725***	13.240***	6.741***	6.354***	14.229***	12.447***
	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sigma$_t$	0.904	-0.121	-0.806	-1.015**	-0.478**	-0.470**	-0.604	-0.812
	(0.474)	(0.925)	(0.190)	(0.046)	(0.046)	(0.022)	(0.297)	(0.102)
ChgTurnover$_t$	0.051**	-0.016	0.028***	0.003	0.010**	0.001	0.027***	-0.000
	(0.021)	(0.490)	(0.007)	(0.758)	(0.010)	(0.871)	(0.005)	(0.964)
DisAccruals$_t$	1.376***	0.472	0.253	0.166	0.098	0.081	0.385*	0.216
	(0.005)	(0.166)	(0.254)	(0.299)	(0.267)	(0.194)	(0.075)	(0.160)

SqDisAccruals$_t$	-1.379**	-0.009	-0.303	-0.137	-0.107	-0.025	-0.412	-0.069
	(0.017)	(0.985)	(0.266)	(0.565)	(0.323)	(0.781)	(0.117)	(0.758)
N	10,092	10,133	10,092	10,133	10,092	10,133	10,092	10,133
R^2	0.021	0.029	0.017	0.034	0.020	0.039	0.019	0.035
Tests of Diff. between High and Low:								
NonGaapFreq$^{NG>G}_t$ (*p*-value)	(0.08)		(<0.01)		(<0.01)		(<0.01)	

This table reports the relation between non-GAAP reporting frequency and stock price crash risk conditional on the level of accrual management. Variable definitions are available in Appendix A. Constant terms, industry-, and year- fixed effects are included but not reported. We report z(*t*)-statistics based on robust standard errors to heteroscedasticity, which we also cluster at the firm level, in parentheses in columns 1-2 (in columns 3-8). ∗∗∗, ∗∗, ∗ denote statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 5
Managerial Incentives

Panel A: Market Sentiment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Crash$_{t+1}$		*NSkewness*$_{t+1}$		*LnDuVol*$_{t+1}$		*Crash Composite*$_{t+1}$	
Par. Var. = *MktSent*$_t$	High	Low	High	Low	High	Low	High	Low
NonGaapFreq$^{NG>G}_t$	**0.266*** **	**0.115**	**0.136*** **	**0.036**	**0.059*** **	**0.018**	**0.145*** **	**0.047**
	(0.009)	**(0.146)**	**(0.002)**	**(0.272)**	**(0.001)**	**(0.181)**	**(0.001)**	**(0.155)**
Other variables:	Included		Included		Included		Included	
N	7,938	11,726	7,938	11,726	7,938	11,726	7,938	11,726
R^2	0.030	0.030	0.019	0.024	0.024	0.027	0.024	0.026
Tests of Diff. between High and Low:								
NonGaapFreq$^{NG>G}_t$ (*p*-value)	(0.10)		(<0.01)		(<0.01)		(<0.01)	

Panel B: Non-GAAP to Meet-or-Beat Earnings Forecasts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Crash$_{t+1}$		*NSkewness*$_{t+1}$		*LnDuVol*$_{t+1}$		*Crash Composite*$_{t+1}$	
Par. Var. = *FreqMBE*$_t$	High	Low	High	Low	High	Low	High	Low
NonGaapFreq$^{NG>G}_t$	**0.203***	**0.110**	**0.099***	**0.045**	**0.038***	**0.017**	**0.100****	**0.049**
	(0.083)	**(0.127)**	**(0.052)**	**(0.156)**	**(0.069)**	**(0.187)**	**(0.045)**	**(0.121)**
Other variables:	Included		Included		Included		Included	
N	4,308	13,763	4,308	13,763	4,308	13,763	4,308	13,763
R^2	0.042	0.032	0.031	0.032	0.033	0.036	0.033	0.035
Tests of Diff. between High and Low:								
NonGaapFreq$^{NG>G}_t$ (*p*-value)	(0.10)		(0.10)		(0.10)		(0.10)	

Panel C: Sensitivity of Compensation to Share Price

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Crash_{t+1}$		$NSkewness_{t+1}$		$LnDuVol_{t+1}$		$Crash\ Composite_{t+1}$	
Par. Var. = $Delta_t$	High	Low	High	Low	High	Low	High	Low
$\boldsymbol{NonGaapFreq^{NG>G}_t}$	**0.160***	**0.005**	**0.129*****	**-0.029**	**0.052*****	**-0.007**	**0.120*****	**-0.017**
	(0.089)	**(0.962)**	**(0.003)**	**(0.528)**	**(0.002)**	**(0.731)**	**(0.004)**	**(0.714)**
Other variables:	Included		Included		Included		Included	
N	5,987	6,000	6,006	6,007	6,006	6,007	6,006	6,007
R^2	0.032	0.031	0.030	0.037	0.039	0.044	0.034	0.038
Tests of Diff. between High and Low:								
$NonGaapFreq^{NG>G}_t$ (*p*-value)	(0.05)		(<0.01)		(<0.01)		(<0.01)	

Panel D: Opportunistic Insider Sales

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Crash_{t+1}$		$NSkewness_{t+1}$		$LnDuVol_{t+1}$		$Crash\ Composite_{t+1}$	
Par. Var. = $OpptunSales_t$	High	Low	High	Low	High	Low	High	Low
$\boldsymbol{NonGaapFreq^{NG>G}_t}$	**0.170****	**0.096**	**0.097*****	**0.031**	**0.042*****	**0.011**	**0.101*****	**0.036**
	(0.025)	**(0.165)**	**(0.003)**	**(0.313)**	**(0.002)**	**(0.366)**	**(0.002)**	**(0.230)**
Other variables:	Included		Included		Included		Included	
N	10,112	17,654	10,112	17,654	10,112	17,654	10,112	17,654
R^2	0.031	0.028	0.024	0.034	0.029	0.038	0.029	0.036
Tests of Diff. between High and Low:								
$NonGaapFreq^{NG>G}_t$ (*p*-value)	**(<0.01)**		**(<0.01)**		**(<0.01)**		**(<0.01)**	

This table reports the relation between non-GAAP reporting frequency and stock price crash risk conditional on the level of market sentiment (*MktSent*), frequency of using non-GAAP reporting to help meet or beat analyst earnings forecasts (*FreqMBE*), sensitivity of executive compensation to share price (*Delta*), and opportunistic insider sales (*OpptunSales*). Variable definitions are available in Appendix A. Constant terms, industry-, and year- fixed effects are included but not reported. We report z(*t*)-statistics based on robust standard errors to heteroscedasticity, which we also cluster at the firm level, in parentheses in columns 1-2 (columns 3-8). ∗∗∗, ∗∗, ∗ denote statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 6
Sign of Exclusions Using I/B/E/S Data and Stock Price Crash Risk

	Dependent Variables			
	(1)	(2)	(3)	(4)
	$Crash_{t+1}$	*$NSkewness_{t+1}$*	*$LnDuVol_{t+1}$*	*$Crash\ Composite_{t+1}$*
$NonGaapFreq^{NG>G}_t$	**0.155*** **	**0.049*** **	**0.020*** **	**0.059*** **
	(0.000)	**(0.007)**	**(0.006)**	**(0.001)**
$NonGaapFreq^{NG<G}_t$	**-0.003**	**-0.014**	**-0.003**	**-0.009**
	(0.970)	**(0.613)**	**(0.793)**	**(0.734)**
$NSkewness_t$	0.081***	0.050***	0.022***	0.051***
	(0.000)	(0.000)	(0.000)	(0.000)
$Size_t$	0.020*	0.027***	0.011***	0.023***
	(0.061)	(0.000)	(0.000)	(0.000)
MTB_t	0.010**	0.005**	0.002**	0.005**
	(0.033)	(0.035)	(0.017)	(0.014)
$Leverage_t$	-0.121	-0.091**	-0.042**	-0.091**
	(0.209)	(0.026)	(0.011)	(0.024)
ROA_{t+1}	-0.616***	-0.452***	-0.170***	-0.421***
	(0.000)	(0.000)	(0.000)	(0.000)
$Return_t$	14.382***	14.422***	6.725***	13.662***
	(0.000)	(0.000)	(0.000)	(0.000)
$Sigma_t$	1.274*	-0.800**	-0.455***	-0.541*
	(0.098)	(0.016)	(0.001)	(0.090)
$ChgTurnover_t$	0.026*	0.017***	0.007***	0.016***
	(0.053)	(0.003)	(0.004)	(0.004)
$DisAccruals_t$	0.363***	0.083	0.036*	0.117**
	(0.002)	(0.117)	(0.086)	(0.022)
$SqDisAccruals_t$	-0.307	-0.162*	-0.054	-0.151*
	(0.119)	(0.090)	(0.148)	(0.095)
N	30,336	30,336	30,336	30,336
R^2	0.026	0.025	0.030	0.028
F-tests (Chi-squared):				
$NonGaapFreq^{NG>G} = NonGaapFreq^{NG<G}$				
	4.35**	4.34**	3.49*	5.21**

This table reports the relation between non-GAAP reporting frequency and stock price crash risk conditional on the sign of net total exclusions and using I/B/E/S data from 2003-2015 to identify non-GAAP reporting. Variable definitions are available in Appendix A except that we replace non-GAAP EPS from managers with I/B/E/S Actual EPS. Constant terms, industry-, and year- fixed effects are included but not reported. We report z(*t*)-statistics based on robust standard errors to heteroscedasticity, which we also cluster at the firm level, in parentheses in column 1 (columns 2-4). ∗∗∗, ∗∗, ∗ denote statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 7
Difference-in-Differences Design around Regulation G using I/B/E/S Data

	Dependent Variables							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Crash$_{t+1}$	*NSkewness*$_{t+1}$	*LnDuVol*$_{t+1}$	*Crash Composite*$_{t+1}$	*Crash*$_{t+1}$	*NSkewness*$_{t+1}$	*LnDuVol*$_{t+1}$	*Crash Composite*$_{t+1}$
Treatment	0.812***	0.237***	0.089***	0.273***	0.952***	0.280***	0.109***	0.332***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Post × Treatment	**-0.607****	**-0.245*****	**-0.085****	**-0.248*****				
	(0.013)	**(0.002)**	**(0.010)**	**(0.003)**				
Post -1 × Treatment					**-0.306**	**-0.085**	**-0.040**	**-0.119**
					(0.450)	**(0.387)**	**(0.375)**	**(0.281)**
Post 0 × Treatment					**-0.770****	**-0.312****	**-0.116****	**-0.333*****
					(0.019)	**(0.012)**	**(0.019)**	**(0.007)**
Post +1 × Treatment					**-0.726****	**-0.263****	**-0.094***	**-0.282****
					(0.030)	**(0.017)**	**(0.055)**	**(0.019)**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12,142	12,160	12,160	12,160	12,142	12,160	12,160	12,160
R^2	0.114	0.084	0.092	0.088	0.115	0.084	0.092	0.088

This table reports the relation between non-GAAP reporting and stock price crash risk using a difference-in-differences research design around Regulation G. Variable definitions are available in Appendix A. Constant terms, industry-, and year- fixed effects are included but not reported. We report z(*t*)-statistics based on robust standard errors to heteroscedasticity, which we also cluster at the firm level, in parentheses in columns 1 and 5 (columns 2-4 and 6-8). ∗∗∗, ∗∗, ∗ denote statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 8
Future Stock Return

	Dependent Variable		
	(1)	(2)	(3)
	$BHAR_{t+1,\ t+1}$	$BHAR_{t+1,\ t+2}$	$BHAR_{t+1,\ t+3}$
$\boldsymbol{NonGaapFreq_t}$	**0.079*****	**0.108*****	**0.078*****
	(0.000)	**(0.000)**	**(0.005)**
$\boldsymbol{Crash_{t+1}}$	**-0.018***	**-0.015**	**-0.091*****
	(0.086)	**(0.198)**	**(0.000)**
$\boldsymbol{NonGaapFreq_t \times Crash_{t+1}}$	**-0.270*****	**-0.319*****	**-0.302*****
	(0.000)	**(0.000)**	**(0.000)**
$NSkewness_t$	-0.011*	-0.002	0.046***
	(0.058)	(0.825)	(0.000)
$Size_t$	-0.010***	-0.009**	0.005
	(0.000)	(0.017)	(0.394)
MTB_t	-0.002**	-0.006***	0.032***
	(0.031)	(0.002)	(0.000)
$Leverage_t$	0.191***	0.240***	-0.144**
	(0.000)	(0.000)	(0.045)
ROA_{t+1}	0.844***	0.848***	1.669***
	(0.000)	(0.000)	(0.000)
$Return_t$	-10.474***	70.774***	60.575***
	(0.000)	(0.000)	(0.000)
$Sigma_t$	2.470***	6.192***	6.043***
	(0.000)	(0.000)	(0.000)
$ChgTurnover_t$	0.005	0.015**	0.091***
	(0.132)	(0.027)	(0.000)
$DisAccruals_t$	-0.109***	-0.120***	-0.226
	(0.000)	(0.002)	(0.223)
$SqDisAccruals_t$	0.059	0.079	0.903***
	(0.192)	(0.236)	(0.008)
N	29,722	29,722	29,722
R^2	0.063	0.318	0.153

This table reports the results from estimating the joint effect of non-GAAP reporting frequency and stock price crash risk on future stock return. Variable definitions are available in Appendix A. Constant terms, industry-, and year- fixed effects are included but not reported. We report *t*-statistics based on robust standard errors to heteroscedasticity, which we also cluster at the firm level, in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.