The Use of Non-financial Performance Measures in CEO Compensation Contracts and Stock Price Crash Risk*

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ABSTRACT: This study examines whether the adoption of non-financial performance measures (NFPMs) in chief executive officer (CEO) compensation contracts is related to stock price crash risk. Given that NFPMs motivate managers to focus on long-term perspectives and are leading indicators of long-term performance (e.g., Feltham and Xie 1994; Hemmer 1996; Banker et al. 2000), we hypothesize and find that the use of NFPMs in CEO compensation contracts mitigates future crash risk. We also find that a decline in crash risk following the use of NFPMs is more pronounced for firms with a higher level of opaqueness and for those with CEO option-induced excessive risk taking incentives. Overall, this study contributes to the literature by showing a negative relation between the use of NFPMs and future crash risk as well as identifying circumstances in which such a relation is more evident.

Keywords: non-financial performance measures; CEO compensation; stock price crash risk; opaqueness; risk taking incentives.

Data Availability: Data are available from the public sources cited in the text.

I. INTRODUCTION

This study examines whether the use of non-financial performance measures (NFPMs) in chief executive officer (CEO) compensation contracts affects future stock price crash risk ("crash risk" hereafter). We also investigate whether the association between NFPMs and crash risk varies depending on the level of financial reporting opacity and CEO excessive risk taking incentives.

Crash risk, which captures asymmetry in risk, has drawn increasing attention in the literature as it is an important dimension of investment decisions and risk management (e.g., Jin and Myers 2006; Hutton, Marcus, and Tehranian 2009; Kim, Li, and Zhang 2011a, b; DeFond, Hung, Li, and Li 2015). Specifically, these studies suggest that managers have a general tendency to withhold and accumulate bad news for an extended period. Once the accumulated bad news is released all at once, stock price can crash (e.g., Jin and Myers 2006). Further, a theoretical study by Benmelech, Kandel, and Veronesi (2010) shows that equity-based compensation incentivizes managers to hide bad news related to future growth options, eventually leading to a subsequent crash in stock price. This suggests that a firm's crash risk can be attributed to the design of the firm's CEO compensation program.

As leading indicators of long-term performance, NFPMs are used in the design of CEO compensation contracts to improve performance measurement systems by aligning managerial actions to a firm's strategy (e.g., Kaplan and Norton 1996). A widespread use of NFPMs in CEO compensation contracts has drawn considerable interest in the literature (e.g., Ittner, Larker, and Rajan 1997; Said, HassabElnaby, and Wier 2003; Banker and Mashruwala 2007). However, despite the growing popularity of NFPMs incorporated in CEO compensation contracts and the increased attention to crash risk, the link between these two issues is unexplored. This study seeks to fill this void.

Numerous studies suggest that, compared with financial performance measures, NFPMs often lead to a better strategic alignment and thus result in higher long-term performance and firm value (e.g., Kaplan and Norton 1996; Ittner and Larcker 1998a, b; Banker, Potter, and Srinivasan 2000; Nagar and Rajan 2001; Said et al. 2003; Banker and Mashruwala 2007).[1] Based primarily on these prior findings, we expect the use of NFPMs in CEO compensation contracts to mitigate crash risk because of several reasons.

First, prior studies suggest that the use of NFPMs generally induces manager efforts to attain long-term perspectives and reduces myopic manager behavior (e.g., Feltham and Xie 1994; Hemmer 1996; Davila and Venkatachalam 2004). For instance, in their theoretical work, Feltham and Xie (1994) postulate that NFPMs can add value by motivating managers to exert long-term focused effort. Consistent with this view, Banker et al. (2000) show that NFPMs complement the short-term perspective of financial figures as drivers of a firm's long-term goals. Accordingly, these long-term oriented attributes of NFPMs will reduce managers' short-term oriented behaviors, such as concealment of bad news, thereby lowering crash risk.

Second, the use of NFPMs can also reduce excessive managerial risk taking incentives, which some practitioners and academics (e.g., Bebchuk 2009; Kim et al. 2011a) have blamed for having caused recent financial crises. While NFPMs generally encourage risk taking and innovation (e.g., Chow and Van der Stede 2006), their long-term orientation can attenuate *excessive* risk taking incentives, which reflect managerial incentives to seek short-term performance with the sacrifice of long-term value and can thus be viewed undesirable from

[1] For example, Nagar and Rajan (2001) show that nonfinancial quality measures, including on-time deliveries and defect rates, are leading indicators of future sales. Ittner and Larcker (1998a) find that, for firms in the telecommunication industry, customer satisfaction is positively associated with future financial performance. Banker et al. (2000) report a similar inference for hotels managed by a hospitality firm.

the shareholders' standpoint.[2,3] Thus, to the extent that financial crises are manifested as stock price crashes, the adoption of NFPMs is expected to attenuate an abrupt decline in stock price.

Third, by incorporating important information that is not captured by financial performance measures (FPMs), NFPMs can predict a firm's future financial performance better than do financial performance measures (e.g., Banker et al. 2000; Nagar and Rajan 2001; Dikolli, Kinney Jr. and Sedatole 2007).[4] Thus, as leading indicators, NFPMs integrated in executive compensation contracts can help managers obtain an early indication of a potential decline in future performance and respond to such a negative signal more timely than when considering only FPMs.[5] Moreover, to the extent that the leading indicator attribute of NFPMs helps early inform stakeholders of negative news, managers will face high pressure from those stakeholders to make prompt responses. Such responses, if made properly, would result in a decline in crash risk.

On the other hand, some NFPMs might not fully identify what they are intended to capture (Nagar and Rajan 2001). For instance, product quality measures might not accurately reflect how customers perceive the company's product. Moreover, survey evidence (e.g.,

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[2] For example, Bebchuk and Spamann (2010, 274) suggest that "when pay arrangements reward executives for short-term gains, executives may have incentives to seek short-term gains even when doing so may adversely affect the expected long-term value of shareholder interests by creating an excessive risk of an implosion down the road."

[3] Some firms clearly indicate in their proxy statements that NFPMs help reduce the potential for excessive risk taking. For example, in its proxy statement (dated March 22, 2011), American Express Company states that "customer and employee goals reinforce the long-term strength of our business and help reduce the potential for excessive risk taking."

[4] For example, Ittner and Larcker (1998a, 1) state that "improvements in areas such as quality, customer or employee satisfaction, and innovation represent investments in firm-specific assets that are not fully captured in current accounting measures."

[5] Note that this argument does not necessarily imply an asymmetric treatment of bad vs. good news with respect to NFPMs. That is, we do not rule out the possibility that the use of NFPMs provides an early signal of improvements in future performance. In this case, firms will need to continue the operations with positive signals. However, we do not focus on this possibility, which has little clear implication for crash risk.

Ittner and Larcker 2003) reveals that few firms realize the benefits of NFPMs in practice. Further, NFPMs might be more easily manipulated than FPMs (Ittner et al. 1997). Therefore, it is an empirical question whether the use of NFPMs effectively attenuates crash risk.

The expected negative relation between use of NFPMs and crash risk can vary depending on two circumstances: (1) the level of financial reporting opacity and (2) the existence of excessive managerial risk taking incentives. First, existing literature reports that opaque stocks are more likely to crash, resulting in large negative returns (e.g., Jin and Myers 2006; Hutton et al. 2009). We conjecture that, compared to firms in transparent reporting environments, those in opaque reporting environments are more likely to enjoy the benefits of using NFPMs because NFPMs can serve a monitoring role constraining managers from hiding bad news. As such, if the inclusion of NFPMs in CEO compensation contracts helps mitigate subsequent crash risk, we predict that such a relation will be more evident for firms with a higher level of opaqueness.

Second, several studies imply a positive association between crash risk and managerial excessive risk taking behaviors, such as risky investments, induced by stock options (Bebchuk 2009; Kim et al. 2011a). Moreover, Coles, Daniel, and Naveen (2006) report that CEOs with higher vega (i.e., the sensitivity of a manager's option portfolio value to stock return volatility) implement riskier policy choices. These prior findings suggest that, as a proxy for CEOs' excessive risk taking incentives, extremely high CEO vega is positively associated with crash risk. As previously discussed, however, the use of NFPMs is likely to attenuate short-term oriented incentives, such as excessive managerial risk taking incentives. Accordingly, we expect a positive relation, if any, between extremely high values of CEO vega and future crash risk to be weaker for firms that use NFPMs in their CEO compensation arrangements.[6]

Following the literature (e.g., Chen, Hong, and Stein 2001; Hutton et al. 2009; Kim et al. 2011a), we use three proxies for firm-specific crash risk: (1) the probability of extremely negative firm-specific weekly returns, (2) the negative skewness of weekly returns, and (3) the asymmetric volatility of negative and positive weekly returns. We hand-collect data on NFPMs for firms listed on the Standard and Poor 500 (S&P 500) index over the years 2006-2012, to focus on the period after year 2006 when the U.S. Securities and Exchange Commission (SEC) required firms to disclose the details of their executive compensation plans and performance measures. Overall, we find some evidence of the use of NFPMs mitigating crash risk. Specifically, the association between the adoption of NFPMs and future crash risk is significantly negative for the last two measures of crash risk. We also find that a decline in crash risk following the use of NFPMs is more evident for firms with a higher level of opaqueness and for firms with extremely high CEO vega. These results are generally consistent with our predictions.

This study makes several contributions to the literature. First, extant literature shows that NFPMs promote firms' long-term performance, thereby enhancing firm values. In particular, NFPMs contribute to performance measurement systems by providing more timely feedback and mitigating inherent risk (e.g., Feltham and Xie 1994; Said et al. 2003). Our study extends this line of research by showing that the use of NFPMs leads to a lower future crash risk, especially under certain circumstances (i.e., more opaque financial reporting environments and CEOs with excessive risk taking incentives).

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[6] While Kim et al. (2011a) do not find a significant positive relation between CEO vega and crash risk, they state (p. 726): "However, given the extensive risk taking behavior of the financial industry before the financial crisis, it is still early to completely rule out the role of excessive risk taking in creating crashes." We test this conjecture with a focus on extremely high (but not all) values of CEO vega.

Second, our study contributes to the literature on crash risk. Unlike the risks related to symmetric volatilities, crash risk captures asymmetric volatilities and cannot be attenuated through portfolio diversification (Sunder 2010). Accordingly, mitigating crash risk is an important issue in investment and risk management decisions. By highlighting the unique role of NFPMs in reducing crash risk, our study adds value to the research on portfolio and risk management.

Third, by providing an alternative mechanism (i.e., NFPMs) through which managerial incentives affect crash risk, this paper sheds light on the relation between managerial incentives and crash risk. In particular, Kim et al. (2011a) argue that option-induced managerial risk taking itself might not lead to a higher crash risk. However, we provide evidence that extremely high levels of CEO vega are positively related to future crash risk, and that the use of NFPMs mitigates such a positive relation.

Finally, our study has important implications for investors as well as firms. Recent financial crises and stock market instability have led investors to pay increased attention to the importance of stock price crashes because of the widespread use of equity-based compensation. This study identifies and shows the use of NFPMs as another important mechanism that attenuates future crash risk.

The remainder of this paper is organized as follows. Section II discusses background and hypotheses. Section III describes the sample selection and variable measurement. Section IV presents the empirical results. Section V concludes.

II. BACKGROUND AND HYPOTHESES

Stock Price Crash Risk

Several theoretical studies identify managers' bad news hoarding as the main cause of stock price crashes. For instance, Benmelech et al. (2010) show that equity-based compensation motivates managers to hide bad news related to future growth options, and this bad news hoarding eventually results in a stock price crash. Jin and Myers (2006) also suggest that accumulation of bad news over an extended period causes stock price to decline abruptly when the accumulated bad news reaches a certain "tipping point." Relatedly, Bleck and Liu (2007) document that failure of stakeholders to discern negative net present value (NPV) projects at an early stage allows managers to continue bad projects whose poor performance accumulates and materializes, resulting in a crash in asset prices.

A number of empirical studies confirm these theories, by providing evidence of firm-specific crash risk relating to the opaqueness of financial reporting (Hutton et al. 2009), executive equity incentives (Kim et al. 2011a), and corporate tax avoidance (Kim, Li, and Zhang 2011b). In particular, Hutton et al. (2009) examine the relation between the opaqueness of financial reporting and the distribution of stock returns and find that opaque firms are more prone to stock price crashes. Focusing on executive equity incentives, Kim et al. (2011a) show that the sensitivity of a chief financial officer's option portfolio value to stock price is positively associated with the firm's future crash risk. Collectively, existing evidence suggests that effective design of executive compensation contracts can reduce the likelihood of stock price crashes, and that such effectiveness varies with the degree of opaqueness of financial reporting and managerial risk taking incentives.

Non-financial Performance Measures in CEO Compensation Contracts

Existing theoretical studies suggest that NFPMs can provide incremental information about CEOs' actions regarding financial measures (e.g., Banker and Datar 1989; Feltham and Xie 1994; Hemmer 1996). For instance, Hemmer (1996) claims that NFPMs reflect activities not fully captured by contemporaneous operating results. This is consistent with the view that NFPMs might be useful in compensation contracts if they provide incremental information about the agent's effort beyond accounting measures (e.g., Banker and Datar 1989; Davila and Venkatachalam 2004).[7] In a related study, Feltham and Xie (1994) also assert that NFPMs are useful in evaluating managers' performances because they can be used to supplement noisy financial measures.

Traditional financial measures typically capture past and current operating performances. Conversely, NFPMs are indicators of current managerial actions that continue to have positive effects on future performance (Kaplan and Norton 1996). Consistent with this view, numerous studies report that NFPMs lead to better strategic alignment and result in higher future performance and firm value (e.g., Hauser, Simester, and Wernerfelt 1994; Kaplan and Norton 1996; Ittner and Larcker 1998a, b; Banker et al. 2000; Nagar and Rajan 2001; Said et al. 2003; Banker and Mashruwala 2007). For instance, Hauser et al. (1994) provide empirical evidence that use of customer satisfaction increases long-term sales. Banker et al. (2000) also show that, by motivating managers to focus more on long-term perspective behavior, a customer satisfaction measure is significantly associated with future financial performance in the hospitality industry. Moreover, Banker and Mashruwala (2007) demonstrate that both employee satisfaction and customer satisfaction contribute to future profitability. In sum, the findings from existing literature suggest that use of NFPMs not only provides incremental information over financial measures, but also leads to higher operational performance.

Hypothesis Development

As discussed previously, we predict the use of NFPMs to attenuate crash risk for the following reasons. First, NFPMs promote managers' long-term aspects of actions and thus reduce managers' bad news hoarding, which is the main cause of stock prices crashes.

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[7] Banker and Data (1989) show that multiple performance measures are available for evaluating managerial performance. If the intensity of any measure is greater, the optimal performance evaluation will depend on earnings number and the more intense measure.

Second, the integration of NFPMs in CEO compensation contracts can help attenuate excessive managerial risk taking incentives that would otherwise result in stock price crashes. Third, as leading indicators of future performance, NFPMs will provide managers with an early signal of a potential decline in future performance, allowing them to respond more timely.

In contrast, the aforementioned anticipated benefits of NFPMs might not be realized for several reasons. First, some NFPMs might not fully reflect what they are intended to capture. For example, customer satisfaction measures might not accurately reflect customers' perceptions of the products, for which customers would be willing to make future purchases, and defect rate measures might not correctly identify the types of defects that are important to customers (Nagar and Rajan 2001). Under these circumstances, the benefits of NFPMs could be compromised. Second, survey evidence reveals that few firms realize the benefits of NFPMs in practice because they fail to choose and act on the right NFPMs, especially when too many nonfinancial measures are used (Ittner and Larcker 2003). Third, relative to FPMs, several NFPMs including customer satisfaction survey results might be more prone to managerial manipulation, while being less subject to public verification (Ittner et al. 1997). As a result, investors and analysts might believe that reported NFPMs are biased, and their computation method can change over time (Eccles and Mavrinac 1995). These arguments suggest that managers might use NFPMs opportunistically while still withholding bad news.

In sum, while the inclusion of NFPMs in CEO compensation arrangements is expected to reduce crash risk, it is *ex ante* unclear whether this prediction will hold empirically. Keeping this tension in mind, we state our first hypothesis in alternative form, as follows:

H1: The use of NFPMs in CEO compensation contracts mitigates crash risk.

The anticipated effect of using NFPMs on crash risk can vary depending on the level of financial reporting opacity and the degree of managerial risk taking incentives. To address these issues, we first examine whether the association of NFPMs with crash risk is more evident for firms that operate in a more opaque environment. Previous studies suggest that crash risk increases with financial reporting opacity, which facilitates managerial bad news hoarding through specific mechanisms such as earnings management (Hutton et al. 2009) and complex tax planning (Kim et al. 2011b). In a similar vein, Jin and Myers (2006) provide international evidence that stocks in opaque countries are more likely to crash compared to stocks in transparent countries. Together, prior evidence suggests that opaque firms are more likely to withhold bad news from investors.

We conjecture that, compared to firms operating in transparent reporting environments, those in opaque reporting environments are more likely to enjoy the benefits from using NFPMs. In a transparent reporting environment where bad news hoarding is typically less feasible, the long-term focus of NFPMs might not add much in terms of reducing the withholding of bad news. In contrast, in an opaque reporting environment in which managers are likely to hide bad news easily, the adoption of NFPMs can motivate managers to limit the withholding of bad news. Thus, if the use of NFPMs mitigates crash risk, the expected negative association between use of NFPMs and crash risk is expected to be more evident when the firm operates in a more opaque reporting environment.

On the other hand, several studies document that NFPMs can be more subject to managerial manipulation (Ittner et al. 1997; Banker et al. 2000). This implies that the adoption of NFPMs can exacerbate crash risk for firms operating in opaque environments, where NFPMs as well as FPMs are likely to be managed. Therefore, it remains equivocal as to whether the expected negative association between crash risk and use of NFPMs is more pronounced for firms operating in more opaque reporting environments. This leads to the second hypothesis in alternative form, as follows:

H2: A decline in crash risk for firms using NFPMs in CEO compensation contracts is more pronounced for firms with a higher level of opaqueness.

Next, we examine whether the expected relation between use of NFPMs and crash risk is influenced by managers' option-induced excessive risk taking incentives. Prior studies argue that excessive risk taking incentives induced by stock options are the main cause of recent financial crises (e.g., Bebchuk 2009; Kim et al. 2011a). To the extent that a financial crisis is manifested as stock price crashes, this argument implies a positive association between crash risk and managerial excessive risk taking behaviors, such as risky investments, induced by stock options. Moreover, in terms of investment policy, Coles et al. (2006) report that a higher CEO vega is associated with riskier policy choices. This evidence suggests that extremely high CEO vega is attributable to crash risk. Note that the use of NFPMs is likely to attenuate short-term oriented incentives, such as excessive managerial risk taking incentives. Therefore, we predict that a positive association, if any, between extremely high CEO vega and subsequent crash risk will be weakened for firms that use NFPMs in their CEO compensation contracts.[8] This leads to our third hypothesis, stated in alternative form:

H3: A decline in crash risk for firms using NFPMs in CEO compensation contracts is more pronounced for firms with extremely high CEO vega.

III. SAMPLE SECLECTION AND VARIABLE MEASUREMENT

Sample Construction

[8] Regarding the role of NFPMs in curtailing managerial risk taking incentives, Bouwens and van Lent (2010) examine a setting where a firm considers using NFPMs in evaluating the performance of business unit managers. They suggest that the firm is more concerned about receiving early signals about the potential outcome of a project when the business unit manager in charge has higher risk taking preferences, partially in order to prevent the unit manager from taking further risks in case the project is likely unprofitable. As a result, the firm puts a higher weight on NFPMs to evaluate the performance of business unit managers with higher risk taking preferences. While Bouwens and van Lent (2010) focus on business unit managers' innate preferences for risk taking, we shift the focus to CEOs' risk taking incentives induced by stock options.

We create a sample from the intersection of the S&P 500, CRSP, Compustat, ExecuComp, and I/B/E/S databases for the years 2006-2012. In particular, we collect information about NFPMs from proxy statements on the SEC's EDGAR database, based on the procedure described in Gan, Park, and Simerly (2016). Appendix A provides examples of proxy disclosures about the use of NFPMs in CEO compensation contracts. Specifically, based on the balanced scorecard framework, we provide a representative example for each of the following three categories: customer satisfaction, internal business processes, and learning and growth.

Our sample period starts in 2006, when the SEC required firms to disclose the details of their CEO compensation plans and performance measures. Prior to 2006, the extent to which firms disclosed those details varied substantially, leading to a potential non-random sampling issue (Chen, Matsumura, Shin, and Wu 2015). Focusing on the year 2006 and thereafter helps mitigate this issue.

To test our hypotheses, we employ a propensity-score matching technique to alleviate selection bias in our sample. Specifically, for the sample of S&P 500 firms that use NFPMs ("NFPM firms") and those that do not use NFPMs ("non-NFPM firms"), we estimate a logistic model of determinants that affect firms' decision to use NFPMs. For each NFPM firm, a non-NFPM firm with the closest propensity score is matched within a caliper width of 0.01 without replacement. A total of 424 NFPM firm-years are matched with the control sample, resulting in a final sample of 848 (= 424 x 2) firm-year observations.

Following Ittner et al. (1997) and Said et al. (2003), we use the following constructs that affect firm decision to use NFPMs: organizational strategy, quality strategy, regulatory environment, financial performance, product development cycle, exogenous noise in financial performance measures, and CEO influence. We collect the information necessary to compute these constructs based on the procedures described in related studies. Appendix B provides details of these constructs and discusses the results for estimating the logistic model.

Table 1 provides the distribution of NFPM firms by industry. The highest frequency occurs in the manufacturing industry (25.2 percent), followed by the computer industry (17.9 percent). Extractive and retail industries both comprise 8.5 percent of the sample.

[Insert Table 1 here]

Measurement of Crash Risk

Our analysis employs three measures of crash risk, which are computed following the literature on crash risk (e.g., Chen et al. 2001; Hutton et al. 2009; Kim et al. 2011a). All of the three measures require estimation of firm-specific weekly returns for each firm-year observation, which is obtained from the following expanded market model:

$$r_{j,\tau} = \alpha_j + \beta_{1j} r_{m,\tau-2} + \beta_{2j} r_{m,\tau-1} + \beta_{3j} r_{m,\tau} + \beta_{4j} r_{m,\tau+1} + \beta_{5j} r_{m,\tau+2} + \varepsilon_{j,\tau}, \qquad (1)$$

where $r_{j,\tau}$ is the return on stock j in week τ, and $r_{m,\tau}$ is the return on the CRSP value-weighted market index in week τ. The firm-specific weekly return for firm j in week τ, denoted as $W_{j,\tau}$, is measured as the natural log of one plus the residual from equation (1).

The first measure of crash risk captures the likelihood of extreme negative returns in a given fiscal year. Specifically, a firm is defined to have experienced a stock price crash in a given fiscal year if the firm-specific weekly return is 3.2 standard deviations below the mean firm-specific weekly returns at least once over the entire fiscal year. The resulting measure of crash risk for a given firm-year, denoted as *CRASH*, is an indicator variable that is equal to one if at least one crash week (as defined above) occurs during the fiscal year, and zero otherwise.

The second measure of crash risk, denoted as *NCSKEW*, is the negative conditional skewness of firm-specific weekly returns over the fiscal year. Specifically, we compute

NCSKEW for a given firm-year by taking the negative of the third moment of weekly returns during the same year and dividing it by the standard deviation of weekly returns raised to the third power, as follows:

$$NCSKEW_{j,t} = -[n(n-1)^{3/2}\sum W^3_{j,t}] / [(n-1)(n-2)(\sum W^2_{j,t})^{3/2}], \tag{2}$$

where $W_{j,\tau}$ is the firm-specific weekly return as defined above, and n is the number of weekly returns during year t. Since a negative sign is placed before the third moment, a higher value of *NCSKEW* indicates higher crash risk.

The third measure of crash risk, denoted as *DUVOL*, is the down-to-up volatility measure of crash likelihood, which captures the conditional skewness of return distribution in a similar vein to *NCSKEW*. Specifically, for each firm-year, we partition all weeks with firm-specific weekly returns into two groups, i.e., the weeks when the returns are below the annual mean ("down" weeks) and those when the returns are above the annual mean ("up" weeks). We then compute the standard deviation for each of these groups. *DUVOL* is calculated as the log of the ratio of the standard deviation on the down weeks to the standard deviation on the up weeks, as follows:

$$DUVOL_{j,t} = \log\{(n_u - 1)\sum_{down}W^2_{j,t} / (n_d - 1)\sum_{up}W^2_{j,t}\}, \tag{3}$$

where n_u and n_d are the numbers of up and down weeks in year t, respectively. A higher value of *DUVOL* indicates higher crash risk. Appendix C provides the definitions of all variables used in this study.

IV. EMPIRICAL RESULTS

Descriptive Statistics

Table 2 reports descriptive statistics. Panel A presents the descriptive statistics for the variables used in our regression analysis. The statistics for the three measures of crash risk are comparable to those reported in related studies (e.g., Kim et al. 2011a). Our proxy for opaqueness, *OPAQUE*, has a mean (median) of 0.006 (0.003). The mean (median) of *VEGA_RAW* (divided by 1,000) is 0.293 (0.205).[9] The distributions of control variables, which are defined in the next sub-section, are largely consistent with those reported in related studies. Panel B of Table 2 compares the descriptive statistics between NFPM firms and non-NFPM firms. For the three measures of crash risk, we do not find any meaningful difference between the two groups.

[Insert Table 2 here]

Results for Hypothesis 1: Effect of Use of NFPMs on Crash Risk

Hypothesis 1 predicts that the use of NFPMs in CEO compensation contracts results in a decline in crash risk. We test this hypothesis by estimating the following regression model:

$$CRASH\_RISK_{t+1} = \beta_0 + \beta_1 NFPM_t + Controls + Industry\ FE + \varepsilon_{t+1}, \quad (4)$$

where $CRASH\_RISK_{t+1}$ is each of the three measures of crash risk for year $t+1$ as defined above, $NFPM_t$ is an indicator variable that is equal to one if a firm uses one or more NFPMs in year t and zero otherwise. All regressions include industry fixed effects (*Industry FE*). We measure the dependent variable in the year after the use of NFPMs in order to mitigate a potential endogeneity issue. To the extent that the use of NFPMs results in a decline in crash risk, β_1 is expected to be negative.

Following the literature on crash risk (e.g., Chen et al. 2001; Hutton et al. 2009; Kim et al. 2011a, 2011b), we include control variables that are potential predictors of crash risk. *NCSKEW* is the negative skewness of firm-specific weekly returns as defined above. *TURNOVER* is the average monthly share turnover for the current year less the average monthly share turnover for the previous year. *RET* is the mean of firm-specific weekly

[9] *VEGA_RAW* is the raw value of the change in option value for a 0.01 change in stock-return volatility for a CEO's option portfolio divided by 1,000. Similarly, *DELTA* in Table 2 is the raw value of the change in a CEO's personal portfolio in response to a 1 percent change in the stock price divided by 1,000.

returns over the year, multiplied by 100. *SIGMA* is the standard deviation of firm-specific weekly returns over the year. *SIZE* is the log of the market value of equity. *BM* is the book value of equity divided by the market value of equity. *LEV* is total long-term debts divided by total assets. *ROA* is income before extraordinary items divided by beginning total assets. *ABSDA* is the absolute value of discretionary accruals, where discretionary accruals are estimated based on the modified Jones model (Dechow, Sloan, and Sweeney 1995). All of these control variables are measured for year *t* (year subscripts omitted for brevity in this paragraph).

Table 3 provides the results for the estimation of equation (4). For all regression analyses, we report test statistics based on the standard errors adjusted by a two-dimensional cluster at the firm and year levels (Petersen 2009). The results generally indicate that the variable of interest, *NFPM*, exhibits a negative association with one-year-ahead crash risk. Specifically, the coefficient on *NFPM* is significantly negative when the dependent variable is *NCSKEW* or *DUVOL*, while it is negative but insignificant in the regression of *CRASH*. Turning to the results for control variables, in the third column, we find that firms with a larger size, a lower leverage, and a higher absolute level of discretional accruals are associated with a higher level of *DUVOL*, consistent largely with prior studies. However, we note that the coefficients on other control variables are generally insignificant, possibly because our matching procedure reduces the variations in the values of those variables.

Overall, the results reported in Table 3 generally suggest that using NFPMs in CEO compensation contracts results in a decline in future crash risk, consistent with Hypothesis 1. The results are consistent with the notion that, by inducing managers to reduce short-term oriented behaviors, NFPMs can serve to mitigate crash risk.

[Insert Table 3 here]

Results for Hypothesis 2: Effect of Use of NFPMs on Crash Risk for Firms in Opaque Reporting Environments

Hypothesis 2 predicts that a decline in crash risk for firms using NFPMs in CEO compensation, as shown above, is more pronounced for firms with a higher level of opaqueness. To test this hypothesis, we estimate the following regression model:

$$CRASH\_RISK_{t+1} = \beta_0 + \beta_1 NFPM_t + \beta_2 OPAQUE_t + \beta_3 NFPM_t * OPAQUE_t + Controls + Industry\ FE + \varepsilon_{t+1}, \quad (5)$$

where $OPAQUE_t$ intends to capture opaqueness of a firm's reporting environment for year *t* and is calculated as the standard deviation of I/B/E/S analysts' forecasts as of year *t* of the firm's earnings in the following year, normalized by the mean forecast, and then divided by the square root of the number of analysts following that firm, as in Jin and Myers (2006). A higher value of $OPAQUE_t$ indicates a higher level of opaqueness of the firm's reporting environment. The control variables are the same as in equation (4). The variable of interest, $NFPM_t*OPAQUE_t$, is expected to have a negative coefficient to the extent that using NFPMs is effective in decreasing crash risk for firms with high opaqueness.

Table 4 presents the results for the estimation of equation (5). We first observe a positive association between the level of opaqueness ($OPAQUE_t$) and future crash risk, while the association is significant in the *NCSKEW* and *DUVOL* regressions. These results largely confirm the prior finding that crash risk is higher for firms operating in more opaque reporting environments. Turning to the main results, we find that the coefficient on $NFPM_t*OPAQUE_t$ is negative and significant at the 5% level for the regression of $NCSKEW_{t+1}$ and at the 10% level for the regressions of $CRASH_{t+1}$ and $DUVOL_{t+1}$. Further, an F-test indicates that the sum of the coefficients on $NFPM_t$ and $NFPM_t*OPAQUE_t$ is negative and significant at the 5% level from the regressions of $CRASH_{t+1}$ and $NCSKEW_{t+1}$ and at the 10% level from the regression of $DUVOL_{t+1}$. These results suggest that a decline in crash risk following the use of NFPMs is more pronounced for firms with opaque reporting environments, consistent with Hypothesis 2.

Overall, the results reported in Table 4 indicate that crash risk is positively related to a firm's opaqueness, and the use of NFPMs weakens such a positive relation. This implies that NFPMs serve a monitoring role to constrain managers from manipulating performance measures that could have been managed in a more opaque environment.

[Insert Table 4 here]

Results for Hypothesis 3: Effect of Use of NFPMs on Crash Risk for Firms Having CEOs with Excessive Risk Taking Incentives

Hypothesis 3 predicts that a decline in crash risk for firms using NFPMs in CEO compensation is more pronounced for firms that have CEOs with extremely high vega. To test this hypothesis, we estimate the following regression model:

$$CRASH\_RISK_{t+1} = \beta_0 + \beta_1 NFPM_t + \beta_2 HIGHVEGA_t + \beta_3 NFPM_t {*} HIGHVEGA_t + Controls + Industry\ FE + \varepsilon_{t+1}, \quad (6)$$

where $HIGHVEGA_t$ is equal to one if the change in option value for a 0.01 change in stock-return volatility for a CEO's option portfolio for year t, calculated as in Core and Guay (2002), is in the top quartile for a given year-industry combination, and zero otherwise.[10] While this method results in approximately 11% of the firm-year observations being classified as high CEO vega due to the relatively small size of our sample, it effectively captures CEOs' *excessive* risk taking incentives, which are considered to be the main cause of recent financial crises, as discussed in Bebchuk (2009) and Kim et al. (2011a). For the control variables, we additionally include $DELTA_t$ which is the change in a CEO's personal portfolio in response to a 1 percent change in the stock price. All other variables are as defined

[10] As Guay (1999) reports that option vega is substantially higher than stock vega, we measure a CEO's overall vega using only the vega from his option portfolio.

previously. The variable of interest, $NFPM_t*HIGHVEGA_t$, is expected to have a negative coefficient to the extent that a decline in crash risk following the use of NFPMs is more pronounced for firms with higher CEO vega.

Table 5 provides the results for the estimation of equation (6). We first note a positive relation between $HIGHVEGA_t$ and all three measures of crash risk, while the relation is significant when crash risk is proxied by *NCSKEW* and *DUVOL*. These results suggest that firms with extremely high levels of CEO vega are more likely to experience stock price crashes. While our results are in contrast to Kim et al.'s (2011a) finding that CEO vega is not significantly associated with future crash risk, the discrepancy in the results might be attributable to the differences in the measurement of CEO vega and the sample size. Turning to the main results, we find that $NFPM_t*HIGHVEGA_t$ is negatively associated with all three proxies for crash risk at least at the 10 percent level. Moreover, an F-test indicates that the sum of the coefficients on $NFPM_t$ and $NFPM_t*HIGHVEGA_t$ is significantly different from zero for all three measures of crash risk at the 5 percent level. These results suggest that a decline in crash risk following the use of NFPMs is more marked for firms with higher CEO vega, consistent with Hypothesis 3.

Overall, the results reported in Table 5 suggest that CEOs' excessive risk taking incentives are positively associated with future crash risk, and that using NFPMs in CEO compensation contracts helps mitigate such a positive association. This is consistent with the notion that the use of NFPMs can effectively constrain CEOs' excessive risk taking incentives, thereby leading to lower future crash risk.

[Insert Table 5 here]

Analysis Using NFPM Weights

The key variable, $NFPM_t$, that has been used thus far is an indicator variable capturing whether or not a firm uses NFPMs in a given year. However, this binary variable does not fully reflect the relative importance of NFPMs in CEO compensation contracts. To address this concern, we use the weight placed on NFPMs as an alternative variable to test our baseline hypothesis, H1. That is, we estimate equation (4) after substituting the weight on NFPMs ($NFPM\_W_t$) for $NFPM_t$.

Table 6 reports the results. We first note that the sample size is substantially smaller than in Table 3, but the reduction in sample size due to the use of NPFM weights in analyses is often reported in prior studies (e.g., Chen et al. 2015). Turning to the results, we observe a significantly negative association between the weight on NFPMs and future crash risk. Specifically, the coefficient on $NFPM\_W_t$ is negative and significant at the 10 percent level for all three measures of crash risk. Therefore, by using the weight placed on NFPMs, we corroborate our previous finding that the use of NFPMs in CEO compensation contracts results in a decline in future crash risk.

[Insert Table 6 here]

Analysis by NFPM Type

Our data indicate that NFPMs consist of many different types, leading to a question of what components of NFPMs drive our results. Accordingly, we repeat the baseline analyses using NFPM types. To do so, following previous studies (e.g., Bento and White 2010), we decompose NFPMs based on the three nonfinancial perspectives used in balanced scorecards (BSCs); customer satisfaction and market share (the customer perspective); quality process, re-engineering, new product development, innovation, and operational performance (the internal business process perspective); and employee or job satisfaction, productivity, efficiency, and job safety (the learning and growth perspective). All other NFPMs are classified as "others."

The results are reported in Table 7. We find that the negative relation between the use of NFPMs and crash risk is statistically significant only for the measures in the customer perspective category. For this category, the coefficient on $NFPM_t$ is significantly negative at the 5% level for the regression of $CRASH_{t+1}$ and at the 10% level for $NCSKEW_{t+1}$ and $DUVOL_{t+1}$. These results suggest that the negative association between the use of NFPMs and crash risk is mainly driven by customer-related measures, which prior research (e.g., Ittner et al. 1997; Chen et al. 2015) has found to be the most commonly used NFPMs in executive bonus contracts.

[Insert Table 7 here]

V. CONCLUSION

This study examines whether the inclusion of NFPMs in CEO compensation contracts is associated with crash risk. We also investigate whether the association between NFPMs and crash risk varies depending on the level of financial reporting opacity. We further examine how the use of NFPMs impacts the relation between CEOs' excessive risk taking incentives and crash risk.

Based on the prior evidence suggesting that NFPMs are leading indicators of long-term performance, we hypothesize and find that the use of NFPMs in CEO compensation contracts mitigates future crash risk. We also find that a decline in crash risk following the use of NFPMs is more pronounced for firms with a higher level of opaqueness and for CEOs with extremely high CEO vega. By showing that a firm's use of performance metrics in CEO compensation contracts has a significant effect on its crash risk especially under certain circumstances, our study provides new insights into the literature that examines NFPM issues in accounting research. Nonetheless, there are some caveats in our study. For instance, our findings should be interpreted with caution because our sample is limited to S&P 500 firms.

APPENDIX A
Examples of the Use of NFPMs in CEO Compensation Contracts in Proxy Statements

Customer Satisfaction: Cisco Systems, Inc. [emphasis added]

The Compensation Committee believes that the compensation programs for Cisco's executive officers should be designed to attract, motivate, and retain talented executives responsible for the success of Cisco and should be determined within a framework based on the achievement of designated financial targets, individual contribution, *customer satisfaction*, and financial performance relative to that of Cisco's competitors. Within this overall philosophy, the Compensation Committee's objectives are to: … provide annual variable cash incentive awards that take into account Cisco's overall financial performance in terms of designated corporate objectives, as well as individual contributions and a measure of *customer satisfaction*.

Internal Business Process: Bristol-Myers Squibb Co. [emphasis added]

For Mr. Andreotti, the Committee considered his leadership in: … effectively developing and preparing for the launch of several new products; *streamlining and simplifying our organizational structure and business processes*; and creating long-term sustainability through an industry-leading R&D pipeline as well as industry-leading expense management. The Committee also considered his agility at assuming the CEO role, creating and energizing his Senior Management Team, and mobilizing the organization behind our business strategy.

Learning and Growth: Qualcomm Inc. [emphasis added]

We intend for our compensation amounts to be internally fair and equitable relative to roles, responsibilities, and relationships among our NEOs. Accordingly, we also consider many other factors in the process of determining compensation levels for each NEO, including: the Compensation Committee's evaluation of the CEO and other NEOs; … *individual expertise, skills, and knowledge*; and leadership, including *developing and motivating employees,* collaborating within Qualcomm, *attracting and retaining employees and personal development*.

APPENDIX B
Estimation of the Logistic Model of the Determinants that Affect Firm Decision to Use NFPMs

In all regressions, we implement a propensity-score-matching (PSM) technique to alleviate selection bias that might be present in our sample. Specifically, we first estimate a logit regression to model the probability of the inclusion of NFPMs in CEO compensation contracts, following Ittner et al. (1997). In this stage, our treatment samples are firms that use NFPMs in CEO compensation contracts, and control samples are those that do not use NFPMs. The propensity scores are calculated as the predicted probabilities from the logit model. We match each treatment firm to a control firm using the propensity scores with a caliper width of 0.01 without replacement. Table A.1 provides the results for the estimation of the logit regression.

Table A.1
Estimation of the Logistic Model

Variable	Predicted Sign by Ittner et al. (1997)	Standardized Estimate	Wald Chi-square
STRATEGY	(+)	-0.058	1.723
QUAL	(+)	-0.315	0.003
TEL&UTIL	(+)	-0.096*	3.388
DISTRESS	(-)	-0.104***	23.129
DCYCLE	(+)	0.023	0.337
MNOISE	(-)	-0.045	1.319
LTCNTL	(-)	-0.104**	5.187
N		1,043	
Max-rescaled R^2		0.067	

*, **, and *** indicate statistical significance at the 0.1, 0.5, and 0.01 levels (two-tailed), respectively.

This table reports the results for the estimation of the following logit regression based on Ittner et al. (1997):

$$NFPM = \beta_0 + \beta_1 STRATEGY + \beta_2 QUAL + \beta_3 TEL\&UTIL + \beta_4 DISTRESS + \beta_5 DCYCLE + \beta_6 MNOISE + \beta_7 LTCNTL + \varepsilon$$

Variable definitions (all measured for year *t*):
NFPM is an indicator variable that is equal to one if the firm uses one or more NFPMs in CEO compensation contracts, and zero otherwise; *STRATEGY* is a factor score from *RDS*, *MtoB*, and *EMPS*, where *RDS* is the ratio of R&D to sales, average over five years prior to NFPM proxy date, *MtoB* is the market-to-book ratio, average over five years prior to NFPM proxy date, and *EMPS* is the ratio of

employees to sales, average over five years prior to NFPM proxy date. If R&D is missing but SG&A expense is not missing, then we set R&D to zero; *QUAL* is an indicator variable that takes the value of one if the firm received a major quality award, and zero otherwise; *TEL&UTIL* is an indicator variable that takes the value of one if the firm belongs to telecommunication or utility industry, and zero otherwise; *DISTRESS* is the average value of Altman Z-score over five years prior to NFPM proxy date; *DCYCLE* is an indicator variable that takes the value of one if the firm is classified as having a long-term product development cycle based on the National Academy of Engineering (1992), and zero otherwise; *MNOISE* is a factor score from *zROA, zROE*, and *zROS*, where *zROA* is the Fisher z-score for the correlation between annual market return and return on assets for a firm's three-digit SIC industry over the prior five years; *zROE* is the Fisher z-score for the correlation between annual market return and return on equity for a firm's three-digit SIC industry over the prior five years; and *zROS* is the Fisher z-score for the correlation between annual market return and return on sales for a firm's three-digit SIC industry over the prior five years; and *LTCNTL* is the market value of a CEO's equity holdings (stocks and exercisable options) divided by the CEO's annual salary and bonus.

Ittner et al. (1997) predict that firms with a prospector strategy (a higher value of *STRATEGY*), the use of quality management practices (*QUAL*), higher regulatory and competitive pressures (*TEL&UTIL*), and longer product development cycles (*DCYCLE*) are more likely to rely on NFPMs, while those with financial distress (a higher value of *DISTRESS*), less noise in financial measures (a higher value of *MNOISE*), and more CEO equity holdings (*LTCNTL*) are less likely to implement NFPMs. The results reported in Table A.1 indicate that the coefficients on *DISTRESS* and *LTCNTL* are significantly negative as predicted, whereas those on other determinants are insignificant. While our results are different from Ittner et al.'s (1997), this discrepancy might have arisen from the differences in samples and data. Specifically, Ittner et al. (1997) use private data from 1993-1994, whereas we use a larger sample from S&P 500 firms for more recent years 2006-2012.

APPENDIX C
Variable Definitions

Variable	Definition
Dependent variables: Crash risk measures	
$CRASH_{t+1}$	An indicator variable that is equal to one if the firm experiences one or more crash weeks during year *t+1*, and zero otherwise.
$NCSKEW_{t+1}$	The negative conditional skewness of firm-specific weekly returns over year *t+1*.
$DUVOL_{t+1}$	The down-to-up volatility measure of crash likelihood over year *t+1*.
Variables of interest	
$NFPM_t$	An indicator variable that is equal to one if the firm uses one or more NFPMs in CEO compensation contracts in year *t*, and zero otherwise.
$OPAQUE_t$	The standard deviation of I/B/E/S analysts' forecasts as of year *t* of the firm's earnings in the following year, normalized by the mean forecast, and then divided by the square root of the number of analysts following that firm.
$HIGHVEGA_t$	The top quartile of *VEGA* for a given year-industry combination, where *VEGA* is the change in option value for a 0.01 change in stock-return volatility for a CEO's option portfolio for year *t.*
Control variables (all measured for year *t*, unless specified otherwise)	
$NCSKEW_t$	The negative conditional skewness of firm-specific weekly returns.
$TURNOVER_t$	The average monthly share turnover for the current year less the average monthly share turnover for the previous year, where monthly share turnover is computed as the monthly trading volume divided by the total number of shares outstanding during the month.
RET_t	The mean of firm-specific weekly returns over the fiscal year, multiplied by 100.
$SIGMA_t$	The standard deviation of firm-specific weekly returns over the fiscal year.
BM_t	The book value of equity divided by the market value of equity
$SIZE_t$	The log of the market value of equity.
LEV_t	Total long-term debts divided by total assets.
ROA_t	Income before extraordinary items divided by beginning assets.
$ABSDA_t$	The absolute value of discretionary accruals, where discretionary accruals are estimated based on the modified Jones model.
$DELTA_t$	The change in a CEO's personal portfolio in response to a 1 percent change in the stock price.

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TABLE 1
Sample Composition of NFPM Firms by Industry

Industry (SIC Codes)	Number of Observations	%
Mining and Construction (1000–1999 exc. 1300-1399)	22	5.19%
Food (2000–2111)	23	5.42%
Textiles and printing/publishing (2200–2799)	33	7.78%
Chemicals (2800–2824, 2840–2899)	9	2.12%
Pharmaceuticals (2830–2836)	26	6.13%
Extractive (1300–1399, 2900–2999)	36	8.49%
Durable manufactures (3000-3999 exc. 3570-3579 & 3670-3679)	107	25.24%
Transportation (4000–4799)	5	1.18%
Telecommunication and Utilities (4800-4899, 4900-4999)	25	5.90%
Retail (5000–5999)	36	8.49%
Financial industry (6000-6799)	2	0.47%
Computers (3570–3579, 3670–3679, 7370–7379)	76	17.92%
Services (7000–8999 exc. 7370–7379)	24	5.66%
Total	424	100.00%

TABLE 2
Descriptive Statistics

Panel A: Full Sample (*N* = 848)

Variable	Mean	Median	Std. Dev	Q1	Q3
$CRASH_{t+1}$	0.283	0.000	0.451	0.000	1.000
$NCSKEW_{t+1}$	0.083	0.061	0.758	-0.353	0.460
$DUVOL_{t+1}$	-0.002	-0.008	0.355	-0.242	0.204
$NFPM_t$	0.500	0.500	0.500	0.000	1.000
$OPAQUE_t$	0.006	0.003	0.018	0.002	0.007
$HIGHVEGA_t$	0.111	0.000	0.314	0.000	0.000
$VEGA\_RAW_t$	0.293	0.205	0.295	0.100	0.382
$DELTA_t$	1.179	0.509	2.431	0.254	1.079
$NCSKEW_t$	0.093	0.060	0.755	-0.350	0.451
$TURNOVER_t$	0.084	0.039	0.805	-0.312	0.459
RET_t	-0.071	-0.048	0.069	-0.089	-0.029
$SIGMA_t$	0.035	0.031	0.015	0.024	0.043
BM_t	0.605	0.594	0.231	0.428	0.768
$SIZE_t$	8.936	8.959	0.965	8.333	9.560
LEV_t	0.216	0.209	0.135	0.117	0.303
ROA_t	0.077	0.081	0.078	0.042	0.120
$ABSDA_t$	0.675	0.089	1.820	0.033	0.383

Panel B: NFPM Adopters vs. Non-NFPM Adopters

Variable	NFPM (*N* = 424)		Non-NFPM (*N* = 424)		Difference (*p*-Value)	
	Mean	Median	Mean	Median	Mean	Median
$CRASH_{t+1}$	0.309	0.000	0.257	0.000	0.094	0.094
$NCSKEW_{t+1}$	0.084	0.066	0.082	0.056	0.965	0.992
$DUVOL_{t+1}$	-0.003	-0.008	-0.001	-0.006	0.914	0.904
$OPAQUE_t$	0.007	0.003	0.006	0.003	0.716	0.545
$HIGHVEGA_t$	0.134	0.000	0.087	0.000	0.029	0.029
$VEGA\_RAW_t$	0.313	0.228	0.273	0.180	0.051	0.010
$DELTA_t$	1.337	0.495	1.021	0.535	0.059	0.527
$NCSKEW_t$	0.095	0.041	0.091	0.073	0.932	0.987
$TURNOVER_t$	0.011	-0.023	0.157	0.081	0.008	0.002
RET_t	-0.074	-0.050	-0.069	-0.046	0.272	0.209
$SIGMA_t$	0.036	0.032	0.034	0.031	0.237	0.209
BM_t	0.622	0.624	0.588	0.563	0.030	0.032
$SIZE_t$	9.031	8.989	8.841	8.916	0.004	0.013
LEV_t	0.212	0.216	0.219	0.202	0.450	0.767
ROA_t	0.080	0.077	0.074	0.085	0.305	0.705
$ABSDA_t$	0.778	0.113	0.572	0.076	0.099	0.005

In Panel A, Std. Dev. represents the standard deviation, and Q1 and Q3 represent the first and third quartiles, respectively. *VEGA_RAW* is the raw value of the change in option value for a 0.01 change in stock-return volatility for a CEO's option portfolio divided by 1,000. See Appendix C for the definition of other variables. In Panel B, the reported p-values are for two-tailed t-tests (Wilcoxon tests) of differences in means (medians).

TABLE 3
The Effect of Use of NFPMs on Future Crash Risk

Variable	***$CRASH_{t+1}$*** **(Z-stat.)**	***$NCSKEW_{t+1}$*** **(t-stat.)**	***$DUVOL_{t+1}$*** **(t-stat.)**
INTERCEPT	2.265*	-0.253	-0.137
	(1.83)	(-0.51)	(-0.68)
$NFPM_t$	-0.082	-0.049*	-0.030***
	(-0.56)	(-1.68)	(-3.44)
$NCSKEW_t$	-0.005	-0.078*	-0.043**
	(-0.10)	(-1.92)	(-2.13)
$TURNOVER_t$	-0.098	0.011	0.005
	(-0.53)	(0.29)	(0.28)
RET_t	-0.170	1.197	0.477
	(-0.04)	(0.57)	(0.48)
$SIGMA_t$	-1.822	8.012	3.729
	(-0.07)	(0.74)	(0.72)
BM_t	-0.017	0.166	0.080
	(-0.04)	(1.10)	(1.12)
$SIZE_t$	-0.102	0.065	0.041**
	(-0.66)	(1.57)	(2.25)
LEV_t	-0.370	-0.533	-0.302*
	(-0.69)	(-1.55)	(-1.87)
ROA_t	-1.622*	0.240	0.217
	(-1.65)	(0.48)	(0.84)
$ABSDA_t$	0.092**	0.025**	0.014***
	(2.21)	(2.30)	(2.78)
N	848	848	848
Year & industry fixed effects	Included	Included	Included
Pseudo-/adjusted R^2	0.210	0.004	0.022

*, **, and *** indicate statistical significance at the 0.1, 0.5, and 0.01 levels (two-tailed), respectively.

This table reports the results for regressions of future crash risk on NFPM adoption. All variables are defined in Appendix C. The *Z*-statistics (*t*-statistics) presented in parentheses are based on standard errors clustered by firm and year.

TABLE 4
The Effect of Use of NFPMs on Future Crash Risk for Firms in Opaque Reporting Environments

Variable	$CRASH_{t+1}$ (Z-stat.)	$NCSKEW_{t+1}$ (t-stat.)	$DUVOL_{t+1}$ (t-stat.)
INTERCEPT	-0.605	-0.203	-0.116
	(-0.52)	(-0.43)	(-0.60)
$NFPM_t$	0.046	-0.008	-0.014
	(0.26)	(-0.27)	(-1.32)
$OPAQUE_t$	9.125	3.62*	1.557*
	(1.28)	(1.89)	(1.74)
$NFPM_t$ * $OPAQUE_t$	-19.780*	-6.051**	-2.503*
	(-1.95)	(-2.04)	(-1.90)
$NCSKEW_t$	0.009	-0.075*	-0.042**
	(0.15)	(-1.79)	(-2.03)
$TURNOVER_t$	-0.124	0.005	0.002
	(-0.66)	(0.12)	(0.12)
RET_t	-2.524	0.635	0.247
	(-0.53)	(0.35)	(0.27)
$SIGMA_t$	-10.510	5.745	2.789
	(-0.40)	(0.56)	(0.57)
BM_t	-0.068	0.141	0.069
	(-0.17)	(0.88)	(0.92)
$SIZE_t$	-0.109	0.066*	0.041**
	(-0.73)	(1.74)	(2.49)
LEV_t	-0.379	-0.541	-0.306*
	(-0.74)	(-1.55)	(-1.86)
ROA_t	-1.622	0.221	0.209
	(-1.59)	(0.44)	(0.80)
$ABSDA_t$	0.087**	0.024**	0.013***
	(2.11)	(2.41)	(2.85)
N	848	848	848
Year & industry fixed effects	Included	Included	Included
Pseudo-/adjusted R^2	0.191	0.007	0.024
Coefficient F-tests	p-value	p-value	p-value
$NFPM_t$ + $NFPM_t$ * $OPAQUE_t$	0.04	0.04	0.06

*, **, and *** indicate statistical significance at the 0.1, 0.5, and 0.01 levels (two-tailed), respectively.

This table reports the results for regressions of future crash risk on NFPM adoption, the proxy for opaque reporting environments, and the interaction between these two. All variables are defined in Appendix C. The *Z*-statistics (*t*-statistics) presented in parentheses are based on standard errors clustered by firm and year.

TABLE 5
The Effect of Use of NFPMs on Future Crash Risk for Firms Having CEOs with Excessive Risk Taking Incentives

Variable	$CRASH_{t+1}$ (Z-stat.)	$NCSKEW_{t+1}$ (t-stat.)	$DUVOL_{t+1}$ (t-stat.)
INTERCEPT	-0.661 (-0.64)	-0.177 (-0.37)	-0.123 (-0.63)
$NFPM_t$	-0.053 (-0.34)	-0.036 (-1.22)	-0.023** (-2.44)
$HIGHVEGA_t$	0.492 (1.45)	0.198*** (3.44)	0.071*** (2.69)
$NFPM_t$ * $HIGHVEGA_t$	-0.325* (-2.02)	-0.140* (-1.66)	-0.069* (-1.65)
$DELTA_t$	-0.009 (-0.28)	-0.009 (-0.57)	-0.004 (-0.45)
$NCSKEW_t$	-0.012 (-0.28)	-0.081** (-1.98)	-0.044** (-2.18)
$TURNOVER_t$	-0.100 (-0.56)	0.010 (0.25)	0.004 (0.27)
RET_t	-0.100 (-0.02)	1.218 (0.60)	0.490 (0.50)
$SIGMA_t$	-1.351 (-0.05)	8.286 (0.81)	3.842 (0.78)
BM_t	-0.003 (-0.01)	0.160 (1.15)	0.077 (1.15)
$SIZE_t$	-0.120 (-0.87)	0.057 (1.51)	0.040** (2.33)
LEV_t	-0.407 (-0.76)	-0.535 (-1.53)	-0.303* (-1.84)
ROA_t	-1.591 (-1.63)	0.256 (0.51)	0.223 (0.85)
$ABSDA_t$	0.093** (2.20)	0.026** (2.25)	0.014*** (2.67)
N	848	848	848
Year & industry fixed effects	Included	Included	Included
Pseudo-/adjusted R^2	0.188	0.004	0.020
Coefficient F-tests	p-value	p-value	p-value
$HIGHVEGA_t$ + $NFPM_t$ * $HIGHVEGA_t$	0.04	0.04	0.02

*, **, and *** indicate statistical significance at the 0.1, 0.5, and 0.01 levels (two-tailed), respectively.

This table reports the results for regressions of future crash risk on NFPM adoption, the proxy for CEOs' excessive risk taking incentives, and the interaction between these two. All variables are defined in Appendix C. The *Z*-statistics (*t*-statistics) presented in parentheses are based on standard errors clustered by firm and year.

TABLE 6
The Effect of Use of NFPMs on Future Crash Risk: Analysis Using NFPM Weights

Variable	***$CRASH_{t+1}$*** **(Z-stat.)**	***$NCSKEW_{t+1}$*** **(t-stat.)**	***$DUVOL_{t+1}$*** **(t-stat.)**
INTERCEPT	-0.927 (-0.17)	-0.348 (-0.45)	-0.002 (-0.01)
$NFPM\_W_t$	-3.473* (-1.67)	-0.805* (-1.88)	-0.332* (-1.93)
$NCSKEW_t$	-0.780*** (-2.87)	-0.042 (-0.35)	-0.015 (-0.29)
$TURNOVER_t$	-0.214 (-1.04)	-0.032 (-0.47)	-0.004 (-0.13)
RET_t	0.281 (0.03)	5.165*** (5.16)	2.164*** (5.71)
$SIGMA_t$	22.692 (0.33)	31.252*** (3.30)	13.040*** (3.58)
BM_t	1.390 (0.73)	-0.131 (-0.35)	-0.146 (-0.81)
$SIZE_t$	-0.091 (-0.27)	0.046 (0.82)	0.015 (0.45)
LEV_t	1.045 (0.27)	-0.242 (-0.27)	-0.109 (-0.30)
ROA_t	-8.941 (-1.54)	-1.596 (-1.18)	-0.688 (-1.16)
$ABSDA_t$	0.430*** (2.73)	0.006 (0.20)	-0.004 (-0.27)
N	208	208	208
Year & industry fixed effects	Included	Included	Included
Pseudo-/adjusted R^2	0.361	0.008	0.027

*, **, and *** indicate statistical significance at the 0.1, 0.5, and 0.01 levels (two-tailed), respectively.

This table reports the results for regressions of future crash risk on NFPM adoption using the weight on NFPMs (*NFPM_W*). All other variables are defined in Appendix C. The Z-statistics (t-statistics) presented in parentheses are based on standard errors clustered by firm and year.

TABLE 7
The Effect of Use of NFPMs on Future Crash Risk: Analysis Using NFPM Types

Variable	*NFPM = NFPM_CUSTOMER*			*NFPM = NFPM_PROCESS*		
	$CRASH_{t+1}$ (Z-stat.)	$NCSKEW_{t+1}$ (t-stat.)	$DUVOL_{t+1}$ (t-stat.)	$CRASH_{t+1}$ (Z-stat.)	$NCSKEW_{t+1}$ (t-stat.)	$DUVOL_{t+1}$ (t-stat.)
INTERCEPT	2.017	-1.571	-0.899	7.665**	-0.004	-0.291
	(0.87)	(-1.07)	(-1.24)	(2.25)	(-0.01)	(-0.93)
$NFPM_t$	-2.048**	-0.252*	-0.104*	0.232	-0.120	-0.062
	(-2.21)	(-1.70)	(-1.65)	(0.66)	(-1.15)	(-1.28)
$NCSKEW_t$	-0.215	-0.006	-0.0162	-0.233	-0.137	-0.055
	(-0.78)	(-0.09)	(-0.43)	(-0.70)	(-1.57)	(-1.38)
$TURNOVER_t$	-0.622**	-0.137*	-0.076*	0.289	0.118**	0.048*
	(-2.02)	(-1.79)	(-1.85)	(0.93)	(1.97)	(2.03)
RET_t	44.883**	8.807*	3.821*	8.798	2.455	0.714
	(2.24)	(1.79)	(1.69)	(0.75)	(0.94)	(0.58)
$SIGMA_t$	199.491*	45.317**	20.160*	22.309	7.740	2.455
	(1.83)	(2.06)	(1.97)	(0.42)	(0.52)	(0.35)
BM_t	-3.078	0.305	0.211	-2.231*	-0.320	-0.148*
	(-1.38)	(0.56)	(0.78)	(-1.96)	(-1.56)	(-1.68)
$SIZE_t$	-0.566*	0.040	0.019	-0.604***	-0.022	0.004
	(-1.79)	(0.32)	(0.32)	(-2.66)	(-0.49)	(0.24)
LEV_t	4.850***	0.915*	0.475	-0.408	0.001	-0.008
	(2.74)	(1.69)	(1.42)	(-0.17)	(0.00)	(-0.04)
ROA_t	-11.550**	-0.825	0.003	-5.254***	0.227	0.304
	(-2.51)	(-0.37)	(0.00)	(-3.78)	(0.49)	(1.15)
$ABSDA_t$	-0.189	-0.068	-0.029	0.0683	-0.024	-0.013
	(-0.65)	(-1.50)	(-1.21)	(0.47)	(-0.79)	(-1.16)
N	234	234	234	444	444	444
Year & industry fixed effects	Included	Included	Included	Included	Included	Included
Pseudo-/adjusted R^2	0.412	0.076	0.067	0.309	0.142	0.135

TABLE 7 (continued)

Variable	NFPM = NFPM_LEARNING			NFPM = NFPM_OTHERS		
	$CRASH_{t+1}$ (Z-stat.)	**$NCSKEW_{t+1}$ (t-stat.)**	**$DUVOL_{t+1}$ (t-stat.)**	**$CRASH_{t+1}$ (Z-stat.)**	**$NCSKEW_{t+1}$ (t-stat.)**	**$DUVOL_{t+1}$ (t-stat.)**
INTERCEPT	3.202	-0.101	-0.469	-13.651***	-0.860	-0.579**
	(0.80)	(-0.24)	(-1.57)	(-4.15)	(-1.47)	(-2.23)
$NFPM_t$	-0.220	-0.017	0.005	-0.357	-0.130	-0.077**
	(-0.69)	(-0.08)	(0.06)	(-0.80)	(-1.63)	(-2.10)
$NCSKEW_t$	-0.377**	-0.067*	-0.001	-0.266	-0.156***	-0.061**
	(-2.77)	(-1.69)	(-0.05)	(-1.57)	(-2.64)	(-2.45)
$TURNOVER_t$	0.081	0.054	0.044	-0.084	0.014	0.015
	(0.26)	(0.69)	(1.02)	(-0.32)	(0.27)	(0.62)
RET_t	8.771	1.676	0.348	7.553	6.504**	2.363*
	(0.95)	(1.49)	(0.35)	(0.78)	(2.14)	(1.66)
$SIGMA_t$	12.681	5.948**	0.408	17.487	31.434**	12.519**
	(0.34)	(1.98)	(0.08)	(0.45)	(2.49)	(2.04)
BM_t	0.390	0.320**	0.036	0.219	0.517**	0.256**
	(0.39)	(2.13)	(0.23)	(0.15)	(2.40)	(2.24)
$SIZE_t$	-0.405	0.072	0.040**	-0.193	0.106	0.064**
	(-1.15)	(1.60)	(2.36)	(-0.59)	(1.32)	(2.00)
LEV_t	1.072	0.830	0.314	0.727	0.004	0.011
	(0.40)	(1.06)	(1.03)	(0.34)	(0.01)	(0.05)
ROA_t	-4.763	0.897	0.742	-5.743*	-0.328	-0.005
	(-1.25)	(1.08)	(1.36)	(-1.68)	(-0.66)	(-0.02)
$ABSDA_t$	-0.129	-0.037**	-0.022**	0.199***	0.020***	0.008***
	(-1.05)	(-2.36)	(-2.10)	(4.18)	(2.87)	(2.80)
N	358	358	358	560	560	560
Year & industry fixed effects	Included	Included	Included	Included	Included	Included
Pseudo-/adjusted R^2	0.264	0.090	0.028	0.290	0.051	0.041

*, **, and *** indicate statistical significance at the 0.1, 0.5, and 0.01 levels (two-tailed), respectively.

TABLE 7 (continued)

This table reports the results for regressions of future crash risk on NFPM adoption by NFPM type. In each regression analysis, we re-define the variable *NFPM* as the adoption of NFPMs related to customers (*NFPM_CUSTOMER*), internal business process (*NFPM_PROCESS*), learning and growth (*NFPM_LEARNING*), and others (*NFPM_OTHERS*). *NFPM_CUSTOMER* is an indicator variable that equals one for the adopters of NFPMs related to customers and zero for other firms. *NFPM_PROCESS*, *NFPM_LEARNING*, and *NFPM_OTHERS* are defined similarly. All other variables are defined in Appendix C. The *Z*-statistics (*t*-statistics) presented in parentheses are based on standard errors clustered by firm and year.