Does Accounting Conservatism Reduce Stock Price Crash Risk? Firm-level Evidence

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ABSTRACT: This study provides strong and robust evidence that conservatism in financial reporting reliably predicts stock price crash risk. Using a large sample of U.S. firms over the period of 1964–2007, we find that accounting conservatism, as measured by the Khan and Watts (2009) CSCORE, reduces the likelihood of a firm experiencing stock price crashes. This finding holds even after controlling for firm and year fixed effects, investor heterogeneity, information opaqueness, and other firm-specific features that are possible contributing factors to negative extreme outcomes in stock returns. We further find that the predictive power of accounting conservatism with respect to crash risk is more pronounced for firms with higher information asymmetries, namely those with relatively higher R&D investment, higher industry concentration or lower product market competition, and lower analyst coverage. Overall, our results are consistent with the notion that accounting conservatism limits managerial incentive and ability to overstate performance and hide bad news from investors, which, in turn, reduces stock price crash risk.

JEL classification: G12; M41

Keywords: Accounting conservatism; Stock price crashes; Negative return skewness; Information asymmetry

August 2011

We thank Sudipta Basu, Paul Brockman, Zhihong Chen, Agnes Cheng, Yuyan Guan, Li Jiang, Mo Khan, Kalin Kolev, Jing Li, Tiemei (Sarah) Li, Yinghua Li, Mingzhi Liu, Cathy Pang, Francis Kim, Annie Qiu, Haina Shi, Dan Simunic, Byron Song, Shyam Sunder, Haiping Wang, Zheng Wang, Ross Watts, Franco Wong, Cheong Yi, Yong Yu, and participants of research workshops at City University of Hong Kong, Concordia University, Lehigh University Accounting Conference, and National Taiwan University for their useful comments. J.-B. Kim acknowledges partial financial support for this research from the Social Sciences and Humanities Research Council of Canada via the Canada Research Chair program and Accounting & Corporate Governance Unit at City University of Hong Kong. L. Zhang acknowledges financial support from the Faculty Research Development Program of the John Molson School of Business.

1. Introduction

Corporate managers have incentives to overstate financial performance through strategically withholding bad news and accelerating the release of good news, hoping that poor current performance will be camouflaged by strong future performance. This asymmetric disclosure incentive stems from a variety of factors, including formal compensation contracts and career concerns (Ball, 2009; Graham et al., 2005; Khan and Watts, 2009; Kothari et al., 2009; LaFond and Watts, 2008). If managers are able to withhold and accumulate bad news for an extended period, negative information is likely to be stockpiled within a firm. However, there is an upper limit to the amount of bad news that managers can absorb or successfully accumulate. This is because once the amount of accumulated bad news reaches a certain threshold, it becomes too costly or impossible to continue to withhold it. When the accumulation of bad news reaches a tipping point, it will all be released at once, leading to large, negative, market-adjusted stock returns on the individual stocks concerned, that is, stock price crashes (Hutton et al., 2009; Jin and Myers, 2006).

In this study, we investigate the firm-level relation between conservatism[1] in financial reporting and stock price crashes. Conservatism refers to the accounting tendency to require a higher degree of verification to recognize good news as gains than to recognize bad news as losses (Basu, 1997). Watts (2003a, b) and LaFond and Watts (2008) argue that conservatism is a governance mechanism that curbs managerial incentives and ability to accelerate the disclosure of good news and delay the release of bad news. The asymmetric verifiability requirement of conservative accounting offsets the managers' tendency to hide bad news and accelerate good news recognition in audited financial statements. Moreover, the asymmetric timeliness of earnings reported in audited financial statements could, in turn, discipline other management disclosures, such as voluntary disclosures, by providing a benchmark that makes managers *ex post* accountable. Specifically, conservative audited

[1] In this study, we focus on "conditional conservatism," as captured by the asymmetric timeliness of earnings. Throughout the paper, we use the terms *conservatism, conditional conservatism,* and *asymmetric timeliness* interchangeably.

earnings dampen managerial incentives to disclose unverifiable favorable information and, instead, bring forth disclosures of unverifiable unfavorable information (LaFond and Watts, 2008). Viewed this way, we expect that the more conservative a firm's accounting practices, the lower the probability that firm-specific bad news is hidden and accumulated. We therefore predict that all else being equal, accounting conservatism reduces the likelihood of future stock price crashes.

Furthermore, accounting conservatism can also reduce crash risk by disciplining managers' investment decisions, in addition to their disclosure behaviors. Using a hidden action model, Benmelech et al. (2010) show that when a firm experiences a decline in the growth rate of investment opportunities, the CEO of the firm have an incentive to invest in negative NPV projects to maintain the pretense that investment opportunities are still strong. However, the strategy cannot be kept forever, "at some point the firm experiences a cash shortfall, the true state is revealed and the stock price sharply declines as the firm needs to recapitalize" (Benmelech et al., 2010: 2). Moreover, Bleck and Liu (2007) make a related point that the hidden, negative information about a firm prevents the boards from discerning and liquidating negative-NPV projects at an early stage. This will allow bad projects to be kept alive and their bad performance to accumulate, until an asset price crash. Building on the frameworks of Benmelech et al. (2010) and Bleck and Liu (2007), we argue that conditional conservatism can reduce investment-activity-induced crashes because "timely loss recognition makes managers less likely to make investments they expect ex ante to be negative-NPV, and less likely to continue operating investments with ex post negative cash flows" (Ball and Shivakumar, 2005: 84).

For our empirical tests, we obtain firm-specific measures of crash risk and conservatism, since we are interested in the *firm-level* relation between the two. Following the literature (Chen et al., 2001; Hutton et al., 2009), we proxy for firm-specific crash risk using two measures: (i) the likelihood that extreme negative firm-specific weekly returns occur and (ii) the negative conditional skewness of firm-specific weekly returns. Since our research question is related to the ability of *news-dependent*, conditional conservatism to forecast future crash risk, we proxy for conservatism using the firm-level asymmetric timeliness measure, *CSCORE*, developed by Khan and Watts (2009).

Using a sample of 137,571 firm–years over the period of 1964–2007, we find that a greater extent of conservatism, or the greater timeliness of losses versus gains, in financial reporting significantly reduces the likelihood of a firm experiencing future stock price crashes. Moreover, results from the Cox (1972) proportional hazard model estimation show that conservatism also reduces the instantaneous likelihood of crash occurrence, conditional on the past history of crashes. The above results hold after controlling for firm and year fixed effects, the measure of heterogeneity of investor beliefs of Chen et al. (2001), the measure of information opaqueness of Hutton et al. (2009), and several other firm-specific factors identified in the literature as associated with stock price crashes. The results of robustness tests using the Basu (1997) and Ball and Shivakumar (2006; 2008) piecewise linear regressions are, overall, consistent with our main results using the Khan and Watts (2009) conservatism measure.

In examining the cross-sectional variation in the relation between conservatism and crash risk, we find that the predictive power of conservatism with respect to future crash risk is stronger in an environment where investors are faced with larger information asymmetries. Specifically, we find that the predictive ability of conservatism is greater for firms with intensive research and development (R&D), firms with higher industry concentration or lower product market competition, and firms with lower levels of analyst coverage. In short, our results provide strong and robust evidence that conservatism significantly reduces stock price crash risk. Our evidence is in line with the notion that conservatism is an equilibrium response to a standard agency problem associated with management incentives to hide firm-specific bad news for private gain (LaFond and Watts, 2008; Watts, 2003a).

This paper contributes to the literature in several important ways. First, our study adds to the conservatism literature. Ever since Basu (1997) first provided systematic evidence for the existence of conservatism, many studies have examined various country-wide and firm-specific factors that explain the demand for conservatism in financial reporting.[2] However, existing research pays little attention to the economic consequences of or benefits from conservative accounting. Three notable exceptions are Ahmed et al. (2002), Wittenberg-Moerman (2008), and Zhang (2008), who document the benefits of conservatism in the debt market. To our knowledge, however, our study is the first to provide systematic evidence that conservatism has desirable consequences in the equity market because it reduces future crash risk, consistent with the theory in LaFond and Watts (2008) that equity investors demand conservatism. This evidence is intriguing and important, particularly because crash risk has received increased attention from both academic researchers and the investment community, as demonstrated by the prominent "volatility smirk" phenomenon observed in option markets after the 1987 stock market crash.

Second, our study contributes to the understanding of accounting factors that explain stock price crashes and negative return skewness. This study provides evidence that accounting conservatism, as a governance mechanism, is an important factor that determines future crash risk, and its ability to predict future crashes is incrementally significant over and beyond the measure of investor heterogeneity of Chen et al. (2001) and the measure of information opaqueness of Hutton et al. (2009).

Third, a unique feature of this study is the employment of both the logit and hazard models for forecasting crash risk, whereas prior stock price crash studies, such as that of Hutton et al. (2009), use only the logit model. Unlike the logit model, the hazard model takes into account prior crash

[2] See Watts (2003b) for an excellent, structured review of the earlier literature on the existence of alternative explanations for conservatism.

history (occurrence, duration between crashes, and magnitude) when evaluating a firm's instantaneous crash risk. This is important because future crash risk is influenced not only by the timing (or the duration between crashes) but also by the magnitude of past crashes, and simply controlling for the lagged crash indicator in a logit model setting is not sufficient to address the issue (Jin and Myers, 2006). Using the hazard model approach, we are able to confirm the validity of Chen et al. (2001) and Hutton et al. (2009), as well as that of our own findings from the logit model estimation.

Fourth, our findings will be of interest to options pricing researchers and options traders. Negative return skewness and negative jump risk (i.e., risk of future crash) are important inputs to options pricing models that extend the original Black–Scholes model, such as stochastic volatility and jump-diffusion models (Bates, 2000; Pan, 2002). Therefore, the finding that accounting conservatism is associated with lower crash likelihood and/or negative skewness in returns is of obvious value to options market participants who focus on tail events.

Finally, our results have implications for accounting standard setting bodies. It appears that the U.S. Financial Accounting Standards Board (FASB) and the International Accounting Standards Board (IASB) are seeking to eliminate conservatism from their new conceptual frameworks, favoring fair value or neutral accounting instead (FASB, 2008). Both the FASB and IASB argue that conservatism introduces biases into financial reporting and increases information asymmetry (LaFond and Watts, 2008; Watts, 2003a). However, the results of this study suggest that conservatism is associated with lower stock price crash risk.

This paper proceeds as follows. Section 2 offers a brief review of the relevant literature and develops our hypotheses. Section 3 describes the sample and data, and explains our research procedures. Section 4 presents descriptive statistics and the results of the multivariate regressions. Section 5 provides additional analyses and robustness checks. Section 6 presents our conclusions.

2. Literature review and hypothesis development

Basu (1997) defines conservatism as "capturing accountants' tendency to require a higher degree of verification for recognizing good news than bad news in financial statements." Watts (2003) attributes the existence and prevalence of conservatism for five centuries to the need for and the use of verifiable accounting numbers in debt and compensation contracts, shareholder litigation, regulatory and political processes, and taxation. According to Watts, conservatism is a governance mechanism that constrains managerial incentives and ability to overstate accounting numbers used in a contract. More recently, LaFond and Watts (2008) focus on equity market demand for conservatism. They argue that information asymmetries between corporate insiders and outside equity investors engender conservatism in financial reporting. This is because conservatism reduces information asymmetry by curbing managers' incentives, opportunities, and ability to overstate income and net asset values. While LaFond and Watts provide empirical evidence consistent with their argument, their analysis does not focus on the economic consequences or benefits of conservatism in the equity market. This paper aims to complement the line of research that examines the informational role of conservatism by examining the firm-level relation between conservatism and stock price crash risk.

As mentioned in the Introduction, managers have a general tendency to strategically withhold bad news or delay the disclosure of bad news and accelerate the release of good news. This tendency may stem from a variety of managerial incentives, such as earnings-based compensation contracts, career concerns, reputation concerns, and empire building (see Ball (2009) for an extensive discussion). Empirically, Kothari et al. (2009) provide evidence suggesting that managers tend to delay the release of bad news to outside investors. The managerial tendency to conceal bad news from outside investors engenders crash risk, or, more generally, negative return skewness. This is because the asymmetric disclosure behavior of managers leads to stockpiling within a firm of negative information unknown to outside investors. When the accumulated bad news reaches some tipping point or when managerial incentive for hiding bad news collapses, the large amount of negative information will suddenly and immediately be released to the market, which leads to an abrupt decline in stock price or a crash (Hutton et al., 2009; Kim et al., 2010). Moreover, the hiding of bad news allows firms with aggressive accounting to keep bad projects for a longer period, compared with firms with conservative accounting. When the accumulated bad performance eventually surfaces, one observes stock price crashes (Bleck and Liu, 2007).

This study predicts that accounting conservatism reduces crash risk for the following reasons. First, the asymmetric verifiability requirement for the recognition of losses versus gains accelerates the recognition of bad news as losses, while delaying the recognition of unverifiable good news as gains in audited financial statements. This thus offsets the managerial tendency to hide bad news from outside investors and accelerate the release of good news to the market (LaFond and Watts, 2008). As a result, bad news flows into the market in a timelier manner, compared with unverifiable good news. One can therefore expect that conservatism prevents bad news from being stockpiled, and thus reduces the likelihood that a large amount of bad news will be released to the market at once. As a result, the higher the level of conservatism, the lower the probability that bad news will be hidden and accumulate, and thus, the lower the crash risk.

Second, by their nature, conservative accounting reports provide verifiable, “hard” information that can be used as a benchmark for evaluating the credibility of competing, alternative sources of unverifiable, “soft” information, such as management forecasts and other voluntary disclosures of nonfinancial information (LaFond and Watts, 2008). The availability of this hard information may play the role of disciplining managers’ voluntary disclosure behavior through *ex* *post* accountability for their own voluntary disclosures (Ball, 2001; Ball et al., 2009a). Moreover, any reticence (with respect to bad news) or puffery (with respect to good news) in voluntary disclosures will be discovered sooner for conservative firms than for non-conservative firms. For non-conservative firms, the misleading voluntary disclosures are unlikely to be discovered till the manager has moved on, and hence, this manager is more likely to mislead outside investors through voluntary disclosures. For conservative firms, misleading voluntary disclosures are likely to be discovered sooner, so their managers are less likely to mislead outside investors through voluntary disclosures. Thus, conservatism constrains the incentives and ability of managers to delay the release of bad news and accelerate the release of good news in voluntary disclosures. This reduces crash risk, as well as the likelihood of inflating stock price bubbles, an important source of crash risk.

Third, while the above discussion focuses on how conservatism reduces crash risk through improving the flow of both hard and soft information to the market, conservatism could also reduce crash risk via its impact on real decision making. The timelier recognition of losses than gains can be an early warning mechanism that enables shareholders and board of directors to promptly identify unprofitable projects and force managers to discontinue them. This prevents the bad performance of bad projects from accumulating and reduces the probability of asset price crashes (Ball, 2001; Bleck and Liu, 2007). For example, Francis and Martin (2010) find that conservative firms act more quickly to divest unprofitable acquired companies. The above discussions lead to the following hypothesis in alternative form:

H1: *Conservatism in financial reporting reduces the likelihood of future crash occurrence, ceteris paribus.*

Note that although the crash risk models such as Jin and Myers (2006) is built on the concept of *bad news* hoarding, it should not be taken literally that it only applies to bad news in reality. Managers can also hide bad performance by recognizing unverifiable good news in accounting income or disclose them through other channels. For example, Enron launched EnronOnline in 1999, and adopted mark to market accounting to report its performance. Enron's managers were able to hide the firm's real losses by recognizing anticipated future profits from any deal of EnronOnline as if real today. We discuss this point to emphasize the importance of our adopting the asymmetric verifiability version of conservatism, which includes both the concept of timely loss recognition and the postponing of good news recognition until they are verifiable.

Moreover, a key point underlying H1 is that conservatism curbs the managers' incentive to hide private negative information. However, the amount of value-relevant, negative information that managers withhold can vary across firms. As an example, consider a firm with relatively high R&D investment. In the extreme case of no information asymmetry, managers have no incentive for strategic disclosure, and thus conservatism plays no role in controlling manager disclosure behavior. However, the long-term effects of R&D projects are difficult for outside investors to evaluate, and the information about this effect is idiosyncratic to managers. This creates information asymmetry between managers and outside investors. In an environment of high information asymmetry, the costs from managers withholding negative information about an R&D project are likely to be lower, and the associated benefits, including the protection of proprietary information, are likely to be higher. As a result, managers are more likely to be motivated to withhold negative information.

Given evidence that information asymmetries in the equity market engender conservative financial reporting (LaFond and Watts, 2008), we argue that in an environment of high information asymmetry, conservatism plays a more important role in countering managerial incentive to withhold negative information, and, thus, the impact of conservatism on reducing crash risk is more pronounced for firms with high information asymmetry. To uncover systematic evidence for the above argument, we test the following hypothesis:

H2: *Conservatism in financial reporting reduces the likelihood of future crash occurrence to a greater extent for firms with high information asymmetry than for firms with low information asymmetry, ceteris paribus.*

Our main hypotheses are based on the notion that conservative accounting limits the incentive and ability of managers to withhold and accumulate adverse private information from outside investors, which, in turn, leads to lower future crash likelihood for conservative firms. One can argue, however, that outside investors can get access to adverse private information in a timely manner via their private information search activities, which, in turn, reduces the likelihood of future crashes for non-conservative firms. In other words, to the extent that the cost of private information search is not prohibitively high, it could substitute for conservatism. In such a case, there would be no significant difference in future crash likelihoods between conservative and non-conservative firms. However, Aboody and Lev (2000), among others, argue that private information search is costly and optimal information acquisition by outsiders will generally fall short of completely exhausting a manager's private information. We therefore expect that the impact of conservatism on future crash risk remains significant even when market participants engage actively in private information search.

3. Sample and measurement of key variables

3.1. Sample and data

Initially, our sample is drawn from the intersection of data from the Center for Research in Security Prices (CRSP) and Compustat for the period 1962–2007. We then impose the following selection criteria: First, similar to Khan and Watts (2009), we require that total assets and book values of equity for each firm be greater than zero and that the share price at the fiscal year-end be greater than $1. Second, to be included in the sample, a firm must have at least 26 weekly returns for each fiscal year. Third, following Khan and Watts (2009), we exclude firms in each sample year that fall in the top and bottom percentiles of earnings, annual returns, market value of equity, market-to-book ratio, or leverage.[3] Throughout this paper, our sample year is defined as the 12-month period ending three months after fiscal year-end. We delete firm–years with missing data for the research variables used in our regressions. After applying these selection criteria, we obtain a final sample of 137,571 firm–years spanning the period 1964–2007.

3.2. Measurement of firm-specific conservatism

Since our hypotheses are related to the ability of news-dependent, conditional conservatism to forecast the likelihood of future crash occurrence, we measure the degree of accounting conservatism for each firm in each sample year, using the firm–year conditional conservatism measure, *CSCORE*, developed by Khan and Watts (2009). To obtain the *CSCORE* measure, we begin with the Basu (1997) model, which is designed to capture the asymmetric timeliness of earnings in recognizing bad news versus good news. Specifically, the Basu model can be written to allow coefficients to vary across firms and over time as follows:

$$X_{jt} = \beta_{1t} + \beta_{2t} D_{jt} + \beta_{3jt} R_{jt} + \beta_{4jt} D_{jt} * R_{jt} + \varepsilon_{jt}, \tag{1}$$

where j indexes the firm, t indexes the year, X represents earnings before extraordinary items divided by market value of equity, R is the cumulative market adjusted return over the fiscal year period, D is a dummy variable that equals one if $R < 0$, and zero otherwise, and ε is the error term. In Eq. (1), β_{4jt} measures incremental timeliness for bad news over good news, or the extent of conservatism for each firm in each year.

The firm–year-specific coefficients β_{3jt} (timeliness of good news) and β_{4jt} (conservatism) are then expressed by linear functions of firm–year-specific characteristics that are correlated with the timeliness of good news and conservatism:

[3] All the empirical results remain identical if we do not trim data.

$$GSCORE \equiv \beta_{3jt} = \mu_{1t} + \mu_{2t} MKV_{jt} + \mu_{3t} MB_{jt} + \mu_{4t} LEV_{jt}, \quad (2)$$

$$CSCORE \equiv \beta_{4jt} = \lambda_{1t} + \lambda_{2t} MKV_{jt} + \lambda_{3t} MB_{jt} + \lambda_{4t} LEV_{jt}, \quad (3)$$

where *MKV* is the natural log of the market value, *MB* is the market-to-book ratio, and *LEV* is the debt-to-equity ratio. Replacing β_{3jt} and β_{4jt} in Eq. (1) by Eqs. (2) and (3), respectively, yields the following empirical model:

$$\begin{aligned} X_{jt} &= \beta_{1t} + \beta_{2t} D_{jt} + R_{jt} (\mu_{1t} + \mu_{2t} MKV_{jt} + \mu_{3t} MB_{jt} + \mu_{4t} LEV_{jt}) \\ &+ D_{jt} * R_{jt} (\lambda_{1t} + \lambda_{2t} MKV_{jt} + \lambda_{3t} MB_{jt} + \lambda_{4t} LEV_{jt}) \\ &+ (\delta_{1t} MKV + \delta_{2t} MB + \delta_{3t} LEV + \delta_{4t} D_{jt} MKV + \delta_{5t} D_{jt} MB + \delta_{6t} D_{jt} LEV) + \varepsilon_{jt} . \end{aligned} \quad (4)$$

We estimate Eq. (4) using five-year rolling panel regressions[4] and calculate our measure of conservatism, *CSCORE*, using Eq. (3) with the estimated coefficients λ_{1t}, λ_{2t}, λ_{3t}, and λ_{4t} from Eq. (4). Here, firms with a higher *CSCORE* are considered more conservative. Khan and Watts (2009) conduct a series of tests on the properties of this conservatism measure and conclude that the *CSCORE* measure captures variations in conservatism very well. Since our research questions are related to the "asymmetric" disclosure behavior and the asymmetric timeliness of earnings (news-dependent, conditional conservatism), the *CSCORE* measure fits our purpose well. Moreover, this paper hypothesizes that for conservative firms, the higher levels of monitoring and better governance reduce the amount of private information withheld by managers. This hypothesis, based on hidden private information, allows the use of the Basu model (and hence *CSCORE*) since the Basu model does not require that the market be efficient with respect to private information. Basu simply assumes that the market knows more than what is in earnings.

[4] Therefore, our *CSCORE* is the *PC_SCORE*, as in Khan and Watts (2009). We use this specification because Khan and Watts report that this measure of conservatism performs best in their "horse racing tests." However, our results are robust to the use of Khan and Watts' *C_SCORE.*

3.3. Measurement of firm-specific crash risk

Following Hutton et al. (2009) and Kim et al. (2010), we define crash weeks (extreme events) in a given fiscal year for a given firm as those weeks during which the firm experiences firm-specific weekly returns 3.2 standard deviations below the mean firm-specific weekly returns over the entire fiscal year, with 3.2 chosen to generate a frequency of 0.1% in the normal distribution.[5] The firm-specific weekly return, denoted by *W*, is defined as the natural log of 1 plus the residual return from the following expanded market model regression:

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

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. We include the lead and lag terms for the market index return to allow for nonsynchronous trading (Dimson, 1979). Specifically, the firm-specific weekly return for firm *j* in week τ is $W_{j,\tau} = \ln(1+\varepsilon_{j.\tau})$. Our first measure of crash likelihood for each firm in each year, denoted by *CRASH*, is an indicator variable that equals one for a firm–year that experiences one or more crash weeks (as defined above) during the fiscal year period, and zero otherwise.

Following Chen et al. (2001) and Kim et al. (2010), our second measure of crash likelihood is the negative conditional return skewness (*NCSKEW*) measure. Specifically, we calculate *NCSKEW* for a given firm in a fiscal year by taking the negative of the third moment of firm-specific weekly returns during the same fiscal year, and dividing it by the standard deviation of firm-specific weekly returns raised to the third power. Specifically, for each firm *j* in year *t*, we obtain *NCSKEW* as

$$NCSKEW_{jt} = -\left[n(n-1)^{3/2} \sum W^3{}_{j\tau}\right] \Big/ \left[(n-1)(n-2)\left(\sum W^2{}_{j\tau}\right)^{3/2}\right]. \tag{6}$$

[5] Our definition of crash results in substantial negative weekly returns. Untabulated statistics show that the mean (median) firm-specific return for crash weeks is -20.7% (-18.6%), and the mean (median) raw return is -22.2% (-20.0%).

We introduce this second measure of crash risk for two major reasons. First, one may suspect that less conservative firms are, in general, related to longer tails; that is, they have not only more crashes but also more positive jumps. The use of negative skewness as an alternative measure mitigates this concern.[6] Second, some option and asset pricing applications require future return skewness as an input. Building a model that predicts skewness could thus contribute to this line of research (Barberis and Huang, 2008; Boyer et al., 2010).

4. Empirical results

4.1. Descriptive statistics and correlation matrix

Table 1 presents descriptive statistics for the major variables discussed in Section 3, along with additional variables that are used as control variables in our multivariate analysis. Appendix I provides detailed definitions of all variables. The mean value of *CRASH* is 0.12, suggesting that, on average, 12% of firm–years experience one or more firm-specific weekly returns that fall within 3.2 standard deviations below the annual mean. Though not tabulated, a closer look at the data reveals that only less than 0.2% of firm–years experience two crash events during a sample year, and only one firm–year experiences more than two crash events (three) during a sample year. The mean and median values of *NCSKEW* are -0.229 and -0.209, respectively. Here, *NCSKEW* is slightly lower than the values reported by Chen et al. (2001), which is expected since these authors use daily returns to construct their variables (Das and Sundaram, 1999). The mean and median values of *CSCORE* are 0.088 and 0.084, respectively, similar to those reported by Khan and Watts (2009).

Table 2 presents a Pearson correlation matrix for all the variables used in our regression analysis. The two measures for crash risk, *CRASH* and *NCSKEW*, are significantly and positively

[6] To further address this concern, we also construct a variable *COUNT*, which is the difference between the frequency of extreme negative returns and the frequency of extreme positive returns (Jin and Myers (2006)). We then rerun all regressions by replacing *NCSKEW* with *COUNT*. Though not reported, we find that all the regression results reported in the paper are qualitatively similar to those using this alternative dependent variable.

correlated with each other. The year t conservatism measure, $CSCORE_t$, is significantly and negatively correlated with the two measures of year t + 1 crash risk, which is consistent with our prediction that more conservative firms have lower crash risk.

4.2. Test of H1

4.2.1. Logistic regressions of crash likelihood on conservatism

To test whether more conservative firms experience lower crash risk (H1), we first estimate the following logit model that links conservatism in year t with the likelihood of stock price crash in year t + 1 (firm subscripts are suppressed):

$$CRASH_{t+1} = \alpha_0 + \alpha_1 CSCORE_t + \sum_{q=2}^{m} \alpha_q (q^{th} ControlVariables_t) + \varepsilon_t, \tag{7}$$

where $CRASH_{t+1}$ is an indicator variable that equals one if a firm experiences one or more crash events in year t + 1, and zero otherwise, and $CSCORE_t$ refers to the Khan and Watts (2009) conservatism measure in year t. Hypothesis H1 translates as $\alpha_1 < 0$.

To isolate the effect of conservatism on crash risk from the effects of other variables, we include several control variables known to influence crash likelihood. Our main control variables are those used in Chen et al. (2001), that is, detrended share turnover ($DTURN_t$), negative skewness of firm-specific weekly returns ($NCSKEW_t$), standard deviations of firm-specific weekly returns ($SIGMA_t$), firm-specific average weekly returns (RET_t), and firm size ($SIZE_t$). We control for the de-trended share turnover in year t because Chen et al. show that it proxies for differences of opinion among investors and has a significant positive impact on negative return skewness or crash risk in year t + 1. Firms with high return skewness in year t are likely to have high return skewness in year t + 1 as well (Chen et al., 2001). To control for this possibility, we include $NCSKEW_t$ in Eq. (8). We control for weekly return volatility (*$SIGMA_t$*) because stocks with high return volatility in year t are more likely to experience crashes in year t + 1. Chen et al. (2001) provide evidence that past returns have predictive power with respect to future crash risk. In particular, the authors find that future crash risk is higher for stocks with higher past returns (as far back as 36 months). We therefore control for past one-year average weekly returns (*RET_t*). To control for the size effect, we include firm size (*$SIZE_t$*) measured by the natural log of sales rather than the natural log of market capitalization, because the latter is one of three major inputs for computing our *CSCORE* measure, as shown in Eq. (3).

In alternate specifications, we also include the market-to-book ratio (*MB_t*) and financial leverage (*LEV_t*) as additional control variables. It should be pointed out, however, that the results from these specifications may suffer from multicollinearity problems, since these two variables are also used to construct *$CSCORE_t$*, as shown in Eq. (3). Furthermore, potential effects of *MB_t* and *LEV_t* on *$CRASH_{t+1}$* are likely to be captured by other control variables, such as year t stock returns and return volatilities. Therefore, we do not include such variables in our main regression specifications. Finally, we also estimate alternative regression specifications where the Hutton et al. (2009) measure of information opaqueness (*$OPAQUE_t$*) and future operating performance (*ROA_{t+1}*) are additionally included as controls. By including *$OPAQUE_t$*, we intend to (i) validate the effects of information opaqueness on crash risk, as evidenced in Hutton et al. (2009) and Jin and Myers (2006), using our sample, and (ii) ensure that our conservatism measure has the incremental predictive power for crash risk over and beyond *$OPAQUE_t$*. We measure *$OPAQUE_t$* using the procedures followed by Hutton et al., the details of which are provided in Appendix. Finally, similar to Hutton et al., we also include *ROA_{t+1}*, to control for possible contemporaneous relations between profitability and crash risk.[7]

[7] We do not include ROA_{t+1} in our main specification because our exercise is to forecast crash risk in year t+1 given all information available in year t.

Table 3 reports the logistic regression results for Eq. (7). To address potential cross-sectional and serial dependence in the data, we report *p*-values (two-tailed) that are based on robust standard errors adjusted for firm and year double clustering. Following Petersen (2009), all regressions in Table 3 also include year dummies, to control for year fixed effects.

Model 1 presents the results of our baseline regressions of $CRASH_{t+1}$ on $CSCORE_t$, where our major control variables, namely, $DTURN_t$, $NCSKEW_t$, $SIGMA_t$, RET_t, and $SIZE_t$ are included. Note that these control variables are similar to the set of crash determinants examined by Chen et al. (2001). In model 1, the coefficient of our key variable of interest, that is, $CSCORE_t$, is highly significant, with an expected negative sign and $p = 0.00$, suggesting that conservatism in year t reduces crash risk in year $t + 1$, even after controlling for other determinants of crash risk. In model 2, where we introduce two additional variables, MB_t and LEV_t, into the regressions, the coefficient of $CSCORE_{t+1}$ remains significantly negative, with $p = 0.00$.

To assess the economic significance of our test results, using the coefficients in model 1, we compute the marginal effect of *CSCORE*, that is, the change in *CRASH* (the probability of a crash) arising from a change of one standard deviation in *CSCORE*, holding all other independent variables at their mean values. The marginal effect of *CSCORE* in model 1 is about -0.031, suggesting that a one standard deviation increase in *CSCORE* results in a 3.1% decrease in the probability of a crash. This is economically significant, given that the average, unconditional probability of a crash in our sample is 12%, as reported in Table 1.

Finally, using a reduced sample of firm–years, we estimate our logistic regression in Eq. (8) after including two additional variables that are considered in Hutton et al. (2009), that is, $OPAQUE_t$ and ROA_{t+1}. The results are reported in model 3. We find that the coefficient of $CSCORE_t$ remains negative and significant, with $p = 0.013$, suggesting that the predictive ability of conservatism for crash likelihood is incremental over and beyond prior period accounting opaqueness, current period profitability, and other firm-specific determinants of future crash risk.

Turning to the control variables, we observe several interesting findings. First, the coefficient of $DTURN_t$ is significantly positive, with $p = 0.00$, across all models. In Chen et al. (2001), this detrended share turnover variable is the key test variable that proxies for investor belief heterogeneity or differences of opinion among investors. Chen et al. (2001) examine the effect of $DTURN_t$ on negative return skewness, but not its effect on extreme outcomes, namely, crash probability (*CRASH*). Our results therefore provide corroborating evidence for the theory of Chen et al. that investor heterogeneity increases crash risk. Second, the coefficient of the opaqueness measure ($OPAQUE_t$) of Hutton et al. (2009) is significantly positive, with $p = 0.004$, which is consistent with the authors' findings. Third, with respect to the relative significance of *CSCORE*, *DTURN*, and *OPAQUE*, untabulated results show that the marginal effect of *CSCORE* is significantly greater than those of both *DTURN* and *OPAQUE*.

Fourth, we find that the signs of the coefficients of past skewness ($NCSKEW_t$) are significantly positive, consistent with Chen et al. (2001). We find the coefficients of past return volatility ($SIGMA_t$) in models 1 and 2 to be positive but insignificant, while significantly positive in model 3. We also find that the coefficients of the stock return (RET_t) and market-to-book ratio (MB_t) are, overall, significantly positive, which is consistent with the "stochastic bubble theory," that stocks with high past returns and growth stocks are more crash prone (Harvey and Siddique, 2000). The coefficients of firm size are significantly positive, with $p = 0.00$, in model 3, while they are insignificant in models 1 and 2. Hutton et al. (2009) also report a significantly positive coefficient for *SIZE*, suggesting that large firms are more likely to experience crashes. However, we are unaware of any theory that predicts a positive relation between $SIZE_t$ and $CRASH_{t+1}$. The coefficients of LEV_t are insignificant in model 2, while significantly negative, with $p = 0.043$, in model 3. Finally, we find that ROA_{t+1} is negatively associated with $CRASH_{t+1}$, which is consistent with the findings of Hutton et al. (2009).

To obtain further insights into the inverse relation between $CSCORE_t$ and $CRASH_{t+1}$, we construct decile portfolios based on the ranked values of $CSCORE_t$ at the beginning of each sample year. We then compute the implied likelihood of future crashes, $CRASH_{t+1}$. In so doing, we use the estimated coefficients for Eq. (7) reported in model 1 of Table 4, with all variables other than *CSCORE* set equal to their sample means (reported in Table 2). We then plot the implied likelihood values against the mean *CSCORE* for each decile. As illustrated in Figure 1, crash likelihood in year $t + 1$ decreases monotonically as we move from the lowest *CSCORE* decile to the highest. We also note that the relation between the two variables, overall, appears to be linear, though the impact of conservatism on reducing crash risk is more pronounced in the two extreme deciles. For example, the implied crash likelihood decreases from 0.133 to 0.105 as we move from the bottom decile to the top decile of *CSCORE*, which accounts for 23.3% (= 2.8/12) of the variation in crash risk. In short, the *CSCORE–CRASH* relation depicted in Figure 1 provides further evidence that more conservative firms experience a lower likelihood of future stock price crashes.

Collectively, the results reported in Table 3 and Figure 1 reveal that, consistent with H1, the higher the conservatism in year t, the lower the likelihood of crashes in year $t + 1$, and this relation is highly significant across all specifications. This result holds even after controlling for the measures of investor heterogeneity of Chen et al. (2001) and the measure of information opaqueness of Hutton et al. (2009). Our results are, overall, consistent with the view that conservatism plays a significant role in limiting management incentives and its ability to withhold bad news or delay the timing of its disclosure, thereby lowering the probability of bad news being stockpiled within a firm and thus reducing the likelihood of a stock price crash.

4.2.2. OLS regression of negative return skewness on conservatism

To uncover further evidence on the relation between conservatism and crash risk, we also use the negative conditional skewness (*NCSKEW*) of the weekly firm-specific return distribution (Chen et al., 2001) as an alternative proxy for future crash risk. Table 4 reports the results of OLS regressions for Eq. (9) using $NCSKEW_{t+1}$ as the dependent variable. As in Table 3, all reported *p*-values are adjusted using standard errors corrected for firm and year double clustering.

As shown in Table 4, the coefficients of $CSCORE_t$ are significantly negative, with $p = 0.00$, across all models, which strongly supports the prediction in H1. This result is economically significant as well. Consider the results in model 1 as an example. The *CSCORE* coefficient of -1.293 indicates that a one standard deviation increase in $CSCORE_t$ leads to an approximately 40% (= 1.293*0.07/0.229) decrease in $NCSKEW_{t+1}$. The signs and significance of other coefficients are, overall, consistent with those reported in Table 3. Consistent with the finding of Chen et al. (2001), the coefficients of *DTURN* and *RET* are all significantly positive across all models, with $p = 0.00$. Note also that the coefficient on *OPAQUE* is also significantly positive, with $p = 0.024$, in model 3.

4.2.3. The Cox proportional hazard model approach

Jin and Myers (2006) argue that time can enter investors' assessment of crash probabilities because the probability increases as time passes. To incorporate this time effect, we employ the Cox (Cox, 1972) proportional hazard method:

$$\ln h_{jk}(t) = \mu(t - t_{j(k-1)}) + \varphi_1 CSCORE_{jk} + \sum_{q=2}^{m} \varphi_q (q^{th} ControlVariable_{jk}) + \varepsilon_{jk}\,, \qquad (8)$$

where $h_{jk}(t)$ is the "hazard," or instantaneous likelihood of crash occurrence, for firm j at time t, conditional on k crashes having occurred in firm j by time t;[8] $t_{j(k-1)}$ is the time of the (k - 1)th event; and $\mu(.)$ is an unspecified function that captures the baseline hazard. Hypothesis H1 translates as $\varphi_1 < 0$, which can be interpreted in such a way that the hazard of crash occurrences decreases with conservatism, or the instantaneous likelihood of crash occurrences decreases with conservatism, given past crash history.

An important feature of the above hazard model that distinguishes it from the logit model in Eq. (7) is that the former takes into account both the timing and magnitude of past crash occurrences when forecasting a firm's instantaneous crash risk. The bankruptcy and insurance literature shows that the hazard model is more accurate in identifying factors that can predict rare events (Lee and Urrutia, 1996; Shumway, 2001).

To estimate the hazard model in Eq. (8), we identify a sample of firms with at least one crash event during the sample period. For each firm crash event, we calculate the crash interval, which is the length of time (in weeks) from the current firm crash event to the next. If no further firm crash event is observed, the interval is the length of time from the current event until the firm's delisting date or the ending date of the sample period, whichever occurs first. The control variables are the same as in Eq. (7) and year dummies are included. The model is estimated by partial likelihoods using the well-known method of stratification (Cox, 1975). The partial likelihood estimation makes it possible to estimate φ_1 to φ_m without specifying a particular functional form of $\mu(.)$. Firm-level stratification allows different firms to have different baseline hazard functions, while constraining the coefficients to be the same across firms (Allison, 2005). Table 7 reports the estimated coefficients

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[8] Specifically, the hazard function $h_j(t) = \lim_{\Delta t \to 0} \frac{\Pr[N_j(t+\Delta t) - N_j(t) = 1]}{\Delta t}$, where $N_j(t)$ is the number of events that have occurred to firm j by time t.

and p-values for the stratified hazard model regressions. All reported p-values are adjusted using standard errors corrected for firm and year double clustering.

As shown in Table 5, the coefficients of *CSCORE* are significantly negative in all models, with $p = 0.00$, which strongly supports H1. To assess the economic significance of our test variable, consider the results reported in model 1 as an example: The coefficient of *CSCORE* is -4.212, suggesting that a one standard deviation increase in *CSCORE* leads to an approximately 25% (= 1 - $e^{(-4.212\times0.07)}$) reduction of the subsequent crash hazard rate, even after controlling for all other determinants of crash occurrence. These results can also be interpreted in such a way that the instantaneous crash likelihood of conservative firms at time t is lower than that of aggressive firms, conditional on k crashes having occurred by time t. Table 5 also shows that the coefficients of $DTURN_t$ and $OPAQUE_t$ are significantly positive, which lends further support to the findings of Chen et al. (2001) and Hutton et al. (2009).

4.3. Test of H2: does information asymmetry matter?

Hypothesis H2 predicts that the impact of conservatism on reducing the likelihood of future crashes is more pronounced for firms with high information asymmetry than for firms with low information asymmetry. To test this hypothesis, we consider three proxies for information asymmetry between managers and equity market participants:

(i) The relative amount of R&D investment. Prior literature argues that R&D investment is a major source of private information from the investor’s perspective (Aboody and Lev, 2000). Many R&D projects, such as new drugs or software programs under development, are unique to the firms concerned, whereas most capital investment projects share common characteristics across firms. Therefore, it is difficult for outside investors to infer the productivity and value of a firm’s R&D from observing the R&D performance of other firms. In addition, unlike many other physical and financial assets, there is no organized market for R&D and hence no asset prices from which to derive valuation implications of firm-specific R&D. Aboody and Lev (2000) provide evidence suggesting that R&D is a major contributor to information asymmetry between corporate insiders and outsiders, and thus an important source of insider gains. In light of H2, we expect that the impact of conservatism on reducing crash risk is more pronounced for more R&D-intensive firms.

(ii) The degree of industry concentration or product market competition. Economists argue that product market competition mitigates managerial agency problems (Giroud and Mueller, 2010). Dhaliwal et al. (2008) provide evidence that intense product market competition induces managers to be more conservative in financial reporting. Ali et al. (2009) find that firms in more concentrated industries (with, therefore, low competition) have a more opaque information environment. This finding suggests that information asymmetries are higher for firms with high industry concentration. Thus, we expect that the impact of conservatism on reducing crash risk is accentuated for firms with high industry concentration or low product market competition.

(iii) Analyst coverage. Financial analysts play an important role of information intermediation between managers and less-informed outside investors. Furthermore, analysts play a role in monitoring managerial disclosure behavior (Ball, 2001). Evidence shows that analysts' information intermediation and/or monitoring is value-adding because it reduces information asymmetry between corporate insiders and outsiders (Lang et al., 2003). Yu (2008) finds that firms with high analyst coverage engage less in opportunistic earnings management, a finding consistent with the monitoring role of analysts. The above findings, taken together, suggest that information asymmetry in the equity market is lower for firms with higher analyst coverage. In light of H2, we expect that the impact of conservatism on reducing crash risk is attenuated for firms with high analyst coverage.

Table 6 reports the results from the augmented model of Eq. (7), where $CRASH_{t+1}$ is the dependent variable and three proxies for information asymmetry and their interactions with our measure of conservatism, $CSCORE_t$, are additionally introduced. Table 7 reports the same results, using $NCSKEW_{t+1}$ as the dependent variable. In both Tables 6 and 7, $R\&D_t$ is an indicator variable that equals one for firms with R&D investment in year *t*, and zero otherwise; $HICON_t$ is an indicator variable that equals one if firms have an above-median Herfindahl index in year *t*, and zero otherwise; and $NEGCOV_t$ is the natural log of 1 plus the number of analysts following a firm in year *t*, multiplied by minus one. For all three measures, higher values indicate higher information asymmetry. In all regressions, we include the same set of control variables, that is, $DTURN_t$, $NCSKEW_t$, $SIGMA_t$, RET_t, and $SIZE_t$.

Ai and Norton (2003) and Norton et al. (2004) demonstrate that both the effects and standard errors of interaction terms in logit or probit models are biased (with their coefficients sometimes exhibiting opposite signs) and suggest a method to correct for these biases. Accordingly, we follow their suggestion when estimating the magnitude and standard errors of the interaction effect in logit models: In Table 6, for non-interaction terms, we estimate the coefficients and standard errors using the double-clustering method, as in Table 3. For interaction terms, we use the procedure of Norton et al. (2004) to estimate the effects and standard errors.[9]

The results in both Tables 6 and 7 show that the coefficients of *CSCORE*R&D*, *CSCORE*HICON*, and *CSCORE*NEGCOV* are all significantly negative, suggesting that the impact of conservatism on reducing the likelihood of crash occurrence is more pronounced for firms with higher information asymmetry. Similar to H1, we also use the hazard model approach to provide further support for H2, with Table 8 reporting the results. Overall, the results in Table 8 are

[9] The implications are same if we do not use the Norton et al. (2004) procedure.

consistent with those reported in Tables 6 and 7. Overall, the results presented in Tables 6 through 8 provide strong support for H2.

5. Additional tests and robustness checks

5.1. Longer forecast windows

In our logit and OLS regressions, we only examine the relation between the current year's conservatism and crash probability in the one-year-ahead forecasting window. It is interesting to further examine how far out our conservatism predicts future crash risk. Toward this end, we now expand the measurement window of crash risk into two- and three-year-ahead windows. Specifically, we estimate *CRASH* and *NCSKEW* using firm-specific weekly returns during the two- and three-year periods starting three months after the current fiscal year-end. In so doing, we require at least 100 and 150 weekly returns available for each firm for the two- and three-year window tests, respectively. Using the two- or three-year crash risk measure as our dependent variable, we re-estimate our baseline prediction model, namely, model 1, of Tables 3 and 4 and report the estimated results in Table 9.

Panel A of Table 9 displays the logistic regression results. As shown in panel A, the coefficients of *CSCORE* are significantly negative for both model 1 (two-year-ahead forecasting window, dependent variable: $CRASH_{t+2}$) and model 2 (three-year-ahead forecasting window, dependent variable: $CRASH_{t+3}$). Panel B of Table 9 presents the results of OLS regressions with *NCSKEW* as a measure of crash risk. Again, the coefficients of *CSCORE* are significantly negative for both the two- and three-year forecasting windows (dependent variable: $NCSKEW_{t+2}$ and $NCSKEW_{t+3}$, respectively). The above results indicate that the predictive ability of conservatism for future crash risk is significant and robust, even when the measurement window of crash likelihood is extended up to three years ahead. Simply put, conservatism reliably predicts future crash risk as far as three years into the future, at least.

5.2. Alternative measures of conditional conservatism

Khan and Watts (2009) recommend the use of alternative measures of conservatism in place of *CSCORE* to test the robustness of results. In this section, we test the robustness of our main results by using two other measures of conditional conservatism. First, we run Basu (1997) panel piecewise linear regressions, following Francis and Martin (2010). Specifically, we augment the Basu model by including interaction terms as follows:

$$X_{j,t} = \beta_1 + \beta_2 D_{j,t} + \beta_3 R_{j,t} + \beta_4 D_{j,t} * R_{jt} + \beta_5 CRASH_{j,t+1} + \beta_6 CRASH_{j,t+1} * D_{j,t} \\ + \beta_7 CRASH_{j,t+1} * R_{j,t} + \beta_8 CRASH_{j,t+1} * D_{j,t} * R_{j,t} + \varepsilon_{j,t}, \tag{9}$$

where all variables are as defined previously. A negative coefficient for $CRASH_{t+1} * D_{jt} * R_{jt}$ is consistent with our prediction that accounting conservatism reduces future crash risk (i.e., $\beta_8 < 0$). Note that *X, D,* and *R* are measured in year *t*, while *CRASH* is measured in year $t + 1$. We also replace $CRASH_{t+1}$ with $NCSKEW_{t+1}$ in Eq. (9) to examine the relation between conservatism and negative firm-specific return skewness.

We estimate Eq. (9) using panel regressions on all firm-year observations in our sample and report the results in Table 10. Reported *p*-values are on an adjusted basis using standard errors corrected for two-dimensional (firm and year) clustering. As seen in Table 10, both *CRASH* and *NCSKEW* in year $t + 1$ are negatively associated with the current period asymmetric timeliness of earnings, consistent with our main results using *CSCORE* as a measure of conservatism. We also estimate the augmented Basu model by replacing $CRASH_{t+1}$ ($NCSKEW_{t+1}$) with $CRASH_{t+2}$ or

$CRASH_{t+3}$ ($NCSKEW_{t+2}$ or $NCSKEW_{t+3}$). As shown in panel A of Table 10, the coefficients of *CRASH*D*R* are significantly negative for models 1 and 2, though insignificant with a negative sign for model 3. As reported in panel B of Table 10, the coefficients of *NCSKEW*D*R* are highly significant, with an expected negative sign, for all models 1 through 3. Overall, these results are consistent with our results reported in Table 9, corroborating our earlier finding that conservatism predicts crash risk as far as three years into the future.

Second, following Ball and Shivakumar (2006; 2008), we use a conditional conservatism measure that is not based on stock returns to repeat our main tests.[10] Specifically, we run the following panel regressions:

$$\begin{aligned} ACC_{j,t} &= \gamma_0 + \gamma_1 \Delta REV_{j,t} + \gamma_2 GPPE_{j,t} + \gamma_3 DCF_{j,t} + \gamma_4 CF_{j,t} + \gamma_5 DCF_{j,t} * CF_{j,t} \\ &+ \gamma_6 CRASH_{j,t+1} + \gamma_7 CRASH_{j,t+1} * \Delta REV_{j,t} + \gamma_8 CRASH_{j,t+1} * GPPE_{j,t} \\ &+ \gamma_9 CRASH_{j,t+1} * DCF_{j,t} + \gamma_{10} CRASH_{j,t+1} * CF_{j,t} + \gamma_{11} CRASH_{j,t+1} * DCF_{j,t} * CF_{j,t} + \varepsilon_{jt}, \end{aligned} \tag{10}$$

where all variables are as defined in Table 11. A negative coefficient for $CRASH_{j,t+1} * DCF_{j,t} * CF_{j,t}$ is consistent with our prediction that accounting conservatism reduces future crash risk (i.e., $\gamma_{11} < 0$). Similar to Eq. (9), we also replace $CRASH_{t+1}$ with $NCSKEW_{t+1}$ in Eq. (10) to examine the relation between conservatism and negative firm-specific return skewness. The results in Table 11 are generally consistent with those from the Basu regressions.

6. Conclusions

This study investigates whether conservatism in financial reporting has the ability to predict stock price crash risk. Using a large sample of firm–years over the period of 1964–2007, we find that the extent of conservatism, or the timelier recognition of bad news as losses than of good news as

[10] For this test, we exclude firms from financial and utility industries.

gains, in financial reporting reduces crash risk as reflected in the likelihood of a firm experiencing future crashes and/or negative firm-specific return skewness. This finding holds even after controlling for the investor heterogeneity, information opaqueness, and other firm-specific factors deemed to cause large negative return outliers. Our results are robust to the use of different measures of crash risk and conservatism, alternative model specifications, and a variety of sensitivity checks. We further find that the predictive power of conservatism with respect to crash risk is more pronounced for firms with higher information asymmetry, namely, those with relatively higher R&D investments, higher industry concentration, and lower analyst coverage. Overall, our results are not only statistically significant but also economically significant. We find, for example, that a one standard deviation increase in the *CSCORE* of Khan and Watts (2009) is associated with a 3.1% reduction in crash probability, a 25% reduction in crash hazard or instantaneous crash likelihood, and a 43% reduction in negative return skewness, all else being equal. In short, we provide strong and robust evidence that conditional conservatism is a reliable predictor of future stock price crash risk.

Our results are consistent with the notion that accounting conservatism is associated with less withholding of bad news or more timely release of bad news to outside investors, thereby reducing stock price crash risk. LaFond and Watts (2008) provide evidence that conservatism plays an important role in the equity market by reducing information asymmetry. Our study complements LaFond and Watts (2008) by providing evidence that conservatism is associated with desirable economic consequences in the equity market through the reduction of future crash risk. This evidence on the relation between conservatism and higher moments of stock returns is timely and interesting, given the heightened salience of forecasting extreme outcomes following the recent market debacle.

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Appendix

Procedures for estimating *OPAQUE*

Following Hutton et al. (2009), we employ the modified Jones model (Dechow et al. (1995)) to estimate discretionary accruals. Specifically, we first run the following cross-sectional regressions for each Fama and French (1997) industry for each fiscal year from 1988 to 2007:

$$\frac{TACC_{jt}}{TA_{jt-1}} = \alpha \frac{1}{TA_{jt-1}} + \beta_1 \frac{\Delta SALE_{jt}}{TA_{jt-1}} + \beta_2 \frac{PPE_{jt}}{TA_{jt-1}} + \varepsilon_{jt} \quad , \qquad \text{II-(1)}$$

where TA_{jt-1} is total assets for firm j at the begging of year t, $TACC_{jt}$ is total accruals form firm j during year t, which is calculated as income before extraordinary items minus cash flow from operating activities adjusted for extraordinary items and discontinued operations, $\Delta SALE_{jt}$ is change in sales for firm j in year t, and PPE_{jt} is property, plant, and equipment for firm j at the end of year t.

The estimated coefficients from II-(1) are then applied to discretionary accruals ($DISACC_{jt}$):

$$DISACC_{jt} = \frac{TACC_{jt}}{TA_{jt-1}} - \hat{\alpha} \frac{1}{TA_{jt-1}} - \hat{\beta}_1 \frac{\Delta SALE_{jt} - \Delta REC_{jt}}{TA_{jt-1}} + \hat{\beta}_2 \frac{PPE_{jt}}{TA_{jt-1}} \quad , \qquad \text{II-(2)}$$

where ΔREC_{jt} is change in accounts receivable and $\hat{\alpha}$, $\hat{\beta}_1$, $\hat{\beta}_2$ are the estimated coefficients from equation II-(1). The variable $OPAQUE_t$ is the moving sum of discretionary accruals over the last three years (year t-1, t-2, and t-3).

Table 1
Descriptive statistics.

Variable	Mean	Std	Q1	Median	Q3	N
$CRASH_{t+1}$	0.120	0.325	0.000	0.000	0.000	137,571
$NCSKEW_{t+1}$	-0.229	0.727	-0.616	-0.209	0.175	137,571
$CSCORE_t$	0.088	0.070	0.043	0.084	0.127	137,571
$DTURN_t$	0.002	0.053	-0.010	0.000	0.012	115,252
$NCSKEW_t$	-0.227	0.704	-0.612	-0.213	0.165	137,317
$SIGMA_t$	0.055	0.027	0.035	0.049	0.069	137,317
RET_t	-0.183	0.191	-0.234	-0.119	-0.059	137,317
$SIZE_t$	5.022	2.015	3.669	4.947	6.357	137,571
MB_t	2.509	19.150	0.992	1.570	2.605	137,571
LEV_t	0.227	0.182	0.066	0.205	0.350	137,571
ROA_{t+1}	0.033	0.146	0.009	0.042	0.084	137,442
$OPAQUE_t$	0.323	0.277	0.134	0.236	0.419	48,771
$R\&D_t$	0.368	0.482	0.000	0.000	1.000	137,571
$HICON_t$	0.496	0.500	0.000	0.000	1.000	137,571
$NEGCOV_t$	-1.015	-1.052	0.000	-0.693	-1.946	100,486

The sample period is from 1964 to 2007 for major variables, except for *OPAQUE*, and *NEGCOV*. *OPAQUE* is measured from 1990 to 2007. *NEGCOV* is measured from 1982 to 2007. $CRASH_{t+1}$ is an indicator variable equal to 1 if a firm experiences one or more firm-specific weekly returns falling 3.2 or more standard deviations below the mean firm-specific weekly return for fiscal year $t+1$, zero otherwise. $NCSKEW_{t+1}$, is the negative coefficient of skewness of firm-specific weekly return in fiscal year $t+1$. $CSCORE_t$ is the conservatism score in fiscal year *t*. $DTURN_t$ is average monthly turnover in fiscal year *t*, minus average monthly turnover in fiscal year $t-1$. $NCSKEW_t$ is the negative coefficient of skewness of firm-specific weekly return in fiscal year *t*. $SIGMA_t$ is the standard deviation of firm-specific weekly return in fiscal year *t*. RET_t is average firm-specific weekly return in fiscal year *t* times 100. $SIZE_t$ is log of sales in fiscal year *t*. MB_t is market to book ratio in fiscal year *t*. LEV_t is financial leverage in fiscal year *t,* which is total long-term debt divided by total assets. $OPAQUE_t$ is opaqueness of the firm's financial reports in fiscal year *t* (see Appendix for details). ROA_{t+1} is return on assets in fiscal year $t+1$. $R\&D_t$ is an indicator variable that takes the value of 1 if the firm reports non-zero research and development expenses in fiscal year *t*, zero otherwise. $HICON_t$ is an indicator variable that takes the value of 1 if the firm's Herfindahl index is above the median in fiscal year *t*, zero otherwise. $NEGCOV_t$ is the log of 1 plus the number of analysts following in fiscal year *t*, multiplied by minus one.

Table 2
Correlation matrix for major variables.

Variable		A	B	C	D	E	F	G	H	I	J	K
$CRASH_{t+1}$	A	**1.000**										
$NCSKEW_{t+1}$	B	**0.541**	**1.000**									
$CSCORE_t$	C	**-0.030**	**-0.159**	**1.000**								
$DTURN_t$	D	**0.019**	**0.048**	**-0.039**	**1.000**							
$NCSKEW_t$	E	**0.034**	**0.097**	**-0.132**	**0.023**	**1.000**						
$SIGMA_t$	F	**0.000**	**-0.062**	**0.182**	**0.099**	**-0.056**	**1.000**					
RET_t	G	**0.003**	**0.062**	**-0.172**	**-0.105**	**0.076**	**-0.964**	**1.000**				
$SIZE_t$	H	**0.023**	**0.178**	**-0.396**	**0.022**	**0.194**	**-0.376**	**0.354**	**1.000**			
MB_t	I	**0.013**	**0.010**	**-0.038**	**0.016**	**-0.001**	**0.039**	**-0.041**	**-0.017**	**1.000**		
LEV_t	J	**-0.026**	**-0.021**	**0.245**	-0.004	**-0.014**	**-0.080**	**0.075**	**0.148**	**0.008**	**1.000**	
ROA_{t+1}	K	**-0.010**	**0.037**	**-0.156**	**0.026**	**0.021**	**-0.250**	**0.267**	**0.220**	**-0.027**	**-0.035**	**1.000**
$OPAQUE_t$	L	**0.024**	**0.011**	**0.093**	**-0.009**	0.003	**0.260**	**-0.237**	**-0.181**	**0.149**	**-0.123**	**-0.093**

This table reports the pooled firm-year correlation matrix for major variables used in our empirical tests. The sample period is from 1964 to 2007 for major variables. *OPAQUE* is measured from 1990 to 2007. All variables are defined in Table 1. Bold face indicates *p*-value <0.05.

Table 3
Forecasting crashes: logistic regression of *CRASH* on *CSCORE*.

Variable	Pred. Sign	Model 1 Coefficient	Model 1 *p-value*	Model 2 Coefficient	Model 2 *p-value*	Model 3 Coefficient	Model 3 *p-value*
$\boldsymbol{CSCORE_t}$	**-**	**-1.630**	***<0.001***	**-1.494**	***<0.001***	**-1.166**	***0.013***
$DTURN_t$	+	0.917	*0.001*	0.923	*0.001*	0.989	*<0.001*
$NCSKEW_t$	+	0.059	*0.001*	0.059	*0.001*	0.084	*0.001*
$SIGMA_t$	+	5.076	*0.182*	5.022	*0.188*	11.354	*0.016*
RET_t	+	1.007	*0.039*	1.009	*0.039*	1.898	*0.003*
$SIZE_t$	?	-0.005	*0.687*	-0.002	*0.868*	0.032	*0.004*
MB_t	+			0.001	*0.051*	0.025	*0.005*
LEV_t	?			-0.092	*0.355*	-0.257	*0.043*
$OPAQUE_t$	+					0.206	*0.004*
ROA_{t+1}	-					-0.212	*0.017*
N		115,174		115,174		47,036	
$p>Chi^2$		*<0.001*		*<0.001*		*<0.001*	
Pseudo R^2		0.031		0.031		0.015	

This table presents logistic regressions to predict crash risk. The sample period is from 1964 to 2007. Due to data restrictions from *OPAQUE*, the sample period for model (3) is from 1990 to 2007. The dependent variable is $CRASH_{t+1}$, which is an indicator variable equal to 1 if a firm experiences one or more firm-specific weekly returns falling 3.2 or more standard deviations below the mean firm-specific weekly return for fiscal year $t+1$, zero otherwise. All other variables are defined in Table 1. The *p-values* (two-tailed) are based on standard errors clustered by both firm and time. All estimations also contain fiscal year dummies. The key variable of interest is highlighted by bold face.

Table 4
Forecasting negative skewness using *CSCORE.*

Variable	Pred. Sign	Model 1 Coefficient	Model 1 *p-value*	Model 2 Coefficient	Model 2 *p-value*	Model 3 Coefficient	Model 3 *p-value*
$\boldsymbol{CSCORE_t}$	**-**	**-1.293**	***<0.001***	**-1.370**	***<0.001***	**-1.862**	***<0.001***
$DTURN_t$	+	0.465	*<0.001*	0.460	*<0.001*	0.382	*<0.001*
$NCSKEW_t$	+	0.042	*<0.001*	0.042	*<0.001*	0.036	*<0.001*
$SIGMA_t$	+	1.747	*0.050*	1.789	*0.045*	3.674	*0.001*
RET_t	+	0.305	*0.002*	0.309	*0.002*	0.537	*<0.001*
$SIZE_t$	?	0.038	*<0.001*	0.036	*<0.001*	0.026	*<0.001*
MB_t	+			0.000	*0.356*	0.006	*0.082*
LEV_t	?			0.064	*0.007*	0.040	*0.228*
$OPAQUE_t$	+					0.040	*0.024*
ROA_{t+1}	-					0.051	*0.139*
N		115,174		115,174		47,036	
R^2		0.074		0.074		0.065	

This table presents regressions to predict negative skewness in weekly returns. The sample period is from 1964 to 2007. Due to data restrictions from *OPAQUE*, the sample period for model (3) is from 1990 to 2007. The dependent variable, $NCSKEW_{t+1}$, is the negative coefficient of skewness of firm-specific weekly returns in fiscal year $t+1$. All other variables are defined in Table 1. The *p-values* (two-tailed) are based on standard errors clustered by both firm and time. All estimations also contain fiscal year dummies. The key variable of interest is highlighted by bold face.

Table 5
Instantaneous crash risk: Cox proportional hazard model.

Variable	Pred. Sign	Model 1 Coefficient	Model 1 *p-value*	Model 2 Coefficient	Model 2 *p-value*	Model 3 Coefficient	Model 3 *p-value*
$\boldsymbol{CSCORE_t}$	**-**	**-4.212**	***<0.001***	**-3.883**	***<0.001***	**-6.662**	***<0.001***
$DTURN_t$	+	1.639	*<0.001*	1.615	*<0.001*	1.670	*0.001*
$NCSKEW_t$	+	0.087	*0.004*	0.088	*0.004*	0.058	*0.220*
$SIGMA_t$	+	4.542	*0.183*	4.611	*0.177*	3.342	*0.569*
RET_t	+	0.975	*0.031*	0.982	*0.030*	0.556	*0.446*
$SIZE_t$	?	0.000	*0.992*	0.008	*0.813*	0.128	*0.121*
MB_t	+			0.009	*0.564*	0.006	*0.826*
LEV_t	?			-0.158	*0.489*	-0.643	*0.108*
$OPAQUE_t$	+					0.637	*0.001*
ROA_t	?					0.868	*0.024*
N		15,752		15,752		7,460	
$p>Chi^2$		<0.001		<0.001		<0.001	
Pseudo R^2		0.026		0.026		0.063	

This table presents Stratified (firm-strata) Cox proportional hazard model estimations to predict instantaneous crash risk. The sample period is from 1964 to 2007. Due to data restrictions from *OPAQUE*, the sample period for columns (3) is from 1990 to 2007. The dependent variable, ln*h(t)*, is the instantaneous risk of crash at time(week) t. For each firm-crash event, we calculate the crash interval (*DUR*), which is the length of time (in weeks) from the current firm-crash event to the next firm-crash event. If no further firm-crash event is observed by the end of the sample period, the interval is the length of time from the current crash event until the firm's delisting date or the sample period end date (2007-12-31), whichever is earlier (right-censored). A crash event is defined as the week when a firm experiences firm-specific weekly return falling 3.2 or more standard deviations below the mean firm-specific weekly return for fiscal year *t*, where fiscal year *t* is the fiscal year in which the current week is located. The independent variables are measured as in fiscal year *t* and are defined in Table 1. The *p-values* (two-tailed) are based on standard errors clustered by both firm and time. All estimations also contain fiscal year dummies. The key variable of interest is highlighted by bold face.

Table 6
Forecasting Crashes: the effect of R&D expenditure, product market competition, and analyst coverage.

	Pred. Sign	Model 1		Model 2		Model 3	
		Coefficient	*p-value*	Coefficient	*p-value*	Coefficient	*p-value*
$CSCORE_t$	-	**-1.284**	***<0.001***	**-2.535**	***<0.001***	**-1.500**	***<0.001***
$R\&D_t$	?	0.126	*0.001*				
$CSCORE_t$*$R\&D_t$	-	**-0.074**	***0.025***				
$HICON_t$	?			0.157	*<0.001*		
CSCORE*$HICON_t$	-			**-0.144**	***<0.001***		
$NEGCOV_t$	?					-0.071	*0.003*
CSCORE*$NEGCOV_t$	-					**-0.031**	***0.084***
$DTURN_t$	+	0.933	*<0.001*	0.911	*0.001*	0.909	*0.001*
$NCSKEW_t$	+	0.059	*0.001*	0.059	*0.001*	0.045	*0.015*
$SIGMA_t$	+	4.433	*0.25*	4.951	*0.196*	5.465	*0.176*
RET_t	+	0.973	*0.049*	0.989	*0.045*	1.033	*0.045*
$SIZE_t$	?	-0.005	*0.703*	-0.004	*0.78*	-0.024	*0.109*
N		115,174		115,174		89,762	
$p>Chi^2$		*<0.001*		*<0.001*		*<0.001*	
Pseudo R^2		0.031		0.031		0.014	

This table presents the logistic regression analysis using $CRASH_{t+1}$ as the dependent variable. The sample period is from 1964 to 2007 for model 1 and model 2 and is from 1982 to 2007 for model 3. $CRASH_{t+1}$ is an indicator variable equal to 1 if a firm experiences one or more firm-specific weekly returns falling 3.2 or more standard deviations below the mean firm-specific weekly return for fiscal year *t+1*, zero otherwise. See Table 1 for detailed definitions of all other variables. The interaction effects and their p-values are estimated using Norton et al. (2004) procedure. The *p-values* (two-tailed) for all other coefficients are based on standard errors clustered by both firm and time. All estimations also contain fiscal year dummies. The key variables of interest are highlighted by bold face.

Table 7
Forecasting negative skewness: The effect of R&D expenditure, product market competition, and analyst coverage.

	Pred. Sign	Model 1		Model 2		Model 3	
		Coefficient	*p-value*	Coefficient	*p-value*	Coefficient	*p-value*
$CSCORE_t$	-	**-1.158**	***<0.001***	**-1.477**	***<0.001***	**-1.212**	***<0.001***
$R\&D_t$	?	0.039	*<0.001*				
$CSCORE_t$*$R\&D_t$	-	**-0.424**	***<0.001***				
$HICON_t$	?			0.022	*0.013*		
CSCORE*$HICON_t$	-			**-0.258**	***0.003***		
$NEGCOV_t$	?					-0.056	*<0.001*
CSCORE*$NEGCOV_t$	-					**-0.216**	***0.012***
$DTURN_t$	+	0.461	*<0.001*	0.463	*<0.001*	0.456	*<0.001*
$NCSKEW_t$	+	0.042	*<0.001*	0.042	*<0.001*	0.031	*<0.001*
$SIGMA_t$	+	1.745	*<0.001*	1.755	*0.046*	1.773	*0.072*
RET_t	+	0.305	*<0.001*	0.304	*0.002*	0.315	*0.004*
$SIZE_t$	?	0.037	*<0.001*	0.038	*<0.001*	0.020	*<0.001*
N		115,174		115,174		89,762	
R^2		0.074		0.074		0.069	

This table presents the regression analysis using $NCSKEW_{t+1}$ as the dependent variable. The sample period is from 1964 to 2007 for model 1 and model 2 and is from 1982 to 2007 for model 3. $NCSKEW_{t+1}$, is the negative coefficient of skewness of firm-specific weekly returns in fiscal year *t+1*. See Table 1 for detailed definitions of all other variables. The *p-values* (two-tailed) are based on standard errors clustered by both firm and time. All estimations also contain fiscal year dummies. The key variables of interest are highlighted by bold face.

Table 8
Cox proportional hazard model: the effects of R&D expenditure, product market competition, and analyst coverage.

	Pred. Sign	Model 1		Model 2		Model 3	
		Coefficient	*p-value*	Coefficient	*p-value*	Coefficient	*p-value*
$CSCORE_t$	-	**-3.793**	***<0.001***	**-3.554**	***<0.001***	**-5.802**	***<0.001***
$R\&D_t$	?	0.123	*0.307*				
$CSCORE_t$*$R\&D_t$	-	**-1.368**	***0.085***				
$HICON_t$	?			0.036	*0.690*		
CSCORE*$HICON_t$	-			**-1.496**	***0.090***		
$NEGCOV_t$	?					-0.032	*0.518*
CSCORE*$NEGCOV_t$	-					**-0.743**	***0.066***
$DTURN_t$	+	1.621	*<0.001*	1.618	*<0.001*	1.504	*<0.001*
$NCSKEW_t$	+	0.086	*0.004*	0.087	*0.004*	0.075	*0.026*
$SIGMA_t$	+	4.529	*0.183*	4.708	*0.164*	6.789	*0.069*
RET_t	+	0.980	*0.029*	0.978	*0.030*	1.120	*0.021*
$SIZE_t$	?	-0.001	*0.986*	-0.000	*0.993*	-0.004	*0.919*
N		15,752		15,752		14,243	
$p>Chi^2$		<0.001		<0.001		<0.001	
Pseudo R^2		0.026		0.026		0.029	

This table presents Stratified (firm-strata) Cox proportional hazard model estimations to predict the instantaneous crash risk. The sample period is from 1964 to 2007. Due to data restrictions from *NEGCOV*, the sample period for model 3 is from 1982 to 2007. The dependent variable, ln*h(t)*, is the instantaneous risk of crash at time(week) *t*. For each firm-crash event, we calculate the crash interval (*DUR*), which is the length of time (in weeks) from the current firm-crash event to the next firm-crash event. If no further firm-crash event is observed by the end of the sample period, the interval is the length of time from the current crash event until the firm's delisting date or the sample period end date (2007-12-31), whichever is earlier (right-censored). A crash event is defined as the week when a firm experiences firm-specific weekly return falling 3.2 or more standard deviations below the mean firm-specific weekly return for fiscal year *t*, where fiscal year *t* is the fiscal year in which the current week is located. The independent variables are measured as in fiscal year *t* and defined in Table 1. The *p-values* (two-tailed) are based on standard errors clustered by both firm and time. All estimations also contain fiscal year dummies. The key variable of interest is highlighted by bold face.

Table 9
Forecasting crash likelihood (*CRASH*) and negative conditional skewness (*NCSKEW*): longer forecast windows.

Panel A: Logistic Regression Using CRASH as the Dependent Variable

		Model 1: Two-Year Window		*Model 2: Three-Year Window*	
	Pred. Sign	Coefficient	*p-value*	Coefficient	*p-value*
$CSCORE_t$	**-**	**-1.082**	***<0.001***	**-0.764**	***0.002***
$DTURN_t$	+	0.879	*<0.001*	1.072	*<0.001*
$NCSKEW_t$	+	0.051	*0.001*	0.065	*<0.001*
$SIGMA_t$	+	2.631	*0.409*	1.343	*0.610*
RET_t	+	0.655	*0.092*	0.526	*0.108*
$SIZE_t$	?	0.002	*0.879*	0.011	*0.224*
N		111,849		98,782	
$p>Chi^2$		*<0.001*		*<0.001*	
Pseudo R^2		0.035		0.044	

Panel B: OLS Regression Using NCSKEW as the Dependent Variable

		Model 1: Two-Year Window		*Model* 2: Three-Year Window	
	Pred. Sign	Coefficient	*p-value*	Coefficient	*p-value*
$CSCORE_t$	**-**	**-1.719**	***<0.001***	**-1.774**	***<0.001***
$DTURN_t$	+	0.563	*<0.001*	0.595	*<0.001*
$NCSKEW_t$	+	0.054	*<0.001*	0.060	*<0.001*
$SIGMA_t$	+	3.733	*<0.001*	3.371	*0.001*
RET_t	+	0.455	*<0.001*	0.482	*<0.001*
$SIZE_t$	?	0.051	*<0.001*	0.056	*<0.001*
N		111,849		98,782	
R^2		0.079		0.100	

This table presents the results of forecasting longer-windows of future crash risk. The sample period is from 1964 to 2007. In Panel A, the dependent variable is *CRASH*, which is an indicator variable equal to 1 if a firm experiences one or more firm-specific weekly returns falling 3.2 or more standard deviations below the mean firm-specific weekly return during the two-year–ahead (three-year-ahead) window, zero otherwise, for model 1 (model 2).
In Panel B, the dependent variable is *NCSKEW*, which is the negative coefficient of skewness of firm-specific weekly returns during the two-year-ahead (three-year-ahead) window for model 1 (model 2).
All other variables are defined in Table 1. The *p-values* (two-tailed) are based on standard errors clustered by both firm and time. All estimations also contain fiscal year dummies. The key variable of interest is highlighted by bold face.

Table 10
Asymmetric timeliness and future crash risk: Basu (1997) piece-wise linear regressions.

Panel A: Crash Risk Measured *by CRASH*

		Model 1: $CRASH_{t+1}$		Model 2: $CRASH_{t+2}$		Model 3: $CRASH_{t+3}$	
	Pred. Sign	Coefficient	*p-value*	Coefficient	*p-value*	Coefficient	*p-value*
D_t	?	-0.021	*<0.001*	-0.021	*<0.001*	-0.021	*<0.001*
R_t	+	0.005	*0.383*	0.007	*0.202*	0.009	*0.114*
D_t*R_t	+	0.100	*<0.001*	0.102	*<0.001*	0.101	*<0.001*
$CRASH_{t+1/2/3}$	?	-0.015	*<0.001*	-0.011	*0.002*	-0.012	*<0.001*
$CRASH_{t+1/2/3}*D_t$	?	0.004	*0.250*	-0.001	*0.801*	0.001	*0.596*
$CRASH_{t+1/2/3}*R_t$	?	-0.001	*0.817*	-0.007	*0.032*	-0.009	*0.011*
$\boldsymbol{CRASH_{t+1/2/3}*D_t*R_t}$	**-**	**-0.028**	***0.018***	**-0.017**	***0.061***	**-0.014**	***0.113***
N		97,723		95,359		85,053	
R^2		0.089		0.090		0.091	

Panel B:Crash Risk Measured *by NCSKEW*

		Model 1: $NCSKEW_{t+1}$		Model 2: $NCSKEW_{t+2}$		Model 3: $NCSKEW_{t+3}$	
	Pred. Sign	Coefficient	*p-value*	Coefficient	*p-value*	Coefficient	*p-value*
D_t	?	-0.020	*<0.001*	-0.020	*<0.001*	-0.019	*<0.001*
R_t	+	0.005	*0.370*	0.005	*0.360*	0.006	*0.372*
D_t*R_t	+	0.089	*<0.001*	0.090	*<0.001*	0.089	*<0.001*
$NCKEW_{t+1/2/3}$	?	-0.012	*<0.001*	-0.012	*<0.001*	-0.013	*<0.001*
$NCSKEW_{t+1/2/3}*D_t$	?	0.007	*0.004*	0.006	*0.002*	0.009	*0.001*
$NCSKEW_{t+1/2/3}*R_t$	?	-0.001	*0.589*	-0.004	*0.030*	-0.003	*0.173*
$\boldsymbol{NCSKEW_{t+1/2/3}*D_t*R_t}$	**-**	**-0.023**	***<0.001***	**-0.014**	***0.002***	**-0.014**	***0.001***
N		97,723		95,359		85,053	
R^2		0.091		0.093		0.094	

This table reports the Basu (1997) type regression analysis on the relation between conservatism and future crash risk. The sample period is from 1964-2007. In Panel A, future crash risk is proxied by *CRASH*, which is an indicator variable equal to 1 if a firm experiences one or more firm-specific weekly returns falling 3.2 or more standard deviations below the mean firm-specific weekly return during the measurement window, zero otherwise. In Model 1, $CRASH_{t+1}$ is measured over a one-year-ahead window; In Model 2, $CRASH_{t+2}$ is measured over a two-year-ahead window (width is two years); and in Model 3, $CRASH_{t+3}$ is measured over a three-year-ahead window (width is three years). In Panel B, future crash risk is proxied by *NCKEW*, which is the negative coefficient of skewness of firm-specific weekly returns in the measurement window. In Model 1, $NCSKEW_{t+1}$ is measured over a one-year-ahead window; In Model 2, $NCSKEW_{t+2}$ is measured over a two-year-ahead window (width is two years); and in Model 3, $NCSKEW_{t+3}$ is measured over a three-year-ahead window (width is three years). D_t is a dummy variable equal 1 if the market-adjusted return in year *t* is negative, zero otherwise. R_t is annual market-adjusted return in fiscal year *t*. The dependent variable is earnings in year *t*, which is defined as earnings before extraordinary items deflated by lag market-value of equity. The *p-values* (two-tailed) are based on standard errors clustered by both firm and time. The key variable of interest is highlighted by bold face.

Table 11
Asymmetric Timeliness and Future Crash Risk: Ball & Shivakumar (2006) Piecewise Linear Accruals Regressions.

Panel A: Crash risk measured by CRASH

	Pred. Sign	*Model 1: $CRASH_{t+1}$* Coefficient	*p-value*	*Model 2: $CRASH_{t+2}$* Coefficient	*p-value*	*Model 3: $CRASH_{t+3}$* Coefficient	*p-value*
ΔREV_t	+	0.089	*<0.001*	0.089	*<0.001*	0.087	*<0.001*
$GPPE_t$	?	-0.003	*0.069*	-0.001	*0.613*	0.000	*0.870*
DCF_t	?	0.021	*<0.001*	0.021	*<0.001*	0.020	*<0.001*
CF_t	-	-0.387	*<0.001*	-0.402	*<0.001*	-0.432	*<0.001*
DCF_t*CF_t	+	0.232	*<0.001*	0.243	*<0.001*	0.263	*<0.001*
$CRASH_{t+1/2/3}$	?	0.001	*0.603*	0.007	*0.001*	0.005	*0.048*
$CRASH_{t+1/2/3}$*ΔREV_t	?	0.007	*0.396*	0.011	*0.012*	0.012	*0.004*
$CRASH_{t+1/2/3}$* $GPPE_t$	?	-0.005	*0.029*	-0.011	*<0.001*	-0.011	*<0.001*
$CRASH_{t+1/2/3}$*DCF_t	?	0.004	*0.059*	0.002	*0.085*	0.004	*0.069*
$CRASH_{t+1/2/3}$*CF_t	?	0.076	*0.001*	0.050	*0.003*	0.073	*<0.001*
$CRASH_{t+1/2/3}$*DCF_t *CF_t	**-**	**-0.103**	***<0.001***	**-0.048**	***0.018***	**-0.062**	***0.008***
N		99,151		96,626		85,480	
R^2		0.347		0.352		0.362	

Panel B:Crash risk measured by NCSKEW

	Pred. Sign	*Model 1: $NCSKEW_{t+1}$* Coefficient	*p-value*	*Model 2: $NCSKEW_{t+2}$* Coefficient	*p-value*	*Model 3: $NCSKEW_{t+3}$* Coefficient	*p-value*
ΔREV_t	+	0.091	*<0.001*	0.089	*<0.001*	0.089	*<0.001*
$GPPE_t$	?	-0.004	*0.021*	-0.004	*0.026*	-0.005	*0.009*
DCF_t	?	0.022	*<0.001*	0.022	*<0.001*	0.022	*<0.001*
CF_t	-	-0.365	*<0.001*	-0.374	*<0.001*	-0.386	*<0.001*
DCF_t*CF_t	+	0.202	*<0.001*	0.214	*<0.001*	0.225	*<0.001*
$NCKEW_{t+1/2/3}$	?	0.002	*0.151*	0.002	*0.064*	0.003	*0.134*
$NCSKEW_{t+1/2/3}$*ΔREV_t	?	0.006	*0.183*	-0.003	*0.051*	-0.002	*0.231*
$NCSKEW_{t+1/2/3}$* $GPPE_t$	?	-0.003	*0.003*	-0.001	*0.589*	0.000	*0.982*
$NCSKEW_{t+1/2/3}$*DCF_t	?	0.001	*0.691*	0.000	*0.807*	0.001	*0.507*
$NCSKEW_{t+1/2/3}$*CF_t	?	0.068	*<0.001*	0.056	*<0.001*	0.057	*<0.001*
$NCSKEW_{t+1/2/3}$*DCF_t *CF_t	**-**	**-0.082**	***<0.001***	**-0.056**	***0.001***	**-0.044**	***0.020***
N		99,151		96,626		85,480	
R^2		0.349		0.352		0.362	

This table reports the Ball & Shivakumar (2006) piecewise linear accruals regression analysis on the relation between conservatism and future crash risk. The sample period is from 1964-2007. In Panel A, future crash risk is proxied by *CRASH*, which is an indicator variable equal to 1 if a firm experiences one or more firm-specific weekly returns falling 3.2 or more standard deviations below the mean firm-specific weekly return during the measurement window, zero otherwise. In Model 1, $CRASH_{t+1}$ is measured over a one-year-ahead window; In Model 2, $CRASH_{t+2}$ is measured over a two-year-ahead window (width is two years); and in Model 3, $CRASH_{t+3}$ is measured over a three-year-ahead window (width is three years). In Panel B, future crash risk is proxied by $NCKEW$, which is the negative coefficient of skewness of firm-specific weekly returns in the measurement window. In Model 1, $NCSKEW_{t+1}$ is measured over a one-year-ahead window; In Model 2, $NCSKEW_{t+2}$ is measured over a two-year-ahead window (width is two years); and in Model 3, $NCSKEW_{t+3}$ is measured over a three-year-ahead window (width is three years). ΔREV_t is change in revenue in year *t*, scaled by average total assets. $GPPE_t$ is gross property, plant, and equipment in year *t*, scaled by average total assets. DCF_t is a dummy variable equal 1 if industry-median adjusted operating cash flow in year *t* is negative, zero otherwise. CF_t is industry-median adjusted operating cash flow in year *t*, scaled by average total assets. Operating cash flow is defined as income before extraordinary items minus total accruals, where total accruals are defined as current accruals minus depreciation. The dependent variable is current accruals in year *t*, scaled by average total assets. Current accruals are defined as: (change of current assets-change of cash)-(change of current liabilities-change of debt in current liabilities-change of tax payable). The *p-values* (two-tailed) are based on standard errors clustered by both firm and time. The key variable of interest is highlighted by bold face.

FIGURE 1

Annual crash probability as a function *of CSCORE*

The horizontal axis is the average value of *CSCORE* for decile portfolios (time-series average for each portfolio) formed by ranking on *CSCORE* annually. The vertical axis is the implied probability of a crash during the year for each value of *CSCORE*, based on Model 1 of Table 5, with all other right-hand variables set equal to their sample means from Table 2.