Accounting Conservatism and Stock Price Crash Risk: Firm-level Evidence*

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ABSTRACT

Using a large sample of U.S. firms during 1964–2007, we find that conditional conservatism is associated with a lower likelihood of a firm's future stock price crashes. This finding holds for multiple measures of conditional conservatism and crash risk and is robust to controlling for other known determinants of crash risk and firm-fixed effects. Moreover, we find that the relation between conservatism and crash risk is more pronounced for firms with higher information asymmetry. Overall, our results are consistent with the notion that conditional conservatism limits managers' incentive and ability to overstate performance and hide bad news from investors, which, in turn, reduces stock price crash risk.

Prudence comptable et risque d'effondrement boursier : données recueillies auprès des sociétés

RÉSUMÉ

En analysant un vaste échantillon de sociétés des États-Unis sur la période s'échelonnant de 1964 à 2007, les auteurs constatent que la prudence conditionnelle est associée à une probabilité moins grande d'effondrement futur du cours de l'action d'une société. L'application de différents indicateurs de prudence conditionnelle et de risque d'effondrement confirme cette observation qui résiste au contrôle d'autres déterminants connus du risque d'effondrement et des effets fixes de l'entreprise. De plus, les auteurs constatent que la relation entre la prudence et le risque d'effondrement est plus accentuée dans le cas de sociétés pour lesquelles l'asymétrie de l'information est plus marquée. Dans l'ensemble, les résultats obtenus par les auteurs accréditent la notion selon laquelle la prudence conditionnelle limite la propension des gestionnaires à surévaluer la performance et à dissimuler les mauvaises nouvelles aux investisseurs et la possibilité qu'ils ont de le faire, ce qui réduit en retour le risque d'effondrement des cours.

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1. Introduction

Corporate managers have incentives to overstate financial performance by 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 (e.g., Ball 2009; Graham, Harvey, and Rajgopal 2005; Kothari, Shu, and Wysocki 2009). If managers withhold and accumulate bad news for an extended period, negative information is likely to be stockpiled within a firm. Once the amount of accumulated bad news reaches a certain threshold, it will be released all at once, leading to stock price crashes (Hutton, Marcus, and Tehranian 2009; Jin and Myers 2006).

This study investigates the firm-level relation between conditional conservatism in financial reporting and stock price crashes. Conditional conservatism refers to accountants' tendency to require a higher degree of verification to recognize good news as gains than to recognize bad news as losses (Basu 1997).[1] This asymmetric verifiability requirement of conservative accounting policy offsets managers' tendencies to hide bad news and accelerate good news recognition in audited financial statements (Kothari, Ramanna, and Skinner 2010; Watts 2003a).[2] Moreover, conservative audited earnings dampen managerial incentives to disclose unverifiable favorable information and, instead, bring forth disclosures of unverifiable unfavorable information (Ball, Jayaraman, and Shivakumar 2012; LaFond and Watts 2008). Accordingly, we expect that the more conservative a firm's accounting policy, the lower the probability that firm-specific bad news is hidden and accumulated and, thus, the lower the likelihood of future stock price crashes.

Following prior research (Chen, Hong, and Stein 2001; Hutton et al. 2009; Kim, Li, and Zhang 2011a,b), we proxy for firm-specific crash risk using two measures: (i) the likelihood of extremely negative firm-specific weekly returns, and (ii) the negative conditional skewness of firm-specific weekly returns. We measure conditional conservatism using Basu's (1997) asymmetric timeliness coefficient, Ball and Shivakumar's (2005) accrual-based measure of asymmetric timeliness, and Khan and Watts's (2009) firm-year measure of conditional conservatism. Using a sample of 114,548 firm-years over 1964–2007, we find that the degree of conditional conservatism is significantly and negatively associated with the likelihood of a firm experiencing future stock price crashes. The results are consistent across all three measures of conditional conservatism and both measures of crash risk. The results are also robust to controlling for firm size, market-to-book ratio, leverage, and other firm-specific determinants of crash risk, as well as firm-fixed effects. Moreover, we find that changes in the degree of conditional conservatism are also significantly and negatively associated with changes in future crash risk.

Further, we find that the predictive power of conservatism with respect to future crash risk is stronger in an environment where investors are faced with higher 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, and firms with lower levels of analyst coverage. Overall, our evidence is in line with the notion that conditional conservatism is an ex ante response to ex post opportunistic incentives to hide firm-specific bad news for private gain (Gao 2012; LaFond and Watts 2008; Watts 2003a).

1. This definition is in contrast to that of unconditional conservatism, which refers to news-independent early recognition of expenses and revenue deferrals, such as the immediate expensing of R&D expenditures.
2. In developing the theory for this study, we maintain that conservative accounting policy is chosen by a firm's corporate governance system or imposed by mandatory accounting rules. In section 5, we provide a more detailed discussion on the potential endogenous choice of conservatism.

This article contributes to the literature in several ways. First, it adds to the conservatism literature. Ever since Basu (1997) first provided systematic evidence for the existence of accounting conservatism, many studies have examined various country-wide and firm-specific factors that explain the demand for conservatism.[3] However, existing research pays little attention to the economic consequences of or benefits from conservative accounting. Dechow, Ge, and Schrand (2010, 364) argue that "the findings in studies of equity market demand as a determinant of asymmetric timeliness imply only that equity market *perceive* asymmetric timeliness as improving earnings quality. They cannot speak to whether equity market *should* demand timely loss recognition." Kothari et al. (2010, 256) also conclude that "the efficiency of conditional conservatism in equilibrium is an empirical question, although its survival over many decades and in many contractual settings suggests that it is efficient." Our study is one of the first efforts to provide systematic evidence of the benefit of conservatism in the equity market. Our findings on the relation between conservatism and crash risk are particularly interesting because stock price crashes have a devastating impact on investor welfare.

Second, our results have implications for accounting standard setting bodies. An important issue in the debate on accounting standard setting is the extent to which certain long-standing attributes of financial reporting, such as conservatism, should be included as part of the Generally Accepted Accounting Principles (Kothari et al. 2010). Recently, the Financial Accounting Standards Board (FASB) and the International Accounting Standards Board (IASB) eliminated the conservatism principle from their updated joint conceptual framework. In support of the above decision, the IASB and FASB (2010) claim that conservatism introduces biases into financial reporting and increases information asymmetry. Our study, however, shows that conditional conservatism is related to less managerial bad news hoarding and lower stock price crash risk, increasing investor welfare.

Finally, this study contributes to the literature on the relation between accounting properties and stock price crashes (e.g., Hutton et al. 2009; Kim and Zhang 2014). It is also related to the literature on the relation between accounting and stock market crashes (for a complete review, see Waymire and Basu 2011). Barton and Waymire (2004) find that firms with higher accounting quality (including conservatism) before October 1929 experienced smaller stock price declines during the market crash. Our study extends this literature by examining firm-specific crash risk.

This article proceeds as follows. Section 2 reviews the relevant literature and develops our hypotheses. Section 3 describes the data and research design. Section 4 presents the main empirical results. Section 5 provides robustness checks and additional analyses. Section 6 concludes the article.

2. Literature review and hypothesis development

Basu (1997, 4) defines conservatism as "capturing accountants' tendency to require a higher degree of verification for recognizing good news than bad news in financial statements." Watts (2003a) attributes the existence and prevalence of conservatism for centuries to the use of verifiable accounting numbers in debt and compensation contracts, shareholder litigation, regulatory and political processes, and taxation. According to Watts (2003a), conservatism is a governance mechanism that constrains managerial incentives and abilities to overstate accounting numbers used in a contract. More recently, LaFond and Watts (2008) have analyzed equity market demand for conservatism. They argue that information asymmetries between corporate insiders and outside equity investors engender

3. See Watts (2003b) for an excellent structured review of the earlier literature on alternative explanations for conservatism. Ball, Kothari, and Nikolaev (2011) provide an updated list of conservatism studies.

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. LaFond and Watts provide empirical evidence consistent with their argument by showing that bid–ask spreads decrease after increases in conservatism.[4] This study aims to complement the line of research on the informational role of conservatism in the equity market by examining the firm-level relation between conservatism and stock price crash risk.

Managers can strategically withhold bad news or delay the disclosure of bad news and accelerate the release of good news. This behavior stems from a variety of managerial incentives, such as earnings- or equity-based compensation contracts, career and reputation concerns, and empire building (Ball 2009; Core, Guay, and Verrecchia 2003). 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 (McNichols 1988). 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 a certain tipping point or when the managerial incentive for hiding bad news collapses, the large amount of negative information will suddenly and immediately be released to the market, leading to an abrupt decline in stock price or a crash (Hutton et al. 2009). Moreover, the hiding of bad news allows firms with aggressive accounting to keep bad projects for a longer period, compared to firms with conservative accounting (Ahmed and Duellman 2011; Francis and Martin 2010). When the accumulated bad performance eventually surfaces, one observes stock price crashes (Benmelech, Kandel, and Veronesi 2010; 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. Conservatism 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 more quickly than unverifiable good news. 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 can discipline managers' voluntary disclosures through ex post accountability for their own voluntary disclosures (Ball 2001; Ball et al. 2012). Moreover, any reticence (with respect to bad news) or puffery (with respect to good news) in voluntary disclosures will be discovered sooner in conservative firms than in nonconservative firms. For nonconservative firms, the misleading voluntary disclosures are unlikely to be discovered until 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

4. Several recent studies examine the economic consequences of conservatism in the context of the debt market (e.g., Ahmed, Billings, Morton, and Stanford-Harris 2002; Ball, Bushman, and Vasvari 2008; Beatty, Weber, and Jiewei Yu 2008; Nikolaev 2010; Wittenberg-Moerman 2008; Zhang 2008).

mislead outside investors through voluntary disclosures. Thus, conservatism constrains the incentives and ability of managers to delay the release of bad news and accelerates 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 can 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 boards of directors to promptly identify unprofitable projects and force managers to discontinue them (Ball and Shivakumar 2005). 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.[5] The above discussions lead to the following hypothesis in alternative form:

HYPOTHESIS 1. *The degree of conditional conservatism is negatively related to the likelihood of future crash occurrence, ceteris paribus.*

Although the crash risk models, such as that of Jin and Myers (2006), are built on the concept of *bad news* hoarding, managers can also hide bad performance by recognizing unverifiable good news in accounting income or disclosing it 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 realized today (Benston 2006; Benston and Hartgraves 2002). We discuss this example 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 the profit is verifiable.

Moreover, a key point underlying Hypothesis 1 is that conservatism curbs managerial incentives to hide private negative information. However, the amount of value-relevant, private information can vary across firms. In the extreme case of no information asymmetry, managers have no incentive for strategic disclosure, and thus conservatism plays no role in controlling managerial disclosure behavior. On the other hand, if the amount of private information that a manager can possibly hide is inherently higher, such as in firms with more R&D investment, the disciplinary role of conditional conservatism is likely to be more important. Thus, 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 has a stronger impact on crash risk. This leads to our second hypothesis:

HYPOTHESIS 2. *The relation between conditional conservatism and future crash risk is more pronounced for firms with high information asymmetry than for firms with low information asymmetry, ceteris paribus.*

Our main hypotheses rely on the argument 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 discover adverse private

5. Ahmed and Duellman (2011), Biddle, Hilary, and Verdi (2009), and Bushman, Piotroski, and Smith (2011) make similar points.

information by searching for private information, which, in turn, reduces the likelihood of future crashes for nonconservative firms. In other words, to the extent that a private information search is not prohibitively costly, it can substitute for conservatism. In such a case, there would be little difference in future crash likelihoods between conservative and nonconservative firms. However, Aboody and Lev (2000), among others, argue that private information search is costly and optimal information acquisition by outsiders generally does not exhaust a manager's private information. We therefore expect that the impact of conservatism on future crash risk is important even when market participants actively search for private information.

3. Sample and measurement of key variables

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.[6] 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.[7] We delete firm-years with missing data for the research variables used in our regressions. After applying these selection criteria, we obtain a sample of 114,548 firm-years spanning the period 1964–2007.[8]

Measurement of conditional conservatism

For our empirical tests, we use three measures of conditional conservatism. Our first measure of conditional conservatism is Basu's (1997) asymmetric timeliness coefficient. Specially, Basu (1997) estimates the following piecewise linear regression:

$$X_{jt} = \beta_1 + \beta_2 D_{jt} + \beta_3 R_{jt} + \beta_4 D_{jt} \times R_{jt} + \varepsilon_{jt}, \tag{1}$$

for firm j and year t, X is net income scaled by the lagged market value of equity, R is the compound return over the 12-month period ending at the fiscal year-end, and D is a dummy equal to one if the return is negative and zero otherwise.[9] The Basu coefficient, that is, β_4, measures the incremental timeliness of earnings in recognizing bad news relative to good news. A larger Basu coefficient indicates a higher degree of conditional conservatism.

Our second measure of conditional conservatism is Ball and Shivakumar's (2005, 2006, 2008) nonreturn-based measure of asymmetric timeliness.[10] Specifically, Ball and Shivakumar estimate the following piecewise linear regression:

$$TCA_{jt} = \Gamma_0 + \Gamma_1 \Delta REV_{jt} + \Gamma_2 GPPE_{jt} + \Gamma_3 DCF_{jt} + \Gamma_4 CF_{jt} + \Gamma_5 DCF_{jt} \times CF_{jt} + \varepsilon_{jt}, \tag{2}$$

6. We exclude observations with negative book value, following the treatment of most prior research. However, our results are very similar if we do not exclude these observations.
7. All the empirical results remain identical if we do not trim the data.
8. We stop our sample in 2007 because we need to run predictive regressions. In addition, we want to avoid the undue influence of the recent financial crisis.
9. The results are qualitatively similar if we use earnings before extraordinary items and market-adjusted returns in the Basu regressions.
10. For this measure, we exclude firms from financial and utility industries because the nature of accruals in these regulated industries is different from that of other industries.

for firm j and year t, TCA is current accruals scaled by average total assets; ΔREV is change in revenue scaled by average total assets; $GPPE$ is gross property, plant, and equipment scaled by average total assets; CF is the industry median-adjusted operating cash flow scaled by average total assets; and DCF is a dummy variable equal to one if CF is negative and zero otherwise. The coefficient of $DCF \times CF$ measures the incremental timeliness of accruals in recognizing negative cash flow news relative to positive cash flow news. A larger coefficient for $DCF \times CF$ indicates a higher degree of conditional conservatism.

Our third measure of conditional conservatism is Khan and Watts's (2009) firm-year conservatism measure, $CSCORE$. The estimation of $CSCORE$ begins with the Basu (1997) model. Specifically, the Basu model can be written to allow coefficients to vary across firms and over time as follows:

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

Then, the firm-year-specific coefficients β_{3jt} (timeliness of good news) and β_{4jt} (conditional conservatism) are expressed as linear functions of firm-year-specific characteristics that are correlated with the timeliness of good news and conservatism, respectively:

$$GSCORE = \beta_{3jt} = \mu_{1t} + \mu_{2t}MKV_{jt} + \mu_{3t}MB_{jt} + \mu_{4t}LEV_{jt}, \tag{4}$$

$$CSCORE = \beta_{4jt} = \lambda_{1t} + \lambda_{2t}MKV_{jt} + \lambda_{3t}MB_{jt} + \lambda_{4t}LEV_{jt}, \tag{5}$$

where MKV is the natural log of the market value, MB is the market-to-book equity ratio, and LEV is the debt-to-equity ratio, all of which are measured at the beginning of the year. Replacing β_{3jt} and β_{4jt} in equation (3) by equations (4) and (5), respectively, yields the following empirical model:

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

We then estimate equation (6) using five-year rolling panel regressions[11] and calculate our third measure of conservatism, $CSCORE$, using equation (5) with the estimated coefficients λ_{1t}, λ_{2t}, λ_{3t}, and λ_{4t} from equation (6). In this case, 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 conditional conservatism very well.

The estimation of Basu's (1997) coefficient assumes that the market is efficient with respect to publicly available information. Our study hypothesizes that, for conservative firms, 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, because Basu does not require the market to be efficient with respect to private information. The model simply requires that there be information in returns earlier than in earnings (i.e., there exist other information sources). Basu uses publicly available news as a benchmark to capture the asymmetric timeliness of a firm's earnings in reflecting bad news versus good news. The observed asymmetric timeliness implies the differential verification standards required for bad news recognition versus

11. Therefore, our *CSCORE* is the *PC_SCORE*, as for 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*.

good news recognition by the firm's accounting policy. As a maintained assumption of most conditional conservatism research, the accounting policy's differential verification standards, although inferred from publicly available information, have disciplinary effects on managers' privately observed information (Chen, Hemmer, and Zhang 2007; Gao 2012; LaFond and Watts 2008).[12]

Measurement of firm-specific crash risk

Following Hutton et al. (2009) and Kim et al. (2011a,b), we define crash weeks (extreme events) in a given fiscal firm-year 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,[13] with 3.2 chosen to generate a frequency of 0.1 percent in the normal distribution.[14] The firm-specific weekly return, denoted by W, is defined as the natural log of one plus the residual return from the following expanded market model regression:

$$r_{j\tau} = \alpha_j + \beta_{1j} r_{m(\tau-2)} + \beta_{2j} r_{m(\tau-1)} + \beta_{3j} r_{m\tau} + \beta_{4j} r_{m(\tau+1)} + \beta_{5j} r_{m(\tau+2)} + \varepsilon_{jt}, \tag{7}$$

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; Scholes and Williams 1977).[15] 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. (2011a,b), 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:

$$NCSKEW_{jt} = -[n(n-1)^{\frac{3}{2}} \sum W_{j\tau}^3] / [(n-1)(n-2)(\sum W_{j\tau}^2)^{\frac{3}{2}}]. \tag{8}$$

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 (e.g., Kim et al. 2011a,b).[16] Second,

12. For example, Basu (1997, Table 4) specifically tests the impact of conservatism on managers' privately observed information. See also DeFond and Park (2001) for similar tests.
13. Our crash risk measures are estimated over the 12-month period ending three months after the fiscal year-end to account for the effect of earnings release.
14. Returns are certainly not normally distributed (e.g., Mandelbrot 1963). Here, we simply use this criterion from the normal distribution as a convenient way to define extreme returns. 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 percent (−18.6 percent) and the mean (median) raw return is −22.2 percent (−20.0 percent). All the untabulated results mentioned in this study are available upon request.
15. The use of the market model is standard in this literature. The idea is to screen out market-level crashes. However, using factor models, such as Carhart's (1997) four-factor model, to derive firm-specific returns does not change the results.
16. 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.

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 (Hutton et al. 2009).

Control variables

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 detrended 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). 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. 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 total assets rather than the natural log of market capitalization, because the latter is one of three major inputs for computing our $CSCORE$ measure. We also include the market-to-book ratio (MB_t), financial leverage (LEV_t), and future operating performance (ROA_{t+1}) as additional control variables.[17] Finally, we estimate alternative regression specifications where the information opaqueness measure ($OPAQUE_t$) of Hutton et al. (2009) is additionally included as a control to ensure that our conservatism measure has incremental predictive power for crash risk over and beyond $OPAQUE_t$. Following Hutton et al. (2009), we measure $OPAQUE_t$ as the prior three years' moving sum of the absolute value of discretionary accruals, where discretionary accruals are estimated by the modified Jones model.[18]

4. Empirical results

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. The mean value of $CRASH$ is 0.12, suggesting that, on average, 12 percent of firm-years experience one or more firm-specific weekly returns that fall more than 3.2 standard deviations below the annual mean. Though not tabulated, a closer look at the data reveals that less than 0.2 percent 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 -0.20 and -0.19, respectively. Here, $NCSKEW$ is slightly lower than the values reported by Chen et al. (2001), which is expected, because these authors use daily returns to construct their variables (Fogler and

17. The results using the $CSCORE$ measure may suffer from multicollinearity problems when MB and LEV are included as controls, because these two variables are also used to construct $CSCORE$. However, untabulated tests show that the results are very similar if we exclude them.
18. Because the measure of Hutton et al. (2009) requires statements of cash flow data, the sample period for specifications with $OPAQUE$ starts in 1990. We do not describe the detailed procedures here, because we use exactly the same procedure as Hutton et al. (2009).

TABLE 1
Descriptive statistics

Variable	Mean	SD	Q1	Median	Q3	N
$CRASH_{t+1}$	0.122	0.327	0.000	0.000	0.000	114,548
$NCSKEW_{t+1}$	−0.200	0.711	−0.579	−0.185	0.193	114,548
$CSCORE_t$	0.154	0.085	0.101	0.146	0.190	114,548
$DTURN_t$	0.002	0.053	−0.010	0.000	0.012	114,548
$NCSKEW_t$	−0.199	0.686	−0.579	−0.192	0.181	114,548
$SIGMA_t$	0.054	0.026	0.034	0.048	0.067	114,548
RET_t	−0.177	0.186	−0.224	−0.113	−0.057	114,548
$SIZE_t$	5.544	2.005	4.028	5.409	6.934	114,548
MB_t	2.213	2.064	1.017	1.579	2.570	114,548
LEV_t	0.228	0.179	0.069	0.210	0.351	114,548
ROA_{t+1}	0.035	0.103	0.009	0.042	0.081	114,548
$OPAQUE_t$	0.317	0.270	0.132	0.233	0.412	46,585
X_t	0.061	0.130	0.030	0.069	0.112	95,938
R_t	0.155	0.450	−0.131	0.096	0.357	95,938
D_t	0.387	0.487	0.000	0.000	1.000	95,938
TCA	0.021	0.085	−0.017	0.014	0.056	88,734
ΔREV_t	0.140	0.288	0.008	0.109	0.249	88,734
$GPPE_t$	0.593	0.362	0.320	0.526	0.810	88,734
CF_t	0.016	0.123	−0.033	0.020	0.077	88,734
DCF_t	0.393	0.488	0.000	0.000	1.000	88,734

Notes:

The sample period is from 1964 to 2007 for major variables, except for $OPAQUE$, which is measured from 1990 to 2007 due to the need of statement of cash flows data. $CRASH_{t+1}$ is an indicator variable equal to one 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 $t + 1$, and zero otherwise; $NCSKEW_{t+1}$, is the negative coefficient of skewness of firm-specific weekly returns in fiscal year $t + 1$; $CSCORE_t$ is the conservatism score in fiscal year t; $DTURN_t$ is the average monthly turnover in fiscal year t minus the average monthly turnover in fiscal year $t - 1$; $NCSKEW_t$ is the negative coefficient of skewness of firm-specific weekly returns in fiscal year t; $SIGMA_t$ is the standard deviation of firm-specific weekly returns in fiscal year t; RET_t is the average firm-specific weekly return in fiscal year t times 100; $SIZE_t$ is the log of total assets in fiscal year t; MB_t is the 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; ROA_{t+1} is return on assets in fiscal year $t + 1$; $OPAQUE_t$ is the Hutton et al. (2009) measure of opaqueness of the firm's financial reports in fiscal year t; X_t is net income divided by lagged market value; R_t is the annual accumulated return in fiscal year t; D_t is a dummy equal to one if the return (i.e., R_t) in year t is negative, and zero otherwise; TCA_{t} 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). 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 to one if the industry median-adjusted operating cash flow in year t is negative, and zero otherwise; and CF_t is the 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.

Radcliffe 1974). The mean and median values of *CSCORE* are 0.15 and 0.15, respectively, slightly larger than those reported by Khan and Watts (2009).[19]

Table 2 presents the Pearson and Spearman correlation matrix for all the variables used in our regression analysis. The two measures for crash risk, *CRASH* and *NCSKEW*, are significantly and positively correlated with each other. The year t conservatism measure, *CSCORE*, 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. The first and second moments of returns (i.e., *RET* and *SIGMA*) are highly correlated, which is expected.[20]

Figure 1 plots the time-series trend of (lagged) conditional conservatism and the frequency of firm-specific crashes over the period 1965 to 2007. Figure 1 shows a clear increasing pattern in the time-series distribution of crash risk, with two peaks in 1987 and 2001. Consistent with prior research, we find a strong increasing trend in conservatism from 1967 to 1979.[21] The level of conservatism drops significantly in the early 1980s and then increases gradually until 1990. The level of conservatism drops again in the first two years of 1990s and then increases sharply until the mid-1990s. The second half of the 1990s sees a decreasing trend of conservatism and the early 2000s sees an increasing trend of conservatism. Overall, there is an increasing trend in the level of conditional conservatism (e.g., Basu 1997; Givoly and Hayn 2000; Holthausen and Watts 2001; Pope and Walker 1999; Ryan and Zarowin 2003).

Test of Hypothesis 1

Basu piece-wise linear regression

To test whether more conservative firms experience lower crash risk, we first estimate the following augmented Basu (1997) model following the method of Francis and Martin (2010):

$$\begin{aligned} X_{jt} = {} & \beta_1 + \beta_2 D_{jt} + \beta_3 R_{jt} + \beta_4 D_{jt} \times R_{jt} + \beta_5 CRASH_{j(t+1)} + \beta_6 CRASH_{j(t+1)} \times D_{jt} \\ & + \beta_7 CRASH_{j(t+1)} \times R_{jt} + \beta_8 CRASH_{j(t+1)} \times D_{jt} \times R_{jt} + \beta_k ControlVar_{jt} \\ & + \beta_l ControlVar_{jt} \times D_{jt} + \beta_m ControlVar_{jt} \times R_{jt} + \beta_n ControlVar_{jt} \times D_{jt} \times R_{jt} + \varepsilon_{jt}, \quad (9) \end{aligned}$$

where the dependent variable X_{jt} is firm j's earnings in year t scaled by lagged market value and all independent variables are as defined previously. The term *ControlVar* represents the set of control variables defined in section 3, excluding *ROA*.[22] Note that X, D, and R are measured in year t, while *CRASH* is measured in year $t + 1$. The control variables are all measured at the beginning of year t. A negative coefficient for $CRASH \times D \times R$ is consistent with our prediction that accounting conservatism is negatively associated with future crash risk (i.e., $\beta_8 < 0$). We also replace *CRASH* with *NCSKEW* in equation (9) to examine the relation between conservatism and negative firm-specific return skewness.[23]

19. Khan and Watts (2009) report a mean (median) *CSCORE* of 0.10 (0.10). This is partially caused by our using of *MKV*, *LEV*, and *MB* at the beginning of the year in estimating the augmented Basu regression to eliminate reverse causation. Khan and Watts (2009) use the ending balances of these variables. We thank Sudipta Basu for the suggestion of using year-beginning values.
20. In later regression analyses (Table 5), we find that the variance inflation factors (VIFs) of both *SIGMA* and *RET* are around 15, suggesting some multicollinearity problems. However, our main results are unchanged if we drop one of these two control variables. The VIFs of all other independent variables are below two. The rule of thumb is that there is a multicollinearity problem if VIF is greater than 10.
21. Note that the Basu coefficient is lagged by one year.
22. We exclude *ROA* from this regression because the dependent variable in equation (9) is earnings scaled by market value.
23. For simplicity, we suppress variable subscripts when discussing results.

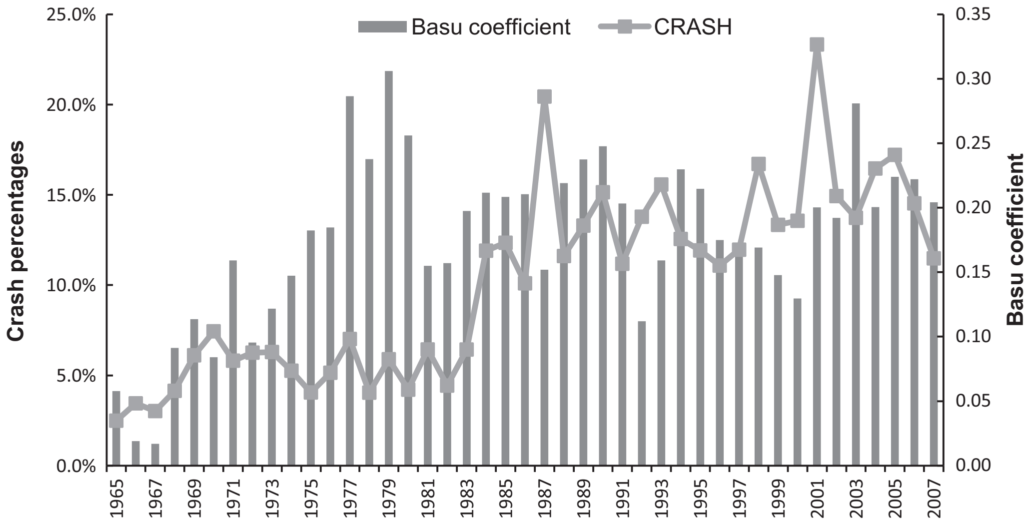
TABLE 2
Pearson (below) and Spearman (above) correlation matrix for major variables

Variable		A	B	C	D	E	F	G	H	I	J	K	L
$CRASH_{t+1}$	A		0.43	−0.03	0.02	0.03	−0.02	0.02	0.00	0.03	−0.02	0.00	0.02
			(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.69)	(0.00)	(0.02)	(0.74)	(0.08)
$NCSKEW_{t+1}$	B	0.49		−0.17	0.05	0.10	−0.10	0.10	0.18	0.13	−0.01	0.10	−0.05
		(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.25)	(0.00)	(0.00)
$CSCORE_t$	C	−0.03	−0.14		0.00	−0.19	0.22	−0.22	−0.39	−0.43	0.29	−0.32	0.13
		(0.00)	(0.00)		(0.84)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$DTURN_t$	D	0.01	0.04	0.04		0.00	0.06	−0.06	0.07	0.09	0.01	0.07	−0.02
		(0.16)	(0.00)	(0.02)		(0.91)	(0.02)	(0.02)	(0.00)	(0.00)	(0.31)	(0.00)	(0.37)
$NCSKEW_t$	E	0.02	0.09	−0.16	0.01		−0.13	0.14	0.19	0.08	0.00	0.06	−0.05
		(0.00)	(0.00)	(0.00)	(0.44)		(0.00)	(0.00)	(0.00)	(0.00)	(0.87)	(0.00)	(0.00)
$SIGMA_t$	F	−0.02	−0.09	0.19	0.11	−0.12		−1.00	−0.53	0.06	−0.07	−0.12	0.39
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RET_t	G	0.03	0.09	−0.19	−0.12	0.15	−0.97		0.54	−0.06	0.07	0.12	−0.39
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$SIZE_t$	H	0.00	0.17	−0.27	0.02	0.18	−0.52	0.48		0.00	0.23	−0.01	−0.35
		(0.86)	(0.00)	(0.00)	(0.27)	(0.00)	(0.00)	(0.00)		(0.94)	(0.00)	(0.60)	(0.00)
MB_t	I	0.02	0.06	−0.18	0.04	0.04	0.09	−0.09	−0.06		−0.08	0.38	0.12
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
LEV_t	J	−0.02	−0.01	0.31	0.00	0.00	−0.04	0.02	0.19	−0.02		−0.29	−0.16
		(0.02)	(0.13)	(0.00)	(0.76)	(0.54)	(0.03)	(0.33)	(0.00)	(0.08)		(0.00)	(0.00)
ROA_{t+1}	K	0.00	0.07	−0.20	0.04	0.05	−0.18	0.19	0.03	0.17	−0.22		−0.04
		(0.97)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.20)	(0.00)	(0.00)		(0.00)
$OPAQUE_t$	L	0.02	−0.03	0.08	0.01	−0.03	0.33	−0.30	−0.31	0.17	−0.11	−0.09	
		(0.08)	(0.00)	(0.00)	(0.74)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

Notes:

This table reports the time-series average of a cross-sectional correlation matrix for the major variables used in our empirical tests. The sample period is from 1964 to 2007 for the major variables. The variable *OPAQUE* is measured from 1990 to 2007. All variables are defined in Table 1. The *p*-values in the parentheses are based on Fama–Macbeth *t*-statistics.

Figure 1 Time-series distribution of percentage of crashes and conditional conservatism



Description:

The left vertical axis is the percentage of firms that experience a crash in the year and the right vertical axis is the cross-sectional Basu coefficient in the previous year. The horizontal axis represents year.

Several recent studies criticize the validity of the Basu (1997) model in capturing conditional conservatism and claim that the Basu coefficient is biased (e.g., Patatoukas and Thomas 2011). However, proponents of the Basu model reject those criticisms based on both analytical and empirical evidence (e.g., Basu 2009; Ball, Kothari, and Nikolaev 2011, 2013; Ryan 2006). Specifically, Ball et al. (2013) suggest that the inclusion of firm-fixed effects can eliminate the biases documented by Patatoukas and Thomas (2011).[24] Accordingly, we use firm-fixed effect models to estimate equation (9). For comparison, we also report the ordinary least squares (OLS) regression results without firm-fixed effects.[25]

Table 3 reports the results of estimating equation (9). To save space, we omit the coefficient estimates of the control variables (except for *OPAQUE*) and intercept terms (i.e., those terms without *R*).[26] The *t*-statistics in parentheses are based on robust standard errors adjusted for firm and year clustering (Petersen 2009). Panel A of Table 3 presents the results with *CRASH* as the measure of future crash risk. Model (1) reports the results of estimating equation (9) with firm-fixed effects but without additional firm-level control variables. The coefficient of the interaction term $D \times R$ is 0.048 and significant at the 1 percent level (t = 4.91), suggesting that our sample firms, on average, recognize economic losses more quickly than economic gains. The coefficient of $CRASH \times D \times R$ is −0.038 and is statistically significant at the 1 percent level (t = −2.70), which is consistent with our prediction that the degree of conditional conservatism is negatively associated with future crash risk. Model (2) reports the results of estimating equation (9) with firm-fixed effects and all other control variables except *OPAQUE*. The impact of conservatism on future crash risk continues to be significantly negative (the coefficient of $CRASH \times D \times R$

24. Patatoukas and Thomas (2011) attribute the biases to scaled-related effects. However, Ball et al. (2013) show that Patatoukas and Thomas's biases are essentially due to correlated omitted variables. See both Patatoukas and Thomas (2011) and Ball et al. (2013) for more discussions on this issue.

25. Ball et al. (2013) argue that controlling for firm characteristics (risk factors) can also help reduce the biases. Thus, our OLS regression results with firm-level control variables are likely reliable.

26. The full results are available upon request.

TABLE 3

Conditional conservatism and future stock price crash risk: Basu (1997) asymmetric timeliness regression

Panel A: *CRASH* as the crash risk measure

	The dependent variable is X_t, which is earnings scaled by market value					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
R_t	0.060***	0.076***	0.079***	0.066***	0.069***	0.071***
	(8.44)	(4.10)	(3.35)	(3.16)	(3.31)	(3.29)
$D_t \times R_t$	0.048***	0.031	−0.014	0.099*	0.097*	0.110**
	(4.91)	(0.59)	(−0.18)	(1.85)	(1.81)	(1.96)
$CRASH_{t+1} \times R_t$	−0.009*	−0.004	−0.008	0.003	0.003	0.000
	(−1.66)	(−0.84)	(−1.25)	(0.78)	(0.79)	(0.04)
$CRASH_{t+1} \times D_t \times R_t$	−0.038***	−0.028**	−0.033**	−0.046***	−0.046***	−0.045***
	(−2.70)	(−1.98)	(−2.55)	(−2.92)	(−2.86)	(−3.12)
$OPAQUE_t \times R_t$					−0.022**	−0.031**
					(−2.33)	(−2.01)
$OPAQUE_t \times D_t \times R_t$					−0.005	0.027
					(−0.27)	(1.26)
Firm-fixed effects	Yes	Yes	No	Yes	Yes	No
Observations	95,938	95,938	95,938	37,194	37,194	37,194
Number of firms	10,777	10,777	10,777	6,331	6,331	6,331
Adjusted R^2(%)	8.66	11.44	14.97	11.68	11.71	15.85

Panel B: *NCSKEW* as the crash risk measure

	Dependent variable is X_t, which is earnings scaled by market value					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
R_t	0.059***	0.076***	0.079***	0.065***	0.069***	0.071***
	(8.61)	(4.04)	(3.35)	(3.11)	(3.26)	(3.26)
$D_t \times R_t$	0.033***	0.011	−0.041	0.086	0.084	0.088
	(3.36)	(0.22)	(−0.57)	(1.56)	(1.52)	(1.55)

(The table is continued on the next page.)

TABLE 3 (continued)

Panel B: *NCSKEW* as the crash risk measure

	Dependent variable is X_t, which is earnings scaled by market value					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
$NCSKEW_{t+1} \times R_t$	−0.004	−0.002	−0.007	0.003	0.003	−0.000
	(−1.04)	(−0.62)	(−1.45)	(0.81)	(0.81)	(−0.02)
$NCSKEW_{t+1} \times D_t \times R_t$	−0.029***	−0.024***	−0.033***	−0.013	−0.013	−0.022***
	(−3.93)	(−3.46)	(−5.46)	(−1.21)	(−1.18)	(−2.83)
$OPAQUE_t \times R_t$					−0.022**	−0.031**
					(−2.36)	(−2.01)
$OPAQUE_t \times D_t \times R_t$					−0.005	0.027
					(−0.27)	(1.26)
Firm-fixed effects	Yes	Yes	No	Yes	Yes	No
Observations	95,938	95,938	95,938	37,194	37,194	37,194
Number of firms	10,777	10,777	10,777	6,331	6,331	6,331
Adjusted R^2 (%)	8.77	11.52	15.04	11.72	11.75	15.93

Notes:

This table reports the results of a Basu-type (1997) regression analysis on the relation between conditional conservatism and future crash risk. For models (1) to (3), the sample period is from 1964 to 2007. For models (4) to (6), the sample period is from 1990 to 2007. The dependent variable is earnings in year t, defined as net income deflated by the lagged market value of equity. To save space, we omit the coefficient estimates of the control variables (except for *OPAQUE*) and intercept terms (i.e., those terms without R_t). All variables are defined in Table 1. The t-statistics (in parentheses) are based on standard errors clustered by both firm and year.

Here *, **, and *** indicate, respectively, 10 percent, 5 percent, and 1 percent significance (two-tailed).

= −0.028, t = −1.98), even after controlling for firm size, market-to-book, leverage, and other firm characteristics that impact crash risk. The adjusted R^2 increases from 8.66 percent in model (1) to 11.44 percent in model (2). Following Francis and Martin (2010), we assess the economic significance of the impact of conservatism on crash risk by using a bootstrapping method. Specifically, we first estimate equation (1) 500 times based on randomly selected samples with observations equal to 10 percent of the full sample. The mean and standard deviation of the Basu coefficient from this process are 0.145 and 0.013, respectively. Thus, a one standard deviation increase in the Basu coefficient leads to a decrease in crash probability of 46.4 percent (100 × 0.013/0.028), based on the results of model (2) in panel A of Table 3, which is economically significant.

Model (3) re-estimates the specification of model (2) by OLS regression without firm-fixed effects. The results continue to hold. The adjusted R^2 in model (3) is 14.97 percent, which is larger than the R^2 of 11.44 percent of model (2). This finding suggests that equation (9) is more useful in explaining cross-sectional variations than within-firm time-series variations. Models (4) to (6) estimate equation (9) using a reduced sample from 1990 to 2007 with nonmissing values for *OPAQUE*. The impact of conservatism on future crash risk continues to be significantly negative for this reduced sample, irrespective of whether we control for earnings management (i.e., *OPAQUE*).

Panel B of Table 3 reports the results of estimating equation (9) using *NCSKEW* as the measure of crash risk. In all specifications, the impact of conservatism on future negative skewness, as captured by the coefficient of $NCSKEW \times D \times R$, is negative. The results are also statistically significant, except for those in models (4) and (5). This result is likely due to the reduced power of the model when estimating within-firm effects using a shorter time series. As seen in panel B, model (6), the impact of conservatism on future negative skewness is significantly negative, even for the shorter time series from 1990 to 2007, when we draw power from cross-sectional variations using pooled OLS regression. The adjusted R^2 in model (6) is also significantly larger than those of models (4) and (5). Overall, the results in Table 3 show that conditional conservatism as measured by the Basu coefficient has a significant and negative impact on future stock price crash risk, supporting Hypothesis 1.[27]

Ball–Shivakumar piecewise linear regression

Our second set of tests use the Ball and Shivakumar (2005, 2006, 2008) accrual-based measure of asymmetric timeliness to examine the impact of conditional conservatism on future crash risk. Specifically, we estimate the following regression:

$$\begin{aligned} TCA_{jt} = & \gamma_0 + \gamma_1 \Delta REV_{jt} + \gamma_2 GPPE_{jt} + \gamma_3 DCF_{jt} + \gamma_4 CF_{jt} + \gamma_5 DCF_{jt} \times CF_{jt} \\ & + \gamma_6 CRASH_{j(t+1)} + \gamma_7 CRASH_{j(t+1)} \times DCF_{jt} + \gamma_8 CRASH_{j(t+1)} \times CF_{jt} \\ & + \gamma_9 CRASH_{j(t+1)} \times DCF_{jt} \times CF_{jt} + \gamma_k ControlVar_{jt} + \gamma_l ControlVar_{jt} \times DCF_{jt} \\ & + \gamma_m ControlVar_{jt} \times CF_{jt} + \gamma_n ControlVar_{jt} \times DCF_{jt} \times CF_{jt} + \varepsilon_{jt}, \end{aligned} \tag{10}$$

where the dependent variable TCA_{jt} is total current accruals for firm j in year t scaled by average total assets and all independent variables are as defined previously. The term *ControlVar* represents the set of control variables defined in section 3, excluding *ROA*. A negative coefficient of $CRASH \times DCF \times CF$ is consistent with our prediction that accounting conservatism is negatively associated with future crash risk (i.e., $\gamma_9 < 0$). Similar to the

27. Due to severe multicollinearity problems, we do not discuss the coefficients of the control variables in the Basu and Ball–Shivakumar regressions. Therefore, we omit these coefficients from Table 3 and 4 to save space. Note, however, that the VIFs of *CRASH* or *NCSKEW* and the interaction terms with *CRASH* or *NCSKEW* are all below two.

TABLE 4
Conditional conservatism and future crash risk: Ball and Shivakumar (2006) piecewise linear accruals regressions

Panel A: Crash risk measured by *CRASH*

	Dependent variable is TCA_t, which is total current accruals scaled by average assets					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
CF_t	−0.542***	−0.483***	−0.211***	−0.571***	−0.608***	−0.268***
	(−25.04)	(−12.23)	(−3.42)	(−11.02)	(−14.40)	(−5.58)
$DCF_t \times CF_t$	0.176***	−0.321***	−0.643***	−0.134*	−0.083	−0.436***
	(6.74)	(−4.28)	(−7.09)	(−1.71)	(−1.02)	(−4.14)
$CRASH_{t+1} \times CF_t$	0.042***	0.037**	0.052**	0.033*	0.033*	0.033*
	(2.62)	(2.48)	(2.55)	(1.91)	(1.95)	(1.79)
$CRASH_{t+1} \times DCF_t \times CF_t$	−0.076***	−0.061**	−0.070**	−0.112***	−0.113***	−0.103***
	(−2.77)	(−2.23)	(−2.31)	(−2.97)	(−3.04)	(−2.60)
$OPAQUE_t \times CF_t$					0.124***	0.114***
					(3.76)	(3.63)
$OPAQUE_t \times DCF_t \times CF_t$					−0.173**	−0.115**
					(−2.41)	(−2.23)
Firm-fixed effects	Yes	Yes	No	Yes	Yes	No
Observations	88,734	88,734	88,734	33,179	33,179	33,179
Adjusted R^2 (%)	51.06	53.84	43.76	47.58	47.68	36.60

Panel B: Crash risk measured by *NCSKEW*

	Dependent variable is TCA_t, which is total current accruals scaled by average assets					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
CF_t	−0.530***	−0.473***	−0.200***	−0.559***	−0.596***	−0.257***
	(−25.63)	(−12.56)	(−3.31)	(−11.49)	(−15.06)	(−5.48)
$DCF_t \times CF_t$	0.153***	−0.335***	−0.661***	−0.159*	−0.109	−0.462***
	(5.49)	(−4.42)	(−7.30)	(−1.76)	(−1.16)	(−4.12)

(The table is continued on the next page.)

TABLE 4 (continued)

Panel B: Crash risk measured by *NCSKEW*

	Dependent variable is TCA_t, which is total current accruals scaled by average assets					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
$NCSKEW_{t+1} \times CF_t$	0.041***	0.041***	0.050***	0.035***	0.034***	0.031***
	(5.49)	(4.95)	(5.48)	(3.32)	(3.29)	(2.82)
$NCSKEW_{t+1} \times DCF_t \times CF_t$	−0.063***	−0.041***	−0.052***	−0.038***	−0.036***	−0.036***
	(−4.28)	(−2.86)	(−3.99)	(−2.74)	(−2.61)	(−2.99)
$OPAQUE_t \times CF_t$					0.121***	0.113***
					(3.74)	(3.54)
$OPAQUE_t \times DCF_t \times CF_t$					−0.165**	−0.115**
					(−2.27)	(−2.26)
Firm-fixed effects	Yes	Yes	No	Yes	Yes	No
Observations	88,734	88,734	88,734	33,179	33,179	33,179
Adjusted R^2 (%)	51.24	53.96	43.95	47.61	47.71	36.63

Notes:

This table reports the Ball and Shivakumar (2006) piecewise linear accruals regression analysis on the relation between conservatism and future crash risk. For models (1) to (3), the sample period is from 1964 to 2007. For models (4) to (6), the sample period is from 1990 to 2007. The dependent variable is current accruals in year t, scaled by average total assets. To save space, we omit the coefficient estimates of the control variables (except for *OPAQUE*) and intercept terms (i.e., those terms without CF_t). All variables are defined in Table 1. The t-statistics (in parentheses) are based on standard errors clustered by both firm and year.

Here *, **, and *** indicate, respectively, 10 percent, 5 percent, and 1 percent significance (two-tailed).

Basu regression tests, we also replace *CRASH* with *NCSKEW* in equation (10) to examine the relation between conservatism and negative firm-specific return skewness.

Table 4 reports the results of estimating equation (10). Similar to Table 3, Table 4 omits the coefficient estimates of the control variables and intercept terms. Because the model specifications of Table 4 are largely the same as in Table 3, except for the difference in the conservatism measurement, we discuss the results in Table 4 briefly. Overall, we can see from Table 4 that the impact of conditional conservatism on future crash risk, as captured by the coefficients of $CRASH \times DCF \times CF$ or $NCSKEW \times DCF \times CF$, is negative and significant at less than the 5 percent level across all model specifications. The results of models (4) and (5) in panel B are noteworthy. The impact of conservatism on future negative return skewness in the Ball–Shivakumar firm-fixed effect specification is significant with a negative sign, even for the shorter time series from 1990 to 2007, while the same impact in the Basu firm-fixed effect specification is insignificant, as reported in models (4) and (5) in panel B of Table 3.

Khan and Watts's (2009) firm-year conservatism measure

Our third set of tests for Hypothesis 1 estimates the following regression:

$$CRASH_{j(t+1)} = \alpha_0 + \alpha_1 CSCORE_{jt} + \sum_{q=2}^{m} \alpha_q (q^{th} ControlVar_{jt}) + \varepsilon_{j(t+1)}, \tag{11}$$

where $CRASH_{j(t+1)}$ is an indicator variable that equals one if firm j experiences one or more crash events in year $t+1$ and zero otherwise and $CSCORE_{jt}$ refers to Khan and Watts's (2009) conservatism measure for firm j in year t. The term *ControlVar* represents the set of control variables defined in section 3. Hypothesis 1 predicts that $\alpha_1 < 0$.

Table 5, panel A, reports the logistic regression results for equation (11). All regressions in Table 5 also include year dummies to control for temporary economic shocks to crash risk. Model (1) presents the results of our baseline regressions of one-year-ahead *CRASH* on our control variables, namely, *DTURN, NCSKEW, SIGMA, RET*, *SIZE*, *MB*, *LEV*, and *ROA*. These control variables represent the combined set of crash determinants examined by Chen et al. (2001) and Hutton et al. (2009). Model (1) shows that the coefficient of *DTURN* is significantly positive. For 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. The authors examine the effect of *DTURN* 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. The coefficient of past skewness (*NCSKEW*) is significantly positive, consistent with Chen et al. (2001). The coefficient of past return volatility (*SIGMA*) is positive but insignificant. Consistent with Chen et al. (2001), model (1) shows that the coefficients of past stock returns (*RET*) and of the market-to-book ratio (*MB*) are 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 coefficient of firm size is not significant, inconsistent with Chen et al. (2001). However, the coefficient of firm size is significantly positive when we use the *NCSKEW* of Chen et al. (2001) to measure crash risk (as shown in panel C of Table 5).[28] Finally, the coefficient of *LEV* is significantly negative and the coefficient of *ROA* is negative but not significant.

28. The coefficient of firm size is positive and insignificant if we replace total assets with market value (0.022, $t = 1.38$). We use total assets in the regression model to minimize the multicollinearity problem because market value is used to construct *CSCORE*. As expected, the coefficient of *CSCORE* is less significant when we replace total assets with market value in model 2 (-1.075, $t = 2.49$).

TABLE 5
Conditional conservatism and future crash risk: Khan and Watts's (2009) firm-year conservatism measure

Panel A: Logistic regression using $CRASH_{t+1}$ as the dependent variable

Variables	(1)	(2)	(3)	(4)
$CSCORE_t$		−1.448***	−1.304**	−1.274**
		(−4.21)	(−2.32)	(−2.26)
$DTURN_t$	1.085***	1.101***	1.033***	1.060***
	(4.25)	(4.32)	(4.85)	(4.98)
$NCSKEW_t$	0.080***	0.067***	0.089***	0.089***
	(4.30)	(3.53)	(3.57)	(3.54)
$SIGMA_t$	3.373	2.944	11.311**	10.633**
	(0.83)	(0.76)	(2.47)	(2.32)
RET_t	0.956*	0.895*	1.903***	1.865***
	(1.86)	(1.79)	(3.03)	(2.97)
$SIZE_t$	−0.011	−0.027**	0.009	0.014
	(−0.67)	(−2.11)	(0.52)	(0.74)
MB_t	0.001**	0.001*	0.030***	0.028***
	(1.99)	(1.91)	(3.27)	(3.24)
LEV_t	−0.221**	−0.005	−0.185	−0.187
	(−2.45)	(−0.04)	(−1.20)	(−1.21)
ROA_{t+1}	−0.082	−0.117*	−0.145*	−0.146*
	(−1.18)	(−1.74)	(−1.94)	(−1.94)
$OPAQUE_t$				0.195***
				(2.62)
Firm-fixed effects	No	No	No	No
Observations	114,548	114,548	46,585	46,585
Pseudo R^2 (%)	3.01	3.11	1.42	1.45

Panel B: Economic significance of the coefficients from the logistic regression Model (4)

	Unconditional crash probability = 12%			
Variables	MF (marginal effect)	STD	STD×MF (%)	(STD×MF)/0.12 (%)
$CSCORE_t$	−0.145	0.085	−1.23	−10.3
$DTURN_t$	0.134	0.053	0.71	5.9
$NCSKEW_t$	0.011	0.686	0.78	6.5
$SIGMA_t$	1.350	0.026	3.57	29.7
RET_t	0.242	0.186	4.50	37.5
$SIZE_t$	0.002	2.005	0.42	3.5
MB_t	0.004	2.064	0.90	7.5
LEV_t	−0.026	0.179	−0.47	−3.9
ROA_{t+1}	−0.041	0.103	−0.43	−3.5
$OPAQUE_t$	0.024	0.270	0.64	5.4

(The table is continued on the next page.)

TABLE 5 (continued)

Panel C: OLS regression using $NCSKEW_{t+1}$ as the dependent variable

Variables	(1)	(2)	(3)	(4)
$CSCORE_t$		−0.813***	−0.577***	−0.571***
		(−9.41)	(−4.34)	(−4.26)
$DTURN_t$	0.503***	0.522***	0.428***	0.435***
	(7.76)	(7.97)	(8.25)	(8.28)
$NCSKEW_t$	0.051***	0.042***	0.035***	0.035***
	(9.34)	(8.13)	(5.18)	(5.15)
$SIGMA_t$	3.346***	3.292***	4.351***	4.191***
	(3.31)	(3.55)	(4.11)	(3.93)
RET_t	0.464***	0.446***	0.625***	0.615***
	(4.26)	(4.35)	(4.90)	(4.81)
$SIZE_t$	0.058***	0.050***	0.056***	0.057***
	(14.72)	(15.42)	(15.29)	(15.99)
MB_t	0.000**	0.000**	0.021***	0.020***
	(2.05)	(2.16)	(7.34)	(7.39)
LEV_t	−0.130***	0.012	−0.117***	−0.117***
	(−6.82)	(0.50)	(−3.29)	(−3.31)
ROA_{t+1}	0.153***	0.127***	0.122***	0.122***
	(5.74)	(4.99)	(3.68)	(3.64)
$OPAQUE_t$				0.045**
				(2.53)
Firm-fixed effects	No	No	No	No
Observations	114,548	114,548	46,585	46,585
Adjusted R^2 (%)	6.22	6.79	6.09	6.11

Notes:

This table presents regression results on the relation between conservatism and crash risk. Panel A reports the logit regression results using *CRASH* as the dependent variable, and panel C reports the ordinary least squares (OLS) regression results using *NCSKEW* as the dependent variable. The sample period is from 1964 to 2007 for models (1) and (2) and is 1990 to 2007 for models (3) and (4). All variables are defined in Table 1. The *Z* and *t*-statistics (in parentheses) are based on standard errors clustered by both firm and year. All estimations contain fiscal year dummies.

Here *, **, and *** indicate, respectively, 10 percent, 5 percent, and 1 percent significance (two-tailed).

Model (2) presents the results of adding *CSCORE* to the baseline regression specification in model (1). The coefficient of *CSCORE* is highly significant, with an expected negative sign and $t = -4.21$, suggesting that conservatism in year t is negatively related to crash risk in year $t + 1$, even after controlling for other determinants of crash risk. In models (3) and (4), the coefficients of *CSCORE* continue to be significantly negative for the period 1990 to 2007, irrespective of whether *OPAQUE* is controlled for. In addition, the coefficient of the opaqueness measure (*OPAQUE*) of Hutton et al. (2009) is significantly positive, with $t = 2.62$. To assess the economic significance of our test results, using the coefficients of model (4) in panel A, we compute the marginal effect of *CSCORE* and other control variables (McCloskey and Ziliak 1996; Ziliak and McCloskey 2004). Panel B of Table 5 presents the marginal effect analysis for the results of model (4). The marginal effect of *CSCORE* (−1.23 percent) in model (4) suggests that a one standard deviation increase in *CSCORE* results in a 1.23 percentage point decrease in the probability of a crash. This effect represents about a 10 percent decrease in crash risk (0.012/0.12). The marginal effect of *CSCORE* is about twice those of *DTURN* (0.007) and *OPAQUE* (0.006).

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 5, panel C, reports the results of OLS regressions using one-year-ahead *NCSKEW* as the dependent variable. As shown in panel C of Table 5, the coefficients of *CSCORE* are significantly negative at less than the 1 percent level across all models, which strongly supports the prediction in Hypothesis 1. This result is economically significant as well. Consider the results in model (4) as an example. The *CSCORE* coefficient of −0.571 indicates that a one standard deviation increase in *CSCORE* in year t leads to an approximately 24 percent ($0.571 \times 0.085/0.200$) decrease in *NCSKEW* in year $t + 1$.

We also evaluate the usefulness of *CSCORE* in improving the explanatory power of the crash prediction model using incremental adjusted R^2s (Darlington 1968). For this purpose, we focus on the OLS regression model, because there are no real R^2s for logit models and pseudo-R^2 values are not generally meaningful in evaluating incremental explanatory power. Panel C of Table 5 shows that the adjusted R^2 of model (2) with *CSCORE* is 6.79 percent and the adjusted R^2 of model (1) without *CSCORE* is 6.22 percent. This result suggests that adding *CSCORE* to the baseline model improves the explanatory power of the model by about 9.2 percent [(6.79 − 6.22)/6.22]. For comparison, *OPAQUE* increases the explanatory power of the crash prediction model by only about 0.3 percent [(6.11 − 6.09)/6.09].

Overall, the results reported in Tables 3–5 reveal that, consistent with Hypothesis 1, the higher the conservatism in year t, the lower the likelihood of crashes in year $t + 1$, and this relation is robust to different measures of conservatism and crash risk. This result holds after controlling for investor heterogeneity (Chen et al. 2001) and information opaqueness (Hutton et al. 2009). Our results are consistent with the view that conservatism plays a significant role in limiting managerial incentives and ability to withhold or delay the disclosure of bad news, thereby lowering the probability of bad news being stockpiled within a firm and thus reducing the likelihood of a stock price crash.

Test of Hypothesis 2

Hypothesis 2 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 four proxies for information asymmetry between managers and equity market participants.

The first measure is 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 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 Hypothesis 2, we expect that the impact of conservatism on reducing crash risk is more pronounced for more R&D-intensive firms.

The second measure is the degree of industry concentration or the lack of product market competition. Economists argue that product market competition mitigates managerial agency problems (Giroud and Mueller 2010). Dhaliwal, Huang, Khurana, and Pereira (2013) and Hui, Klasa, and Yeung (2012) provide evidence that intense product market competition induces managers to be more conservative in financial reporting. Ali, Klasa, and Yeung (2013) and Li (2010) 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.

The third measure is analyst coverage. Financial analysts intermediate 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 or monitoring is value adding because it reduces information asymmetry between corporate insiders and outsiders (Lang, Lins, and Miller 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 Hypothesis 2, we expect that the impact of conservatism on reducing crash risk is attenuated for firms with high analyst coverage. Finally, we construct a comprehensive measure of information asymmetry using principal component analysis.

Columns (1) to (4) of Table 6 report the results from the augmented model of equation (11), where one-year-ahead *CRASH* is the dependent variable and four proxies for information asymmetry and their interactions with our measure of conservatism, *CSCORE,* are added. Columns (5) to (8) of Table 6 report the same results, using one-year-ahead *NCSKEW* as the dependent variable. In Table 6, *R&D* is an indicator variable that equals one for firms with R&D expenditure in year *t*, and zero otherwise; *HICON* is an indicator variable that equals one if firms have an above-median Herfindahl–Hirschman index (estimated using sales) in year *t* and zero otherwise; *NEGCOV* is the natural log of one plus the number of analysts following a firm in year *t,* multiplied by minus one; and *IA_FACTOR* is the first principal component of the previous three measures. For all four measures, higher values indicate higher information asymmetry. In all regressions, we include the same set of control variables, that is, *DTURN, NCSKEW, SIGMA, RET*, *SIZE, MB, LEV,* and *ROA*. To save space, we do not report the regression coefficients for control variables.

Ai and Norton (2003) and Norton, Wang, and Ai (2004) demonstrate that both the effects and standard errors of interaction terms in logit or probit models are biased 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: for noninteraction terms, we estimate the coefficients and standard errors using the double-clustering method, as in Table 5. For interaction terms, we use the procedure of Norton et al. (2004) to estimate the marginal effects and standard errors.[29]

The results of Table 6 show that the coefficients of *CSCORE*×*R&D*, *CSCORE*×*HICON*, *CSCORE*×*NEGCOV,* and *CSCORE*×*IA_FACTOR* are all negative. The estimated coefficients of these interaction terms are also highly significant, except for that of model (3). For example, the marginal effect on the interaction term *CSCORE*×*R&D* of model (1) is 0.9 percent (0.085 × 0.106), suggesting that a one standard deviation increase in *CSCORE* reduces crash risk by about one percentage point more for firms with high information asymmetry than for firms with low information asymmetry. Overall, the results in Table 6 are generally consistent with Hypothesis 2, suggesting that the impact of

29. We find that our statistical inferences remain the same even when we do not use the procedure of Norton et al. (2004).

TABLE 6
Conditional conservatism and stock price crash risk: The impact of information asymmetry

	Dependent variable: $CRASH_{t+1}$				Dependent variable: $NCSKEW_{t+1}$			
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$CSCORE_t$	−1.142***	−1.069***	−1.000*	−1.230***	−0.711***	−0.730***	−0.763***	−0.734***
	(−3.33)	(−3.14)	(−1.95)	(−3.24)	(−8.30)	(−8.78)	(−5.30)	(−6.81)
$R\&D_t$	0.203***				0.075***			
	(4.13)				(5.80)			
$CSCORE_t \times R\&D_t$	−0.106***				−0.294***			
	(−3.45)				(−3.77)			
$HICON_t$		0.148**				0.041***		
		(2.18)				(3.21)		
$CSCORE \times HICON_t$		−0.109***				−0.187***		
		(−4.01)				(−2.85)		
$NEGCOV_t$			−0.137***				−0.070***	
			(−3.89)				(−8.16)	
$CSCORE \times NEGCOV_t$			−0.005				−0.142**	
			(−0.43)				(−2.31)	
IA_FACTOR_t				0.006				−0.019*
				(0.14)				(−1.71)
$CSCORE \times IA\_FACTOR_t$				−1.202**				−0.376***
				(−2.31)				(−3.38)

(The table is continued on the next page.)

TABLE 6 (continued)

	Dependent variable: $CRASH_{t+1}$				Dependent variable: $NCSKEW_{t+1}$			
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Controls	Included	Included	Included	Included	Included	Included	Included	Included
Firm-fixed effects	No	No	No	No	No	No	No	No
Observations	114,548	114,548	89,473	89,473	114,548	114,548	89,473	89,473
Pseudo R^2 (%)	3.21	3.21	1.56	1.44	6.85	6.81	6.77	6.27

Notes:

This table presents regression results on the relation between conservatism and crash risk, conditioning on the ex ante information asymmetry proxies.

Columns (1) to (4) report the logit regression results using *CRASH* as the dependent variable, and columns (5) to (8) report the OLS regression results using *NCSKEW* as the dependent variable. The sample period is from 1964 to 2007 for models (1), (2), (5), and (6) and from 1982 to 2007 for models (3), (4), (7), and (8). The controls variables, as in model (1) of Table 4, are included in all regressions but are not reported here to save space. $R\&D_t$ is an indicator variable that takes the value of one if the firm reports non-zero R&D expenses in fiscal year t, and zero otherwise. $HICON_t$ is an indicator variable that takes the value of one if the firm's Herfindahl index is above the median in fiscal year t, and zero otherwise. $NEGCOV_t$ is the log of one plus the number of analysts following in fiscal year t, multiplied by minus one. *IA_FACTOR* is the first principal component of the three measures of information asymmetry. See Table 1 for the detailed definitions of all other variables. The logit regression interaction effects and their Z-values (in parentheses) are estimated using the procedure of Norton et al. (2004). The Z and t-statistics (in parentheses) for all other coefficients are based on standard errors clustered by both firm and year. All estimations also contain fiscal year dummies.

Here *, **, and *** indicate, respectively, 10 percent, 5 percent, and 1 percent significance (two-tailed).

TABLE 7
Time trend analysis

Variables	(1) Logit: *CRASH*	(2) OLS: *NCSKEW*	(3) Logit: *CRASH*	(4) OLS: *NCSKEW*
$TIME$	0.015	0.015***	−0.001	0.006***
	(1.13)	(8.67)	(−0.12)	(3.69)
$TIME \times CSCORE_t$	−0.052***	−0.024***	−0.068***	0.005**
	(−2.68)	(−7.70)	(−5.80)	(2.37)
$TIME \times DTURN_t$	−0.066**	−0.017***	−0.079***	−0.016***
	(−2.37)	(−3.37)	(−2.89)	(−3.23)
$TIME \times NCSKEW_t$	−0.001	−0.001***	−0.003**	−0.001***
	(−0.74)	(−3.60)	(−2.09)	(−3.32)
$TIME \times SIGMA_t$	0.889***	0.106***	0.805***	0.082**
	(4.73)	(3.13)	(4.84)	(2.55)
$TIME \times RET_t$	0.051*	0.009*	0.045*	0.005
	(1.72)	(1.78)	(1.69)	(1.06)
$TIME \times SIZE_t$	0.001	−0.001***	0.000	−0.000**
	(1.25)	(−6.97)	(0.08)	(−2.41)
$TIME \times MB_t$	0.000	−0.000	−0.000	−0.000
	(1.58)	(−1.31)	(−0.00)	(−1.42)
$TIME \times LEV_t$	0.013*	0.002	0.034***	−0.003***
	(1.85)	(1.29)	(5.81)	(−2.72)
$TIME \times ROA_{t+1}$	0.020**	−0.009***	0.046***	−0.006**
	(1.99)	(−2.69)	(4.23)	(−2.07)
$CSCORE_t$	0.009	−0.232***	0.875**	−0.837***
	(0.02)	(−2.97)	(2.51)	(−13.75)
$DTURN_t$	3.376***	1.098***	3.679***	1.099***
	(3.32)	(6.38)	(3.68)	(6.46)
$NCSKEW_t$	0.095*	0.073***	0.162***	0.071***
	(1.74)	(7.48)	(3.21)	(7.30)
$SIGMA_t$	−23.221***	0.549	−20.121***	1.088
	(−3.66)	(0.51)	(−3.56)	(1.07)
RET_t	−0.363	0.256	−0.187	0.363**
	(−0.36)	(1.61)	(−0.20)	(2.35)
$SIZE_t$	−0.062***	0.075***	−0.039**	0.058***
	(−2.80)	(18.27)	(−2.06)	(15.76)
MB_t	−0.003	0.002	0.001	0.003
	(−1.35)	(1.37)	(0.26)	(1.49)
LEV_t	−0.360	−0.011	−1.057***	0.099***
	(−1.63)	(−0.30)	(−5.52)	(2.83)
ROA_{t+1}	−0.773**	0.428***	−1.646***	0.335***
	(−2.22)	(3.67)	(−4.30)	(3.16)
Year Dummies	Yes	Yes	No	No
Observations	114,548	114,548	114,548	114,548
(Pseudo) R^2 (%)	3.26	7.02	2.00	5.72

Notes:

This table presents the regression results on the relation between the trend in conservatism and the trend in crash risk. The sample period is from 1964 to 2007. The trend variable *TIME* is calculated as year minus 1963. All other variables are defined in Table 1. The *t*-statistics (in parentheses) are based on standard errors clustered by firm.

Here *, **, and *** indicate, respectively, 10 percent, 5 percent, and 1 percent significance (two-tailed).

conservatism on reducing the likelihood of a crash is more pronounced for firms with high information asymmetry.

5. Additional tests and robustness checks

Time-series relation

In this subsection, we investigate the time-series relation between conservatism and crash risk by a pooled firm-level regression (e.g., Rajgopal and Venkatachalam 2011). Specifically, we augment equation (11) by including a time-trend variable (*TIME*) and its interactions with all other independent variables. Table 7 presents the results. Models (1) and (2) show that the coefficients of the interaction term $TIME \times CSCORE$ are negative and significant, suggesting that the increasing trend in conservatism contributes *negatively* to the increasing trend in crash risk. Models (3) and (4) re-estimate models (1) and (2) by taking out year fixed effects. The logit regression with *CRASH* as the dependent variable continues to show a significantly negative coefficient for $TIME \times CSCORE$. However, the same coefficient in the OLS regression with *NCSKEW* as the dependent variable becomes positive. This result may suggest that it is important to control for transitory shocks to crash risk.

Robustness checks

The main results of our study hold in the following robustness checks:

1. Controlling for corporate governance proxies (e.g., G-Index);
2. Using firm-fixed effect regression and change analysis to further mitigate the correlated omitted variables problem;
3. Using Cox (1972) proportional hazard method to model future crash likelihood;
4. Expanding the measurement windows of crash risk to two- and three-year-ahead windows.

6. Conclusions

This study investigates the relation between conditional conservatism in financial reporting and future stock price crash risk. Using a large sample of firm-years over the period 1964–2007, we find that the degree of conditional conservatism (i.e., timelier recognition of bad news as losses than of good news as gains) is significantly and negatively associated with future crash risk. This result holds after controlling for 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. In addition, we find that the predictive power of conservatism with respect to future 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.

Our results are consistent with the notion that accounting conservatism is associated with less withholding of bad news or the 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 theirs by providing evidence of one benefit of conservatism in the equity market through the reduction of future crash risk. Our research has implications for standard setting bodies, such as the FASB and IASB, which recently eliminated conservatism from their conceptual framework.

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