Financial Reporting Opacity and Expected Crash Risk: Evidence from Implied Volatility Smirks*

JEONG-BON KIM, *City University of Hong Kong*

LIANDONG ZHANG, *City University of Hong Kong*

1. Introduction

One of the major empirical puzzles documented in the derivatives literature is the pronounced volatility smirk[1] implicit in the prices of stock and index options. The volatility smirk refers to the stylized fact that, for the same underlying instrument, the implied volatility of low strike price options (especially out-of-the-money, or OTM, put options) is higher than that of high strike price options (especially at-the-money, or ATM, call options). This fact is puzzling because the Black–Scholes (1973) option pricing theory suggests that every option should imply the same volatility for the same underlying instrument. Essentially, the volatility smirk indicates that OTM put options are more expensive than ATM call options. Option pricing theories suggest that investor aversion to expected negative jumps or crashes in the prices of underlying instruments could be the driving force for the volatility smirk (Bates 1991; Pan 2002). Using the steepness of the volatility smirk as the proxy for perceived jump risk, several recent studies find that investors demand a large positive risk premium for holding stocks with negative ex ante jump risk, even after controlling for historical jump risk or skewness (e.g., Bollerslev and Todorov 2011; Conrad, Dittmar, and Ghysels 2013; Santa-Clara and Yan 2010; Yan 2011).

This paper examines the relation between financial reporting opacity and ex ante (or perceived) crash risk, as reflected in the steepness of implied volatility smirks. Our investigation is motivated by recent theory and evidence that financial reporting opacity increases stock price crash risk, or negative jump risk (Hutton, Marcus, and Tehranian 2009; Jin and Myers 2006). Kothari, Shu, and Wysocki (2009) find that a range of incentives, including career concerns and compensation contracts, motivates managers to withhold and delay the disclosure of bad news but to reveal good news to investors quickly. Jin and Myers (2006) and Hutton et al. (2009) argue further that the lack of transparency enables managers to hide bad news from investors for extended periods. As a result, negative information is likely to be stockpiled within the firm. When the accumulated bad news reaches a certain tipping point or when managers' incentives for hiding bad news collapse, all of the hitherto unobserved negative information will be suddenly released to the market at once, resulting in an abrupt decline in stock price, that is, a crash. Moreover, Bleck and Liu (2007) develop a model that predicts that opacity in financial reporting hinders shareholder ability to

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1. This paper uses the terms *implied volatility smirk*, *volatility smirk*, and *implied volatility skew* interchangeably.

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discriminate good from bad projects at an early stage. This would allow bad projects to be kept alive and potentially worsen over time. The poor performance of these projects can thus accumulate and only eventually materialize at their final maturity, leading to a crash in the asset price. Jin and Myers (2006) and Hutton et al. (2009), using country- and firm-level data, respectively, provide empirical evidence that supports the above predictions.

Drawing upon the findings of prior research, we predict that financial reporting opacity is positively related to the steepness of the implied volatility smirk. We predict that if investors believe that financial reporting opacity increases the probability and magnitude of future crashes, they will purchase insurance for shares of firms with high reporting opacity in the form of OTM put options. This will make OTM put options more expensive relative to ATM call options, which leads us to observe a steeper volatility smirk. While this argument bears some resemblance to the buying pressure theory of Bollen and Whaley (2004), which requires the assumption of limits to arbitrage and an upward-sloping supply curve, our prediction is also well supported by rational option pricing models that include jump risk factors (Bates 2000; Pan 2002). These models suggest that the volatility smirk is a reflection of the positive compensation for expected jump risk in equilibrium.

Our empirical tests employ three firm-level proxies of financial reporting opacity: (1) a measure of earnings management, as developed by Hutton et al. (2009); (2) the presence of financial statement restatements; and (3) the presence of auditor-attested material internal control weakness (ICW) over financial reporting under the requirements of Section 404 of the Sarbanes-Oxley Act (SOX). Using daily equity option trading data for 1996–2008[2] from the OptionMetrics database, we construct a firm-level measure of the steepness of the implied volatility smirk, following prior derivatives research (Bollen and Whaley 2004; Xing, Zhang, and Zhao 2010). We then merge the options variables with the reporting opacity measures and other control variables. Because of the differential availability of our opacity measures, we use three different samples for our empirical tests, according to the availability of each of the three opacity proxies. Briefly, our results reveal the following.

Using 14,360 firm-year observations from 1996 to 2007, we find that earnings management is significantly and positively associated with the steepness of the implied volatility smirk. This finding is consistent with our prediction that financial reporting opacity increases ex ante crash risk as perceived by investors, which in turn increases the relative expensiveness of OTM put options. The relation is robust to controlling for various firm characteristics, including size, leverage, market-to-book ratio, cash flow volatility, earnings volatility, sales volatility, and market beta. It is also robust to controlling for various stock and option trading variables, such as stock turnover, stock return, stock return volatility, stock return skewness, and ATM option implied volatility. Moreover, the results hold after controlling for unknown firm characteristics using firm fixed effect regressions.

Admittedly, the earnings management measure of financial reporting opacity may be somewhat subjective and suffer from measurement errors, making it less reliable. To alleviate this concern, we confirm the above results by using two additional unambiguous proxies for financial reporting opacity: the occurrence of financial statement restatements and the presence of ICW. Using a sample of 12,096 firm-year observations with option and restatement data from 1997 to 2006, we find that firms that restate their prior earnings reports have a steeper implied volatility smirk than firms that do not restate. In addition, we show that the relation between financial restatements and the slope of the implied volatility smirk is mainly driven by restatement cases, where intentional fraud is involved. Finally, using a sample of 4,128 firm-year observations with internal control quality data during 2004–2007, we find that ICW is significantly and positively associated

2. Since we require option trading data for three months after the fiscal period ends, our test sample period is from fiscal year 1996 to 2007.

with the steepness of the implied volatility smirk. The results are robust to controlling for other determinants of the slope of the volatility smirk, as well as known determinants of ICW.

Our study adds to the literature in the following ways. First, our research extends recent research on the relation between financial reporting opacity and crash risk. Hutton et al. (2009) examine how opacity affects realized stock price crash likelihood. Our study extends theirs by focusing on the implied volatility smirk, which can be seen as a measure of ex ante crash risk. Because crashes are rare events and even high-probability crashes can fail to be realized due to the so-called peso problem,[3] ex ante crash risk perceived by investors can be quite different from the ex post realized distributions of returns. Studying measures of realized crashes gives us a limited picture of the risks that are rationally expected by investors (Jackwerth and Rubinstein 1996; Santa-Clara and Yan 2010).

More importantly, recent studies find that investors price *perceived* crash risk and historical crash probability (or skewness) differently. Specifically, they show that investors demand a much larger risk premium for perceived crash risk (as measured by volatility skew) than for historical crash intensity (e.g., Bollerslev and Todorov 2011; Conrad et al. 2013; Santa-Clara and Yan 2010). Thus, the impacts of financial reporting opacity on realized and perceived crash risk are equally important. Our study suggests that improving financial reporting transparency can reduce investors' perception of crash risk. Moreover, while Hutton et al. (2009) employ a self-constructed measure of opacity, we also use other objective measures of reporting opacity, such as the occurrence of financial restatements and the presence of ICW, which are considered to be unambiguous proxies for low-quality financial information (Ashbaugh-Skaife et al. 2009; Graham, Li, and Qiu 2008; Kim, Song, and Zhang 2011).

Second, our study is related to the option pricing literature. While previous derivative research has focused primarily on testing option pricing models and documenting pricing anomalies relative to those models, our study examines the possible sources of one of the most intriguing anomalies, namely, the volatility smirk. Understanding the sources of option pricing anomalies is important in that it may guide researchers to develop better pricing models. For example, based on empirical evidence reported in our research, future option pricing models could consider whether information opacity plays a role in the pricing of equity options. Related research in this line includes that of Dennis and Mayhew (2002), who examine the relation between various firm characteristics and the implied volatility smirk. However, these authors focus on traditional characteristics such as beta risk, size, and leverage; the impact of financial reporting opacity on option prices is not examined. Bollen and Whaley (2004) and Gârleanu, Pedersen, and Poteshman (2009) also examine the sources of implied volatility smirks and show that net buying pressure for OTM put options partly explains the smirk pattern. However, their analyses are silent with respect to the origin of this buying pressure. The results of our study suggest that financial reporting opacity may be one of its origins.

The paper proceeds as follows. Section 2 reviews the related literature and develops the hypothesis. Section 3 describes empirical procedures, including the definitions of major research variables, model specification, sample, and data sources. Section 4 presents the main empirical results. Section 5 performs additional tests and sensitivity checks. Section 6 concludes the paper.

3. This term comes from the "anomalous" large discount of Mexican pesos in the forward market since 1954, which was fully justified by the huge realized Mexican peso devaluation in August 1976. Economists use this term to refer to rational expectations (of rare events) that do not materialize in the sample. See Sill (2000) for a detailed discussion.

2. Related literature and empirical predictions

Implied volatility smirk

The implied volatility of an option contract is the volatility implied by the market price of the option based on an option pricing model. Specifically, in the Black–Scholes model, it is the volatility that equates the Black–Scholes formula to the market price of the option. With the constant volatility assumption, the Black–Scholes theory predicts that all options on the same underlying asset with the same time to expiration, but different strike prices, should have the same implied volatility. However, the empirical derivatives literature shows that this is not the case. For example, Dumas et al. (1998) and Rubinstein (1994), among others, find that the implied volatility of OTM put options on the Standard & Poor's (S&P) 500 Index is significantly higher than that of ATM call options since the market crash of 1987. Later studies demonstrate that the phenomenon exists in more recent index option data, as well as in individual stock options (Bollen and Whaley 2004; Gârleanu et al. 2009; Xing et al. 2010). This phenomenon has been called the implied volatility smirk in the derivatives literature and the quantitative finance industry. Essentially, the volatility smirk indicates that OTM puts (options with low strike prices) are more expensive than ATM calls (options with high strike prices).

Previous research has attempted to rationalize the implied volatility smirk pattern. One line of research relaxes the Black–Scholes constant volatility assumption and introduces option pricing models with deterministic volatility, stochastic volatility, and random jumps. Bakshi, Cao, and Chen (1997) develop a parsimonious but more general model and evaluate the merits of competing option pricing models. The authors find that stochastic volatility models with jumps perform best in explaining pricing anomalies across moneyness. Bates (2000) argues that volatility smirks represent investors' subjective assessments of future crash probabilities and presents evidence that a jump diffusion model exploring crash fears fits the data well. However, the author also finds large discrepancies between the options implied distributions and objective distributions of the underlying. He then proposes that this may be due to the peso problem or an extreme negative jump risk premium.[4] Using Bates' (2000) framework, Pan (2002) examines the risk premia implicit in the S&P 500 Index options and finds a significant premium of 3.5 percent per year for jump risks. The author points out that investor aversion to negative jumps is the driving force for the implied volatility smirks.

Another line of research focuses on the impact of option market participants' supply and demand for different option series. Bollen and Whaley (2004) argue that due to limits to arbitrage, the supply curve of options is upward sloping. As a result, option series with high market demand will be more expensive. There is evidence that investors, who like equity but are averse to crash risk, purchase portfolio insurance in the form of OTM put options (Bates 2008). This will drive up the expensiveness of OTM put options relative to ATM call options, that is, the volatility smirk. Bollen and Whaley (2004) and Gârleanu et al. (2009) document that net buying pressure for OTM put options contributes significantly to the volatility smirk phenomenon implicit in both index and individual stock option prices.

Financial reporting opacity and crash risk

Managers have a general tendency to strategically withhold bad news or delay its disclosure and to accelerate the release of good news. This tendency may stem from a variety of

4. Pan (2002) discusses the difference between the peso problem explanation and risk premia: The peso problem explanation implies that OTM put options are priced with premia because of the potential occurrence of extreme events that have not yet materialized. In contrast, the risk premium explanation emphasizes investor aversion to such extreme events. Options (especially OTM put options) are priced with premia not only because of the likelihood and magnitude of such events but also because of investor aversion to such events.

managerial incentives, such as meeting a performance threshold specified in compensation contracts and boosting the value of management-held stocks and stock options (Ball 2009; Kothari et al. 2009). Further, nonfinancial incentives, such as maintaining reputation capital and empire building, can also motivate managers to withhold bad news or accelerate the release of good news. Kothari et al. (2009) provide evidence consistent with the above predictions.

The managerial tendency to conceal bad news from outside investors engenders the risk of future crashes. This is because the asymmetric disclosure behavior of managers leads to the stockpiling of negative information within a firm, unknown to outside investors. When the accumulated bad news reaches some tipping point or when the managerial incentive for hiding bad news collapses, a large amount of negative information will be suddenly and immediately released to the market, leading to an abrupt decline in the stock price or a crash. More importantly, hiding bad news hinders outside investors from forcing managers to abandon bad projects at an early stage. As a result, bad projects will be kept alive for longer. When the accumulated bad performance eventually surfaces, one observes asset price crashes. The models of both Bleck and Liu (2007) and Jin and Myers (2006) show that opaque financial reporting environments incentivize and enable managers to withhold bad news for extended periods, which can, in turn, increase the probability and magnitude of future crashes. Using country- and firm-level data, Jin and Myers (2006) and Hutton et al. (2009), respectively, provide evidence that financial reporting opacity increases the odds of realized crashes.

Motivation and empirical predictions

There seems to be a consensus in the options pricing literature that the implied volatility smirk represents investors' ex ante assessment of the probability and magnitude of future negative jumps or crashes as well as investor aversion to those crash risks. For example, using implied volatility skew as the proxy for perceived jump risk, several recent studies find that investors demand a large premium for holding stocks with negative jump risk (e.g., Bollerslev and Todorov 2011; Conrad et al. 2012; Santa-Clara and Yan 2010; Yan 2011).

This study examines the impact of financial reporting opacity on expected crash risk, as proxied by the steepness of implied volatility skew. We predict that firms with opaque financial reporting have steeper implied volatility skew because investors perceive these firms to be more crash prone. It is important to examine investors' perception of crash risk because expected crash risk carries a higher premium than the historical skewness of returns (e.g., Santa-Clara and Yan 2010). Thus, perceived crash risk is sufficiently different from the risk of realized crashes and warrants more research. In discussing responses to the recent financial crisis, International Monetary Fund chief economist Olivier Blanchard argued (*Economist* 2009):

> What is at work is not only objective, but also subjective uncertainty, or what economists, following Chicago economist Frank Knight's early 20th century work, call "Knightian uncertainty." Objective uncertainty is about what Donald Rumsfeld (in a different context) referred to as the "known unknowns." Subjective uncertainty is about the "unknown unknowns." When, as today, the unknown unknowns dominate, and the economic environment is so complex as to appear nearly incomprehensible, the result is extreme prudence, if not outright paralysis, on the part of investors, consumers, and firms. And this behavior, in turn, feeds the crisis.... So what are policymakers to do? First, and foremost, reduce uncertainty. Do so by removing tail risks, and *the perception of tail risks*. (emphasis added)

It is important to emphasize that our empirical predictions do not derive unambiguously from current empirical results, although they may theoretically. Because of the peso problem, jumps that are feared by investors may not materialize in the sample. For example, although Hutton et al. (2009) find that their opacity measure is related to future crashes, Van Buskirk (2011) finds no such relation in his sample. In untabulated tests, we find that ICW does not predict future realized crashes. This does not necessarily mean that ICW does not increase future crash risk; it may simply be that internal control-driven crashes have not materialized yet. More importantly, it does not mean that ICW does not increase investors' fear of future crash risk. On the other hand, predictors of realized crashes may not be *perceived* by investors to be important. For example, the market-to-book ratio is a robust predictor of future crashes. It does not, however, increase investors' perception of crash risk in our empirical tests. This study therefore aims to provide empirical evidence on whether and how financial reporting opacity impacts perceived crash risk.

3. Sample and research design

This section presents empirical procedures, including the definitions of major research variables, model specification, the sample, and data sources. Appendixes 1 and 2 provide more details on variable definitions.

Financial reporting opacity proxies

We use three firm-level proxies for reporting opacity, that is, an accrual-based measure of opacity, financial restatements, and material ICW. The details are as follows.

Earnings management

The first proxy we use is the earnings management measure of information opaqueness of Hutton et al. (2009). Prior studies on earnings management generally use a measure of abnormal accruals estimated from the cross-sectional modified Jones model of Dechow, Sloan, and Sweeney (1995) to identify the presence and magnitude of earnings management. Specifically, the following regression equation is estimated for each of the Fama-French industries and each fiscal year:[5]

$$\frac{TACC_{jt}}{TA_{jt-1}} = \alpha\frac{1}{TA_{jt-1}} + \beta_1\frac{\Delta SALE_{jt}}{TA_{jt-1}} + \beta_2\frac{PPE_{jt}}{TA_{jt-1}} + \varepsilon_{jt}, \tag{1}$$

where TA_{jt-1} is total assets for firm j at the beginning of year t; $TACC_{jt}$ is total accruals for 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.

Using the estimated coefficients from (1), we compute discretionary accruals for firm j and year t ($DISACC_{jt}$) as follows:

$$DISACC_{jt} = \frac{TACC_{jt}}{TA_{jt-1}} - \hat{\alpha}\frac{1}{TA_{jt-1}} - \hat{\beta}_1\frac{\Delta SALE_{jt} - \Delta REC_{jt}}{TA_{jt-1}} - \hat{\beta}_2\frac{PPE_{jt}}{TA_{jt-1}}, \tag{2}$$

where ΔREC_{jt} is change in accounts receivable and $\hat{\alpha}$, $\hat{\beta}_1$, and $\hat{\beta}_2$ are the estimated coefficients from (1). Following Hutton et al. (2009), we then calculate our first proxy for financial reporting opacity in year t as the three-year moving sum of the absolute value of annual discretionary accruals:

$$OPAQUE_t = abs(DISACC_t) + abs(DISACC_{t-1}) + abs(DISACC_{t-2}). \tag{3}$$

5. We exclude the following industries: utilities, banking, insurance, real estate, and financial services.

This measure intends to capture both the abnormally high accruals in the year of overstatement and the subsequent reversal of prior accrual overstatements. A three-year moving sum is used because firms with consistently large absolute values of discretionary accruals over the past three years are more likely to engage in opportunistic earnings management, thus making financial reporting more opaque. In addition, the three-year moving sum of abnormal accruals is more likely to reflect a firm's underlying earnings management policy, compared with a single-year measure.

Financial statement restatements

A concern of the first opacity measure is that it is somewhat subjective and its accuracy in terms of identifying informationally opaque firms depends largely on the validity of the model used to derive the measure. Bearing this in mind, our second measure of financial reporting opacity is based on an external indicator of misreporting: financial statement restatements. Specifically, we define an indicator variable, $RESTATEMENT_t$, that takes the value of one if the firm has restated its earnings during the fiscal year t and zero otherwise.[6] Hennes, Leone, and Miller (2008) argue that researchers can significantly enhance the power of their tests by distinguishing between intentional misstatements and unintentional errors. To see if the restatement effect differs systematically between these two causes, we also introduce two additional indicator variables, $IRREGULARITY$ and $ERROR$, which equal one if the restatement is classified as intentional and unintentional, respectively, and zero otherwise.

Material ICW

Section 404 of SOX requires company management to maintain adequate internal controls over financial reporting and to provide periodic auditor-attested evaluations of internal control effectiveness. Internal controls over financial reporting are designed to provide reasonable assurances regarding the reliability of financial reporting and the preparation of financial statements for external purposes in accordance with generally accepted accounting principles. Ashbaugh-Skaife et al. (2008) and Doyle, Ge, and McVay (2007a) argue that ICW leads to low accrual quality, because weak internal controls introduce either intentional and/or unintentional misstatements. In general, the authors find that ICW is related to lower-quality accruals during the current and previous years. Feng, Li, and McVay (2009) argue that internal control quality also affects the quality of internal financial reports, which, in turn, affects the quality of management earnings forecasts. These authors find that earnings guidance for firms with ICW is less accurate. Based on the innate role of internal control over financial reporting and the above empirical evidence, we view ICW as an unambiguous proxy for a firm's financial reporting opacity. Our third measure of reporting opacity is thus defined as an indicator variable, ICW_t, that takes the value of one if the firm has reported material weakness in internal controls for fiscal year t under SOX Section 404 and zero otherwise.

Implied volatility smirk: Our proxy for expected crash risk

Following prior research (Bollen and Whaley 2004; Van Buskirk 2011; Xing et al. 2010; Yan 2011), we measure the options implied volatility smirk ($IV\text{-}SKEW_{jt}$) as the difference between the implied volatility of OTM puts (IV_{jt}^{OTMP}) and that of ATM calls (IV_{jt}^{ATMC}):

$$IV\text{-}SKEW_{jt} = IV_{jt}^{OTMP} - IV_{jt}^{ATMC}, \tag{4}$$

6. In this paper, we are interested in firm-level rather than event-specific characteristics and therefore use long-window regressions analysis instead of event studies. Thus, we construct our measures of financial reporting opacity as well as volatility smirk in this spirit. Since restatements generally happen within two years after the year of misreporting, this measure should be a reasonably good indication of a firm's recent reporting policy.

where OTM puts are defined as put options with a delta value between −0.375 and −0.125 and ATM calls are defined as call options with a delta value between 0.375 and 0.625. We measure option moneyness using the delta value because we need to utilize options with multiple maturities and delta is sensitive to the volatility of the underlying, as well as the option's time to expiration (Bollen and Whaley 2004). To obtain an annual measure of the volatility smirk, we average the daily *IV-SKEW* over the 12-month period ending three months after the fiscal year-end. When there are multiple put or call option contracts for one stock on a particular day, we calculate the weighted average of the implied volatilities for the put or call options, using option open interest as a weight[7] and use the average to calculate *IV-SKEW* for the day.

We use an annual measure of the volatility smirk, since our proxies for reporting opacity are available in annual intervals. In addition, the use of an annual average measure may mitigate potential problems associated with measurement errors inherent in a daily measure, although this side benefit is accompanied by a loss of statistical power. More importantly, our opacity–smirk story is more about the relatively persistent portion of crash fears caused by financial reporting quality, rather than short-term movements caused by daily events or noises. Thus an annual average measure is more suitable for our purpose because it smoothes out short-term movements in smirk patterns.

The main idea of our study is to examine whether financial reporting opacity is related to investors' perceived crash risk, as proxied by the steepness of the volatility smirk. The use of the volatility smirk as a proxy for ex ante crash perception is based on the theoretical works of Bates (2000) and Pan (2002), among others. It is also consistent with recent asset pricing literature that examines the pricing of ex ante crash risk or skewness (e.g., Bollerslev and Todorov 2011; Conrad et al. 2013; Santa-Clara and Yan 2010; Yan 2011). Several recent empirical studies find that the implied volatility smirk predicts future realized crashes (e.g., Bradshaw et al. 2010; Van Buskirk 2011; Xing et al. 2010). However, it is important to emphasize that our study does not depend on the actual predicting power of the volatility smirk for future crashes. Our study focuses on investors' *perception* or *fear* of crashes, rather than realized crashes. Because of the well-known peso problem, even rationally high ex ante crash risk may not materialize in historical time-series returns. Nonetheless, in this section, we conduct a simple test to see whether the implied volatility smirk is related to future crash risk for our sample. We use similar crash risk measures and empirical model as in prior research (e.g., Hutton et al. 2009; Kim, Li, and Zhang 2011a, b). In general, we find that our measure of ex ante crash risk (i.e., *IV-SKEW*) is significantly and positively associated with future crash risk.[8]

Empirical model

To examine the relation between the implied volatility smirk and financial reporting opacity, we specify the regression equation

$$IV\text{-}SKEW_{it} = \alpha_0 + \beta_1 FRO\_PROXY_{it} + \sum_{q=2}^{m} \beta_q (q^{th} ControlVariables_{it}) + \varepsilon_{it}, \tag{5}$$

where, for firm i and year t, *IV-SKEW* is our measure of the implied volatility smirk as defined in (4) and *FRO_PROXY* represents one of the three proxies for financial reporting opacity, that is, *OPAQUE, RESTATEMENT* (*IRREGULARITY, ERROR*), or *ICW*. We

7. Our results are robust to weighting options by trading volume. We use open interest as a weight for our main tests because we can thus extract information from more listed options for a stock.
8. Please see supporting information, "Appendix S1: Implied Volatility Smirk and Future Crash Risk," as an addition to the online article.

predict that all three opacity measures are positively related to the implied volatility smirk, that is, $\beta_1 > 0$.

To isolate the effect of reporting opacity on the smirk from the effect of other factors, we include in (5) several firm-specific controls, including the ATM implied volatility level, firm size, leverage, market-to-book ratio, earnings volatility, cash flow volatility, sales volatility, average stock turnover, market beta, volatility of stock returns, negative skewness of stock returns, and annual stock returns. The choice of these control variables is mainly motivated by previous studies that examine the determinants of risk-neutral skewness and implied volatility smirks (Dennis and Mayhew 2002; Van Buskirk 2011). We also include in our model variables that are possible determinants of *realized* crash risk (Chen, Hong, and Stein 2001; Hutton et al. 2009). To the extent that the ex post realized crash risk is related to the ex ante expected crash risk, we expect that these variables are also associated with our measure of the implied volatility smirk, that is, a proxy for expected crash risk.

Following Dennis and Mayhew (2002) and Van Buskirk (2011), we include the level of ATM call option implied volatility to control for overall uncertainty. In theory, overall uncertainty should increase the expected crash risk. Van Buskirk finds that ATM implied volatility is positively associated with volatility skew. On the other hand, Dennis and Mayhew show a positive relation between the levels of ATM implied volatility and risk-neutral skewness, which implies a negative relation between the levels of ATM implied volatility and the steepness of the smirk.[9] Given the inconsistent prior results, we predict no sign for this variable.

Firm size is the log of the market value of equity. Hutton et al. (2009) find that firm size is positively related to crash risk; however, they argue that there is no theory to predict this relation, suggesting that the positive relation observed between size and crash risk is caused by their research design or is spurious. We therefore do not make any directional prediction with respect to the size effect but control for it simply to isolate the effect of financial reporting opacity on the volatility smirk from potential size effects.

Leverage is defined as long-term debt divided by total assets. Toft and Prucyk (1997) develop an option pricing model in which options on the equity of highly leveraged firms exhibit a more pronounced implied volatility skew than options on low-leverage equity. Using firm-level data, the authors find empirical support for their predictions. Recent evidence by Van Buskirk (2011) is also consistent with this prediction. On the other hand, Hutton et al. (2009) show a negative relation between realized crash risk and leverage and Dennis and Mayhew (2002) show a positive relation between their risk-neutral skewness measure and leverage, both of which imply a negative relation between implied volatility skew and leverage. Given the mixed findings above, we again do not make any directional prediction on the leverage effect.

Chen et al. (2001) and Hutton et al. (2009) find that the market-to-book ratio is positively related to negative firm-specific return skew and/or crash risk. The authors argue that glamour stocks are more likely to involve bubbles and are more crash prone, which implies a positive relation between the market-to-book and the volatility smirk. However, Van Buskirk's (2011) results show a negative relation between the market-to-book and the implied volatility smirk. We control for the market-to-book ratio with no directional prediction.

It is possible that our opacity measures (e.g., *OPAQUE*) capture inherent operating uncertainty rather than financial reporting quality. To address this concern, we control for inherent uncertainty using three commonly used operating uncertainty proxies: cash flow volatility, earnings volatility, and sales volatility.

9. Note that Dennis and Mayhew's (2002) risk-neutral skewness measure should be negatively correlated with our measure of the implied volatility smirk. See also Section 5A of Xing et al. (2010) for a discussion of the correlations between the risk-neutral skewness measure and the implied volatility smirk.

Hong and Stein's (2003) theory of stock price crashes indicates that investor heterogeneity or differences of opinion among investors increase crash risk. Using trading volume turnover as a proxy for investor heterogeneity, Chen et al. (2001) show that the turnover ratio is positively related to realized future crashes. Thus, we expect to observe a positive relation between turnover and the volatility smirk.

Dennis and Mayhew (2002) find that market risk is important in pricing individual equity options. Specifically, they show that the market beta is negatively related to their measure of risk-neutral skewness. More recently, Duan and Wei (2009) show that a higher amount of systematic risk leads to a higher level of implied volatility and a steeper slope of the implied volatility curve. Thus, we include the market beta in our model to control for systematic risk and expect it to be positively related to the steepness of the implied volatility smirk.[10]

Prior research predicts a positive relation of stock return volatility with future stock price crashes and/or tail risks perceived in the options market (Chen et al. 2001; Van Buskirk 2011). Accordingly, we predict that return volatility is positively related to the implied volatility smirk. We estimate total return volatility using weekly returns over the fiscal year. Moreover, Chen et al. (2011) and Rajgopal and Venkatachalam (2011) find that there is a time-series relation between idiosyncratic return volatility and earnings quality. To the extent that idiosyncratic return volatility is correlated with the volatility smirk, our reporting opacity measures may pick up the effect of idiosyncratic volatility rather than opacity. Therefore, we further control for idiosyncratic return volatility in addition to total return volatility.

The experience of crashes would increase investor aversion to future crash risk (Bates 2000). Thus, we include negative return skewness in our model to control for this effect. However, past crashes can also decrease the probability of future crashes (Jin and Myers 2006). Empirically, however, Van Buskirk (2011) finds no meaningful relation between historical crashes and implied volatility smirks. Thus, we make no directional prediction on the sign of negative return skewness.

Chen et al. (2001) show that stocks with high past returns are more crash prone. This finding implies a positive relation between stock returns and implied volatility skew. On the other hand, Van Buskirk (2011) shows a negative relation between historical return and implied volatility skew and concludes that high-return stocks are perceived to have lower tail risk. Given the mixed evidence on this issue, we do not make any directional prediction on stock returns. We measure past stock return as the cumulative weekly return over the fiscal year. Appendix 1 presents more details on the definitions of all the variables.

Research samples

Table 1 reports the sample construction and distribution of observations over years. We start with the intersection of annual datasets from COMPUSTAT and monthly datasets from the Center for Research in Security Prices (CRSP). We then apply the following data filters:

(1) Total assets and book value are greater than zero;
(2) Year-end share price is greater than \$1;
(3) CRSP price and volume data are available for at least six months during the fiscal year.

10. Duan and Wei (2009) use a measure of systematic risk proportion to measure systematic risk. Following their research, we show that our results remain unchanged if we replace beta with systematic risk proportion. Moreover, our results are also robust to controlling for market-level skew using the implied volatility skew of the S&P 500 Index options.

TABLE 1
Sample distribution

Year	All firms	Firms with nonmissing options data	Percentage of firms with nonmissing options data	Earnings management sample	Restatement sample	SOX 404 internal control sample
1996	3,556	1,028	29%	1,006		
1997	3,663	1,167	32%	1,133	1,168	
1998	3,612	1,259	35%	1,221	1,259	
1999	3,750	1,279	34%	1,246	1,282	
2000	3,543	1,134	32%	1,101	1,135	
2001	3,319	1,093	33%	1,071	1,094	
2002	3,203	1,126	35%	1,101	1,135	
2003	3,287	1,226	37%	1,194	1,231	
2004	3,294	1,302	40%	1,268	1,316	809
2005	3,166	1,322	42%	1,284	1,333	1,029
2006	3,044	1,369	45%	1,338	1,143	1,104
2007	2,908	1,429	49%	1,397		1,186
Total	40,345	14,734	37%	14,360	12,096	4,128

Notes:

This table reports the sample distributions for the three research samples employed in this study. All firms is the sample of firms that have nonmissing COMPUSTAT and CRSP data to calculate the accounting- and stock price-based control variables. Firms with nonmissing options data is the subsample of the All firms sample with nonmissing option data from OptionMetrics. The Earnings management sample is the intersection of Firms with nonmissing options data and our earnings management based measure of reporting opacity. The Restatement sample is to merge Firms with nonmissing options data with financial restatement data. The SOX 404 internal control sample is the intersection of Firms with nonmissing options data and the sample of firms with internal control evaluation data from Audit Analytics.

We also remove firm-year observations missing COMPUSTAT and CRSP data in estimating control variables. This procedure results in a COMPUSTAT/CRSP sample of 40,345 firm-year observations from 1996 to 2007 with nonmissing accounting, stock return, and trading volume data. Throughout this paper, the fiscal year period is defined as the 12-month period ending three months after the fiscal year-end.[11]

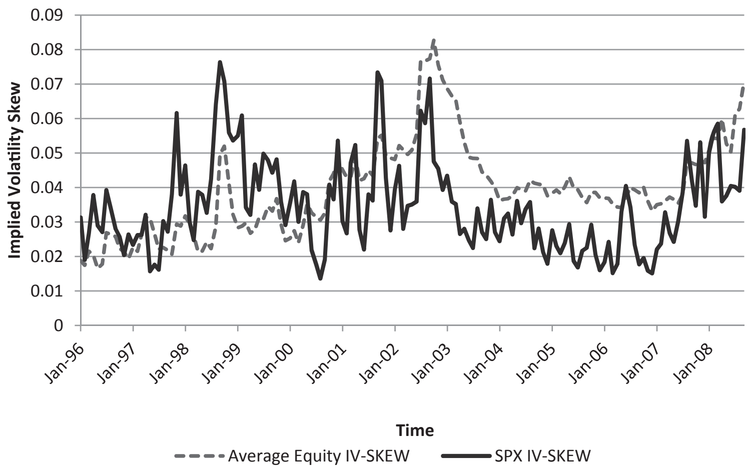
We obtain historical option price data from OptionMetrics' Ivy DB, the October 2008 Release, which covers the period from January 1996 to September 2008. To calculate the annual implied volatility skew measure, we assign the daily option price data to each fiscal year for each firm. Following prior research, we apply the following data filters to the daily option price data:

(1) The implied volatility of the option is between 0.03 and 2;
(2) The open interest of the option is greater than zero;
(3) The total volume of option contracts is not missing;
(4) The best offer price is equal to or greater than the best bid price and the best bid price is not zero;
(5) The absolute value of the option delta is between 0.02 and 0.98.

We then use the daily price data to calculate annual measures of the implied volatility smirk as well as the ATM implied volatility, the put-call ratio, and the S&P 500 Index option

11. The logic of including the three-month data after the fiscal year-end is to make sure that the current fiscal year's financial data are available to outside investors.

Figure 1 Average monthly equity implied volatility skew versus average monthly S&P 500 Index option implied volatility skew, 1996–2008



Notes:

This figure plots the average level of the implied volatility skew for all listed equity options versus the implied volatility skew of the S&P 500 index options for each month during the period January 1996 to September 2008.

smirk. We also require that at least 60 trading days be available within the fiscal year to estimate annual averages. We then merge this dataset with the COMPUSTAT/CRSP sample and obtain a master dataset of 14,734 firm-year observations. On average, 37 percent of the firms in the COMPUSTAT/CRSP sample are covered by OptionMetrics.[12] This is similar to the numbers reported by Roll, Schwartz, and Subrahmanyama (2009).

To obtain a preview of the evolution and features of the implied volatility smirk pattern, we calculate the average monthly implied volatility smirk for all listed options covered by OptionMetrics and plot it in Figure 1. We also plot the implied volatility smirk for the S&P 500 Index options for comparison. Figure 1 displays the magnitude of the average equity option smirk and the index option smirk for 153 months, from January 1996 to September 2008. Prior research documents that the volatility smirk pattern is more pronounced for index options than for individual equity options, which is another major puzzle (the so-called volatility smirk gap) in the derivatives literature (Bates 2003).

Consistent with prior research, we can see from Figure 1 that the magnitude of the implied volatility smirk for the S&P 500 Index options is significantly higher than that for individual equity options before 2002. However, we show that the pattern changes sharply after 2002: The smirk pattern increases significantly for individual equity options, which levels the magnitudes of the volatility smirk of individual equity options and that of index options. Therefore, it seems that the series of accounting scandals during the early years of this century melt the volatility smirk gap.[13] While investigating this sharp shift is beyond the scope of this research, we conjecture that investors perceive that it is not sufficient to hold equity insurance in the form of only OTM put index options in the wake of the huge economic losses caused by several accounting scandals; thus, since 2002 they are beginning to use individual equity options to protect themselves from extreme negative outcomes caused by accounting opacity. However, empirical accounting research generally

12. The real coverage ratio should be higher, since we apply many data restrictions.
13. Hutton et al. (2009) report increased firm-specific crash risk after 2002.

finds that accounting quality actually improved following 2002, perhaps due to SOX and other regulatory changes. Therefore, investors' need to protect themselves from extreme negative outcomes should have declined following SOX. The increased level of smirk since 2002 may indicate that the fear of crash and real crash risk are not always consistent.

In addition, Figure 1 shows that the time-series pattern of the implied volatility smirk is very similar to that of idiosyncratic volatility as documented by Chen et al. (2011, Figure 1). For example, there is a peak in both the implied volatility smirk and idiosyncratic volatility around 2002, and both time series rise sharply from 2007 onward due to the recent financial crisis. These similar patterns also make it necessary to control for idiosyncratic volatility in our regression analysis.

Next, we obtain each of the three proxies for financial reporting opacity, independently, and merge them with the master dataset, separately. As a result, we obtain three different research samples that correspond to each of the three opacity proxies. Recall that the *OPAQUE* measure is estimated using accounting data from the COMPUSTAT annual files. After merging earnings management data with the master dataset, we are able to obtain 14,360 firm-year observations for the *OPAQUE* sample.

The financial restatement data are from Hennes et al. (2008), who obtained the restatement announcement data from the 2002 and 2006 reports of the U.S. General Accounting Office. The dataset covers the period from January 1997 to September 2006. Hennes et al. classify all the restatements into two categories: intentional misstatements (*IRREGULARITY*) and unintentional errors (*ERROR*). Following the procedure described in their paper, we keep the first announcements for restatements related to the same misstatement event. We then merge the restatement dataset with the master dataset. We assign zeros to restatement indicator variables for firm-years with no restatements. Our second sample, that is, the restatement sample, consists of 12,096 firm-years over 1997–2006, about 4.7 percent of which actually restated earnings over the same period. The ICW data are from the Audit Analytics database for the fiscal years 2004–2007. After merging the ICW data with the master dataset, we obtain our third sample of 4,128 firm-year observations over the period 2004–2007.

4. Empirical results

Table 2 reports the results of various regressions of *IV-SKEW* on our different proxies for financial reporting opacity. Throughout the paper, reported *t*-values are on an adjusted basis, using robust standard errors corrected for two-dimensional (firm and year) clustering (Gow, Ormazabal, and Taylor 2010; Petersen 2009).

Model 1 of Table 2 presents the regression results with *OPAQUE* as the key independent variable. The coefficient of *OPAQUE* is significantly positive at less than the 5 percent level (0.005 with $t = 2.57$), which is consistent with our prediction that financial reporting opacity increases the expected crash risk of the underlying stock, which in turn increases the steepness of the implied volatility smirk. A one standard deviation change in *OPAQUE* is related to a 3.7 percent change in the level of the implied volatility smirk, which is economically significant.[14]

Regarding our control variables, first, firm size, the market-to-book ratio, cash flow volatility, earnings volatility, sales volatility, beta, stock return skewness, total stock return, and ATM option implied volatility have no significant impact on the implied volatility smirk. Second, *Leverage* has a positive impact on the smirk. This is consistent with the prediction of Toft and Prucyk's (1997) model and with empirical evidence reported by Toft and Prucyk (1997) and Van Buskirk (2011). Third, we find that stock volume

14. Untabulated descriptive statistics show that the standard deviation of *OPAQUE* is 0.269 and the mean *IV-SKEW* for the earnings management sample is 0.036.

TABLE 2
Financial reporting opacity and implied volatility smirk

	(1)	(2)	(3)	(4)
OPAQUE	0.005**			
	(2.57)			
RESTATEMENT		0.006***		
		(2.93)		
IRREGULARITY			0.013***	
			(3.52)	
ERROR			0.003	
			(1.04)	
ICW				0.004*
				(1.84)
ATM-IV	−0.004	−0.005	−0.005	0.013
	(−0.29)	(−0.34)	(−0.35)	(1.38)
Firm Size	−0.001	−0.001	−0.001	−0.003***
	(−0.93)	(−0.85)	(−0.87)	(−5.62)
Leverage	0.010***	0.009**	0.008**	0.010***
	(3.10)	(2.51)	(2.50)	(2.80)
Market-to-Book	0.000	−0.000	−0.000	0.001*
	(0.11)	(−0.09)	(−0.09)	(1.90)
Cash Flow Volatility	0.010	0.013**	0.014**	0.001
	(1.54)	(1.97)	(2.00)	(0.08)
Earnings Volatility	0.008	0.012	0.012	−0.001
	(1.00)	(1.63)	(1.60)	(−0.08)
Sales Volatility	0.002	0.003	0.003	0.009**
	(1.01)	(1.18)	(1.13)	(2.45)
Stock Turnover	0.027***	0.028***	0.028***	0.001
	(4.73)	(4.21)	(4.23)	(0.27)
Beta	−0.000	−0.000	−0.000	−0.000
	(−0.42)	(−0.65)	(−0.64)	(−1.27)
Idiosyncratic Volatility	−0.178***	−0.189***	−0.190***	−0.055
	(−4.15)	(−3.84)	(−3.90)	(−0.50)
Total Volatility	0.163***	0.175***	0.176***	0.073
	(4.03)	(3.71)	(3.78)	(0.68)
Negative Skewness	0.000	0.001	0.001	−0.001
	(0.55)	(0.93)	(0.88)	(−1.34)
Stock Return	−0.000	−0.000	−0.000	−0.001**
	(−0.48)	(−0.56)	(−0.49)	(−2.50)
Organizational Change				−0.001**
				(−2.52)
Complexity				−0.001
				(−1.21)
Financial Challenge				0.007***
				(3.27)
Observations	14,360	12,096	12,096	4,128
Adjusted R^2	0.027	0.026	0.027	0.100

(The table is continued on the next page.)

TABLE 2 (continued)

Notes:

This table reports the results of an ordinary least squares (OLS) regression of the implied volatility skew (*IV-SKEW*) on the financial reporting opacity measures. In column (1), reporting opacity is proxied by the *OPAQUE* measure of Hutton et al. (2009) and the sample period is from 1996 to 2007. In columns (2) and (3), reporting opacity is proxied by accounting restatements and the sample period is from 1997 to 2006. In column (4), reporting opacity is proxied by the existence of ICW, as reported under SOX Section 404, and the sample period is from 2004 to 2007. See Appendix 1 for definitions of all the variables. Here *, **, and *** indicate, respectively, 10 percent, 5 percent, and 1 percent significance (two-tailed). The *t*-values in parentheses are based on standard errors that are clustered by firm and year.

turnover has a positive impact on the volatility smirk. This finding is consistent with the notion that investors' belief heterogeneity causes the expected crash risk to increase (Chen et al. 2001; Hong and Stein 2003). Finally, we find a significantly negative coefficient for idiosyncratic volatility and a significantly positive coefficient for total return volatility. The opposite signs are caused by the high correlation between the two volatility variables. If we include them one by one, both variables load positive (although less significant) signs.

Model 2 of Table 2 displays the regressions results using *RESTATEMENT* as the main independent variable of interest. As can be seen, the coefficient of *RESTATEMENT* is significant at the 1 percent level. We interpret the results as evidence that firms with opaque financial reporting (as evidenced by accounting misstatements) have significantly higher expected crash risk and a steeper implied volatility smirk. Our results are robust to the inclusion of various sets of control variables.

In Model 3, we replace *RESTATEMENT* by *IRREGULARITY* and *ERROR* to see if the smirk-increasing effect of intentional misstatement is more severe than that of unintentional errors. The coefficient of *IRREGULARITY* is large and highly significant (0.013, t = 3.52), while the coefficient of *ERROR* is much smaller and not significant (0.003, t = 1.04). The difference between the two coefficients is also very significant (F = 9.11). This is consistent with our expectation that focusing only on intentional misstatements (captured by *IRREGULARITY*) significantly increases the power of the test, as noted by Hennes et al. (2008). For economic significance, the implied volatility smirk is steeper by a magnitude of 0.013 for firms that have intentional misstatements, compared with those that do not. Given that the sample mean implied volatility smirk is 0.038, this difference is very large and economically significant (34.2 percent of the sample mean).

Model 4 of Table 2 reports the regression results using *ICW* as the independent variable of interest. Prior research suggests that it is important to control for determinants of ICW when assessing its economic consequences (Ashbaugh-Skaife, Collins, and Kinney 2007; Ashbaugh-Skaife et al. 2009; Doyle et al. 2007b; Feng et al. 2009). To control for known determinants of ICW, similar to Feng et al. (2009), we construct three composite determinants for ICW and include them as additional controls in our regressions.[15] These additional control variables are *Organizational Change, Complexity,* and *Financial Challenge*. The detailed definitions of these variables are in Appendix 2.

Model 4 shows that the coefficient of *ICW* is significantly positive. This finding is robust to the inclusion of other known determinants of implied volatility smirks or of ICW. The above results are consistent with our prediction that firms with ICW have a steeper implied volatility smirk than firms without such problems. The magnitude of

15. Another determinant of ICW according to Feng et al. (2009) is operating volatility. However, our main regression model already has operating volatility variables.

IV-SKEW for firms with ICW is 0.004 (t = 1.84) higher than that of firms without ICW, after controlling for all other variables. This difference accounts for 10.5 percent of the sample mean of *IV-SKEW,* which is economically significant.[16]

Overall, using three different proxies for financial reporting opacity (abnormal accruals, financial restatement, and ICW), we provide robust evidence that the implied volatility smirk increases significantly with financial reporting opacity. Our results strongly support the hypothesis that financial reporting opacity increases investors' expected (perceived) crash risk as captured by the steepness of the implied volatility smirk.

5. Additional tests and robustness checks

Firm fixed effect regressions

An important challenge for our research is that our financial reporting opacity measure (*OPAQUE*) may also capture the inherent uncertainty of firm business or other unknown firm characteristics. To the extent that these firm characteristics are correlated with the implied volatility smirk, we can observe a spurious relation between opacity and smirk. In our main regression analysis, we have controlled for a battery of proxies for uncertainty or risk, such as cash flow volatility, earnings volatility, sales volatility, and return volatility. In this section, we further alleviate the concern of omitted correlated variables by exploring the panel nature of our dataset using a firm fixed effect regression technique. Table 3 presents the results. We can see that *OPAQUE* is significantly and positively associated with the implied volatility smirk, even with the firm fixed effects specification.

Implied volatility level versus smirk

Our study focuses on the steepness of volatility smirk rather than implied volatility level for several reasons.[17] First, one of the main purposes of our study is to extend the strand of research on the relation between financial reporting quality and realized crash risk. We do this by examining whether opacity is also related to ex ante (or perceived) crash risk. Thus it is natural to focus on the volatility smirk because it captures investors' perception of negative jump risk. Second, recent empirical studies document that ex ante negative jump risk carries a positive risk premium, while ex ante positive jump risk does not (e.g., Conrad et al. 2013).[18] This finding makes it more interesting to examine the impact of accounting quality on ex ante negative jumps than positive jumps. Third, recent asset pricing literature finds that the prices of ex ante jump risk (perceived skewness) and ex post jump risk (historical skewness) are dramatically different (e.g., Bates 2000; Santa-Clara and Yan 2010). That is, ex ante jump risk has a much larger risk premium than historical skewness does. On the other hand, the pricing differences between ex ante volatility risk (i.e., implied volatility) and historical volatilities are not as dramatic. Therefore, it is more interesting to extend realized crash risk studies (e.g., Hutton et al. 2009) to the ex ante crash risk regime rather than extend realized volatility studies (e.g., Chen et al. 2010) to ex ante volatility (i.e., implied volatility level).

Nonetheless, for completeness and the reader's full information, in this section we examine the relation between opacity and the implied volatility level. Table 4 presents the results. Consistent with the argument that investors are more uncertain about the future of an opaque firm, we find that both *OPAQUE* and *ICW* are positively and significantly related to the level of implied volatility. However, we find no relation between accounting restatement and implied volatility level.

16. The mean *IV-SKEW* for the ICW sample is 0.038.
17. We control for implied volatility level in our main regressions of smirk.
18. Some studies even find a negative premium for positive jump risk.

TABLE 3
Financial reporting opacity and the implied volatility smirk: Firm fixed effect regression

OPAQUE	0.005**
	(3.53)
ATM-IV	−0.001
	(−0.25)
Firm Size	−0.002**
	(−2.76)
Leverage	0.018**
	(3.97)
Market-to-Book	−0.000*
	(−1.99)
Cash Flow Volatility	−0.003
	(−0.27)
Earnings Volatility	0.021*
	(2.49)
Sales Volatility	0.004
	(1.41)
Stock Turnover	0.029**
	(7.38)
Beta	−0.000
	(−1.31)
Idiosyncratic Volatility	−0.166**
	(−3.66)
Total Volatility	0.165**
	(3.75)
Negative Skewness	−0.000
	(−0.28)
Stock Return	−0.000
	(−0.05)
Observations	14,360
Number of unique firms	2,833
Within-firm R^2	0.020

Notes:

This table reports the results of a firm fixed effect regression of the implied volatility skew (*IV-SKEW*) on the financial reporting opacity measured by the *OPAQUE* measure of Hutton et al. (2009). The sample period is from 1996 to 2007. See Appendix 1 for the definitions of all the variables. Here * and ** indicate, respectively, 5 percent, and 1 percent significance (two-tailed). The t-values in parentheses are based on standard errors that are clustered by firm.

Using options with different maturities

Prior derivatives research normally uses short-term options to estimate implied volatility skew. For example, Xing et al. (2010) use options with a time to maturity of less than 60 days. The preference for the use of short-term options stems not only from their higher liquidity but also from the fact that prior research normally needs to measure smirk by daily or weekly intervals, where highly liquid options are more likely to be available on a daily or weekly basis. In this study, we need to measure the smirk on annual internals and therefore use all options to extract information to minimize potential measurement errors and/or maximize the information content of our measures of the implied volatility smirk.

To make sure that our results are not driven by a specific series of options, we calculate *IV-SKEW* using options with different maturities and check the robustness of our

TABLE 4
Financial reporting opacity and implied volatility levels

	(1)	(2)	(3)	(4)
OPAQUE	0.041***			
	(3.01)			
RESTATEMENT		−0.013		
		(−0.95)		
IRREGULARITY			0.005	
			(0.24)	
ERROR			−0.021	
			(−1.31)	
ICW				0.010**
				(2.09)
Firm Size	−0.054***	−0.056***	−0.056***	−0.039***
	(−18.60)	(−17.87)	(−17.97)	(−27.98)
Leverage	−0.058***	−0.060***	−0.061***	−0.077***
	(−3.63)	(−3.01)	(−3.07)	(−7.10)
Market-to-Book	0.007***	0.007***	0.007***	0.004***
	(4.74)	(4.60)	(4.61)	(5.76)
Cash Flow Volatility	0.267***	0.244***	0.245***	0.170***
	(5.61)	(4.77)	(4.79)	(3.75)
Earnings Volatility	0.211***	0.258***	0.257***	0.132***
	(6.25)	(6.67)	(6.67)	(3.91)
Sales Volatility	0.009	0.015*	0.015	−0.010
	(0.91)	(1.67)	(1.63)	(−1.08)
Stock Turnover	0.266***	0.282***	0.281***	0.207***
	(5.71)	(5.01)	(5.01)	(18.56)
Beta	−0.008***	−0.008***	−0.008***	−0.001**
	(−4.66)	(−4.49)	(−4.48)	(−2.11)
Idiosyncratic Volatility	−0.679**	−1.059***	−1.061***	0.133
	(−1.98)	(−4.49)	(−4.50)	(0.50)
Total Volatility	1.070***	1.428***	1.429***	0.198
	(3.13)	(5.45)	(5.46)	(0.76)
Negative Skewness	0.003	0.002	0.002	0.007***
	(0.74)	(0.52)	(0.50)	(4.64)
Stock Return	−0.000***	−0.000***	−0.000***	−0.002**
	(−3.26)	(−2.77)	(−2.76)	(−2.28)
Organizational Change				0.002
				(1.32)
Complexity				−0.009***
				(−2.94)
Financial Challenge				0.093***
				(14.70)
Observations	14,360	12,096	12,096	4,128
Adjusted R^2	0.600	0.592	0.592	0.710

(The table is continued on the next page.)

TABLE 4 (continued)

Notes:

This table reports the results of an ordinary least squares regression of the implied volatility level (*ATM-IV*) on the financial reporting opacity measures. In column (1), reporting opacity is proxied by the *OPAQUE* measure of Hutton et al. (2009) and the sample period is from 1996 to 2007. In columns (2) and (3), reporting opacity is proxied by accounting restatements and the sample period is from 1997 to 2006. In column (4), reporting opacity is proxied by the existence of ICW, as reported under SOX Section 404, and the sample period is from 2004 to 2007. See Appendix 1 for the definitions of all the variables. Here *, **, *** indicate, respectively, 10 percent, 5 percent, and 1 percent significance (two-tailed). The *t*-values in parentheses are based on standard errors that are clustered by firm and year.

main results. Specifically, we use options of the following four duration series to estimate *IV-SKEW*: less than 60 days, 61–120 days, 121–180 days, and 181–360 days. Using the four additional measures of implied volatility skew, we rerun all the previous regressions. Overall, untabulated results show that the impact of financial reporting opacity on the steepness of the implied volatility smirk is robust to different measures of smirk.

Measuring the volatility smirk after earnings announcements

Van Buskirk (2011) measures a firm's general implied volatility skew using equity options after earnings announcements. This method ensures that the current period accounting reports are available to investors. To account for this concern, in our main regressions we measure *IV-SKEW* using options during the 12-month period ending three months after a firm's fiscal year-end. In this section, we offer additional robustness tests to address this issue. Specifically, we measure a firm-year's *IV-SKEW* using options data during the one-month period starting three days after the current year's annual earnings announcement date. We rerun all the regressions and find that all the previous results stand (untabulated).

Alternative models of discretionary reporting

In our main results, we use the modified Jones model to estimate abnormal accruals and calculate the *OPAQUE* measure in an attempt to facilitate a comparison between our results and those of Hutton et al. (2009). Though not reported for brevity, we find that that all the results reported in the paper are robust to the use of alternative accrual models, such as the performance match method of Kothari, Leone, and Wasley (2005) and Ball and Shivakumar's (2006) accrual model that accounts for conservative accounting.

Comparison with recent studies in the accounting literature

In this section, we discuss the differences between our study and several recent accounting studies related to stock options. Motivated by the empirical finding that option-based measures (e.g., volatility skew) predict future equity returns, Jin, Livnat, and Zhang (2012) examine whether this predictability derives from option traders' information advantage. The authors find that option measures can predict short-term returns around important corporate events, suggesting that option traders have superior information advantage relative to equity traders. Similarly, Van Buskirk (2011) finds that implied volatility skew can only predict future crashes around earning announcement windows. On the other hand, Bradshaw et al. (2010) find that implied volatility skew predicts crash risk over a wider window of one year. Both Van Buskirk (2011) and Bradshaw et al. (2010) also examine whether financial reporting opacity predicts future crashes after controlling for implied volatility skew and find mixed results.[19] A common theme of all three studies is the interaction between option and equity markets.

Both Van Buskirk (2011) and Bradshaw et al. (2010) examine opacity and crash risk, which makes their work more related to our study. However, a key difference is that their work focuses on the relation between opacity/smirk and realized crashes, whereas our study focuses on the relation between opacity and ex ante (or perceived) crash risk. In our research, volatility smirk is largely a proxy for perceived crash risk. We have explained why ex ante crash risk is interesting and different from realized crashes in previous sections. Moreover, the employment of multiple financial reporting opacity measures, including ICW and financial restatements, further distinguishes our study from those of Van Buskirk (2011) and Bradshaw et al. (2010), both of which use only abnormal accruals to capture financial reporting quality. However, the implications from empirical results based on abnormal accruals are limited by the potential inaccuracy inherent in the accrual models (Dechow, Ge, and Schrand 2010). On the other hand, prior research argues that SOX Section 404 auditor-attested evaluations of ICW and financial restatements are potentially more objective and less ambiguous measures of financial reporting opacity (e.g., Ashbaugh-Skaife et al. 2009).

6. Conclusions

Prior derivatives research has documented an intriguing pattern in the prices of equity and index options; that is, the implied volatility of OTM put options being higher than that of ATM call options, popularly known as the implied volatility smirk. This volatility smirk is largely interpreted as reflecting market participants' ex ante expectations of future crash risk and/or the expensiveness of OTM puts relative to ATM calls. Consistent with this interpretation, recent asset pricing literature uses the steepness of the implied volatility smirk as a proxy for ex ante crash risk and finds that investors demand a large premium for holding stocks with *perceived* negative jump risk. This paper investigates whether financial reporting opacity or the lack of financial reporting quality increases investors' perception of crash risk. Using three different internal and external proxies for financial reporting opacity, we find strong and robust evidence that the steepness of volatility smirk increases with financial reporting opacity, even after controlling for all other known determinants of smirk steepness and unknown firm fixed effects.

Our study extends the literature on the relation between financial reporting quality and crash risk. Prior research in this line has largely focused on realized crash risk (e.g., Hutton et al. 2009; Kim et al. 2011b; Kim and Zhang 2012). Our investigation of perceived crash risk contributes significantly to this literature because both realized crashes and perceived crash risk matter (and matter differently in mechanisms and significance) in the capital market. Nonetheless, an important limitation of our study is that we cannot document a strong causal link from financial reporting opacity to expected crash risk. For example, our results may simply be driven by some unobserved and time-varying factors that are correlated with both financial reporting opacity and expected crash risk. Thus, we view our research as an initial attempt to study carefully the impact of financial reporting system on investors' perception of tail risks. We hope future research, perhaps using some (natural) experiments, can further analyze the issue of causality.

19. Both studies use the opacity measure of Hutton et al. (2009). Bradshaw et al. (2010) find that opacity predicts future crash risk, while Van Buskirk (2011) finds no such relation.

Appendix 1

Variable definitions

IV-SKEW is the average daily implied volatility skew over the fiscal year, where the daily implied volatility skew is the difference between the implied volatility of OTM put options and that of ATM call options. The OTM puts are defined as put option con tracts with a delta between −0.375 and −0.125 and the ATM calls are defined as call option contracts with a delta between 0.375 and 0.625. The daily implied volatilities of OTM puts (ATM calls) are the open interest weighted average of all OTM puts (ATM calls) traded during the day. Source: OptionMetrics.

OPAQUE is the measure of reporting opacity of Hutton et al. (2009) based on earnings management, calculated as the prior three years' moving sum of the absolute value of discretionary accruals. Discretionary accruals are measured using the modified Jones model of Dechow et al. (1995). Source: COMPUSTAT.

RESTATEMENT is an indicator variable that takes the value of one if the firm restates its earnings during the fiscal year (before the end of the current fiscal year) and zero otherwise. Available from Professor Andy Leone's home page at http://sbaleone.bus.miami.edu.

IRREGULARITY is an indicator variable that takes the value of one if the firm restates its earnings during the fiscal year and the restatement is classified as an irregularity by Hennes et al. (2008) and zero otherwise.

ERROR is an indicator variable that takes the value of one if the firm restates its earnings during the fiscal year and the restatement is classified as an error by Hennes et al. (2008) and zero otherwise.

ICW is an indicator variable that takes the value of one if the firm reports material weaknesses in internal control over financial reporting under the requirement of Section 404 of SOX and zero otherwise. Source: Audit Analytics.

ATM-IV is the average daily implied volatility of ATM options over the fiscal year. An ATM call option is defined as a call option with a delta between 0.375 and 0.625. The daily implied volatility is calculated as an open interest weighted average of the implied volatility for all ATM call options traded during the day. Source: OptionMetrics.

Market Value is the market value of equity. Source: COMPUSTAT.

Firm Size is the natural log of the market value of equity at the end of the year.

Leverage is the book value of long-term debts divided by total assets at the end of the year. Source: COMPUSTAT.

Market-to-Book is the ratio of the market value of equity to the book value of equity at the end of the year. Source: COMPUSTAT.

Cash Flow Volatility is the standard deviation of operating cash flows (scaled by lagged total assets) over the past five years. Source: COMPUSTAT.

Earnings Volatility is the standard deviation of earnings before extraordinary items (scaled by lagged total assets) over the past five years. Source: COMPUSTAT.

Sales Volatility is the standard deviation of sales revenue (scaled by lagged total assets) over the past five years. Source: COMPUSTAT.

Stock Turnover is the average monthly share turnover over the fiscal year. Source: CRSP.

Beta is the market beta for the firm, which is estimated using daily stock and market returns over the fiscal year period. Source: CRSP.

Idiosyncratic Volatility is the standard deviation of the weekly firm-specific stock return over the fiscal year. The firm-specific weekly return is the residual from the following expanded market model regression:

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

Total Volatility is the standard deviation of the weekly stock return over the fiscal year. Source: CRSP.

Negative Skewness is the negative skewness of weekly stock returns over the fiscal year. Source: CRSP.

Stock Return is the accumulated raw weekly stock return over the fiscal year. Source: CRSP.

Organizational Change is a factor comprised of asset growth, sales growth, leverage, and merger and acquisition activity (see Appendix 2).

Complexity is a factor comprised of the number of segments, the existence of foreign transactions, and restructuring (see Appendix 2).

Financial Challenge is a factor comprised of return on assets (ROA), losses, research and development, and special items (see Appendix 2).

Appendix 2

Determinants of ICW

The determinants of ICW variables are constructed following Appendix 1 (Feng et al. 2009). Specifically, we have the following:

Organizational Change = 0.751 × *Asset Growth* + 0.514 × *Sales Growth* + 0.508 × *Debt/Asset* + 0.317 × *M&A*,

Complexity = 0.614 × *Segments* + 0.579 × *Foreign Transactions* + 0.364 × *Restructuring*,

Financial Challenges = (−0.834) × *ROA* + 0.739 × *Losses* + 0.601 × *R&D* + 0.401 × *SI*,

where *Cash Flow Volatility* is the standard deviation of quarterly total asset-scaled operating cash flows over the prior seven years, *Earnings Volatility* is the standard deviation of quarterly return on assets over the prior seven years, *Sales Volatility* is the standard deviation of quarterly total asset-scaled sales over the prior seven years, *Asset Growth* = (total assets in year t – total assets in year $t-1$)/total assets in year $t-1$ (COMPUSTAT AT), *Sales Growth* = (sales in year t – sales in year $t-1$)/sales in year $t-1$ (COMPUSTAT SALE), *Debt/Asset* is total liabilities (COMPUSTAT LT)/lagged total assets, *M&A* is an indicator variable that takes the value of one if the firm undertakes a large merger or acquisition in year t (COMPUSTAT AFTNT1 = AA) and zero otherwise, *Segments* is the natural log of the total number of geographic and operating segments, *Foreign Transactions* is an indicator variable that takes the value of one if the firm has foreign transactions (COMPUSTAT FCA) in year t and zero otherwise, *Restructuring* is an indicator variable that takes the value of one if the firm recognized restructuring charges (COMPUSTAT RCP) in year t and zero otherwise, *ROA* is earnings before extraordinary items (COMPUSTAT IB) divided by lagged total assets, *Losses* is an indicator variable that takes the value of one if earnings before extraordinary items in years t and $t-1$ sum to less than zero and zero otherwise, *R&D* is research and development expenses (COMPUSTAT

XRD) divided by lagged total assets, and *SI* is the absolute value of special items (COMPUSTAT SPI) divided by lagged total assets. We winsorize the top and bottom 1 percent of continuous variables, following Feng et al. (2009)

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SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article:
Appendix S1. Implied Volatility Smirk and Future Crash Risk.