Opacity, Crash Risk, and the Option Smirk Curve

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Abstract

We investigate three facets of cross-sectional variation in the risk of stock price crashes: actual crash incidence, and two predictors of that risk, accounting opacity and the option smirk curve. We show that all three of these variables are related. Option smirks and accounting opacity each independently predict cross-sectional variation in crash risk and crash magnitude. The slope of the smirk curve and opacity are themselves correlated at extremely high levels of statistical significance, indicating that the market is aware of the link between opacity and crash risk. Nevertheless, even controlling for the option smirk, several measures of accounting opacity continue to be reliably associated with crash risk, suggesting that the options market does not fully utilize the predictive value of accounting opacity. Moreover, some of our results are consistent with behavioral models in which strong recent performance is extrapolated too far into the future, only to result in a major reversal when those expectations are disappointed.

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1. Introduction

Jump risk in security prices has attracted increasing attention in recent years, particularly in the period since the 2008 financial crisis. While that crisis precipitated dramatic market-wide price declines, firm-specific price crashes also are of obvious concern to investors. Part of that interest is practical. Understanding the firm-specific characteristics that can predict extreme outcomes would clearly be useful in portfolio and risk-management applications that focus on tail events, for example, value at risk (Longin, 2000; Berkowitz and O'Brien 2002). Similarly, option valuation depends in part on jump risk (Merton, 1976; Cox and Ross, 1976). Again, understanding the factors that drive cross-sectional variation in such tail risk would be of obvious importance to market participants and allow for more precise option pricing.

Jump risk may also reflect and shed light on deeper issues concerning the flow of information in capital markets. While most benchmark models typically presume continuous prices (and correspondingly, continuous release of information), it is well known that stock prices are more prone to big downward moves than big upward ones (French, Schwert, Stambaugh, 1987; Campbell and Hentschel, 1992; Bekaert and Wu, 2000). Thus, it is useful to distinguish crashes from positive jumps. Several recent papers suggest that firm-specific crash risk may be an outcome of intentional information management (see Kirschenheiter and Melumad, 2002; Jin and Myers, 2006). In this view, managers are able to stockpile negative information, hiding it from investors' view until a tipping point is crossed at which the accumulated information is released all at once, resulting in a stock price crash. Indeed, Hutton, Marcus, and Tehranian (2009) demonstrate that firms that more aggressively manage earnings are more prone to stock price crashes, but not to sudden large positive stock price jumps. This asymmetry suggests that crash risk can be a symptom of earnings management.

The Hutton, Marcus, Tehranian (HMT) results raise another question. If firm characteristics such as the proclivity to manage earnings can predict stock price crashes, one immediately wonders whether the market recognizes that predictive value and impounds it into option prices. For example, is the slope of the option smirk curve, widely recognized as an indicator of crash risk (Bates, 1991; Dumas, Fleming and Whaley, 1998; Bates, 2000; Pan, 2002), steeper for firms with higher levels of opacity? We show that measures of earnings management including, but not limited to, the opacity measure introduced in HMT do predict a steeper smirk, consistent with the market impounding information about the association between earnings management and crash risk.

Having established that the market does in fact seem to recognize the impact of opacity on crash risk, we ask next whether the option smirk curve *fully* reflects the information potentially available to the market. Specifically, can information from outside the options market be used to improve on crash expectations already reflected in option prices? If so, that would suggest useful strategies for both risk managers and option traders who have an obvious interest in sharpening their assessments of crash risk. Our results indeed suggest that crash predictions from the option smirk curve can be improved upon using accounting data.

Our results also bear to some extent on widespread interest in accruals anomalies (Sloan, 1996, Chan et al. 2006, Mashruwala, Rajgopal and Shevlin 2006, Pincus, Rajgopal and Venkatachalam 2007). Collectively, this evidence suggests that the market does not fully recognize accruals management as part of a larger earnings manipulation strategy, and fails to recognize that abnormal accruals are prone reversals. Therefore, to the extent that accruals-based measures, such as that of HMT, can be used to predict crashes beyond the predictions already reflected in the smirk curve, further doubt is cast on the ability of the market to fully interpret the accruals data available from standard financial statements.

Some of our results are also consistent with related forms of extrapolation error. We find that strong recent performance (for example, consistent sales and earnings growth) and signals of optimism concerning future growth (for example, high market-to-book ratios) are strongly associated with lower forecasts of crash risk reflected in option prices, but *higher* incidence of actual crashes. This pattern suggests extrapolation error along the lines explored in Lakonishok, Shliefer, and Vishny (1994).

Our empirical work therefore focuses on predictions of crash risk. We construct measures of crash risk using the history of actual stock price crashes and examine the predictive ability of both option smirks and other, accounting-based, variables to explain that risk. Surprisingly, for all the interest in the relation between option smirks and crash risk, there has been relatively little empirical analysis of the ability of cross-sectional variation in the smirk curve (or, for that matter, other variables) to predict cross-sectional variation in crash risk. The major exceptions are studies that examine the impact of systematic risk factors, possibly including jump risk, on cross-sectional variation in the level and/or slope of the option smirk (see, for example, Dennis and Mayhew, 2002; Bakshi, Kapadia and Madan, 2003; Duan and Wei, 2008). However, these papers tend to show how given systematic factors may drive variation in the smirk curve; they do not consider actual crash incidence. In contrast, our focus is on the empirical incidence of crash risk and the comparative ability of option prices and other variables to predict that risk. Using two measures of firm-specific stock price crashes, we confirm that (1) steeper smirk curves are highly significant in predicting both higher crash risk and crashes of greater magnitude; (2) financial statement opacity is also significant in predicting both crash risk and crash magnitude; and (3) earnings management proxies and the slope of the smirk curve are strongly correlated. These results imply that the options market recognizes and prices at least some of the information captured in our accounting-based measure of crash propensities.

Given these results, we next combine option prices (as reflected in smirk curves) with our measure of accounting opacity as well as some sentiment variables to predict crashes. Using the standard argument, if the market efficiently prices options, right-hand side variables other than the smirk should not add predictive power. As it turns out, however, these variables do add power to predict stock price crashes. Therefore, one ought to be able to devise a trading strategy based on them, for example, buying out-of-the-money puts when crash risk is underestimated by the market and selling them when it is overestimated.

In the next section, we review the literature on earnings management, crash risk, and smirk curves, and develop our empirical predictions. Section 3 provides an overview of our data, and Section 4 presents the empirical results. Section 5 presents robustness checks; Section 6 summarizes and concludes.

2. Related Literature & Hypothesis Development

2.1 Smirks and Crash Risk

In the Black-Scholes framework, stock prices are continuous, and volatility is constant. In those circumstances, the implied volatility of all options on a given asset with identical expiration should be equal regardless of strike price. Departures from this implication, reflected in the slope of the volatility skew, or equivalently, the option smirk curve, must reflect departures from the Black-Scholes assumptions. Smirk curves have characterized the implied volatility of individual stock options as well as index options at least since the crash of October 1987 and are widely held to reflect risk of future crashes (Bates, 1991; Dumas, Fleming and Whaley, 1998; Bates, 2000; Pan, 2002). Bakshi, Cao, and Chen (1997) find that allowing for both jumps and stochastic volatility improves the fit of option pricing models. More recently, Bollen and Whaley (2004) ask whether buying pressure on one side of the options market can explain the smirk curve. Bates (2000) fits a jump-diffusion model with stochastic volatility to the prices of index options to estimate the parameters that describe the likelihood of jump or crash risk for the aggregate market. Pan (2002) uses a similar model to estimate the risk premium demanded as compensation for crash risk. In both of these papers, jump and/or crash risks emerge as significant components of stock price dynamics as well as the smirk profile.

2.2 Opacity and Crash Risk

A stock price crash almost by definition implies a sudden and dramatic downward revision of market expectations concerning a firm's prospects. In some cases, the original perceptions may have been fostered by the firm's management. For example, several recent models predict that managers may systematically withhold bad news until a threshold is crossed at which point it is no longer either feasible or optimal to hide that negative information. At this point, the information is released in one large batch, precipitating a stock price crash. For example, in Kirschenheiter and Melumad (2002), higher reported earnings increase the inferred level of permanent earnings and, therefore, firm value. This effect is greater when reported performance is perceived to be more precise, thus encouraging managers to smooth earnings. But when news is particularly bad, managers may under-reports earnings to the greatest extent possible, partially to reduce the inferred precision of the bad news and partially to enable shifting of discretionary income to future periods. This gives rise to occasional big baths, along with stock price crashes.

In Jin and Myers (2006), lack of full transparency concerning firm performance enables managers to capture a portion of cash flow, in the process absorbing (and therefore making nonvisible) part of firm-specific performance. Managers are willing to personally absorb temporary losses to protect their jobs. However, following a run of bad outcomes, they may be unwilling or unable to absorb any more losses. If they abandon their positions, all of the previously unobserved negative firm-specific shocks become public at once, resulting in a crash. Jin and Myers measure opacity using characteristics of the broad capital market in which the firm is situated and find that less transparent markets exhibit more frequent crashes. HMT (2009) test the Jin and Myers model at a finer level by developing a firm-specific measure of opacity and show that opacity does in fact predict higher crash risk. In a related but more extreme scenario, Schrand and Zechman (2010) hypothesize that managerial overconfidence generates an accumulation of earnings management to hide small amounts of bad news, which eventually unwind with the revelation of large-scale financial reporting fraud. Finally, Kothari, Shu, and Wysocki (2009) provide evidence based on the voluntary disclosures of earnings forecasts that managers withhold bad news when possible.

2.3 Optimism and crash risk

While managers may at times attempt to manipulate market expectations of a firm's prospects, several papers also present evidence that market analysts themselves are prone to unrealistic projections of future performance. For example, Lakonishok, Shliefer, and Vishny (1994) and a wide related literature argue that stock analysts extrapolate recent performance too far into the future. Similarly, Hershleifer et al. (2004) conclude that excessive accruals, proxied by balance sheet accruals accumulations, lead to over-optimism by investors and overvaluation of such firms. Ultimately, when the market recognizes errors, prices reverse. The reversal can be dramatic, for example, when a disappointing earnings announcement undoes previous perceptions of abundant growth opportunities (Skinner and Sloan, 2002). In fact, LaPorta, Lakonishok, Shliefer, and Vishny (1997) find that growth stocks tend to underperform value stocks surrounding earnings announcements. Thus, we will consider evidence that strong recent performance and market optimism are associated with lower *ex ante* forecasts of crash risk (as indicated by the slope of the smirk curve) but higher *ex post* crash incidence and crash magnitudes.

3. Sample Development and Research Design

Our primary focus is on the relationship between opacity, firm-specific crash risk, and market recognition of such risk in option prices. In this section, we describe the construction of our sample and how we measure each of these concepts.

3.1. Sample

We combine firms' weekly stock return data from the Center for Research in Security Prices (CRSP) with annual financial data from Compustat and option pricing data from the OptionMetrics Ivy DB database. Weekly stock returns are assigned to each firm's fiscal year so as to match the time period of its reported financial data. Our sample period begins with fiscal year 1997, the earliest data available on the OptionMetrics database. Our sample period ends with the last year for which we have complete CRSP and Compustat data, fiscal year 2008 (which for some firms includes data from calendar year 2009). We begin with all firm-years on CRSP and Compustat between 1997 and 2008 (85,225 firm-years). We exclude financial services firms and utilities (12,611 firm-years); low-priced stocks (average price for the year less than $2.50; 8,527 firm-years); firm fiscal years with fewer than 26 weeks of stock-return data (2,663 firm-years); and firm-years with insufficient financial data to calculate three lags of discretionary accruals (11,234 firm-years) and control variables (4,712 firm-years). We are left with a preliminary sample of 45,478 firm-years. The preliminary sample includes 47 of the 49 Fama-French industry definitions [excludes utilities (#31) and financial services (#48)]. We merge this sample with firms available on the OptionMetrics data base, resulting in 17,543 firm-years representing 3,459 firms falling into 43 of the Fama-French industries. Table 1 provides details on the sample.

[Table 1 near here]

3.2 Accrual manipulation and opacity of financial reports

Following HMT (2009), we measure opacity as the tendency of management to use discretionary accruals to manage reported earnings. Reported earnings are necessarily *estimates* of firm performance, the accuracy of which depends on the quality of the accruals used to estimate the expected future net cash flows associated with past economic transactions. For example, accounts receivable are accruals that represent forecasts of future cash flows due to credit sales. While, over the life of a firm, accruals must sum to zero and earnings must equal net cash flow, during particular accounting periods earnings can deviate substantially from net cash flow, with the difference being total accruals. Disparities between earnings and cash flows are normal, and result from timing differences such as the recognition of credit sales before the ultimate cash collection. Unbiased accruals are generally followed by cash flow realizations that remove or reverse the initial accrual (e.g., account receivables are decreased when cash is received from customers). However, given the unavoidable subjectivity in accounting for transactions and other events, disparities between earnings and net cash flow can also occur due to earnings manipulation, which manifest through intentionally misleading discretionary accruals. In the presence of earnings manipulation, discretionary accruals are eventually reversed by oppositely signed accruals (with an associated impact on earnings) rather than ultimate cash flow realizations.

Following much of the accounting literature, to distinguish between normal and discretionary accruals, we employ the modified Jones model (Dechow, Sloan, and Sweeney, 1995). Specifically, we estimate the following cross-sectional regression equation using the firms in each Fama-French industry for each fiscal year between 1994 and 2008:

$$\frac{TA_{jt}}{Assets_{jt-1}} = \alpha_0 \frac{1}{Assets_{jt-1}} + \beta_1 \frac{\Delta Sales_{jt}}{Assets_{jt-1}} + \beta_2 \frac{PPE_{jt}}{Assets_{jt-1}} + \varepsilon_{jt}\,, \tag{1}$$

where TA_{jt} denotes total accruals for firm j during year t, $Assets_{jt}$ denotes total assets for firm j at the end of year t, $\Delta Sales_{jt}$ denotes change in sales for firm j in year t, and PPE_{jt} denotes property, plant, and equipment for firm j at the end of year t.[1]

Discretionary annual accruals as a fraction of lagged assets for firm j during year t ($DiscAcc_{jt}$) are then calculated using the parameter estimates from Eq. (1):

$$DiscAcc_{jt} = \frac{TA_{jt}}{Assets_{jt-1}} - \left(\hat{\alpha}_0 \frac{1}{Assets_{jt-1}} + \hat{\beta}_1 \frac{\Delta Sales_{jt} - \Delta Receivables_{jt}}{Assets_{jt-1}} + \hat{\beta}_2 \frac{PPE_{jt}}{Assets_{jt-1}}\right) \tag{2}$$

where hats over the coefficients denote estimated values from regression Eq. (1) (see Dechow, Sloan, and Sweeney, 1995 for additional discussion).

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[1] Total annual accruals equal income before extraordinary items and discontinued operations minus cash flow from operating activities.

Following HMT (2009), we define opacity as the three-year moving sum of the absolute value of annual discretionary accruals:

$$OPAQUE = |DiscAcc_{t\text{-}1}| + |DiscAcc_{t\text{-}2}| + |DiscAcc_{t\text{-}3}| \tag{3}$$

Firms with consistently large absolute values of discretionary accruals are more likely to be managing reported earnings. For example, a classic pattern of earnings manipulation entails large positive abnormal accruals in one year, followed by large negative accruals, reflecting the reversal of accruals without associated cash flows. Thus, both positive and negative discretionary accruals contribute to the moving sum of absolute discretionary accruals. Dechow, Sloan, and Sweeney (1996) show that manipulation of reported earnings generally occurs from one to three years before detection. Thus, we use a three-year moving sum (instead of a one-year metric) to capture the multi-year effects of earnings management. Moreover, the moving sum is more likely to reflect an underlying policy of the firm to manage earnings that is less subject to single-year anomalies.

3.3 Other Crash Predictors and Control Variables

Our main focus is on opacity created by earnings management as measured by *OPAQUE*. HMT (2009) justify this measure and demonstrate that it is associated with forced financial restatements. Nevertheless, other variables may also capture the proclivity and/or ability of firms to manage earnings, and one would like to see if our results are consistent across various measures of accounting opacity. As we have noted, extrapolation errors and corrections also could result in firm-specific crashes. Thus, we also consider several alternative crash predictors:

- *SALES_STREAK:* The number of consecutive years with increasing sales revenue. Beneish (1999) finds that high rates of sales growth are significantly associated with the probability of fraudulent statements. Even if recent sales growth is real, Beneish (1999) argues that firms may feel pressure to maintain recent growth rates, which may induce earnings manipulation. An alternative motivation for *SALES_STEAK* comes from the behavioral literature: if high recent growth is unduly extrapolated into forecasts for future growth, then ultimate disappointment could result in sudden, dramatic stock price reversals. We define *SALES_STREAK* as the number of consecutive years with increasing sales revenue, counting backwards from fiscal year –1 to fiscal year –4. *SALES_STREAK* ranges from 0 to 3.

- *EPS_STREAK:* The number of sequential prior years with positive, increasing earnings per share. (Results using EPS or adjusted EPS were effectively identical.) Prior research demonstrates that extended streaks in which EPS only increases may be a sign of earnings management (see e.g., Barth, Elliot and Fin, 1999 and Myers, Myers and Skinner, 2007). Similarly, like sales growth, recent trends in EPS may foster unrealistic expectations of continued growth. We define *EPS_STREAK* as the number of sequential prior years with positive and increasing earnings per share, counting backwards from fiscal year –1 to fiscal year –4. *EPS_STREAK* ranges from 0 to 3.
- *AssetQ_i*: Asset quality index. Following Beneish (1999), we define asset quality for a given year as the ratio of noncurrent assets other than property, plant, and equipment (PP&E) to total assets. This ratio is intended to measure the proportion of the firm's assets for which future benefits are potentially less certain. The asset quality index is the ratio of asset quality in year *t* to asset quality in year *t* – 1:

$$AssetQ\_i \;=\; \frac{1 - [Current\ Assets_t + PP\&E_t\,(net)]/Total\ Assets_t}{1 - [Current\ Assets_{t-1} + PP\&E_{t-1}\,(net)]/Total\ Assets_{t-1}}$$

  When *AssetQ_i* is greater than 1, the company has increased its propensity to capitalize costs with greater uncertainty of future benefits than current assets or PP&E. We expect such an increase in asset realization risk to be positively associated with earnings management and thus subsequent stock price crashes.
- *SIGNED_ACC:* Signed accruals. *OPAQUE* treats both positive and negative discretionary accruals as indicative of potential earnings management. Negative accruals may result from reversals of previous unjustified positive ones. An alternative approach is to focus on *signed* discretionary accruals. The motivation for this measure is that a firm consistently attempting to paint an overly rosy accounting picture will repeatedly run up its abnormal accruals. Eventually, the slack allowed by discretion in GAAP will be exhausted and the firm will be unable to continue dressing up its results. At this point a crash is likely to ensue. Therefore, we define *SIGNED_ACC* as the three-year moving sum of the annual discretionary accruals:

$$SIGNED\_ACC = DiscAcc_{t\text{-}1} + DiscAcc_{t\text{-}2} + DiscAcc_{t\text{-}3}$$

In addition to the above variables, we include standard control variables for cross-sectional variation in crash risk that may be correlated with factors such as size, leverage, market to book, profitability, return volatility and systematic risk. Appendix A describes each of these variables and how they are constructed.

Table 2 presents summary statistics for the variables of interest, including the alternative crash predictors and control variables. Table 3 presents Pearson and Spearman correlations of these same variables. All independent variables have been winsorized at the 1st and 99th percentile. For the median firm in our sample, sales, but not EPS, consistently increased in the prior three years. A propensity to capitalize costs is not evident, as indicated by a mean value for *AssetQ_i* of 0.99. As one might expect, there is a high correlation between *OPAQUE* and *SIGNED_ACC*. Since the correlation is greater than 0.40, we present regressions that include both variables, as well as regressions that exclude one of the two variables to examine the effects of multicollinearity. Also noteworthy is the fact that the correlations of these two discretionary accruals measures with the other crash predictors (*SALES_STREAK*, *EPS_STREAK*, and *AssetQ_i*) are all quite low, less than 0.05.

[Tables 2 & 3 near here]

3.4 Crashes

As our focus is on *firm-level* opacity, we wish to distinguish cross-sectional variation in crash risk from *market-wide* crash risk. Therefore, we define a crash as a large, negative firm-specific residual in the following expanded index model regression:

$$r_{j,t} = \alpha_j + \beta_{1,j} r_{m,t-1} + \beta_{2,j} r_{i,t-1} + \beta_{3,j} r_{m,t} + \beta_{4,j} r_{i,t} + \beta_{5,j} r_{m,t+1} + \beta_{6,j} r_{i,t+1} + \varepsilon_{j,t} \qquad (4)$$

where $r_{j,t}$ is the return on stock *j* in week *t*, $r_{m,t}$ is the CRSP value-weighted market index, and $r_{i,t}$ is the Fama-French value-weighted industry index. We allow for nonsynchronous trading by including lead and lag terms for the market and industry indexes (Dimson, 1979). This framework controls for broad market and industry-wide price movements and thus allows us to focus on firm-specific price crashes. There is no reason that firm-specific crashes based on residuals from Eq. (4) should be expected to vary with market-wide crashes, and in fact, they do not.[2]

The residuals from Eq. (4) are highly skewed. We transform them to a roughly symmetric distribution by defining *Firm-Specific Weekly Return* as the log of one plus the residual return from Eq. (4).[3] We define firm-specific crashes in two ways. Our first measure is *CRASH*, which is an indicator variable signifying whether or not a firm experienced at least one crash week during the fiscal year. Following HMT (2009), *CRASH* is set to 1 for a firm-year if the firm experiences one or more *Firm-Specific Weekly Returns* falling 3.09 standard deviations below the mean weekly firm-specific return for that fiscal year; otherwise, *CRASH* is set equal to zero (3.09 is chosen to generate a frequency of 0.1% in the normal distribution).[4]

Our second measure is *Extr_SIGMA*, which is our attempt to create a more continuous and quantitative measure of crash risk. We express the worst firm-specific weekly return during each firm's fiscal year as the number of (weekly) standard deviations (computed within that firm-year) by which the return falls below the mean. In this way, for example, a 4-sigma event is recognized as more of an outlier than a 3-sigma event, and thus, as a more substantial crash.[5] *Extr_SIGMA* is calculated as:

$$Extr\_SIGMA = -\text{Min}\left[\frac{Firm\ Specific\ Weekly\ Return - Mean(Firm\ Specific\ Weekly\ Return)}{Standard\ Deviation\ (Firm\ Specific\ Weekly\ Return)}\right] \qquad (5)$$

The minus sign in Eq. (5) is added so that larger values of *Extr_SIGMA* signify price crashes of greater magnitude.

As noted above, given our definition of a *CRASH*, if firm-specific returns were normally distributed, one would expect to observe 0.1% of the sample firms crashing in any

[2] The correlation between the market smirk (a measure of expected market-wide crashes) and our two measures of firm-specific crashes (described below) is less than 0.03.

[3] This transformation does seem to make the distribution essentially symmetric, even in the tails, which is our greatest concern. For example, the 1st percentile of the distribution is –0.193 while the 99th percentile is +0.191.

[4] While the mean residual from the index model regression is zero by construction, the mean value of ln(1 + residual return) is not. Therefore, we define *CRASH* and *Extr_SIGMA* using deviations from the firm-year mean of ln(1 + residual return).

[5] Notice that for both *CRASH* and *Extr_SIGMA*, crashes are defined by return outliers defined in terms of standard deviations of that particular firm. One might be tempted to define crashes uniformly across firms in terms of a large percentage price decline. But any such uniform definition would *by construction* result in high-volatility firms being identified as high-crash firms. This is why the skew and kurtosis of each stock are evaluated by expressing the third or fourth moment of returns relative to that stock's standard deviation.

week. The probability of a crash over the course of a year would then be $1 - (1 - 0.001)^{52} = 0.0507$. In fact, while we use the normal distribution to provide a benchmark for extreme events, we expect and observe considerably greater frequency of crashes than the normal distribution would predict. For example, Table 4, Panel A, indicates that 23.3% of the firm-years in our sample exhibit at least one *CRASH*.

Our definition of a *CRASH* implies a substantial price movement. In Table 4, Panel B, we highlight the mean, median, and variance of raw weekly returns for two subsamples of firm-weeks: *CRASH* weeks and *ALL OTHER* weeks. The mean weekly return for *CRASH* weeks is −23.27%, and for *ALL OTHER* weeks, 0.26%. Median returns demonstrate a similar pattern. As expected, the variance of weekly returns is dramatically higher for *CRASH* weeks than for *ALL OTHER* weeks. The next set of columns presents analogous results for the market index. In this panel, *CRASH* weeks refer to any week in which any firm in the sample crashes. The variance of the market index is not higher in *CRASH* weeks; recall that a crash is defined using residuals from an index model. Finally, the last set of columns report statistics averaging across industries. If any firm in an industry crashes in a given week, that is defined as a crash week for the industry. There is little evidence of substantially irregular industry performance in *CRASH* weeks. *Extr_SIGMA* weekly returns are similarly dramatically negative, as these returns are for the worst week of the fiscal year for each firm.

[Table 4 near here]

3.5 Volatility Smirk

We obtain our option pricing data from OptionMetrics. Its Ivy DB database contains price and implied volatility data for the entire U.S. listed index and equity options markets. The data are provided daily, using closing prices. Implied volatilities on each option are computed from a binomial option pricing model that assumes continuous log-normal returns, but accounts for dividend payments and allows for early exercise of both calls and puts. The implied volatility is obtained by iterating on sigma until the model price converges to the market price. Therefore, these implied volatilities may exhibit smirks if the true stock price process exhibits either stochastic volatility (Heston, 1993) or discrete jumps, but they are not subject to the dividend-induced distortions characteristic of Black-Scholes implied volatilities.

Given the implied volatility of each option, OptionMetrics computes a volatility surface across two dimensions: (log of) days to expiration and moneyness (delta). The surface is estimated by interpolating using a kernel-smoothing algorithm. At each grid point on the surface, volatility is calculated as a weighted average of the implied volatilities of traded options within a given distance from that grid point; weights are proportional to each option's vega but decline with the differences between (i) option maturity and the date of the grid point and (ii) option delta and the delta at that grid point. Thus, more similar and more volatility-sensitive options have greater influence on implied volatility at any point. For more detail, see OptionMetrics (2008).

This interpolated volatility surface offers an advantage in our framework. Option-specific implied volatilities are intrinsically noisy due to issues such as bid-ask spread or stale pricing. Therefore, one needs to subject these estimates to some sort of smoothing. Bollen and Whaley (2004) use an approach similar in spirit to the OptionMetric methodology when they average volatility estimates across a bucket of options with similar characteristics, for example, all options with deltas in a stipulated range. Another tactic is to use a smoothed price curve, as in Bates (2000), who imputes implied volatility using option prices from a cubic spline fitted to actual prices. Here, OptionMetrics employs the entire set of options to compute the smoothed volatility surface and weights options according to their distance measure from each grid point. Therefore, from that surface we can select options of precise maturity and moneyness.

We use implied volatilities at horizons of 91 days. This maturity is selected as a compromise between two competing considerations. On one hand, jumps are more relevant for short-expiration options, while the potential impact of stochastic volatility may be greater at longer horizons (Bates, 2000). On the other hand, most of the variables of interest, e.g., opacity, are accounting-based and measured annually. Thus, we compromise by using a 91-day implied volatility. We sample implied volatilities annually, using the 10 trading days prior to the start of the firm's fiscal year in which we observe crash occurrences and calculate *Extr_SIGMA*. Our measure of implied volatility is a 10-day average of implied volatilities on 91-day options measured from day −10 to day −1 relative to the start of the firm's fiscal year.

The use of a 10-day average eliminates undue reliance on data from one particular day, which might be affected by stale prices or bid-ask spread.

We define the volatility smirk as the slope of the implied volatility curve relative to the moneyness of the option. As in Bollen and Whaley (2004), we measure moneyness using the option delta, Δ. We compute implied volatility for two put options, ranging from roughly at the money (with $\Delta = -0.5$), to fairly deep out of the money. As the edge of the volatility surface provided by OptionMetrics is $\Delta = -0.2$ for puts, we take these as our out-of-the-money puts.

At-the-money (ATM) put	$\Delta_{ATM} = -0.5$
Out-of-the-money (OTM) put	$\Delta_{OTM} = -0.2$

Denoting implied volatilities as $\hat{\sigma}$, we define the slope of the volatility smirk for puts as:

$$Put\_SMIRK = \hat{\sigma}_{OTM} \Big/ \hat{\sigma}_{ATM} \tag{6}$$

In principle, put-call parity implies that the implied volatilities for corresponding strike price call options should match those computed from the puts, at least for non-dividend paying European-style options. Nevertheless, as our sample is composed of American-style options on dividend-paying stocks, there may be differences in implied volatility. Moreover, as Bollen and Whaley (2004) emphasize, transaction costs create some wiggle room for the implied volatilities on calls and puts to differ. Therefore, we also compute the smirk curve using these analogous formulas for calls

At-the-money (ATM) call	$\Delta_{ATM} = 0.5$
In-the-money (ITM) call	$\Delta_{ITM} = 0.8$

Analogously to the put smirk, the slope of the volatility smirk for calls is:

$$Call\_SMIRK = \hat{\sigma}_{ITM} \Big/ \hat{\sigma}_{ATM} \tag{7}$$

Bollen and Whaley note further that there is deeper trading of low-strike-price puts than calls, potentially making put pricing more reliable than call pricing. Therefore, we rely primarily on put smirks, using calls for corroboration.

Of course, these option smirks presumably reflect crash risk from all sources, firm-specific as well as market-wide. Therefore, as we are interested in the impact of firm-specific contributors to crash risk, we focus our analysis on firm-specific smirks as indicators of that firm-specific crash risk. Accordingly, we define the firm-specific smirk as the ratio of the put or call smirk to the market-wide smirk as follows:

$$Put\_SMIRK\_FS = Put\_SMIRK \; / \; Market\_SMIRK$$
$$Call\_SMIRK\_FS = Call\_SMIRK \; / \; Market\_SMIRK$$

where the *Market_SMIRK* is defined by the implied volatilities of S&P 500 option contracts (the SPX contract) using the same deltas and maturities as for individual-stock puts and calls and using the same 10-day averaging procedure. In any year, of course, the *Market_SMIRK* is identical for all firms, and so would have no bearing on cross-sectional variation, but to the extent that market crash risk and the *Market_SMIRK* change over time, and that fiscal years do not all end on identical dates, these firm-specific smirks should be more precisely related to firm-specific crash risk.[6]

Table 2 presents summary statistics for our measures of the put smirk curve. The fact that *Put_SMIRK* is greater than 1 for the median firm in the sample (and in fact is greater than 1 even for the first quartile firm) is evidence that individual stock price crashes are viewed as more likely than positive jumps. In fact, untabulated findings indicate that this belief about crash risk characterizes each year of our sample period (i.e., the median *Put_SMIRK* is greater than one in each year 1997 – 2008). The firm-specific smirk, *Put_SMIRK_FS*, is less than 1 for the median and Q3 firms in the sample. This reflects a generally steeper smirk for the index compared to individual stock options, and is consistent with conclusions of earlier research (e.g., Bakshi, Kapadei and Madan, 2003; Bollen and Whaley, 2004).

[6] The cross-sectional dispersion of the firm-specific smirk is roughly the same magnitude as its typical time-series variation within firms. For example, the cross-sectional standard deviation of the smirk averages .060 across the 12 years of the sample, and ranges from 0.042 in 2000 to 0.078 in 2006. The within-firm time-series standard deviation of the firm-specific smirk averages 0.057 across the sample. Thus, within-firm variability and across-firm variability contribute roughly equally to total variability in the smirk.

4. Empirical Results

As noted, we test two broad groups of hypotheses. First, we compare market-based and accounting-based predictors of crash risk. We ask whether either or both actually track the likelihood of firm-specific crashes. We also test whether the implied volatility smirk curve tends to be steeper for firms demonstrating greater opacity. This is a less stringent test of rational option pricing in that it asks only whether the crash risk implied by opacity shows up to any extent in the option smirk curve. Clearly, if we can predict crash risk using accounting and other data, we would expect to see at least some evidence of this in the slope of the smirk.

In the second and more interesting tests, we run a horse race between accounting-based predictors of crash risk and predictors based on option prices. If the smirk curve crowds out opacity measures in a predictive model of crashes, one might conclude that such risk is fully reflected in option prices. If, on the other hand, those alternative predictors are significant even after accounting for the information in the smirk curve, then it would appear that the market is not fully utilizing available information, and that trading and/or risk management strategies can be devised to take advantage of that information.

4.1 Opacity and the Option Smirk Curve

We start by examining whether option-market and accounting-based predictors of crash risk are mutually associated. At a simple, univariate level, they are highly associated. The Pearson (Spearman) correlation between *OPAQUE* and *Put_SMIRK_FS* is 0.128 (0.181), significant at better than a 1% level. Even controlling for other variables, this statistical relation is very strong. Table 5 presents OLS regressions of the firm-specific put option smirk, *Put_SMIRK_FS,* on *OPAQUE*, several additional accounting-based predictors of crash risk, and key control variables. The *t*-statistics on *OPAQUE* exceed 10. These and all regressions presented below employ standard errors clustered at the firm level. Additionally, all of the explanatory variables have been winsorized at the 1st and 99th percentile.

[Table 5 near here]

Model 1 includes several alternative measures of earnings management, additional accounting-based predictors of crash risk, along with the usual control variables: lagged size (the natural log of market value of equity), lagged market-to-book ratio, lagged leverage, and lagged standard deviation of *Firm Specific Weekly Returns*. The market-to-book ratio places firms along a growth-versus-value spectrum and thus could be systematically related to crash risk, as growth firms are more vulnerable to a sudden loss of confidence in the value of future growth opportunities. Higher leverage by itself might increase crash risk through its impact on the sensitivity of equity returns to macroeconomic conditions; on the other hand, in a fuller equilibrium, firms with less crash risk will presumably be willing to incur higher levels of indebtedness.

Duan and Wei (2009) demonstrate that slopes of smirk curves are related to systematic risk, measured as the proportion of systematic variance in total variance. Thus, we also incorporate the *R-Square* from the following weekly market-model regression in our analyses as a control variable:

$$r_{j,t-1} = \alpha_j + \beta_{1,j} r_{m,t-1} + \beta_{2,j} r_{m,t} + \beta_{3,j} r_{m,t+1} + \varepsilon_{j,t} \tag{8}$$

where $r_{j,t}$ is the return on stock *j* in week *t* and $r_{m,t}$ is the CRSP value-weighted market index. We allow for nonsynchronous trading by including lead and lag terms for the market index (Dimson, 1979). We use the *R-square* estimated over the prior fiscal year in our regressions.

Leverage is negatively but not significantly related to crash risk. The coefficient on *Size* is positive and statistically significant, indicating greater asymmetry in forecasts of crashes versus jumps for larger firms. Put simply, while investors apparently expect that it is unlikely for a very large firm’s value to increase by say 50% in the next 91 days, it is at least conceivable that the large firm’s value could be cut in half. For smaller firms, investors’ assessments of the likelihood of a positive versus a negative jump are more symmetric. Consistent with Duan and Wei (2009), *R-Square* is positively related to the slope of the smirk curve, while *SD(lnres*) is negatively related to the slope of the smirk curve.

M/B and *SALES_STREAK* are negatively, and statistically significantly, related to the option smirk. In our regressions below, both *M/B* and *SALES_STREAK* are *positively* related to realized crashes, measured using either *CRASH* or *Extr_SIGMA*. Together, these findings are generally consistent with the view that extreme market-to-book ratios may reflect undue optimism about a firm's prospects based on recent strong performance (Lakonishok, Shleifer and Vishny, 1994). The excessive optimism shows up as a downward bias in forecasts of crash risk reflected in the options market relative to objective crash risk.

AssetQ_i, as expected, has a positive and statistically significant relation to the option smirk. *Signed_ACC* has an unexpected negative relation to the smirk. However, given the strong correlation between *Signed_ACC* and *OPAQUE*, Models 2 and 3 in Table 5 present the relation between discretionary accruals and the option smirk including only one of these measures. When *OPAQUE* is excluded (Model 3), the estimated coefficient on *Signed_ACC* is as predicted, positive and significant. On the other hand, the estimated coefficient for *OPAQUE* is virtually unaffected by the exclusion of *Signed_ACC* (Model 2).

It is worth noting that the economic impact of *OPAQUE* in explaining the firm-specific smirk curve is non-trivial. A one standard deviation swing in *OPAQUE* implies an increase in the smirk of 0.010 (= 0.0032×3.124), which is 16.7% of the average cross-sectional sample standard deviation of *Put_SMIRK_FS* (see footnote 6). Thus, our broad conclusion from these regressions is that firm opacity is in fact significantly related to the assessment of crash risk reflected in option prices.

4.2 Crash Risk

We turn now to the ability of either opacity or the option smirk curve to explain cross-sectional variation in crash risk. We present findings first using a dichotomous measure of crash risk (*CRASH*) and then using a continuous measure of that risk (*Extr_SIGMA*).

Table 6 presents logit analysis. Each firm-year is assigned a zero if the firm experiences no crash during the fiscal year and a one if there is at least one week during the fiscal year in which the stock price crashes.

[Table 6 near here]

Of primary interest, Model 1 of Table 6 demonstrates that both *OPAQUE* and the put option smirk, *Put_SMIRK_FS,* are highly significant in predicting crash risk. Consistent with

HMT, *ROE* is highly significant with a negative coefficient.[7] *Leverage* (lagged) is highly negatively associated with crashes, as is *R-Square*. *Signed_ACC*, *EPS_STREAK*, *AssetQ_i* and *Size* (lagged) have little relation, while, as noted earlier, both *M/B* and *SALES_STREAK* are highly predictive of crashes. The positive coefficients on *M/B* and *SALES_STREAK* are consistent with the view that growth firms are more crash prone, as their prices are more vulnerable to reversals of confidence in growth opportunities (see e.g., Skinner and Sloan, 2002).

The comparison of the Table 5 and 6 regressions is instructive. Table 5 explains the smirk, which may be interpreted as an *ex ante* measure of crash risk. Table 6 analyzes actual crashes, an *ex post* measure of realized crashes. The role of *OPAQUE* as a predictor of both *ex ante* and *ex post* crash risk is noteworthy. However, the tables also reveal some inconsistencies. We have already pointed out that the negative coefficients on *M/B* and *SALES_STREAK* in Table 5 are inconsistent with the positive coefficients in Table 6, and may signify that a high market-to-book ratio reflects undue extrapolation of good recent performance. Additionally, *R-Square* is positively related to the smirk (Table 5), but negatively related to crash risk (Table 6). Thus, it seems possible that inconsistencies between market assessments of crash risk (Table 5) and actual crash experience (Table 6) might form the basis of a trading strategy.

Our analysis in Table 6 throws away some potentially valuable information by treating crash risk as a simple {0,1} variable. In Table 7 we present OLS regressions that use our quantitative and continuous measure of crash outcome *Extr_SIGMA* (i.e., the number of standard deviations below the annual mean weekly return for the most extreme negative weekly return of the fiscal year).

[Table 7 near here]

Consistent with Table 6, Model 1 of Table 7 demonstrates that both *OPAQUE* and the put option smirk, *Put_SMIRK_FS,* are highly significant in predicting crash risk. It is

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[7] In the accounting literature, studies of the impact of discretionary accruals on stock returns typically include controls for contemporaneous firm performance such as ROE. However, one might prefer to examine stock return characteristics during a given period without allowing for the influence of contemporaneous announcements. We therefore re-estimate all of our regressions without ROE as a control variable. As it turns out, the inclusion of ROE has almost no impact on any of the other regression estimates.

noteworthy that neither variable crowds out the other in predicting crashes. In a fully efficient market, option prices would presumably reflect all relevant information about crash risk, and so other variables would add no additional predictive power. In both Table 6 and Table 7, however, *OPAQUE* remains significant even in the presence of *Put_SMIRK_FS.* This might reflect the fact that we are not using all the information contained in option prices: we consider only two points from the smirk curve, and we may be relying on implied volatilities derived from an overly simplistic option pricing model. Even so, the robustness of *OPAQUE* as a predictor of crash risk is impressive. Moreover, when we use more information from the smirk curve, for example, measuring its slope across two intervals (from $\Delta = -0.5$ to -0.35 and from -0.35 to -0.2) instead of only one (from -0.2 to -0.5), our results are barely affected.

As in Table 6, high *M/B* ratios and a longer *SALES_STREAK* are both positively associated in Table 7 with more dramatic tail risk, consistent with the notion that growth firms suffer dramatic price corrections when forecasts of their prospects are revised downward. Not surprisingly, strong contemporaneous operating performance (*ROE*) is associated with lower crash risk.

Our broad conclusion from the analyses presented in Tables 6 and 7 is that several variables, notably *OPAQUE*, *M/B* ratios, and *SALES_STREAK*, are predictors of firm-specific crash risk as well as the magnitude of such crashes, even controlling for the option smirk.

These results suggest a trading strategy. If option prices do not fully reflect the magnitude or likelihood of crash risk, then one should be able to profit by buying out-of-the-money puts of firms that are more crash prone than reflected by the smirk curve. Our results suggest that those are firms with high opacity, and with strong current stock market sentiment (market-to-book) and sales growth. Because these variables predict crashes even after controlling for the smirk, one could rank firms by opacity, buy puts in firms with above-average opacity, and delta hedge the position. This strategy ought to provide positive risk-adjusted returns.

5. Robustness checks

In this section, we present a series of robustness checks for our empirical results.

5.1 *Call Versus Put Smirks*

As noted above, put-call parity would imply that call and put implied volatilities ought to be equal for identical strike prices and expirations. In practice, however, some options, particularly those that are out of the money, may not trade frequently or in deep markets. Therefore, we repeat the analysis in Tables 5 through 7 using call option data in place of put option data. As it turns out, the results for calls are virtually identical to those for puts in Tables 6 and 7. The only change is in Table 5, where the coefficient on *AssetQ_i* becomes insignificant and the coefficient on *Leverage* become more negative and significant. However, the *t*-statistics on *OPAQUE* continue to exceed 10.

5.2 *Hazard Model*

Table 6 uses logit analysis to estimate crash likelihood. An alternative approach would be to employ a hazard model. Hazard models are common tools for dealing with the outcome and timing of zero-one variables (in our application, whether a crash occurs in any period); unlike logit models, they explicitly allow the likelihood of an event to vary as a function of time. In many applications, time per se matters, for example, as subjects age or become worn out. In our case, this is not an issue, so the logit model should be adequate; nevertheless we estimate hazard regressions to confirm the robustness of our logit analysis.

The so-called hazard rate is the conditional probability that a stock price crash takes place in a given period. The popular Cox proportional hazard model decomposes the hazard rate into a baseline level (that may be a function of time) and the impact of a set of explanatory variables. The model specifies the hazard rate as:

$$h[t, \boldsymbol{x}(t), \boldsymbol{\beta}] = h_0(t)\, exp[\boldsymbol{x}(t)'\boldsymbol{\beta}]$$

where $h_0(t)$ is the baseline hazard rate, $\boldsymbol{x}(t)$ is the vector of possibly time-varying explanatory variables and $\boldsymbol{\beta}$ is a vector of regression coefficients to be estimated. Variation in the vector of explanatory variables, $\boldsymbol{x}(t)$, will shift the hazard function up or down.[8] This specification is called a proportional hazard model because a unit increase in a right-hand side variable

[8] There is no intercept estimated in the hazard model, as the constant term is impounded into the baseline hazard function.

with coefficient β multiples the conditional probability of a crash during the next period by the factor $exp(\beta)$.

Table 8 presents hazard model results, which are remarkably consistent with the logit regressions. Precisely the same variables are statistically significant in both regressions, the signs of all significant coefficients match, and magnitudes are also comparable. The hazard model clearly supports the results of the logit analysis.

[Table 8 near here]

6. Conclusion

We investigate three facets of cross-sectional variation in the risk of stock price crashes: actual crash incidence, and empirical predictors of that risk such as accounting opacity, and the option smirk curve. We show that all three of these variables are related. Option smirks and accounting opacity each independently predict cross-sectional variation in crash risk. The slope of the smirk curve and opacity are themselves correlated at extremely high levels of statistical significance, indicating that the market is aware of the link between opacity and crash risk. Nevertheless, even controlling for the option smirk, some measures of opacity are still reliably associated with crash risk, suggesting that the options market does not fully utilize the predictive value of opacity. Some of our results are consistent with behavioral models in which strong recent performance is extrapolated too far into the future, only to result in a major reversal when those expectations are disappointed.

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Appendix A
Variable definitions

OPAQUE is the prior three years' moving sum of the absolute value of discretionary accruals. Specifically,

$$OPAQUE = |DiscAcc_{t\text{-}1}| + |DiscAcc_{t\text{-}2}| + |DiscAcc_{t\text{-}3}| \ ,$$

where $DiscAcc_t$ is measured using the Modified Jones Model. Winsorized at the 1st and 99th percentile.

SIGNED_ACC is the three-year moving sum of the annual discretionary accruals:

$$SIGNED\_ACC = DiscAcc_{t\text{-}1} + DiscAcc_{t\text{-}2} + DiscAcc_{t\text{-}3}$$

where $DiscAcc_t$ is measured using the Modified Jones Model. Winsorized at the 1st and 99th percentile.

SALES_STREAK is defined as the number of consecutive years with increasing sales revenue, counting backwards from fiscal year –1 to fiscal year –4. *SALES_STREAK* ranges from 0 to 3.

EPS_STREAK is defined as the number of sequential prior years with positive and increasing earnings per share, counting backwards from fiscal year –1 to fiscal year –4. *EPS_STREAK* ranges from 0 to 3.

AssetQ_i is the ratio of asset quality in year t to asset quality in year t – 1:

$$AssetQ\_i \ = \ \frac{1 \ - \ [\text{Current Assets}_t + \text{PP\&}E_t \ (\text{net})]/\text{Total Assets}_t}{1 \ - \ [\text{Current Assets}_{t\text{-}1} + \text{PP\&}E_{t\text{-}1} \ (\text{net})]/\text{Total Assets}_{t\text{-}1}}.$$

Winsorized at the 1st and 99th percentile.

Firm-Specific Weekly Return is equal to ln(1+ residual), where the residual is $\varepsilon_{j,t}$ from the expanded index-model regression, estimated weekly:

$$r_{j,t} = \alpha_j + \beta_{1,j}r_{m,t\text{-}1} + \beta_{2,j}r_{i,t\text{-}1} + \beta_{3,j}r_{m,t} + \beta_{4,j}r_{i,t} + \beta_{5,j}r_{m,t+1} + \beta_{6,j}r_{i,t+1} + \varepsilon_{j,t}$$

SD(lnres) is the standard deviation of the *Firm-Specific Weekly Return* measured during the prior fiscal year.

CRASH is an indicator variable equal to one if within its fiscal year a firm experiences one or more *Firm-Specific Weekly Returns* falling 3.09 or more standard deviations below the mean *Firm-Specific Weekly Return* for its fiscal year and equal to zero otherwise.

We express the worst weekly return of the firm's fiscal year as the number of standard deviations that return falls below the mean:

$$Extr\_SIGMA = -\text{Min}\ [\frac{Firm\ Specific\ Weekly\ Return - Mean(Firm\ Specific\ Weekly\ Return)}{Standard\ Deviation\ (Firm\ Specific\ Weekly\ Return)}]$$

We define the slope of the volatility smirk for puts as:

Put_SMIRK = $\hat{\sigma}_{OTM} / \hat{\sigma}_{ATM}$, where $\hat{\sigma}$ is the implied volatility for two put options, ranging from roughly at the money (with $\Delta = -.5$), to fairly deep out of the money (with $\Delta = -.2$). Winsorized at the 1st and 99th percentile.

Put_SMIRK_FS = *Put_SMIRK* / *Market_SMIRK*, where the *Market_SMIRK* is defined by the implied volatilities of S&P 500 option contracts (the SPX contract) using the same deltas and maturities as for individual-stock puts. Winsorized at the 1st and 99th percentile.

SIZE is the natural log of the market value of equity at the beginning of the fiscal year. Winsorized at the 1st and 99th percentile.

M/B is the ratio of the market value of equity to the book value of equity measured at the beginning of the fiscal year. Winsorized at the 1st and 99th percentile.

LEVERAGE is the book value of all liabilities scaled by total assets, measured at the beginning of the fiscal year. Winsorized at the 1st and 99th percentile.

ROE is contemporaneous return on equity defined as income before extraordinary items divided by the book value of equity. Winsorized at the 1st and 99th percentile.

R-Square is the R^2 of the market-model regression, estimated weekly over the prior fiscal year:

$$r_{j,t\text{-}1} = \alpha_j + \beta_{1,j} r_{m,t-1} + \beta_{2,j} r_{m,t} + \beta_{3,j} r_{m,t+1} + \varepsilon_{j,t}$$

Table 1: Sample Development, Industry Membership, and Fiscal Years of Sample

Panel A: Sample Development

	# firm years
All Compustat firm fiscal years 1997 through 2008	85,225
Excluding firm fiscal years:	
Financial services and utilities	12,611
Low-priced stock	8,527
With incomplete stock return data	2,663
With insufficient financial data to calculate 3 lags of discretionary accruals	11,234
With insufficient financial data to calculate control variables	4,712
Not available on OptionMetrics data base	27,935
Final Sample	**17,543**

Table 1: Sample Development, Industry Membership and Fiscal Years of Sample

Panel B: Fama-French Industries

Industry	# firm years	Industry	# firm years
Aero	75	Hshld	289
Agric	59	LabEq	456
Autos	278	Mach	644
Beer	79	Meals	340
BldMt	242	MedEq	651
Books	192	Mines	83
Boxes	60	Oil	1,042
BusSv	856	Paper	251
Chems	478	PerSv	165
Chips	1,751	Rtail	1,316
Clths	269	Rubbr	76
Cnstr	96	Ships	44
Coal	45	Smoke	17
Drugs	1,467	Soda	48
ElcEq	224	Softw	1,776
FabPr	25	Steel	339
Food	304	Telcm	737
Fun	242	Toys	105
Gold	136	Trans	585
Guns	55	Txtls	55
Hardw	649	Whlsl	609
Hlth	333	**Total**	**17,543**

Source: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_49_ind_port.html

Table 1: Sample Development, Industry Membership and Fiscal Years of Sample

Panel C: Observations in each Fiscal Year

Fiscal Year	**Number of Observations**
1997	1,217
1998	1,373
1999	1,496
2000	1,433
2001	1,260
2002	1,408
2003	1,441
2004	1,433
2005	1,532
2006	1,583
2007	1,670
2008	1,697
	17,543

Table 2: Descriptive Statistics for Variables of Interest

17,543 firm years in the sample period 1997-2008. See Appendix A for all variable definitions.

	Q1	Mean	Median	Q3	Std. Dev.
Market Value	429	7,561	1,219	4,128	24,408
Size (lagged)*	6.15	7.30	7.12	8.30	1.58
OPAQUE*	0.201	1.559	0.449	1.364	3.124
Signed_ACC*	-0.121	0.579	0.100	0.619	2.509
Sales_Streak	1.000	2.013	3.000	3.000	1.245
EPS_Steak	0.000	1.114	0.000	3.000	1.285
AssetQ_i*	0.835	0.795	0.990	1.123	27.06
Put_Smirk*	1.024	1.078	1.068	1.113	0.078
Put_Smirk_FS*	0.819	0.866	0.859	0.903	0.072
Extr_SIGMA	2.103	2.657	2.479	3.032	0.777
ROE*	-0.011	-0.012	0.095	0.172	0.488
M/B (lagged)*	1.757	3.962	2.755	4.564	3.974
Leverage (lagged)*	0.284	0.460	0.473	0.620	0.214
SD(lnres) (lagged)	0.033	0.054	0.048	0.069	0.029
R-Square (lagged)	0.129	0.276	0.239	0.391	0.187

* Variable has been winsorized at the 1st and 99th percentile.

Table 3: Correlation Matrix for Variables of Interest

	Put_SMIRK_FS	Crash	SIGMA	SD(lnres) (t-1)	OPAQUE	Signed_ ACC	SALES_ STREAK	EPS_ STREAK	AssetQ_i	ROE	Size (t-1)	M/B (t-1)	Lev (t-1)	R-Square (t-1)
Put_SMIRK_FS		0.027	0.032	-0.192	0.128	0.037	-0.024	0.038	0.014	0.059	0.137	-0.042	0.040	0.116
		0.000	<.0001	<.0001	<.0001	<.0001	0.002	<.0001	0.071	<.0001	<.0001	<.0001	<.0001	<.0001
Crash	0.032		0.807	0.031	0.049	0.016	0.041	-0.001	0.004	-0.042	-0.038	0.008	-0.053	-0.055
	<.0001		<.0001	<.0001	<.0001	0.032	<.0001	0.873	0.638	<.0001	<.0001	0.261	<.0001	<.0001
SIGMA	0.038	0.732		0.033	0.044	0.021	0.058	0.010	0.005	-0.047	-0.035	0.018	-0.057	-0.059
	<.0001	<.0001		<.0001	<.0001	0.0064	<.0001	0.1713	0.5428	<.0001	<.0001	0.0174	<.0001	<.0001
SD(lnres) (t-1)	-0.226	0.045	0.033		-0.020	-0.004	-0.081	-0.252	-0.006	-0.322	-0.533	0.079	-0.299	-0.382
	<.0001	<.0001	<.0001		0.008	0.554	<.0001	<.0001	0.442	<.0001	<.0001	<.0001	<.0001	<.0001
OPAQUE	0.181	0.042	0.044	-0.020		0.430	0.007	-0.011	0.004	-0.047	0.009	0.046	-0.050	-0.073
	<.0001	<.0001	<.0001	0.008		<.0001	0.321	0.155	0.614	<.0001	0.254	<.0001	<.0001	<.0001
Signed_ACC	0.080	0.008	0.011	0.013	0.401		0.005	-0.008	0.003	-0.009	0.032	0.012	-0.055	-0.039
	<.0001	0.320	0.156	0.088	<.0001		0.544	0.290	0.702	0.235	<.0001	0.098	<.0001	<.0001
SALES_STRK	-0.018	0.040	0.060	-0.077	-0.015	0.026		0.257	-0.002	0.143	0.134	0.104	-0.033	-0.001
	0.019	<.0001	<.0001	<.0001	0.051	0.001		<.0001	0.774	<.0001	<.0001	<.0001	<.0001	0.888
EPS_STREAK	0.057	-0.001	0.017	-0.250	-0.046	0.013	0.241		0.009	0.239	0.205	0.012	0.051	0.071
	<.0001	0.857	0.028	<.0001	<.0001	0.092	<.0001		0.254	<.0001	<.0001	0.118	<.0001	<.0001
AssetQ_i	0.018	-0.011	-0.009	-0.034	0.017	0.007	-0.018	0.056		-0.001	0.014	0.007	0.003	-0.007
	0.017	0.146	0.240	<.0001	0.029	0.334	0.016	<.0001		0.925	0.060	0.332	0.734	0.375
ROE	0.070	-0.064	-0.061	-0.418	-0.107	-0.021	0.221	0.353	0.046		0.425	0.364	0.072	0.113
	<.0001	<.0001	<.0001	<.0001	<.0001	0.005	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001
Size (t-1)	0.184	-0.034	-0.024	-0.604	-0.042	0.019	0.137	0.211	0.030	0.425		0.311	0.270	0.477
	<.0001	<.0001	0.001	<.0001	<.0001	0.010	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001

M/B (t-1)	-0.022	0.023	0.024	-0.013	0.073	-0.019	0.194	0.106	0.013	0.364	0.311		0.113	0.014
	0.003	0.003	0.001	0.075	<.0001	0.011	<.0001	<.0001	0.080	<.0001	<.0001		<.0001	0.056
Leverage (t-1)	0.036	-0.057	-0.055	-0.322	-0.157	-0.096	-0.035	0.052	0.011	0.210	0.288	-0.008		0.106
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.149	<.0001	<.0001	0.313		<.0001
R-Square (t-1)	0.159	-0.049	-0.038	-0.426	-0.004	0.024	-0.001	0.075	0.005	0.167	0.458	0.048	0.109	
	<.0001	<.0001	<.0001	<.0001	0.583	0.002	0.878	<.0001	0.536	<.0001	<.0001	<.0001	<.0001	

Pearson above the diagonal; Spearman below the diagonal. 17,543 firm years in the sample period 1997-2008. See Appendix A for all variable definitions.

Table 4: Crashes: Frequency and Weekly Returns

Panel A: Crash Frequency

Panel A reports the frequency of firm-specific crashes. The sample comprises 17,543 firm years in the period 1997-2008. Crashes are defined based on residuals from an expanded index model regression with market and industry returns as explanatory variables. Weekly firm-specific residual returns that are 3.09 standard deviations below the mean for the firm's fiscal year are categorized as crashes.

Frequency of *Crashes* in the firm year

	# of Obs.	% of sample
0	13,455	76.7%
1	3,935	22.4%
2	153	0.9%
3	0	0.0%
	======	
	17,543	

Table 4: Crashes: Frequency and Weekly Returns

Panel B: Return in Crash Weeks vs. All Other Weeks

Panel B reports the mean, median, and variance of raw weekly returns for *CRASH* weeks and *ALL OTHER* weeks. The first set of columns presents statistics for individual firms. The middle set of columns presents analogous results for the market index. In this panel, *CRASH* weeks refer to any week in which any firm in the sample crashes. The last set of columns report statistics averaging across industries. If any firm in an industry crashes in a given week, that is defined as a crash week for the industry. The sample contains weekly returns for 17,543 firm years in the period 1997-2008.

		Firm Returns			**Market Index**			**Industry Index**		
	# of obs.	mean	Median	variance	mean	median	variance	mean	median	variance
***CRASH* Weeks**	4,241	-0.2327	-0.2073	0.0166	0.0038	0.0039	0.0008	0.0031	0.0030	0.0014
***ALL OTHER* Weeks**	898,767	0.0026	0.0000	0.0058	0.0010	0.0025	0.0007	0.0011	0.0021	0.0013

Table 5: Smirk versus Opacity Measures

Ordinary least squares regressions of the slope of the firm-specific put option smirk (see Eq. 6) as a function of opacity. Sample period 1997 - 2008 with 17,543 firm-year observations. *Put_SMIRK_FS* is the dependent variable. Standard errors are clustered at the firm level. See Appendix A for all variable definitions.

	Model 1				**Model 2**				**Model 3**			
	Coef Est	Std Error	t-stat	p-value	Coef Est	Std Error	t-stat	p-value	Coef Est	Std Error	t-stat	p-value
Intercept	0.8677	0.0050	172.19	<.0001	0.8680	0.0050	172.54	<.0001	0.8749	0.0051	172.82	<.0001
OPAQUE	0.0032	0.0003	12.00	<.0001	0.0030	0.0002	13.34	<.0001				
Signed_ACC	-0.0007	0.0003	-2.16	0.031					0.0010	0.0003	3.64	0.0003
SALES_STREAK	-0.0023	0.0005	-4.27	<.0001	-0.0023	0.0005	-4.26	<.0001	-0.0023	0.0005	-4.27	<.0001
EPS_STREAK	0.0000	0.0005	-0.07	0.9422	0.0000	0.0005	-0.05	0.961	-0.0002	0.0005	-0.36	0.719
AssetQ_i	0.00003	0.00001	4.99	<.0001	0.0000	0.0000	4.98	<.0001	0.0000	0.0000	4.87	<.0001
Size (t-1)	0.0025	0.0006	4.48	<.0001	0.00246	0.00056	4.37	<.0001	0.00252	0.00057	4.43	<.0001
M/B (t-1)	-0.0008	0.0002	-5.00	<.0001	-0.0008	0.0002	-4.95	<.0001	-0.0007	0.0002	-4.03	<.0001
Leverage (t-1)	-0.0047	0.0033	-1.42	0.156	-0.0044	0.0033	-1.32	0.1863	-0.0068	0.0034	-2.03	0.042
SD(lnres) (t-1)	-0.3620	0.0256	-14.12	<.0001	-0.3630	0.0256	-14.16	<.0001	-0.3864	0.0260	-14.87	<.0001
R-Square (t-1)	0.0172	0.0038	4.49	<.0001	0.0174	0.0038	4.55	<.0001	0.0130	0.0038	3.40	0.001
R^2	0.060				0.060				0.045			
N	17,543											
No. of clusters	3,459											

Table 6: Logit Analysis: Crash Risk, Smirk Curves and Opacity Measures

Logistic regressions modeling the probability of a stock price crash as a function of smirk curves and opacity measures. Sample period 1997 - 2008 with 17,543 firm-year observations. *CRASH* {0,1} is the dependent variable. Standard errors are clustered at the firm level. See Appendix A for all variable definitions.

	Model 1				**Model 2**				**Model 3**			
	Coef Est	Std Error	z-stat	P>|z|	Coef Est	Std Error	z-stat	P>|z|	Coef Est	Std Error	z-stat	P>|z|
Intercept	-1.8336	0.259	50.01	<.0001	-1.835	0.259	50.13	<.0001	-1.895	0.258	54.14	<.0001
Put_SMIRK_FS	1.0982	0.250	19.27	<.0001	1.102	0.250	19.43	<.0001	1.237	0.246	25.21	<.0001
OPAQUE	0.0264	0.007	16.09	<.0001	0.025	0.006	17.17	<.0001				
Signed_ACC	-0.0048	0.008	0.39	0.530					0.009	0.008	1.41	0.2346
SALES_STREAK	0.0876	0.016	30.61	<.0001	0.088	0.016	30.69	<.0001	0.088	0.016	30.92	<.0001
EPS_STREAK	0.0033	0.015	0.05	0.8235	0.003	0.015	0.05	0.8174	0.003	0.015	0.03	0.855
AssetQ_i	0.0004	0.0004	0.82	0.3638	0.000	0.000	0.82	0.3643	0.000	0.000	0.82	0.3659
ROE	-0.1847	0.036	25.85	<.0001	-0.185	0.036	25.95	<.0001	-0.195	0.036	29.36	<.0001
Size (t-1)	-0.0197	0.016	1.56	0.2124	-0.020	0.0158	1.64	0.200	-0.020	0.0158	1.53	0.217
M/B (t-1)	0.0083	0.005	3.08	0.0795	0.008	0.005	3.116	0.0776	0.010	0.005	4.14	0.0419
Leverage (t-1)	-0.5036	0.091	30.39	<.0001	-0.501	0.091	30.05	<.0001	-0.522	0.091	32.73	<.0001
SD(lnres) (t-1)	-0.7342	0.794	0.86	0.3551	-0.739	0.794	0.87	0.3517	-0.941	0.794	1.41	0.2358
R-Square (t-1)	-0.5921	0.117	25.76	<.0001	-0.590	0.117	25.59	<.0001	-0.633	0.116	29.69	<.0001
Wald ChiSq	187.49				187.43				172.43			
Pr > ChiSq	<.0001				<.0001				<.0001			
Crash = 1	4,088											
Crash = 0	13,455											

Table 7: Crash Risk, Smirk Curves and Opacity Measures

Ordinary least squares regressions of the magnitude of a crash (measured as the number of standard deviations the worst weekly return of the year falls below the mean, see Eq. 5) as a function of smirk curves and opacity. Sample period 1997 - 2008 with 17,543 firm-year observations. *Extr_SIGMA* is the dependent variable. See Appendix A for all variable definitions.

	Model 1				**Model 2**				**Model 3**			
	Coef Est	Std Error	t-stat	p-value	Coef Est	Std Error	t-stat	p-value	Coef Est	Std Error	t-stat	p-value
Intercept	2.355	0.088	26.78	<.0001	2.355	0.088	26.77	<.0001	2.339	0.088	26.64	<.0001
Put_SMIRK_FS	0.438	0.086	5.10	<.0001	0.438	0.086	5.10	<.0001	0.474	0.085	5.55	<.0001
OPAQUE	0.007	0.003	2.55	0.0107	0.007	0.002	2.93	0.0034				
Signed_ACC	0.001	0.003	0.16	0.875					0.004	0.003	1.47	0.1428
SALES_STREAK	0.037	0.005	7.70	<.0001	0.037	0.005	7.69	<.0001	0.038	0.005	7.71	<.0001
EPS_STREAK	0.007	0.005	1.43	0.153	0.007	0.005	1.43	0.1529	0.007	0.005	1.40	0.1614
AssetQ_i	0.0001	0.0001	1.17	0.242	0.000	0.000	1.17	0.2414	0.000	0.000	1.17	0.2414
ROE	-0.081	0.014	-5.84	<.0001	-0.081	0.014	-5.84	<.0001	-0.0834	0.0137	-6.07	<.0001
Size (t-1)	-0.005	0.005	-1.04	0.2972	-0.005	0.005	-1.03	0.3017	-0.005	0.005	-1.05	0.2959
M/B (t-1)	0.005	0.002	2.67	0.0076	0.005	0.002	2.67	0.0077	0.005	0.002	2.86	0.0043
Leverage (t-1)	-0.178	0.030	-5.93	<.0001	-0.178	0.030	-5.93	<.0001	-0.182	0.030	-6.08	<.0001
SD(lnres) (t-1)	-0.234	0.272	-0.86	0.3907	-0.233	0.272	-0.86	0.3921	-0.285	0.272	-1.05	0.2944
R-Square (t-1)	-0.207	0.037	-5.55	<.0001	-0.207	0.037	-5.55	<.0001	-0.217	0.037	-5.83	<.0001
R-Square	0.015				0.015				0.014			
N	17,543											
No. of clusters	3,459											

Table 8: Crash Risk, Smirk Curves and Opacity Measures

Hazard regressions to model firm-specific stock price crashes as a function of smirk curves and opacity. Sample period 1997 - 2008 with 17,543 firm-year observations. See Appendix A for all variable definitions.

	Model 1				Model 2				Model 3			
	Coef Est	Std Error	t-stat	p-value	Coef Est	Std Error	t-stat	p-value	Coef Est	Std Error	t-stat	p-value
Put_SMIRK_FS	0.8619	0.1990	4.33	0.0000	0.8650	0.1989	4.35	0.0000	0.9564	0.1977	4.84	0.0000
OPAQUE	0.0200	0.0046	4.39	0.0000	0.0191	0.0042	4.54	0.0000				
Signed_ACC	-0.0028	0.0054	-0.52	0.6040					0.0077	0.0058	1.34	0.1810
SALES_STREAK	0.0842	0.0128	6.56	0.0000	0.0843	0.0128	6.57	0.0000	0.0852	0.0128	6.63	0.0000
EPS_STREAK	0.0012	0.0117	0.11	0.9150	0.0014	0.0117	0.12	0.9080	0.0006	0.0117	0.05	0.9590
AssetQ_i	0.0004	0.0004	0.86	0.3910	0.0004	0.0004	0.86	0.3920	0.0004	0.0004	0.85	0.3930
ROE	-0.0638	0.0288	-2.21	0.0270	-0.0641	0.0288	-2.23	0.0260	-0.0709	0.0286	-2.48	0.0130
Size (t-1)	-0.0014	0.0125	-0.11	0.9140	-0.0016	0.0125	-0.13	0.8950	-0.0009	0.0125	-0.07	0.9410
M/B (t-1)	0.0083	0.0036	2.28	0.0220	0.0083	0.0036	2.29	0.0220	0.0092	0.0036	2.54	0.0110
Leverage (t-1)	-0.5056	0.0717	-7.05	0.0000	-0.5042	0.0717	-7.03	0.0000	-0.5216	0.0717	-7.28	0.0000
SD(lnres) (t-1)	-0.1206	0.6552	-0.18	0.8540	-0.1256	0.6551	-0.19	0.8480	-0.2137	0.6571	-0.33	0.7450
R-Square (t-1)	-0.4608	0.0943	-4.89	0.0000	-0.4592	0.0943	-4.87	0.0000	-0.4980	0.0938	-5.31	0.0000
Chi-Sq	200.44				199.94				177.98			
p-value	0.000				0.000				0.000			
N	17,543											
No. Failures	4,088											