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Analyst Coverage and Expected Crash Risk: Evidence from Exogenous Changes in Analyst Coverage

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ABSTRACT: Using brokerage mergers and closures as two sources of exogenous shock to analyst coverage, this study explores the causal effect of analyst coverage on *ex ante* expected crash risk as captured by the options implied volatility smirk. We find a significant increase in a firm's *ex ante* expected crash risk subsequent to an exogenous drop in analyst coverage; this positive effect is stronger for firms initially receiving less coverage. Further, we find analysts' ability matters to investors' assessment of future crash risk. Specifically, we find the impact is more pronounced for the coverage terminations of analysts with more firm-specific or general experience, with greater access to resources, or whose prior forecasts are more accurate than those of their peers. Overall, our results suggest that investors in the options market do recognize analysts as important information intermediaries and monitors and, thus, that analyst coverage influences the underlying stock's expected crash risk.

JEL Classifications: G12; M41.

Keywords: analyst coverage; expected crash risk; bad news hoarding.

I. INTRODUCTION

The 2008 financial crisis highlights the importance of understanding investors' perceived crash risk. At the time of the crisis, investors' lack of confidence and fear of further decreases in prices were identified as the major culprits behind the dramatic market-level price declines.[1] In this study, we utilize brokerage mergers and closures as a setting that leads to an exogenous drop in analyst coverage to examine how analysts affect investors' subjective assessment of future crash occurrences at the firm level.

Analysts are especially relevant to investors' assessment of a firm's downside risk for two reasons. First, prior studies suggest that analysts are essential in propagating bad news (Hong, Lim, and Stein 2000b).[2] This is because managers are more likely to be forthcoming about good news, and obfuscate (Li 2008) and hide bad news (Hutton, Marcus, and Tehranian 2009)

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[1] Discussing responses to the 2008 global financial crisis, Olivier Blanchard (2009), then chief economist of the International Monetary Fund, stated, "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).

[2] Anecdotal evidence shows that, apart from making forecasts and stock recommendations, analysts often uncover bad news relating not only to a firm's reporting practices, but also to its operating decisions. For example, false stock sales uncovered by analysts forced Applied Micro Circuits Corporation to restate its revenues. Nationwide customer attribution identified by analysts forced CVS Corporation to reveal its true competitive position in the market and scale back its expansion into new markets. Other examples of analysts uncovering a firm's bad news include firm misuse of off-balance sheet debt (e.g., Adelphia Communications), an overly aggressive capitalization policy (e.g., Charter Communications, Inc.), and the decreased profitability of firm foreign operations (e.g., Fore Systems, Inc.).

or delay its release (Kothari, Shu, and Wysocki 2009; Hong, Kim, and Welker 2017). In particular, prior studies find that investors recognize that managers can use financial reporting practices to hide bad news, which, in turn, leads to a higher likelihood of crash occurrence (Bradshaw, Hutton, Marcus, and Tehranian 2010; Kim and Zhang 2014; Kim, Li, Lu, and Yu 2016), and document that management earnings forecasts increase implied volatilities (Rogers, Skinner, and Van Buskirk 2009). Second, as analysts possess high-level financial skills and high-level information-searching ability, they generate firm-specific information beyond corporate disclosures that is used by both institutional and individual investors (Huang, Zang, and Zheng 2014). Prior studies find that analysts are a new source of information on various firm risks (Lui, Markov, and Tamayo 2007, 2012; Joos, Piotroski, and Srinivasan 2016; Bochkay and Joos 2017). Analysts also provide information on topics such as recent corporate events, business strategies, management team quality, competitiveness, and the macroeconomic environment (Asquith, Mikhail, and Au 2005; Huang et al. 2014; Huang, Lehavy, Zang, and Zheng 2018). In this regard, focusing on analysts allows us to examine how investors respond to a source of firm information from the broad perspective of financial analysts, rather than what firm managers directly reveal to the public (Batta, Qiu, and Yu 2016).

In this study, we focus on how analysts affect investors' forward-looking beliefs and preferences regarding a firm's future prospects; specifically, we investigate how analysts shape investors' assessment of a firm's future crash risk. We exploit brokerage mergers and/or closures that lead to an exogenous drop in analyst coverage. This setting can address potential endogeneity problems inherent in prior studies that use the number of analysts covering a firm as a proxy for the intensity of analysts' activities (Hong and Kacperczyk 2010). For example, analysts tend to cover firms with good prospects, thereby creating concerns of reverse causality. Moreover, unobservable firm heterogeneity, correlated with both analyst coverage and firm performance, could also bias the estimated results. These endogeneity problems could complicate the interpretation of findings in studies that examine the effect of analyst coverage.[3]

We use the steepness of the implied volatility smirk as our proxy for expected crash risk (Bollen and Whaley 2004; Xing, Zhang, and Zhao 2010; Van Buskirk 2011; Kim and Zhang 2014; Kim et al. 2016). Since options are priced based on *ex ante* risk, the implied volatility smirk gives an *ex ante* view of investors' assessment of future share price movements. In contrast, realized crash risk is not forward-looking, as it is based on realized crash events from historical data. Due to the so-called peso problem, actual realizations of crashes are too infrequent to be consistently observed and reflected in estimates drawn from the time-series of asset returns.[4] Since expected crash risk refers to investors' forward-looking beliefs, studying expected crash risk can solve the "peso problem" in measuring crash risk from realized return, and provide a more privileged view of the crash risks perceived by investors than realized crash risk (Aït-Sahalia, Wang, and Yared 2001; Santa-Clara and Yan 2010). Moreover, while expected crash risk refers to the mere possibility of extreme events, investors typically demand a substantially higher risk premium for expected crash risk than for realized crash risk; investors' perceived crash risk accounts for a significant fraction of historically observed equity and variance risk (Santa-Clara and Yan 2010; Bollerslev and Todorov 2011; Conrad, Dittmar, and Ghysels 2013). Thus, by focusing on the impact of an exogenous drop in analyst coverage on investors' expectation of future crashes, our study examines a consequence of analyst coverage that, regardless of how unlikely the crash is to materialize in the future, could have a profound impact on the financial market.

Prior studies suggest that the smirk curve reflects the risk of investors' expectation of future crashes, as well as their aversion to such crash risk (Bates 1991; Dumas, Fleming, and Whaley 1998; Pan 2002). When investors perceive a large drop in the share price, they can purchase portfolio insurance in the form of out-of-the-money (OTM) put options. This will increase the price of OTM put options relative to at-the-money (ATM) call options, leading to a steeper smirk. Moreover, recent studies suggest that investors are uncertainty-averse regarding crash events. Since crash events are rare, investors have very limited information from which to learn about these events. Investors, thus, fear that their estimations of crash likelihood and magnitude are incorrect, and this uncertainty about fundamentals leads them to act as if this were a worst-case scenario, which contributes to a steeper volatility smirk (Liu, Pan, and Wang 2005; Drechsler 2013).

In this paper, we argue that an exogenous drop in analyst coverage increases investors' expected crash risk. This is because such an event increases not only their assessment of the likelihood of future crashes, but also the uncertainty relating to this assessment and, therefore, investors are more likely to assess firms with loss of coverage as crash-prone. Specifically, analysts are not only a monitor of firm performance, but also an information intermediary. A drop in analyst coverage, thus, results in fewer analysts challenging managers' decisions directly (Chen, Harford, and Lin 2015) and less high-quality information produced by analysts that is useful for investors to decipher the consequences of managerial decisions (Hong and Kacperczyk 2010; Kelly and Ljungqvist 2012). In effect, this indicates an increase in agency costs and information asymmetries between

[3] As a demonstration of how this endogeneity problem could introduce bias, Hong and Kacperczyk (2010) show that, depending on the controls used, the impact of coverage on forecast optimism could switch from negative to positive.

[4] This term originates from the unusually large discount of Mexican pesos in the foreign currency forward market. Economists often use this term to refer to rational expectations of rare events that do not materialize in the sample. Refer to Sill (2000), Aït-Sahalia et al. (2001), Barro (2006), and Kim and Zhang (2014) for more details.

inside managers and outside investors. As a result of this, managers have a greater opportunity and ability to engage in value-destroying activities that increase the risk of corporate failure or defer to exercise an abandonment option for loss-making projects; managers are also better able to hoard bad news or delay timing of its release, for example, to reduce detection risk. Both of these increase the probability of future stock price crashes (Jin and Myers 2006; Bleck and Liu 2007).

Moreover, since a drop in analyst coverage reduces the level of high-quality information and, thus, increases uncertainty, investors are more likely to fear that they will underestimate the likelihood and magnitude of crash occurrences and act as if this were a worst-case perturbation. Since news of brokerage mergers and closures can easily reach investors through press releases and media outlets (Dyck, Morse, and Zingales 2010; Matsumoto, Pronk, and Roelofsen 2011), investors in the options market are able to identify firms affected by exogenous drops in analyst coverage and anticipate the negative consequences associated therewith. Consequently, they perceive such firms as more crash-prone. To protect themselves from the increased downside risk, these investors are likely to purchase portfolio insurance in the form of OTM put options, which leads to a steeper implied volatility smirk. We, thus, predict a positive relation between the analyst coverage drop and the steepness of the smirk.

Admittedly, it is possible that investors view analysts in a negative light. Prior studies suggest that analysts may issue biased reports to curry favor with management (e.g., Lin and McNichols 1998; Dechow, Hutton, and Sloan 1999). Analysts could also create excessive market pressure on management to distort earnings or to exacerbate managerial myopia that destroys firm value (e.g., Graham, Harvey, and Rajgopal 2005; He and Tian 2013). While ultimately an empirical question, these arguments work against our directional prediction that an exogenous drop in analyst coverage leads to an increase in expected crash risk.

To test our prediction, consistent with prior studies (e.g., Hong and Kacperczyk 2010; Kelly and Ljungqvist 2012; Irani and Oesch 2013, 2016; Chen et al. 2015), we first identify brokerage house mergers and closures staggered from 2000 to 2011. Our treatment sample consists of stocks that experienced an exogenous decrease in analyst coverage due to either brokerage house mergers or closures. To construct our control sample, we use propensity score matching (PSM), which matches each treated firm to a control firm based on the propensity score (i.e., the predicted likelihood of being treated). Employing a difference-in-differences design, we compare changes in investors' perceived crash risk for the treated firms around an exogenous drop in analyst coverage with those of control firms. By construction, there is no exogenous change in analyst coverage for our control firms during this period.

We find a significant increase in the *ex ante* perception of future crash risk for the underlying stock in the options market subsequent to exogenous drops in analyst coverage. This finding remains incrementally significant after controlling for the intensity of a firm's analyst coverage, the quality of a firm's information environment, and many other determinants known to influence investors' perceived crash risk (Dennis and Mayhew 2002). Overall, our results suggest that investors in the options market perceive analysts' roles of external monitoring and information intermediation to be a relevant factor for assessing an extreme negative tail risk of the underlying stock.

We next explore the settings in which we expect the analyst coverage-crash risk relation to vary across firms. We find that the impact of a drop in analyst coverage is more pronounced for firms with lower initial analyst coverage. These results suggest that a greater reduction in analyst coverage (relative to the pre-event coverage) engenders a greater fear of future crashes among investors. We further find that the impact of a drop in analyst coverage on investors' perceived crash risk is more pronounced when coverage is terminated by analysts who have more firm-specific or general experience, who have greater access to resources, and whose prior forecasts are more accurate than those of their peers. These results suggest that while generally valuing analysts' role of external monitoring and information intermediation, options market participants also consider analysts' discernible ability when assessing a firm's perceived crash risk.

Throughout our analyses, we use firm fixed effects regression to control for unobserved time-invariant firm-specific characteristics. We further conduct a variety of additional tests. We employ alternative measures of implied volatility smirk calculated using options with different maturities. We control for other proxies of financial reporting quality, including accrual quality, accounting conservatism and comparability, and management forecasts. Moreover, we reestimate our main results after controlling for merger and closure fixed effects. We also employ those firms that experienced brokerage merger events, but did not experience a drop in coverage, as an alternative control sample. Finally, we reestimate our main results using a two-stage least squares regression approach based on Yu's (2008) work. We find that our results are robust to these additional tests.

Our study contributes to the literature in several ways. First, our study investigates a consequence of analyst coverage not previously examined in the literature. While prior studies generally find that a drop in analyst coverage has negative financial effects, their focus is on the price risk (first moment) or variance risk (second moment). In contrast, our paper concerns tail risk—the third moment (e.g., Jin and Myers 2006; Kim, Li, and Zhang 2011a, 2011b; DeFond, Hung, S. Li, and Y. Li 2015). More importantly, our study is concerned with the value of option protection against such tail risk. Moreover, we examine tail risk from an *ex ante* perspective. We show that analyst coverage affects investors' forward-looking beliefs about a firm's future crashes. Prior studies show that investors typically demand a substantially higher risk premium for expected crash risk than for realized crash risk; investors' perceived crash risk accounts for a significant fraction of historically observed equity and variance risk. Our results are, therefore, relevant to regulators and academics, who have underscored the importance of understanding and removing the perception of tail risk since the advent of the 2008 financial crisis.

Second, we contribute to a growing body of research on *ex ante* expected crash risk as reflected in options implied volatility smirk. Of late, few studies have examined, as a determinant of the smirk, a firm's financial reporting quality, including accrual quality (Kim and Zhang 2014) and financial statement comparability (Kim et al. 2016).[5] Our study differs from these studies in that it focuses on analysts who (1) are a significant source of corporate information external to a firm, (2) play an important role in propagating bad news that managers tend to hoard and obfuscate or delay its release to the public, and (3) can provide information beyond and above corporate disclosures. Our analysis suggests that investors in the options market do recognize analysts as important gatekeepers who can deter managers from engaging in bad news hoarding and other value-destroying activities, and this influences investors' perception of the underlying stock's future crash risk.

Third, we contribute to the literature that examines analyst attributes. The majority of prior studies focus on how these characteristics affect the quality of analysts' decision outputs, such as forecast error and dispersion (e.g., Stickel 1995; Clement and Tse 2003, 2005). Our study suggests that the expertise and resources of analysts are valued by options market participants.

Finally, we contribute to prior studies that link analysts to the options market (Hayunga and Lung 2014; Lin and Lu 2015).[6] Our study provides evidence on the role of analysts in shaping crash risk perceived by options market participants.

II. RELATED LITERATURE AND HYPOTHESES

Informational and Monitoring Roles of Analysts

The literature has long recognized analysts' roles in both information intermediation and external monitoring that curb managerial opportunism. As an important source of corporate information, analysts specialize in gathering information from both public resources and private research, and processing, interpreting, and disseminating it so that investors can easily understand it. Analysts, therefore, often provide information that is beyond corporate disclosure and not available otherwise to the market. Lui, Markov, and Tamayo (2007, 2012) show that analysts are a substantive source of new information about priced risk and investment risk. Compared with credit rating changes, equity risk rating changes are timelier and have a larger overall stock price impact (Lui et al. 2012). Joos et al. (2016) find that analysts' forecasts of risk spread not only capture a firm's operational riskiness, but also predict future changes in a firm's fundamentals. Analysts recalibrate their assessment by taking into account changes in the firm's systematic risk exposure. Using textual analysis, prior studies find that analyst reports also include textual discussions on a firm's current and future performance, management team quality, business strategies, and firm competitiveness (Asquith et al. 2005; Huang et al. 2014). Examining the thematic content of analyst reports and corporate earnings conference calls, Huang et al. (2018) find that analysts discuss exclusive topics beyond those from the conference calls and interpret topics from the conference calls.

Because of their role in information intermediation, analysts can not only monitor managers directly, but also reduce information asymmetry between inside managers and outside investors, which, in turn, facilitates external monitoring by outside investors. Dyck et al. (2010) find that analysts have played a major role in detecting corporate fraud in firms such as Compaq, Gateway, Motorola, and PeopleSoft. Yu (2008) documents a negative relation between analyst following and earnings management. Of late, several studies have used brokerage house mergers and/or closures as settings that generate an exogenous variation in analyst coverage. These studies find that a drop in analyst coverage causes an increase in the cost of capital (Kelly and Ljungqvist 2012) and earnings management (Irani and Oesch 2013), brings about a decrease in investment efficiency (Chen et al. 2015), weakens investment and financing activities (Derrien and Kecskes 2013), and reduces stock liquidity (Balakrishnan, Billings, Kelly, and Ljungqvist 2014).

Moreover, prior studies suggest that analysts are particularly important in propagating bad news (Hong et al. 2000b; Ivkovic and Jegadeesh 2004; Asquith et al. 2005; Huang et al. 2014). For various reasons, including career concerns and incentive compensation structure, managers tend to accelerate the release of good news and withhold or delay the release of bad news (Li 2008; Kothari et al. 2009). This asymmetric disclosure by managers means that investors are less likely to have advance knowledge of a firm's bad news and more likely to rely on unfavorable content in the analyst reports (Huang et al. 2014).

[5] Early studies have examined various firm-specific fundamental factors as determinants of the implied volatility skewness or smirk (e.g., Dennis and Mayhew 2002).

[6] Hayunga and Lung (2014) find abnormal option trading volumes prior to and in the direction of analyst revisions. Lin and Lu (2015) find stronger predictive power of options on stock returns prior to wide distributions of analyst research.

Ex Ante Stock Price Crash Risk

In finance, investors' perceived crash risk is often indicated by the options implied volatility smirk curve (e.g., Bates 1991; Dumas et al. 1998; Pan 2002). This smirk curve, discovered since the crash of October 1987, refers to the smirk pattern when the volatilities implied by observed option prices are plotted against strike prices (Rubinstein 1994). The smirk curve suggests that the implied volatility of low strike price options, especially OTM put options, is higher than that of high strike price options, especially ATM call options. This asymmetric volatility implies that OTM put options are more expensive than ATM call options, which is a direct departure from the Black and Scholes (1973) option pricing model.

There are various explanations for this asymmetry, but the overall smirk curve is widely deemed to reflect the risk of investors' expectation of future crashes, as well as their aversion to such crash risk (Bates 1991; Dumas et al. 1998; Pan 2002). Rubinstein (1994) attributes the volatility skew to investors' crash-phobia following the crash of 1987. Bollen and Whaley (2004) propose a buying pressure model and argue that when investors obtain the likelihood of a negative event, the demand for OTM put options increases relative to ATM call options, resulting in volatility skew. Bates (2000) proposes a jump-diffusion model to explain the likelihood of crash risk for the aggregate market, offering a more straightforward explanation of the smirk curve. Specifically, Bates (2000) argues that the implied volatility smirk reflects investors' perception that a significant price decline in the underlying asset is more likely. OTM put options provide explicit portfolio insurance against substantial downward movements in the market, and have been traded at high prices relative to ATM call options (Bates 2000, 2008).

Further, recent studies suggest that, in addition to considering the likelihood of crash risk, investors also factor into their decision the possibility that the estimated model for the crash event may not be correct. As crash events are rare, investors have extremely limited information through which to learn about these events. Investors, thus, fear underestimating crash likelihood and magnitude, and act as if it were a worst-case scenario; this time variation in investor uncertainty about fundamentals contributes to the steep volatility skew (Liu et al. 2005; Drechsler 2013).

Link between Analyst Coverage Drop and *Ex Ante* Crash Risk

This study examines whether analyst coverage matters in shaping investor perceptions of crash risk using broker mergers and closures as settings that generate an exogenous variation in analyst coverage. Following a merger or closure of brokerage houses, a number of analysts are usually dismissed, causing some firms to be followed by fewer analysts than before the merger or closure.

We argue that an exogenous drop in analyst coverage increases investors' expected crash risk, because such an event increases not only investors' assessment of the likelihood of future crashes, but also the uncertainty relating to this assessment. Since analysts are both important monitors and information intermediaries, a drop in analyst coverage reduces not only the number of analysts to challenge managers' decisions directly (Chen et al. 2015), but also the level of information available for investors to decipher managers' decisions (Kelly and Ljungqvist 2012). Further, Hong and Kacperczyk (2010) suggest a disciplinary effect of competition among analysts in analyst forecasts, finding that a drop in the number of analysts reduces competition, which increases forecast bias. Thus, because of an exogenous drop in analyst coverage, both the agency costs and information asymmetry between inside managers and outside investors increase. With this weakened monitoring by analysts and investors, managers have a greater opportunity to engage in value-destroying activities that increase the risk of corporate failure, or defer the timing of exercising an abandonment option for loss-making projects. Managers are also better able to hoard bad news or delay timing of its release, for example, to reduce detection risk, thereby increasing the probability of future stock price crashes (Jin and Myers 2006; Bleck and Liu 2007). Moreover, as a drop in analyst coverage reduces the level of high-quality information, which increases uncertainty, investors are more likely to fear that they will underestimate the likelihood and magnitude of crash occurrences and, thus, are more likely to act as if this were a worst-case perturbation (Liu et al. 2005; Drechsler 2013).

Since news of brokerage mergers and closures can easily reach investors through press releases and media outlets, investors may be acutely aware of the increased uncertainties and reduced monitoring of managers' decisions associated with the resulting drop in analyst coverage. For example, New York Stock Exchange Rule 472(f)(5) and NASD Rule 2711(f)(5) specifically require that a brokerage firm inform its clients of its coverage termination, including the rationale behind such termination. Investors could, therefore, perceive that firms experiencing declines in analyst coverage are likely to engage more aggressively in bad news hoarding and other value-destroying activities and, thus, have a higher probability of future crash occurrences. Investors could also worry about underestimating the crash probability and magnitude for firms that lose analyst coverage. Therefore, investors are likely to assess these firms as crash-prone and purchase OTM put options to insure themselves against the increased downside risk, increasing the price of OTM put options relative to ATM call options (steeper smirk). To provide systematic evidence on this prediction, we propose and test the following hypothesis in alternative form.

H: A decrease in analyst coverage increases a firm's *ex ante* expected crash risk perceived by investors in the options market, all else equal.

On the contrary, it is possible that investors view analysts in a negative light, rather than as an external monitor. Prior studies suggest that analysts may issue biased reports to satisfy the needs of the firm they cover (e.g., Lin and McNichols 1998; Dechow et al. 1999; Michaely and Womack 1999; O'Brien, McNichols, and Lin 2005; James and Karceski 2006). Further, analysts are often accused of being responsible for creating excessive market pressure on management to distort earnings.[7] He and Tian (2013) suggest that analysts impose short-term pressure on managers, which exacerbates managerial myopia and impedes firm innovation. Although it is ultimately an empirical question, the view that increasing analyst coverage destroys firm value, if supported, would introduce a conservative bias into our results against finding a positive relation between a drop in analyst coverage and perceived crash risk.

III. SAMPLE AND RESEARCH DESIGN

Sample

To test our prediction, we employ a sample identification strategy consistent with prior studies (Hong and Kacperczyk 2010; Kelly and Ljungqvist 2012; Derrien and Kecskes 2013; Irani and Oesch 2013; Chen et al. 2015). We first identify brokerage house mergers and closures between 2000 and 2011. Both brokerage mergers and closures directly reduce a firm's analyst coverage, but are triggered by the business strategy considerations of the brokers themselves and are, thus, exogenous to the heterogeneous characteristics of the individual firms the brokerage houses cover. Specifically, we use Thomson's SDC Mergers and Acquisitions database to construct a list of brokerage merger events between 2000 and 2011. We require these merger events to have taken place in an industry in which the Standard Industrial Classification (SIC) codes of both the acquirer and the target are 6211 ("Investment Commodity Firms, Dealers, and Exchanges"). We restrict our analysis to completed deals and deals in which 100 percent of the target was acquired. We then manually match all the mergers with brokerage houses in the Institutional Brokers' Estimate System (I/B/E/S) data and retain only those mergers where both merging houses have overlapping coverage, that is, analysts covering at least two of the same stocks. To identify brokerage closures, we use the I/B/E/S database to construct a list of brokers that disappeared from the database between 2000 and 2011. We manually check press releases and various databases and websites to confirm that the brokerage disappearance was due to closure and to identify closure dates.[8] Our list of broker disappearances includes all of Hong and Kacperczyk's (2010) broker mergers and all of Kelly and Ljungqvist's (2012) broker closures during our sample period. In total, we obtain 35 broker merger and 32 broker closure events.[9]

We then identify our treatment sample of unique stocks that experienced an exogenous decrease in analyst coverage due to either broker mergers or closures. We merge broker merger and closure dates with the I/B/E/S unadjusted historical detail dataset. Since the other brokerages can make up for the diminished research resulting from analysts disappearing due to broker mergers and closures and, subsequently, decreased firm monitoring, we aim to select a time window that captures only the direct effects of the exogenous drop in analyst coverage. We select a two-year window consisting of one year (365 days) prior to the merger or closure and one year (365 days) following the merger or closure. For firms that experienced a brokerage merger, we identify treated firms as those that were covered by both merging houses during the one-year window before the merger date and continued to be covered by the remaining brokerage house during the one-year window after the merger date. For firms that experienced brokerage closure, we identify treated firms as those that were covered by the closed broker during the one-year window before the closure date and remained in the I/B/E/S sample during the one-year window after the closure date. To ensure that the drop in coverage is exogenous, we also search the I/B/E/S stop file and only retain firms whose coverage did not stop before the merger or closure date. We exclude firms that are financials or utilities. We require each treatment firm-year observation to have the necessary data from the Center for Research in Security Prices (CRSP), OptionMetrics, Compustat, and I/B/E/S to calculate our measure of *ex ante* expected crash risk and a battery of control variables. The process results in 2,156 treatment firm-year observations. Further, if a firm is affected by more than one merger or acquisition during our sample period, we retain only firm-year observations affected by the first broker merger or closure in a

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[7] Many studies show that beating or meeting analyst forecasts is a major reason for earnings management (Degeorge, Patel, and Zeckhauser 1999; Kasznik 1999; Abarbanell and Lehavy 2003; Graham et al. 2005).

[8] For each broker, we first search BrokerCheck, a search engine for information on brokerage firms on the Financial Industry Regulatory Authority website, to check a brokerage's termination status and termination date. We then verify this information by searching historical press releases in Factiva, Bloomberg Businessweek, and Google and Google archives.

[9] We do not include Lehman in our sample because it is not suitable for identification purposes (Kelly and Ljungqvist 2012; Chen et al. 2015). Untabulated test results show that all our results hold if we further exclude Bear Stearns.

series, to eliminate the potential confounding effect of past broker terminations. This process further reduces the number of our treatment firm-year observations to 837.

To minimize the possibility of variations in analyst coverage and in expected crash risk being caused by other variables that affect both analyst coverage and expected crash risk, we employ PSM to match each treated firm to a control firm in the same industry and same year using the closest propensity score. Specifically, we estimate a logistic regression of an indicator variable of whether a particular firm-year is classified as treated by our matching variables. The matching variables are firm characteristics that prior studies use to control for *ex ante* differences between treated and control firms (e.g., Hong and Kacperczyk 2010; Irani and Oesch 2013, 2016; Chen et al. 2015). These characteristics include total assets (*ASSET*), the market-to-book ratio (*MB*), abnormal accruals (*ACCM*), return on assets (*ROA*), operating cash flow (*OANCF*), stock return (*RET*), and analyst coverage (*COVERAGE*). Appendix A provides detailed definitions of these variables. The predicted probability of a firm being treated (i.e., propensity score) is used to conduct one-to-one firm matching. Our final sample consists of 690 pairs of treated firms and matched control firms.

Measuring Firm-Specific *Ex Ante* Expected Crash Risk

The steepness of the options implied volatility smirk curve has been widely recognized as an indicator of investors' expected crash risk. Consistent with prior research (Bollen and Whaley 2004; Xing et al. 2010; Van Buskirk 2011; Kim and Zhang 2014; Kim et al. 2016), we measure the implied volatility smirk (IV_SKEW_{it}) of stock *i*'s option as the difference between the implied volatility of an OTM put on day *t* ($IV^{OTMP}{}_{it}$) and that of an ATM call ($IV^{ATMC}{}_{it}$) on the same day:

$$IV\_SKEW_{it} = IV^{OTMP}{}_{it} - IV^{ATMC}{}_{it} \tag{1}$$

When there are multiple put or call option contracts for stock *i* on a particular day *t,* we calculate the weighted average of the implied volatilities for the put or call options, using the option open interest (*OPEN_INT*):

$$IV\_SKEW_{it} = \frac{\sum_j OPEN\_INT_j \times IV^{OTMP}_{it\,j}}{\sum_j OPEN\_INT_j} - \frac{\sum_k OPEN\_INT_k \times IV^{ATMC}_{it\,k}}{\sum_k OPEN\_INT_k} \tag{2}$$

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. Following Kim and Zhang (2014) and Kim et al. (2016), we average the daily *IV_SKEW* over the 12-month period ending three months after the fiscal year-end to mitigate potential problems associated with measurement error inherent in a daily measure.[10] Appendix B provides more details of the procedure used to calculate *IV_SKEW*.

Empirical Model

We employ a difference-in-differences design that compares changes in *ex ante* crash risk for treatment firms versus control firms from one year prior to the drop in analyst coverage to one year after the drop. We estimate the following model, which is consistent with prior studies (Dennis and Mayhew 2002; Bradshaw et al. 2010; Van Buskirk 2011; Kim and Zhang 2014; Kim et al. 2016):

$$\begin{aligned} IV\_SKEW_{it} = {} & \beta_0 + \beta_1 TREATED_{it} + \beta_2 AFTERDROP_{it} + \beta_3 AFTER_{it} + \beta_4 SIZE_{it} + \beta_5 LEV_{it} + \beta_6 MB_{it} + \beta_7 IDOSY\_VOL_{it} \\ & + \beta_8 ATM\_IV_{it} + \beta_9 CASHFLOW\_VOL_{it} + \beta_{10} EARNINGS\_VOL_{it} + \beta_{11} SALES\_VOL_{it} + \beta_{12} STOCK\_TURN_{it} \\ & + \beta_{13} BETA_{it} + \beta_{14} TOTAL\_VOL_{it} + \beta_{15} NCSKEW_{it} + \beta_{16} RET_{it} + \beta_{17} ACCM_{it} + \beta_{18} COVERAGE_{it} \\ & + \sum_j Industry\ Fixed\ Effects + \varepsilon_{it} \end{aligned} \tag{3}$$

where *IV_SKEW* is our proxy for *ex ante* crash risk; *TREATED* is an indicator variable that indicates if a firm is part of our treatment sample; and *AFTER* is an indicator variable that is equal to 1 in the period after the merger or closure, and 0 otherwise. Our variable of interest, *AFTERDROP,* is equal to *TREATED* times *AFTER* (*TREATED* × *AFTER*). The coefficient on *AFTERDROP* captures the incremental change in *ex ante* expected crash risk for firms in the treatment sample (as captured by the steepness of the smirk curve) in the post-period of one year after a drop in analyst coverage relative to the change for

[10] Expected crash risk represents investors' forward-looking beliefs and preferences. We include the three months after the fiscal year-end to ensure that the current fiscal year's data are available to outside investors. Untabulated tests show that our results are qualitatively similar if we measure our independent variables at *t*–1.

firms in the benchmark sample in the same period. A positive and significant coefficient for *AFTERDROP* ($\beta_2 > 0$) supports our hypothesis that a decrease in analyst coverage increases a firm's stock price crash risk as perceived by investors in the options market.

We include a set of control variables known to affect the implied volatility smirk. *SIZE* is the log of the market value of equity, which is found to affect volatility (Pástor and Veronesi 2003), realized crash risk (e.g., Chen, Hong, and Stein 2001), and credit risk (Beaver, McNichols, and Rhie 2005). *LEV* is total long-term debt divided by total assets, which is found to be associated with bankruptcy risk (Beaver et al. 2005) and implied volatility smirk (Toft and Prucyk 1997). *MB* is the market value of equity divided by the book value of equity, which is found to be related to bubbles, an indicator of crash proneness (Harvey and Siddique 2000; Chen et al. 2001). *IDOSY_VOL* is a firm's idiosyncratic volatility, calculated as the standard deviation of weekly firm-specific stock returns over the fiscal year. *TOTAL_VOL* is stock return volatility, calculated as the standard deviation of the weekly stock return over the fiscal year. *IDOSY_VOL* and *TOTAL_VOL* are found to make a firm more crash-prone in the future (Chen et al. 2001). *ATM_IV* is the average daily implied volatility of ATM options over the fiscal year, which is found to affect expected crash risk (Dennis and Mayhew 2002). Cash flow volatility (*CASHFLOW_VOL*), earnings volatility (*EARNINGS_VOL*), and sales volatility (*SALES_VOL*) are used to proxy for operating uncertainty. Pástor and Veronesi (2003) find that a firm's stock return volatility is affected by the uncertainty of the firm's profitability. *CASHFLOW_VOL* is the standard deviation of operating cash flows scaled by lagged total assets over the preceding five years. *EARNINGS_VOL* is the standard deviation of earnings before extraordinary items scaled by lagged total assets over the preceding five years. *SALES_VOL* is the standard deviation of sales revenue scaled by lagged total assets over the preceding five years. *NCSKEW* represents a firm's past crash, measured as the negative skewness of firm-specific weekly returns over the fiscal year period. A firm's past crash could decrease the probability of a future crash on one hand (Jin and Myers 2006), and increase investors' aversion to future crash risk on the other hand (Bates 2000). *STOCK_TURN* is average stock turnover, measured as the average monthly share turnover over the fiscal year. *STOCK_TURN* proxies for investors' belief heterogeneity, found to be associated with more negatively skewed stock returns (Hong and Stein 2003). The firm's market beta, *BETA,* is included as a control for market risk, which is found to be associated with steeper implied volatility smirk (Dennis and Mayhew 2002; Duan and Wei 2009; Bradshaw et al. 2010). *RET* is a firm's past return, measured as the yearly stock return over the fiscal year. Chen et al. (2001) suggest that high past returns could indicate a bubble being built up, which makes a firm more crash-prone. However, Bradshaw et al. (2010) and Van Buskirk (2011) find a negative relation between historical return and the slope of implied volatility. *ACCM* is a firm's financial reporting opacity, measured as the prior three-year moving sum of the absolute value of discretionary accruals, estimated from the modified Jones model (denoted *OPAQUE* by Hutton et al. [2009]). *ACCM* is found to be related to a firm's realized crash risks (Hutton et al. 2009) and investors' perceived crash risk (Kim and Zhang 2014). Following prior studies using brokerage house closure and/or mergers as settings to study the impact of analyst coverage (e.g., Irani and Oesch 2013, 2016; Balakrishnan et al. 2014), we also control for analyst coverage, *COVERAGE,* measured as the log of 1 plus the number of analysts following.

IV. EMPIRICAL RESULTS

Descriptive Statistics

After applying the PSM procedures mentioned earlier, we obtain a sample of 690 matched pairs of treated and control firms to test the effect of analyst coverage drop on *ex ante* expected crash risk. Panel A of Table 1 presents the two covariate balance metrics on the seven matching variables measured in the year prior to the analyst drop (*ASSET, MB, ACCM, ROA, OANCF, RET,* and *COVERAGE*). Recall that these seven variables are included in the logistic regression model that predicts the likelihood of a particular firm-year being classified as treated. As shown in the third column of Panel A, the mean differences in all seven variables between the treated and control firms are insignificant. As shown in the last column of Panel A, L_1 for each of the seven matching variables is closer to 0 than to 1, indicating that both treated and control firms have similar univariate distributions (Iacus, King, and Porro 2011; DeFond, Erkens, and Zhang 2017).[11] Overall, the imbalance metrics suggest that our PSM matching is successful in the sense that, with respect to firm characteristics in the year prior to analyst drop, the treated firms are, on average, statistically indistinguishable from their matched control firms. Stated differently, PSM successfully controls for *ex ante* differences in these firm characteristics between treated and control firms.

[11] L_1 measures the difference between the histogram of each of the seven matching variables, which is calculated as the absolute difference between the relative empirical frequencies of the treated observations for a particular bin minus the relative empirical frequency of the control observation in that bin, summed over all bins. L_1 takes all dimensions of the covariates' distribution into account, and it ranges between 0 and 1, where 0 indicates identical distributions between treatment and control and 1 indicates no overlap in the distributions.

TABLE 1

Descriptive Statistics

Panel A: Descriptive Statistics of 690 Pairs of Treated and Control Firms in the Year Prior to the Analyst Drop, Identified by PSM

	Mean			Imbalance Univariate
	Treated Firms	Control Firms	t-statistics	L_1
ASSET	7.364	7.086	0.70	0.07
MB	4.916	4.216	1.02	0.04
ACCM	0.201	0.192	0.34	0.04
ROA	0.066	0.052	0.49	0.05
OANCF	0.136	0.121	0.80	0.05
RET	0.168	0.188	−0.14	0.05
COVERAGE	2.638	2.534	0.96	0.05

Panel B: Descriptive Statistics for the Full Sample (n = 2,760)

	Mean	SD	p25	Median	p75
IV_SKEW	0.046	0.028	0.028	0.041	0.059
SIZE	7.629	1.424	6.601	7.485	8.520
LEV	0.197	0.183	0.011	0.169	0.328
MB	3.959	4.060	1.763	2.727	4.538
IDOSY_VOL	0.057	0.027	0.037	0.050	0.069
ATM_IV	0.490	0.182	0.356	0.455	0.595
CASHFLOW_VOL	0.091	0.119	0.033	0.057	0.104
EARNINGS_VOL	0.100	0.176	0.024	0.048	0.105
SALES_VOL	0.320	0.381	0.105	0.197	0.372
STOCK_TURN	0.254	0.214	0.120	0.193	0.325
BETA	1.124	0.569	0.721	1.060	1.482
TOTAL_VOL	0.069	0.032	0.046	0.061	0.085
NCSKEW	−0.365	0.860	−0.899	−0.366	0.140
RET	0.158	0.619	−0.237	0.053	0.396
ACCM	0.176	0.172	0.080	0.131	0.214
COVERAGE	2.509	0.760	2.197	2.565	2.996

This table reports the descriptive statistics for the sample used for the *ex ante* expected crash risk test. Panel A reports descriptive statistics of 690 pairs of treated and control firms in the year prior to the analyst drop with available data for all dependent and control variables, identified by PSM. Panel B reports descriptive statistics for the regression sample.
See Appendix A for variable definitions.

Panel B of Table 1 presents descriptive statistics on all the variables included in Equation (3) for the full sample of both treated and control firms. All continuous independent variables are winsorized at the bottom and top 1 percent. This sample consists of 2,760 firm-year observations. Overall, the distributional properties of all the variables are largely similar to those reported in previous studies (e.g., Hutton et al. 2009; Kim et al. 2011a; Kim and Zhang 2014; Kim et al. 2016).

Test of Hypothesis

We begin by performing a univariate difference-in-differences test to see if our hypothesis is supported. As shown in Table 2, the mean values of our measure of investors' perceived crash risk, *IV_SKEW,* in the year before the drop in analyst coverage, are 0.041 and 0.040 for the treated and control firms, respectively. The difference in means is insignificant, with a t-statistic of 0.53, suggesting no significance difference in expected crash risk in the year before the brokerage mergers or closures. During the year after the drop in analyst coverage, *IV_SKEW* for the treated firms increases by 0.013, to a mean of 0.054, while it increases only slightly for the control firms, by 0.009, to 0.050. The difference-in-differences of 0.004 is statistically significant

TABLE 2

The Effect of a Decrease in Analyst Coverage on Expected Crash Risk: Univariate Difference-in-Differences Test

	IV_SKEW			
	Mean			
	Before (*AFTER* = 0)	**After (*AFTER* = 1)**	**Diff.**	**t-stat**
Treated Firms	0.041	0.054	0.013***	8.79
Control Firms	0.040	0.050	0.009***	6.33
Diff.	0.001	0.004***	Diff. in Diff. = 0.004***	
t-stat	0.53	2.70	t-stat = 3.95	
n = 690 pairs				

***, **, * Indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.
This table reports the mean of expected crash risk, *IV_SKEW,* for the balanced sample of the treated and control firms for the year before and after an exogenous drop in analyst coverage, and the differences in the mean.
See Appendix A for variable definitions.

(t = 3.95). In terms of economic significance, a drop in analyst coverage in our treatment sample results in an additional increase in *IV_SKEW* of 8.70 percent, or by about 14.28 percent of one standard deviation,[12] compared with that of control firms during the same period. This result supports our hypothesis that a decrease in analyst coverage increases *ex ante* crash risk perceived in the options market.

We next extend the difference-in-differences test using multivariate regression in Equation (3), using the PSM pair sample (n = 2,760). Table 3 reports the regression results. Note that firm fixed effects are not included in column (1), but are in column (2).[13]

Across both specifications (columns (1) and (2) in Table 3), the coefficients of *AFTERDROP,* β_2, are positive and statistically significant. These results support our hypothesis, suggesting that investors perceive a firm that experiences a drop in analyst coverage to be crash-prone, thereby increasing their assessment of the firm's future crash likelihood in the post-merger/closure period.

The coefficient estimates of the control variables shown in the first and second columns of Table 2 are generally consistent with those reported in prior studies (e.g., Chen et al. 2001; Dennis and Mayhew 2002; Hong and Stein 2003; Kim and Zhang 2014; Kim et al. 2016).

In summary, we find strong and reliable evidence suggesting that investors in the options market perceive a drop in analyst coverage as an important factor that increases the underlying stock's downside risk in general, and negative tail risk or crash risk in particular.

High versus Low Initial Analyst Coverage

The number of financial analysts who track and make earnings forecasts differs across firms. According to the Cournot view of competition (Hong and Kacperczyk 2010), the lower the number of analysts covering a firm, the greater the weight each analyst carries. If a firm is covered by fewer analysts initially, then the loss of one represents a greater percentage drop and should, therefore, have a greater influence on the firm's subsequent actions. Thus, if a drop in analyst coverage increases investors' perceived crash risk, then such an effect should be more pronounced for a firm experiencing a greater reduction in analyst coverage, since these firms are more likely to alter their behavior. To test our prediction, we test for differences in the effects of a drop in analyst coverage for high versus low initial analyst coverage. Specifically, we construct an indicator, *ANA_INITIAL,* that equals 1 if the number of analysts covering a firm in the initial year of our sample period is *below* the industry median, and 0 otherwise.[14] We include *ANA_INITIAL* and the interaction between *ANA_INITIAL* and *AFTERDROP* in Equation (3).[15]

[12] These figures are obtained by dividing 0.004 by the sample mean (0.046) and standard deviation (0.028) of *IV_SKEW* shown in Table 1.
[13] In the firm fixed effect regressions, we omit *TREATED,* which is an indicator variable used to control for the fixed difference between treated and control firms.
[14] We also rerun our cross-sectional variation tests in Section IV on partitioned subsamples and find qualitatively similar results.
[15] Our results are qualitatively similar if we use an indicator, *HPCT_DROP,* that equals 1 if the percentage drop in analyst coverage that a treated firm experienced is above the industry median, and 0 otherwise.

TABLE 3

The Effect of a Decrease in Analyst Coverage on Expected Crash Risk

	Dependent Variable = *IV_SKEW*	
	(1)	**(2)**
TREATED	−0.001	
	(−0.74)	
AFTERDROP	0.004***	0.004**
	(2.74)	(2.23)
AFTER	0.008***	0.008***
	(5.90)	(6.00)
SIZE	−0.001	−0.006***
	(−1.38)	(−4.07)
LEV	0.016***	0.025***
	(5.41)	(3.32)
MB	0.000***	−0.000
	(2.67)	(−1.25)
IDOSY_VOL	−0.147*	−0.561***
	(−1.65)	(−6.56)
ATM_IV	0.014	0.018*
	(1.47)	(1.87)
CASHFLOW_VOL	0.010	0.007
	(1.42)	(0.52)
EARNINGS_VOL	−0.007	0.014
	(−0.82)	(1.58)
SALES_VOL	0.003	0.002
	(1.64)	(0.63)
STOCK_TURN	0.016***	0.027***
	(5.37)	(5.61)
BETA	0.004***	0.001
	(3.14)	(0.65)
TOTAL_VOL	0.217**	0.564***
	(2.31)	(6.37)
NCSKEW	−0.001	0.000
	(−1.32)	(0.14)
RET	−0.003***	−0.001
	(−3.47)	(−1.20)
ACCM	0.004	−0.004
	(0.78)	(−0.75)
COVERAGE	−0.000	0.001
	(−0.47)	(0.70)
Constant	0.014	0.057***
	(1.56)	(4.23)
Industry Fixed Effects	Yes	No
Firm Fixed Effects	No	Yes
Adjusted R^2	0.345	0.240
No. of Observations	2,760	2,760

***, **, * Indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

This table reports the regression results of the impact of an exogenous drop in analyst coverage on a firm's expected stock crash risk. All continuous independent variables are winsorized at the top and bottom percentile. t-statistics are shown in parentheses.

See Appendix A for variable definitions; see Appendix B for detailed definition of *IV_SKEW*.

TABLE 4

The Effect of a Decrease in Analyst Coverage on Expected Crash Risk
High versus Low Initial Analyst Coverage

	Dependent Variable = *IV_SKEW*	
	(1)	**(2)**
TREATED	−0.001	
	(−0.73)	
AFTERDROP	0.007***	0.008***
	(2.96)	(3.28)
AFTERDROP × *ANA_INITIAL*	0.005**	0.006**
	(2.05)	(2.41)
ANA_INITIAL	−0.004	
	(−0.78)	
AFTER	0.008***	0.008***
	(5.89)	(6.03)
Control Variables	Yes	Yes
Industry Fixed Effects	Yes	No
Firm Fixed Effects	No	Yes
Adjusted R^2	0.264	0.243
No. of Observations	2,760	2,760

***, **, * Indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.
This table reports the regression results of the impact of an exogenous drop in analyst following on a firm's expected crash risk for firms with high versus low initial analyst coverage. *ANA_INITIAL* equals 1 if the number of analysts covering a firm in the initial year of our sample is below the industry median, and 0 otherwise. All continuous independent variables are winsorized at the top and bottom percentile. t-statistics and z-statistics are shown in parentheses. See Appendix A for the other variable definitions.

As shown in Table 4, the coefficients of *AFTERDROP* × *ANA_INITIAL* are positive and significant at the 5 percent level. These results suggest that the positive impact of a drop in analyst coverage on investor-perceived crash risk is stronger for firms with lower initial coverage, consistent with our prediction that such firms suffered a relatively greater loss of scrutiny.

Coverage Termination of High- versus Low-Ability Analysts

Prior studies suggest that analysts differ in their ability to collect and analyze information, leading to systematic differences in forecasting and recommendation performance among analysts (e.g., Stickel 1995; Mikhail, Walther, and Willis 1997; Clement 1999; Jacob, Lys, and Neale 1999; Hong, Kubik, and Solomon 2000a; Drake and Myers 2011; Bradley, Gokkaya, and Liu 2017; Bradshaw, Lee, and Peterson 2016). The general view is that compared with analysts of low ability, high-ability analysts have superior access to private information and, thus, are better able to identify and process complex information. Therefore, if the previously documented positive relation between a drop in analyst coverage and investors' perceived crash risk is due to investors valuing analysts' ability to deter managerial opportunism and to reduce uncertainty faced by investors when estimating crash risk, then one can expect the relation between the two to be stronger for firms with coverage termination of higher-ability analysts.

We rely on numerous measures to proxy for analysts' ability or expertise, including their general and firm-specific forecasting experience, the size of their employer (brokerage size), and their prior forecast accuracy. Generally, more general and firm-specific forecasting experience makes analysts better at recognizing economic trends and understanding the idiosyncrasies of a particular firm's reporting practices, and allows analysts to gain better access to insiders. A larger brokerage size indicates that analysts gain access to superior resources and obtain better administrative support. These attributes, therefore, contribute positively to their forecasting performance (e.g., Stickel 1992; Clement 1999; Jacob et al. 1999; Mikhail, Walther, and Willis 2003; Drake and Myers 2011).

We discern terminated coverage based on the analysts' attributes mentioned above. Specifically, for each treated firm, we first identify the "lost analysts" due to either brokerage house mergers or closures. We then classify the sample of treated firms into two subsamples based on exogenous termination of coverage by various analyst attributes. Consistent with prior studies (e.g., Mikhail et al. 1997, 2003; Clement 1999; Clement and Tse 2005; Kumar 2010; Jiang, Kumar, and Law 2016), we first measure an analyst's firm-specific experience by using the number of years through year *t* for which the analyst supplied at least one forecast for firm *j*. Second, we measure an analyst's general experience by using the number of years through year *t* for which the analyst supplied at least one forecast for any firm. Third, we measure an analyst's prior forecast accuracy by using the analyst's prior-year forecast accuracy for firm *j,* calculated as the absolute value of the analyst's forecast error for the firm in year $t-1$, scaled by the beginning stock price. Fourth, we measure an analyst's access to resources, using the number of analysts employed by the analyst's brokerage.

We then construct a set of indicator variables. Specifically, *HFIRM_EXP* indicates a high level of firm-specific experience, which equals 1 if the lost analysts' firm-specific experience with the treated firm in the year before coverage termination is above the industry median, and 0 otherwise. *HGE_EXP* indicates a high level of general experience, which equals 1 if the lost analysts' general experience with the treated firm in the year before the coverage termination is above the industry median, and 0 otherwise. *HACCURACY* indicates high forecast accuracy, which equals 1 if the lost analysts' forecast accuracy of the treated firm in the year before the coverage termination is above that of the other analysts covering the same firm, and 0 otherwise.[16] *HRESOURCE* indicates a high level of analyst resources, which equals 1 if the lost analysts' brokerage house size is above the industry median, and 0 otherwise. We include each of these indicators and its interaction with *AFTERDROP* in Equation (3) separately.

As shown in Panels A to D of Table 5, the coefficients of *AFTERDROP* × *HFIRM_EXP, AFTERDROP* × *HGE_EXP, AFTERDROP* × *HRESOURCE,* and *AFTERDROP* × *HACCURACY* are all positive and significant. These results suggest that the impact of a drop in analyst coverage on investors' perceived crash risk is more pronounced for the termination of coverage of analysts with more firm-specific or general experience, with greater access to resources, or with prior forecasts that are more accurate than those of their peers.[17]

Additional Tests

We conduct further tests to confirm the validity of our empirical results. First, to alleviate concerns of our results being driven by options with maturities in a specific interval, we follow Kim and Zhang (2014) and employ alternative measures of implied volatility smirk calculated using different options with differing times to maturity. We find that the results (untabulated) remain unchanged.

Second, to alleviate concerns of our results being confounded by a firm's financial reporting quality, we control for alternative measures of reporting quality. To this end, we measure accrual quality using the standard deviation of firm-level residuals from the Dechow and Dichev (2002) model. We also control for accounting conservatism, measured by the negative of the ratio of non-operating accruals to total assets cumulated over the previous three years (Givoly and Hayn 2000). We control for accounting comparability, captured by the average of the four highest comparability values for a firm, based on the approach of De Franco, Kothari, and Verdi (2011). Untabulated results show that our reported results remain unaltered when controlling for these alternative measures of financial reporting quality.

Third, prior studies find mixed evidence on the impact of an exogenous drop in analyst coverage due to brokerage mergers and closures on management forecasts. For example, Billett, Garfinkel, and Yu (2017) do not find any significant effect. Balakrishnan et al. (2014) find that the effect is only significant for firms that made forecasts in the past. We reestimate our main regression after controlling for the number of management forecasts, and obtain qualitatively similar results (untabulated).

Fourth, we employ an alternative control sample to reestimate our main regression. Specifically, as our control firms, we only consider such firms that did not experience a drop in analyst coverage, but whose analysts' brokerage houses experienced merger events. The treated firms contain only those that experienced an exogenous drop in analyst coverage due to brokerage house mergers. Untabulated results show that our variable of interest, *AFTERDROP,* remains positive and significant ($\beta = 0.004$, $t = 1.72$).

Fifth, to alleviate concerns of our results being due to systematic differences in mergers or closures, we include mergers and closures fixed effects in our tests. Our results continue to hold. We next include the merger fixed effects and their interaction with *AFTERDROP* in our main test. We find that the interaction with *AFTERDROP* is not significant, while our variable of interest, *AFTERDROP,* remains positive and significant (untabulated). These results also suggest that the impact of the drop in coverage on investors' perceived crash risk does not differ between mergers and closures.

Sixth, to enhance the robustness of our results, we employ a two-stage least squares regression approach based on that of Yu (2008). Specifically, we use change of brokerage house as an instrumental variable to capture exogenous variations in analyst coverage, since this affects analyst coverage, but is less susceptible to the selection problem. We obtain consistent results (untabulated). The instrument is significant ($p < 0.001$) and positive, while our variable of interest, i.e., the instrumented coverage, is negative and significant ($\beta = -0.001$, $t = -2.18$).

[16] We use both the mean and median accuracy as an alternative benchmark, and find qualitatively similar results.
[17] We also examine the impact of analysts' portfolio complexity, but do not find that it affects the analyst coverage-crash risk relation.

TABLE 5

The Effect of a Decrease in Analyst Coverage on Expected Crash Risk High- versus Low-Ability Analyst

Panel A: High versus Low Analyst Firm-Specific Experience

	Dependent Variable = *IV_SKEW*	
	(1)	**(2)**
TREATED	0.001	
	(0.51)	
AFTERDROP	0.001	0.001
	(0.37)	(0.50)
AFTERDROP × *HFIRM_EXP*	0.005*	0.004*
	(1.75)	(1.77)
HFIRM_EXP	−0.003*	
	(−1.72)	
AFTER	0.008***	0.008***
	(5.88)	(6.15)

Panel B: High Versus Low General Experience

	Dependent Variable = *IV_SKEW*	
	(1)	**(2)**
TREATED	0.003*	
	(1.69)	
AFTERDROP	−0.003	−0.003
	(−1.01)	(−1.01)
AFTERDROP × *HGE_EXP*	0.009***	0.009***
	(3.16)	(3.20)
HGE_EXP	−0.006***	
	(−2.98)	
AFTER	0.008***	0.008***
	(5.89)	(6.56)

Panel C: High versus Low Resources

	Dependent Variable = *IV_SKEW*	
	(1)	**(2)**
TREAT	0.002	
	(1.11)	
AFTERDROP	−0.005	−0.003
	(−1.53)	(−0.98)
AFTERDROP × *HRESOURCE*	0.011***	0.009***
	(3.62)	(2.95)
HRESOURCE	−0.004**	
	(−2.05)	
AFTER	0.008***	0.008***
	(5.88)	(6.56)

(continued on next page)

TABLE 5 (continued)

Panel D: High versus Low Analyst Forecast Accuracy

	Dependent Variable = *IV_SKEW*	
	(1)	**(2)**
TREATED	−0.001	
	(−0.35)	
AFTERDROP	0.001	0.001
	(0.52)	(0.61)
AFTERDROP × *HACCURACY*	0.005**	0.005**
	(2.11)	(2.10)
HACCURACY	−0.001	
	(−0.57)	
AFTER	0.008***	0.008***
	(5.89)	(6.57)
Control Variables	Yes	Yes
Industry Fixed Effects	Yes	No
Firm Fixed Effects	No	Yes
No. of Observations	2,760	2,760

***, **, * Indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.
This table reports the regression results of the impact of an exogenous drop in analyst coverage on a firm's expected crash risk for firms with terminated coverage of analysts of high versus low ability. All continuous independent variables are winsorized at the top and bottom percentile. t-statistics and z-statistics are shown in parentheses.
See Appendix A for the other variable definitions.

Variable Definitions:
HFIRM_EXP = high firm experience, which equals 1 if the lost analysts' firm-specific experience with the treated firm in the year before the coverage termination is above the industry median, and 0 otherwise;
HGE_EXP = high general experience, which equals 1 if the lost analysts' general experience with the treated firm in the year before the coverage termination is above the industry median, and 0 otherwise;
HRESOURCE = high analyst resources, which equals 1 if the lost analysts' brokerage house size is above the industry median, and 0 otherwise; and
HACCURACY = high forecast accuracy, which equals 1 if the lost analysts' forecast accuracy of the treated firm in the year before the coverage termination is above the accuracy of the other analysts that cover the same firm, and 0 otherwise.

V. CONCLUSIONS

Since the global financial crisis in 2008, the importance of understanding investors' perception of stock price crash risk has received considerable attention from standard setters, securities regulators, and academic researchers. However, empirical studies on the determinants of expected crash risk are rare. We utilize brokerage house mergers and/or closures as a setting that leads to an exogenous drop in analyst coverage, and examine the impact of analyst coverage on investors' perceived crash risk. We find a significant increase in expected crash risk after a reduction in analyst coverage. These results are consistent with our conjecture that investors perceive firms with a loss of coverage as crash-prone, because such an event increases not only the investors' assessment of the likelihood of future crashes, but also the uncertainty relating to this assessment.

Further investigations reveal that the positive effect of an analyst coverage drop on expected crash risk is more pronounced for firms with lower initial analyst coverage, which suffer a greater reduction in coverage. We also discern exogenously terminated coverage based on analyst attributes. We find that the positive impact of a drop in analyst coverage on investors' perceived crash risk is more pronounced for termination of the coverage of analysts with more experience, with greater access to resources, or whose prior forecasts were more accurate than those of their peers.

Our study adds to the prior literature that examines the consequences of analyst monitoring. First, our study suggests that a drop in analyst coverage increases investors' expected crash risk, a forward-looking belief about future share price movements. In this respect, our results are relevant to policymakers, who have underscored the importance of understanding investors' perceptions of extreme negative tail risk. Second, we contribute to the growing literature on *ex ante* expected crash risk as reflected in the options implied volatility smirk. Prior studies find that the quality of a firm's reporting practices matters in investors' assessment of *ex ante* crash risk. Our study suggests that investors do recognize analysts as important gatekeepers who can deter managerial opportunism that may lead to stock price crashes. Third, we contribute to prior studies focusing on the impact of various analyst attributes. Our study suggests that the expertise and resources of analysts are valued by option market participants. Finally, we contribute to prior studies that examine the impact of analysts on investors in the options market. Specifically, our study provides evidence on the role of analysts in shaping options market participants' perceptions of crash risk.

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APPENDIX A

Variable Definitions

Main Variables

IV_SKEW = 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 contracts 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.

TREATED = an indicator variable that equals 1 if the firm experiences exogenous analyst coverage decreases due to either broker house mergers or closures during our sample period, and 0 otherwise.

AFTER = an indicator variable that is equal to 1 in the period after the merger or closure, and 0 otherwise.

AFTERDROP = equal to *TREATED* × *AFTER*.

ANA_INITIAL = 1 if the number of analysts covering a firm in the initial year of our sample period is below the industry median, and 0 otherwise.

HFIRM_EXP = 1 if the lost analysts' firm-specific experience with the treated firm in the year before coverage termination is above the industry median, and 0 otherwise. An analyst's firm-specific experience is measured by the number of years through year t for which the analyst supplied at least one forecast for firm j.

HGE_EXP = 1 if the lost analysts' general experience with the treated firm in the year before the coverage termination is above the industry median, and 0 otherwise. An analyst's general experience is measured as the number of years through year t for which the analyst supplied at least one forecast for any firm.

HACCURACY = 1 if the lost analysts' forecast accuracy of the treated firm in the year before the coverage termination is above that of the other analysts covering the same firm, and 0 otherwise. An analyst's prior forecast accuracy is measured as the analyst's prior-year forecast accuracy for firm j, calculated as the absolute value of the analyst's forecast error for the firm in year $t-1$, scaled by the beginning stock price.

HRESOURCE = 1 if the lost analysts' brokerage house size is above the industry median, and 0 otherwise. An analyst's access to resources is measured as the number of analysts employed by the analyst's brokerage.

Other Variables

ASSET = the log of the firm's total assets.

MB = the market value of equity divided by the book value of equity.

ACCM = the prior three-year moving sum of the absolute value of discretionary accruals estimated from the modified Jones model.

ROA = income before extraordinary items divided by lagged total assets.

OANCF = the firm's operating cash flow divided by lagged total assets.

RET = the yearly stock return over the fiscal year.

COVERAGE = the log of 1 plus the number of analysts following during the fiscal year.

SIZE = the log of the market value of equity.
LEV = total long-term debt divided by total assets.
IDOSY_VOL = the standard deviation of firm-specific weekly returns over the fiscal year.
ATM_IV = 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.
CASHFLOW_VOL = the standard deviation of operating cash flows (scaled by lagged total assets) over the past five years.
EARNINGS_VOL = the standard deviation of earnings before extraordinary items (scaled by lagged total assets) over the past five years.
SALES_VOL = the standard deviation of sales revenue (scaled by lagged total assets) over the past five years.
STOCK_TURN = the average monthly share turnover over the fiscal year.
BETA = the market beta for the firm, estimated using daily stock and market returns over the fiscal year period.
TOTAL_VOL = the standard deviation of weekly stock returns over the fiscal year.
NCSKEW = the negative skewness of firm-specific weekly returns over the fiscal year.
DDAQ = the standard deviation of firm-level residuals from the Dechow and Dichev (2002) model.
CON = accounting conservatism, measured by the negative of the ratio of non-operating accruals to total assets cumulated over the previous three years (Givoly and Hayn 2000).
COMP = the average of the four highest comparability values for a firm, based on De Franco et al. (2011).

APPENDIX B

Measurement of Implied Volatility Smirk

Following prior research (e.g., Bollen and Whaley 2004; Xing et al. 2010; Van Buskirk 2011; Kim and Zhang 2014), we first group options into five different moneyness categories according to their delta (Δ):

Category	Labels	Delta Range
1	Deep in-the-money call	$0.875 < \Delta_C \leq 0.98$
	Deep OTM put	$-0.125 < \Delta_P \leq -0.02$
2	In-the-money call	$0.625 < \Delta_C \leq 0.875$
	OTM put	$-0.375 < \Delta_P \leq -0.125$
3	ATM call	$0.375 < \Delta_C \leq 0.625$
	ATM put	$-0.625 < \Delta_P \leq -0.375$
4	OTM call	$0.125 < \Delta_C \leq 0.375$
	In-the-money put	$-0.875 < \Delta_P \leq -0.625$
5	Deep OTM call	$0.02 < \Delta_C \leq 0.125$
	Deep in-the-money put	$-0.98 < \Delta_P \leq -0.875$

The delta values (Δ_C and Δ_P) are defined as:

$$\Delta_C N\left[\frac{\ln((S - PVD)e^{rT}/X) + 0.5\sigma^2 T}{\sigma\sqrt{T}}\right]$$

and $\Delta_P = \Delta_C - 1$
where S is the current stock price; PVD is daily dividends discounted at the rates corresponding to the ex-dividend dates and summed over the life of the option; X is the option's exercise price; T is the option's time to expiration; σ is the volatility of the stock price; and r is the risk-free rate of interest.

We measure the daily implied volatility skew (IV_SKEW_{it}) of stock i's option as the difference between the implied volatility of OTM puts ($IV^{OTMP}{}_{it}$) and that of ATM calls ($IV^{ATMC}{}_{it}$) that day. When there are multiple put or call option contracts for stock i on a particular day, we calculate the weighted average of the implied volatilities for the put or call options using option open interest (*OPEN_INT*) as a weight:

$$IV\_SKEW_{it} = \frac{\sum_j OPEN\_INT_j \times IV^{OTMP}_{it\,j}}{\sum_j OPEN\_INT_j} - \frac{\sum_k OPEN\_INT_k \times IV^{ATMC}_{it\,k}}{\sum_k OPEN\_INT_k}$$

To obtain an annual measure of the volatility smirk, following Kim and Zhang (2014) and Kim et al. (2016), we average the daily *IV_SKEW* over the 12-month period ending three months after the fiscal year-end.