Essays on predicting downside risk in firms

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Abstract

Understanding and predicting downside risk is central to asset pricing, risk management, and corporate governance. This chapter includes three studies that investigate different dimensions and informational sources of downside risk in equity markets. While all three chapters focus on large, downward movements in stock price, each study investigates a different explanation: managerial discretion, dispersion in investors' beliefs, and directional positioning in the options market.

The first study examines the determinants of the skewness risk premium (SRP), defined as the difference between risk-neutral skewness and realized skewness. SRP reflects the compensation earned by investors who sell crash risk, typically by shorting out-of-the-money (OTM) options. In normal conditions, SRP is positive because realized skewness tends to be smaller than the market's ex-ante expectation. However, when large negative returns occur, realized skewness increases sharply and may exceed the anticipated level, resulting in a negative SRP. This chapter shows that managerial discretion, proxied by discretionary accruals, predicts negative SRP. When firms delay the release of bad news through earnings management, the market underestimates the probability of large negative returns. Once the accumulated bad news is eventually disclosed, realized skewness becomes more negative than expected, resulting in a negative SRP. Accordingly, firms that hoard bad news, as reflected by higher levels of earnings management, are more likely to exhibit lower or negative SRP. The effect is especially pronounced around earnings announcement periods. These findings suggest that financial reporting distortions impair the option market's ability to accurately assess and price downside risk.

The second study explores how investor disagreement, measured from options data, predicts stock price crashes. The key variable is dispersion in investors' beliefs (IDISP), a model-free proxy that reflects the divergence in beliefs among option market participants. High IDISP indicates increased demand for deep out-of-the-money and deep in-the-money options, often driven by investor concern over extreme downside risk. The analysis shows that IDISP significantly predicts future stock price crashes. This relation reflects a buildup of divergent views that cannot be fully expressed due to market frictions, similar to the mechanism behind other disagreement measures in the stock market. This predictive power remains robust after

accounting for firm characteristics and alternative controls. The study also investigates several mechanisms that may amplify this relation. It finds stronger effects when financial reporting quality is low, short-sale constraints are tight, investor sentiment is elevated, or around earnings announcements. These results suggest that belief dispersion interacts with market frictions to increase crash risk.

The third study builds on the previous chapter by shifting the focus from non-directional belief dispersion to directional positioning in the options market. While disagreement captures the extent of divergence in investor opinions, it does not indicate whether informed traders anticipate downside risk. This study examines whether trading patterns in strike asymmetry, particularly in out-of-the-money (OTM) put options, can reveal such directional expectations. The key variable is option strike asymmetry, a model-free measure constructed from strike price and trading volume across different option categories. The analysis covers various combinations of moneyness and option type, with the strongest predictive power observed in deep OTM puts. Lower strike asymmetry, reflecting heavier trading in lower-strike options, is associated with a higher likelihood of future crashes. This relationship remains robust across alternative crash definitions, firm-level controls, and disagreement proxies. The study further explores mechanisms including short-sale constraints, financial reporting quality, and investor sentiment. The findings suggest that directional option positioning reveals private downside beliefs and provides early warnings of crash risk.

Overall, this chapter contributes to the understanding of downside risk by examining how firm-level financial reporting behavior and option market signals relate to large negative stock returns. The three chapters study earnings management as an internal source of crash risk, and use belief dispersion and strike-level positioning to capture investor expectations about potential crashes. The results show that these signals help identify when crashes are more likely to occur. These findings offer useful insights for researchers and investors seeking to better understand and manage the risk of sharp price declines.

Declaration

I, Tao Chen, hereby declare that this is entirely my own work unless referenced to the contrary in the text. No part of this chapter has previously been submitted elsewhere for any other degree or qualification in this or any other institution.

Statement of Copyright

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1 Introduction

1.1 Background and Motivation

Understanding and predicting downside risk is one of the central challenges in modern finance. Investors are particularly concerned with rare but extreme losses in asset prices, as these events cause significant value destruction and often lead to market-wide turmoil. A large body of research shows that managers sometimes withhold bad news, allowing risks to accumulate until a tipping point is reached, resulting in sharp stock price crashes (Sloan, 1996; Jin and Myers, 2006; Hutton, Marcus, and Tehranian, 2009; Chi and Gupta, 2009; Zhu, 2016). These crash episodes are characterized by sudden, extreme drops in firm-specific returns and have been linked to both earnings management behaviour and asymmetric information frictions. In addition to firm-level fundamentals, crash risk may also arise from non-fundamental sources such as investor sentiment, behavioural biases, or even superstition. For example, Bai, Xu, Yu, and Zurbruegg (2020) show that superstition-driven trading behaviour can amplify bad news hoarding and increase stock price crash risk.

At the same time, investors seek protection from such downside events and are willing to pay a premium in the options market to hedge against negative skewness—the asymmetry in return distributions associated with large left-tail outcomes. Empirical studies confirm that even when these hedging options (such as deep out-of-the-money puts) are rarely exercised, they are still highly valued due to their insurance-like properties (Bollen and Whaley, 2004; Driessen and Maenhout, 2007). This willingness to hedge gives rise to the Skewness Risk Premium (SRP)—the difference between risk-neutral skewness (from option prices) and realized skewness (from historical returns) (Kozhan, Neuberger, and Schneider, 2013; Schneider and Trojani, 2015; Pederzoli, 2021). When SRP declines, it signals that realized returns have become extremely negatively skewed, often reflecting the occurrence of downside events that investors feared ex ante. Therefore, SRP serves as both a pricing mechanism for tail risk and a diagnostic indicator of crash realizations.

Another key perspective on downside risk stems from the idea of belief disagreement. When short-sale constraints are present, disagreement can lead to price overvaluation as pessimistic investors are sidelined. If hidden risks accumulate and eventually materialize, prices can crash suddenly. Traditional proxies for disagreement—such as analyst forecast dispersion (Diether, Malloy, and Scherbina, 2002) or trading volume patterns (Chen, Hong, and Stein 2001; Hong and Stein, 2007)—have been linked to negative future returns. Recent research shifts the focus to options markets as a more forward-looking and granular source of belief heterogeneity. Specifically, dispersion in option investors' beliefs (IDISP), defined as the dispersion traded option strikes, captures disagreement among investors regarding a firm's future return distribution (Andreou, Kagkadis, Philip, and Tuneshev, 2018). Higher IDISP reflects greater divergence in opinion and is shown to significantly predict firm-level crash risk (Chang, Hsiao, Ljungqvist, and Tseng, 2022).

While disagreement explains the breadth of opinion variation, it does not fully capture the direction of informed positioning. To address this, options data offer another valuable dimension: the concentration and asymmetry of traded strike prices. Compared to the underlying stock market, options allow greater flexibility for directional bets and hedging. Informed traders often utilize deep OTM puts to bet on or protect against crashes, embedding private information into the trading structure (Easley, O'Hara, and Srinivas, 1998; Chakravarty, Gulen, and Mayhew, 2004). Building on this insight, the third paper in this dissertation proposes Option Strike Asymmetry, a novel, volume-weighted measure that captures whether trading is skewed toward deep downside strikes. The focus on OTM Put Strike Asymmetry enables a directional and model-free assessment of crash anticipation, and empirical findings show that this measure strongly predicts future crashes beyond existing proxies such as IDISP, VIX, or short interest.

This dissertation is organized into three empirical studies that examine different aspects of downside risk in equity markets. Each study focuses on a distinct research question, contributing to a broader understanding of how downside risk is priced, how it emerges through crash events, and how it can be identified in advance using signals from the options market.

The first study investigates whether firm-level managerial discretion, as captured by discretionary accruals, explains the variation in the Skewness Risk Premium (SRP) across firms. While prior research has shown that investors demand compensation for bearing downside risk, the sources of cross-sectional heterogeneity in SRP remain unclear. This study explores whether earnings management behavior, which may mask accumulating bad news, leads to more negatively skewed return distributions. By linking financial reporting opacity to realized skewness, the study evaluates whether SRP incorporates hidden information about downside risk. The central question guiding this analysis is: *Does managerial discretion, as reflected in accrual-based earnings opacity, drive variation in the firm-level skewness risk premium and signal latent crash risk?*

The second study examines investor disagreement as a potential source of crash risk. It introduces a novel options-based measure, differences in options investors' expectations (IDISP), which captures the cross-sectional spread of traded strikes. Traditional disagreement proxies, such as analyst forecast dispersion or abnormal trading volume, are often limited in scope or availability. This study proposes an alternative that is derived from high-frequency option data and directly reflects market-implied differences in beliefs. The analysis investigates whether elevated IDISP predicts future crash events, particularly in environments with short-sale constraints. The research is guided by the question: *Can an options-based belief dispersion measure improve our ability to forecast firm-specific stock price crashes?*

The third study develops a new indicator, Option Strike Asymmetry, designed to capture directional patterns in option trading that may reflect informed downside positioning. This measure is based on the volume-weighted deviation of traded strike prices from the underlying spot price, with a focus on the behavior of out-of-the-money (OTM) put options. Previous research has established that options convey information about future returns, but few studies have examined whether the structure of strike usage provides early signals of crash risk. This study addresses that gap by analyzing the predictive content of strike asymmetry across various option subsets and evaluating its robustness against alternative predictors such as short interest, earnings opacity, investor sentiment, and market-wide volatility. The main research question is: *Does directional concentration in OTM put options signal early warnings of crash risk, and how does this information compare with known crash predictors?*

Together, these three studies contribute to the understanding of downside risk by exploring its underlying causes, information channels, and observable signals in financial markets. By integrating firm-level fundamentals, belief dispersion, and option trading behavior, the dissertation presents a unified empirical framework for identifying and anticipating extreme downside events. These findings offer practical insights for investors, regulators, and researchers concerned with crash prediction and risk monitoring.

1.2 Contributions of This chapter

This chapter contributes to the literature on downside risk in equity markets by addressing both conceptual and methodological questions. Through three empirical studies, it provides new insights into how downside risk is priced, how it is formed, and how it can be detected using forward-looking information from the options market. These contributions extend beyond individual empirical findings by integrating perspectives from asset pricing, earnings quality, investor behaviour, and derivatives microstructure.

First, the thesis advances the measurement of tail risk pricing by introducing a new firm-level perspective on the Skewness Risk Premium (SRP). While previous studies often rely on realized crashes as the outcome of interest, this research emphasizes the ex-ante pricing of downside risk through SRP and links it to managerial behaviour. By showing that discretionary accruals, as a proxy for financial reporting opacity, are associated with lower SRP and more negatively skewed returns, the study connects fundamental accounting information with option-implied crash expectations. This perspective helps clarify how hidden risks, though not always reflected in realized crashes, are anticipated and priced by market participants.

Second, the thesis makes a substantive contribution to the literature on investor disagreement and crash risk by developing an options-based measure of belief dispersion. The proposed variable, differences in options investors' expectations (IDISP), captures heterogeneity in investor expectations through the spread of traded strikes. This improves upon traditional disagreement proxies based on analyst forecasts or trading volume, offering a high-frequency and market-implied alternative. The findings show that firms with high IDISP are more likely to experience crash events, particularly around earnings announcements. This result bridges two strands of research: the effect of investor disagreement and the role of earnings management in triggering extreme returns.

Third, the thesis contributes methodologically by proposing a novel, model-free measure of option strike asymmetry. This measure, which focuses on the volume-weighted moneyness of traded strikes, especially in out-of-the-money (OTM) puts, captures the directional intensity of downside-positioned option trading. Unlike existing metrics such as volatility skew, option-to-stock volume ratios, or implied disagreement, the strike asymmetry variable directly reflects trader intent and embeds information about early crash expectations.

The findings show that OTM Put Strike Asymmetry significantly predicts firm-level crashes, and the signal remains robust after controlling for short interest, sentiment, VIX, and financial reporting quality. This contribution enhances the literature on option-informed trading by offering a more refined lens to detect directional beliefs tied to crash risk.

Collectively, the three studies offer a comprehensive framework for understanding downside risk from pricing, informational, and behavioural dimensions. The research helps uncover the economic mechanisms behind crash risk, highlights the limitations of traditional risk measures, and promotes the use of market-based, real-time indicators from the options market. By connecting financial reporting practices, investor heterogeneity, and trading behaviour, the thesis informs both academic inquiry and practical risk monitoring.

1.3 Structure of This chapter

This chapter is structured as follows. Chapter 2 reviews the existing literature on downside risk and its potential drivers, providing the theoretical foundation for the empirical studies that follow. Chapter 3 presents the first empirical study, which examines the relationship between discretionary accruals and the skewness risk premium, focusing on how managerial discretion affects the pricing of downside risk. Chapter 4 introduces the second empirical study, which explores the role of investor disagreement in predicting stock price crashes, using an options-based measure of belief dispersion. Chapter 5 presents the third empirical study, which develops and tests a novel measure of option strike asymmetry to identify directional downside positioning and forecast crash risk. Chapter 6 concludes the thesis by summarizing the main findings, discussing theoretical and practical implications, and suggesting directions for future research.

2 Literature Review

2.1 Understanding Downside risk

Academic interest in downside risk has intensified over the past two decades, as researchers and practitioners alike began to recognize that traditional volatility measures fail to capture the asymmetry inherent in financial markets. A key concern for investors is the possibility of large, abrupt losses that severely erode wealth. Unlike symmetric risk, downside risk focuses specifically on extreme negative outcomes, which are often more relevant for pricing, hedging, and regulatory assessments. The literature has since proposed two complementary approaches to characterize downside risk: the Skewness Risk Premium (SRP) and Crash Risk.

The Skewness Risk Premium (SRP) captures the gap between investors' expectations about return asymmetry and the actual outcomes observed in the market. It is defined as the difference between risk-neutral skewness, which is implied from option prices, and realized skewness, which is calculated from observed stock returns (Kozhan, Neuberger, and Schneider, 2013; Schneider and Trojani, 2015; Pederzoli, 2021). This premium reflects how much investors are willing to pay to insure against the possibility of negative skewness or extreme downside movements in asset prices. A low SRP indicates that realized returns are more negatively skewed than expected, suggesting that downside risk has materialized. In empirical research, SRP is often extracted through skewness swaps. These are option-based portfolios that allow investors to sell exposure to skewness risk in return for compensation. This structure is commonly used to capture the pricing of tail risk (Bollen and Whaley, 2004; Driessen and Maenhout, 2007).

In comparison, Crash refers to the actual occurrence of large, abrupt declines in stock prices. It is typically identified when firm-specific weekly returns fall substantially below historical averages. A common threshold in the literature is a return that is 3.25 standard deviations below the mean, calculated over a rolling window (Kim, Li, and Zhang, 2011; Hutton, Marcus, and Tehranian, 2009). These crash events are infrequent but highly significant. They often occur when firms release previously withheld negative information all at once. This behavior has been associated with earnings management practices, in which managers attempt to delay bad news to maintain short-term performance. Once the accumulated bad news is disclosed, stock prices can drop sharply (Jin and Myers, 2006; Chi and Gupta, 2009; Zhu, 2016).

Although the Skewness Risk Premium (SRP) is often used to reflect investors' ex-ante pricing of downside risk, its construction relies on the difference between expected and realized skewness. As such, SRP incorporates both forward-looking expectations and backward-looking realizations. It offers a continuous and economically meaningful signal of how much tail risk investors anticipated, relative to what actually materialized. In contrast, Crash captures the occurrence of sharp, discrete price collapses, typically defined by large negative returns beyond a statistical threshold. Compared to SRP, crash events are more extreme in magnitude and rare in frequency.

Together, SRP and Crash provide complementary views of downside dynamics. SRP reflects the market's perceived vulnerability and compensation for tail events, while Crash Risk marks the actual manifestation of such events. These two measures have become essential for understanding the pricing, transmission, and realization of downside risk in financial markets.

2.2 Skewness Risk Premium

The Skewness Risk Premium (SRP) has emerged as a critical concept for capturing how investors price asymmetric downside risk in financial markets. It is defined as the difference between the risk-neutral skewness implied by option prices and the realized skewness computed from actual stock returns (Kozhan, Neuberger, and Schneider, 2013; Schneider and

Trojani, 2015; Pederzoli, 2021). Risk-neutral skewness reflects investor expectations about return asymmetry, while realized skewness captures the ex-post distributional shape of returns. The SRP therefore measures how much investors are willing to pay, ex-ante, to insure themselves against unexpected negative skewness. When SRP is low, it indicates that realized returns are more negatively skewed than anticipated, implying the materialization of tail risk. In practice, SRP is commonly extracted using skewness swap strategies, which are constructed from option portfolios that isolate third-moment risk. These swaps offer a clean and model-free way to trade exposure to left-tail events. Bollen and Whaley (2004) and Driessen and Maenhout (2007) emphasize that such swap returns provide direct insights into investors' aversion to downside asymmetry, especially during times of market uncertainty. Since skewness swaps are replicable and tradable, the associated risk premium can be used to track dynamic shifts in perceived tail risk over time.

Compared to crash risk, which is typically observed as an extreme price drop over a short period, SRP provides a smoother and more continuous signal of downside sentiment. It does not require the actual occurrence of a crash but instead reflects the pricing of potential crash-like events. This forward-looking property makes SRP a useful early indicator of market stress. As shown in Figure 2.1, the cross-sectional average of monthly SRP fluctuates substantially over time. Periods such as the global financial crisis in 2008 and the onset of the COVID-19 pandemic in early 2020 exhibit pronounced declines in SRP, which suggests heightened downside realization relative to prior expectations. These patterns support the interpretation of SRP as a fear gauge rooted in market pricing mechanisms.

[Insert Figure 2.1 here]

An important conceptual distinction arises when comparing SRP with the Variance Risk Premium (VRP). Although both measures are extracted from options data and are positively correlated, they convey different information. The VRP captures compensation for bearing total volatility risk, including both upside and downside deviations. In contrast, SRP isolates skewness-related asymmetry and is more directly linked to downside expectations. Pederzoli (2021) argues that SRP represents a pure bet on the third moment, independent of the mean, variance, or kurtosis. While the VRP responds symmetrically to high return dispersion, the SRP changes sign according to the direction of market movements, offering directional sensitivity that the VRP lacks. Moreover, empirical evidence shows that the variance swap return tends to rise in periods of high realized volatility, regardless of direction. However, the skewness swap return varies with the direction of market moves, often turning negative during downturns. This difference reinforces the view that SRP captures the cost of downside insurance, whereas VRP reflects general uncertainty. As such, SRP provides a more targeted measure of the compensation required to bear left-tail risk and plays a distinct role in understanding investor behaviour during turbulent periods.

2.3 Crash Risk

Another type of downside risk lies in the phenomenon of stock price crashes, referring to rare but extreme downward movements in stock prices. These crash events, while infrequent, are economically significant and have attracted considerable academic interest in recent years. Unlike the Skewness Risk Premium (SRP), which reflects the differences arising from ex-ante expectations about return and the realized return, crash focuses on the ex-post realization of downside events, typically measured by the incidence of large negative outliers in return distributions.

The foundational framework in this area originates from Jin and Myers (2006), who propose a theory in which managers have both the ability and incentive to withhold bad news from the public. In their model, information opacity allows managers to temporarily absorb firm-specific shocks, often through earnings management or selective disclosure, thereby smoothing the flow of negative information. However, once these hidden shocks accumulate beyond a tolerable threshold, managers lose the ability or willingness to continue concealment. The sudden and simultaneous release of accumulated bad news leads to a firm-specific crash, creating a long left tail in the return distribution. Their model further links opacity to increased return synchronicity (i.e., higher R^2), as less firm-specific information is impounded into prices during normal times.

Empirical work by Hutton, Marcus, and Tehranian (2009) lends strong support to this theoretical prediction. Using a measure of opacity based on the three-year moving sum of discretionary accruals, the authors find that firms engaging in persistent earnings management exhibit both higher R^2 and a significantly elevated likelihood of future crashes. Crucially, this opacity-driven crash risk seems to decline in the post-Sarbanes-Oxley (SOX) period, suggesting that stronger regulatory oversight reduces managers' ability to hoard bad news.

Complementary to this line of reasoning, Hong and Stein (2003) emphasize the role of heterogeneous investor beliefs and market frictions in generating crash-like outcomes. In their model, short-sale constraints prevent pessimistic investors from correcting overpricing during the buildup phase, while prices incorporate optimistic views more readily. When bad news is eventually revealed, the absence of short-seller restraint leads to sharp downward corrections, magnifying the crash. This mechanism underscores that crash risk is not only a matter of information flow, but also of market structure and trading dynamics.

Further reinforcing this perspective, recent studies have focused on managerial incentives under financial distress. For instance, Andreou, Andreou, and Lambertides (2021) document a robust and economically significant relationship between short-term increases in financial distress risk and future crashes. The authors argue that distress elevates managers' incentives to obscure poor performance, thus increasing the probability that negative information is released in a lumpy, crash-inducing manner. Their findings provide direct evidence that bad-news hoarding intensifies when firms face heightened economic uncertainty, echoing the agency-based view of crash risk formation.

Standard empirical approaches to identifying crash events typically rely on the 3.25-standard-deviation threshold proposed by Kim, Li, and Zhang (2011), which defines a crash as a firm-specific weekly return falling more than 3.25 standard deviations below the firm's rolling mean. Alternative model-free definitions, such as realized returns below −20%, are also commonly used to validate robustness. These measures serve to isolate truly extreme left-tail events from routine volatility, allowing researchers to quantify crash risk with precision across firms and time periods.

Taken together, the literature reveals that crash risk emerges at the intersection of informational frictions, managerial discretion, and investor limitations. It is not merely a byproduct of volatility, but a distinct form of tail risk shaped by deliberate concealment and abrupt revelation of adverse fundamentals. This makes crash risk not only an empirical reality but also a theoretically rich lens through which to study market dynamics, agency problems, and the limits of transparency in capital markets.

2.4 Managerial Discretion and Discretionary Accruals

Discretionary accruals, widely regarded as a proxy for financial reporting opacity, play a central role in understanding how managerial discretion can obscure underlying firm fundamentals. Under accrual accounting, earnings are constructed based on management's estimates of future cash flows, incorporating non-cash items such as depreciation, provisions, and receivables. While such estimates are legitimate within the bounds of Generally Accepted Accounting Principles (GAAP), managers also possess latitude to adjust accruals opportunistically, particularly to meet short-term performance benchmarks or delay the recognition of adverse news (Larson, Sloan, and Giedt, 2018; Zhang, 2007).

This discretionary use of accruals can lead to systematic distortions in reported earnings, reducing transparency and contributing to a buildup of latent risks. Hutton, Marcus, and Tehranian (2009) show that firms with persistently high discretionary accruals—measured as the three-year moving average of absolute accruals—exhibit higher return synchronicity (R^2) and are significantly more prone to stock price crashes. Their findings support the theoretical framework of Jin and Myers (2006), who posit that managers may stockpile bad news under conditions of limited transparency, only to release it abruptly when concealment becomes untenable, triggering a crash. Additional studies further elaborate on the consequences of earnings opacity. Chi and Gupta (2009) document that overvalued firms are particularly susceptible to income-increasing earnings management via discretionary accruals. Their evidence aligns with the agency-costs-of-overvalued-equity hypothesis (Jensen, 2005), showing that managers facing valuation pressure may manipulate earnings to justify inflated prices, ultimately harming long-term shareholder value. Zhu (2016) reinforces this view, finding that high discretionary accruals correlate with future stock price crashes, especially among firms experiencing strong capital market expectations.

In this context, discretionary accruals are not merely a byproduct of accounting flexibility, but a strategic tool that can mislead market participants. The concealment of economic distress through accruals management delays the realization of downside risk, heightening the potential for sudden and severe corrections once negative fundamentals are revealed. This mechanism connects directly to the study's broader inquiry: how financial reporting behaviour interacts with investor perception and option-implied pricing of tail risk.

The empirical chapters that follow incorporate discretionary accruals both as an independent driver of crash risk and Skewness Risk Premium (SRP). By linking financial reporting quality with both ex-ante and ex-post manifestations of downside risk, the analysis underscores the pivotal role of earnings management in shaping how markets interpret and price firm-specific vulnerabilities.

2.5 Investor Disagreement

Investor disagreement refers to the divergence in expectations about future firm performance. Early literature has primarily relied on analyst forecast dispersion as a proxy for disagreement, where a higher spread in earnings forecasts is taken to reflect a wider gap in investor beliefs (Diether, Malloy, and Scherbina, 2002). However, analyst-based measures suffer from infrequent updates, limited coverage, and potential bias. As a result, alternative proxies such as abnormal turnover and trading volume around earnings announcements have also been proposed (Hong and Stein, 2007; Chang, Hsiao, Ljungqvist, and Tseng, 2022).

The theoretical foundation for using disagreement to forecast negative returns is rooted in the short-sale constraint hypothesis (Miller, 1977; Hong and Stein, 2003). When short selling is costly, pessimistic investors are prevented from expressing their views through trades. Consequently, stock prices tend to reflect the beliefs of optimistic investors, leading to overvaluation. When adverse information is eventually revealed, prices correct sharply, often resulting in crashes. Empirical studies have shown that disagreement is positively related to future return skewness and crash risk, confirming its role in anticipating downside events (Chen, Hong, and Stein 2001; Andreou, Kagkadis, Philip, and Tuneshev, 2018).

Recent advancements have shifted the focus to options-based measures of disagreement, which offer several advantages. This chapter adopts a novel proxy, dispersion in beliefs on individual stocks (IDISP), which captures the dispersion in beliefs among investors based on traded stock options. Following Andreou, Kagkadis, Philip, and Tuneshev (2018), we measure IDISP using the trading volume of stock options across all moneyness levels. The IDISP is the volume weighted average of the deviation of the moneyness level on the volume weighted moneyness level. It reflects how far traded strike prices are distributed around the spot price, thus providing a granular and forward-looking measure of investor expectations. Unlike analyst forecasts or stock turnover data, the IDISP is derived directly from observed market transactions. It can be measured at daily frequency and applies to any stock with actively traded options. Moreover, since it is based on trading volume across a wide range of strike prices, the IDISP captures both optimistic and pessimistic positioning simultaneously. A high IDISP indicates wide dispersion in investor beliefs, suggesting that optimistic and pessimistic investors are simultaneously active, potentially under constraint or holding asymmetric information.

This study uses the IDISP to examine its predictive power for stock price crashes. It also explores how belief dispersion interacts with earnings opacity to jointly affect crash risk. The findings contribute to the literature by introducing a market-implied, high-frequency measure of disagreement that improves the detection of crash-prone firms.

2.6 Option Market Signals of Downside Risk

The equity options market contains rich, forward-looking information that can complement or even exceed the informational content of the underlying stock market. Because of their asymmetric payoff structures and built-in leverage, options are often used by sophisticated investors to express directional beliefs, hedge downside exposure, or speculate on extreme price movements. This makes option trading activity a valuable source for identifying potential signs of downside risk before they are reflected in spot prices (Pan and Poteshman, 2006; Ge, Lin, and Pearson, 2016).

Prior literature has proposed several proxies based on the options market to capture investor sentiment and anticipate return dynamics. For instance, implied volatility skew—commonly defined as the difference between OTM put and ATM call implied volatilities—is widely used to reflect crash fears or left-tail risk (Xing, Zhang and Zhao, 2010). Other studies employ volume-based measures, such as the put-call volume ratio, option-to-stock volume ratio (Johnson and So, 2012), or abnormal buyer-initiated volume (Pan and Poteshman, 2006), to infer information demand. While informative, these proxies face two key limitations in the context of crash prediction. First, most of them lack clear directionality; they indicate aggregate trading intensity or dispersion, but do not reflect where in the strike structure traders are concentrating their activity. Second, they often ignore the moneyness decomposition of option contracts, failing to distinguish between deep OTM and near-the-money strikes that may convey very different market expectations.

Recent studies recognize that the strike prices where trading volume is concentrated may offer unique insights. For example, Bergsma, Csapi, Diavatopoulos, and Fodor (2020) propose a moneyness concentration measure based on the average deviation of strike prices from the spot price. Similarly, Bernile, Gao, and Hu (2019) develop a center-of-mass indicator for strike usage, finding it predictive of returns especially ahead of earnings announcements. These studies demonstrate that strike levels contain meaningful information. Building on this intuition, this chapter introduces a new variable, Option Strike Asymmetry, designed to capture the directional skewness of option strike usage. The measure reflects whether investors concentrate option trading on deep downside strikes, particularly out-of-the-money (OTM) puts, which may signal crash anticipation.

Option Strike Asymmetry is constructed by taking the volume-weighted average deviation of strike prices from the spot price, normalized by moneyness. For each trading day and firm, the Option Strike Asymmetry is defined as:

$$K_{asym_t} = \frac{\sum Volume_{i,t} \cdot \left(\frac{K_{i,t}}{S} - 1\right)}{\sum Volume_{i,t}} \tag{2.1}$$

Where $K_{i,t}$ is the strike price for ith option contract at day t, S is the spot price for the underlying asset. $Volume_{i,t}$ is the trading volume for ith option contract at day t.

To enhance clarity, this study illustrates the construction process using Oracle's options data on 14 December 2011. The charts demonstrate how moneyness levels, deviation from spot, and trading volume combine to compute the final asymmetry measure. The last panel shows the daily evolution of Oracle's OTM Put Strike Asymmetry, highlighting a sharp concentration in downside strikes just prior to a major price crash.

1. Select all PUT options traded in a single day. Based on the daily stock price and calculate the moneyness level for each strike price.

[Insert Figure 2.2 here]

2. The yellow bar charts are OTM PUT options, the blue bar charts are ITM PUT options.

[Insert Figure 2.3 here]

3. Calculate the moneyness level – 1 to show how far this strike is away from the spot price.

[Insert Figure 2.4 here]

4. I check the trading Volume for all PUT options traded in that day and plot them within the same graph.

[Insert Figure 2.5 here]

5. I calculate the (moneyness level – 1) × volume to show how much asymmetry × volume exists in the market on a specific trading day. For OTM PUT Strike Asymmetry, I simply sum all the yellow bar values in Figure 2.5 (the numerator), then divide by the sum of trading volumes in Figure 2.4 (the denominator) to obtain the OTM PUT volume weighted option strike deviation for that specific day.
6. I plot the daily OTM PUT strike asymmetry for Oracle stock from 2011-12-01 to 2011-12-31.

[Insert Figure 2.6 here]

The red dot is the actual stock price crash day, on that day, stock price dropped more than 11%. This Figure 2.6 clearly shows the daily evolution of Oracle's OTM Put strike asymmetry, highlighting a sharp concentration in downside strikes just prior to a major price crash. This example underscores how the proposed metric captures early warning signs of extreme negative returns.

2.7 Research Gaps and Study Contributions

The review of the existing literature reveals several gaps in how downside risk is measured, priced, and anticipated. First, while crash events have been widely studied using ex-post return realizations, such as large price drops beyond a statistical threshold (e.g., Hutton, Marcus, and Tehranian, 2009), these measures only capture realized tail outcomes. They provide limited insight into ex-ante expectations or latent risks that have not yet materialized. On the other hand, option-based measures like the Skewness Risk Premium (SRP) offer a pricing-based perspective on downside risk, but existing studies rarely explore the firm-level determinants of SRP variation, especially those stemming from managerial information opacity.

Second, traditional disagreement proxies, such as analyst forecast dispersion or abnormal turnover (Diether, Malloy, and Scherbina, 2002; Hong and Stein, 2007), are often constrained by low frequency or limited coverage. These measures are also increasingly less effective in recent years (Chang, Hsiao, Ljungqvist, and Tseng, 2022). While newer research has started to extract belief dispersion from options data, few studies examine how such disagreement predicts firm-specific crash risk, or how it interacts with financial reporting practices to generate crash vulnerability.

Third, the literature on option-based signals still largely relies on simple volume or implied volatility metrics. These indicators, such as the put-call ratio or implied skewness, reflect market sentiment but lack directionality and structural granularity. They do not capture *where* in the strike structure investors are trading, nor how intensely they are positioning for tail events.

To address these gaps, this dissertation contributes in three major ways. First, it introduces firm-level SRP as a lens to examine the pricing of latent crash risk, and links it to discretionary accruals as a proxy for financial opacity. This provides a new channel through which earnings management can affect downside risk perception. Second, it develops and validates a novel options-based disagreement measure, IDISP, which quantifies belief dispersion directly from the cross-sectional spread in traded strike moneyness. Unlike survey- or analyst-based metrics, this measure is high-frequency, market-implied, and forward-looking. Third, the dissertation proposes a new variable, Option Strike Asymmetry, which captures directional positioning toward extreme downside strikes by weighting moneyness deviation with trading volume. This measure is model-free, intuitive, and highly responsive to market expectations about crash risk.

Together, these contributions offer a comprehensive framework for understanding downside risk from both pricing and realization perspectives. By integrating financial reporting opacity, investor disagreement, and strike-level trading behavior, this research enhances our ability to interpret and anticipate crash dynamics. It extends the literature by connecting behavioral, informational, and derivative-based signals into a unified empirical agenda on financial fragility.

Figures

Figure 2.1: Average quarterly skewness risk premium

This figure plots the time-series average of skewness risk premium (SRP) for the whole sample from January 1996 to December 2021. The Skewness swap starts on the 4th Monday of each month and matures on the 3rd Friday in the next month. The SRP is the quarterly average return of monthly Skewness swap. In each month, 1 dollar is invested in the Skewness swap, the return is added to the previous gains without compounding.

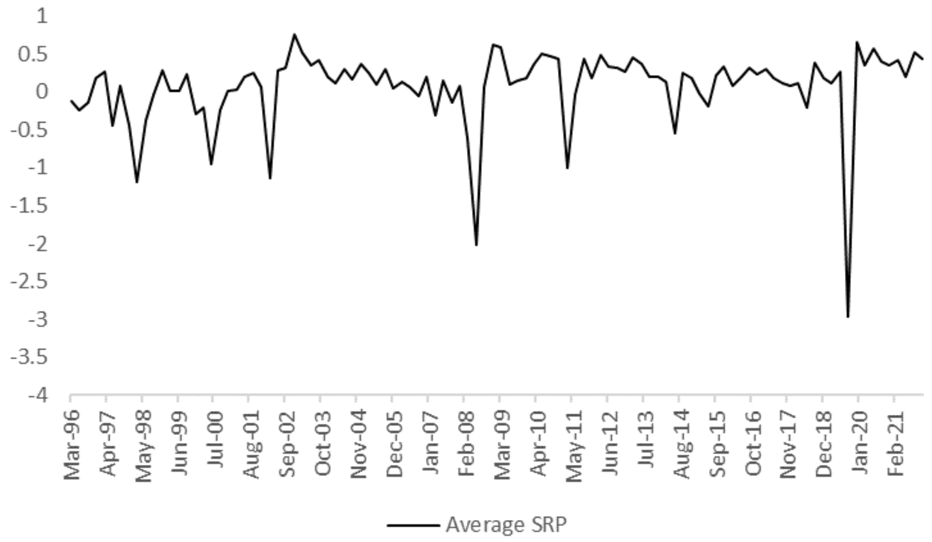


Figure 2.2: Construction of OTM Put Strike Asymmetry for Oracle Corporation

This figure shows the moneyness level for all put options traded a single day for Oracle Corporation. The yellow bar charts are OTM put options, the blue bar charts are ITM put options.

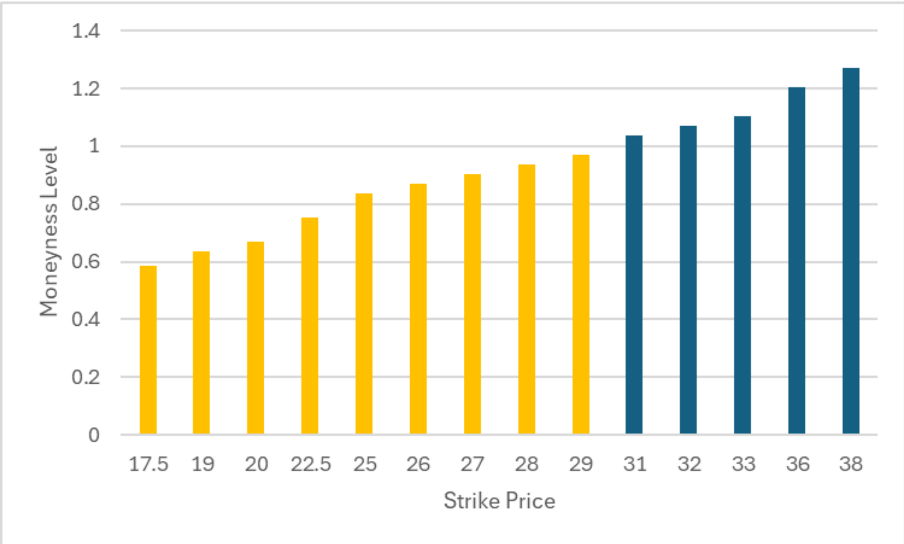


Figure 2.3: Construction of OTM Put Strike Asymmetry for Oracle Corporation

This figure shows how far each strike price is away from the spot price (asymmetry). The yellow bar charts are OTM put options, the blue bar charts are ITM put options.

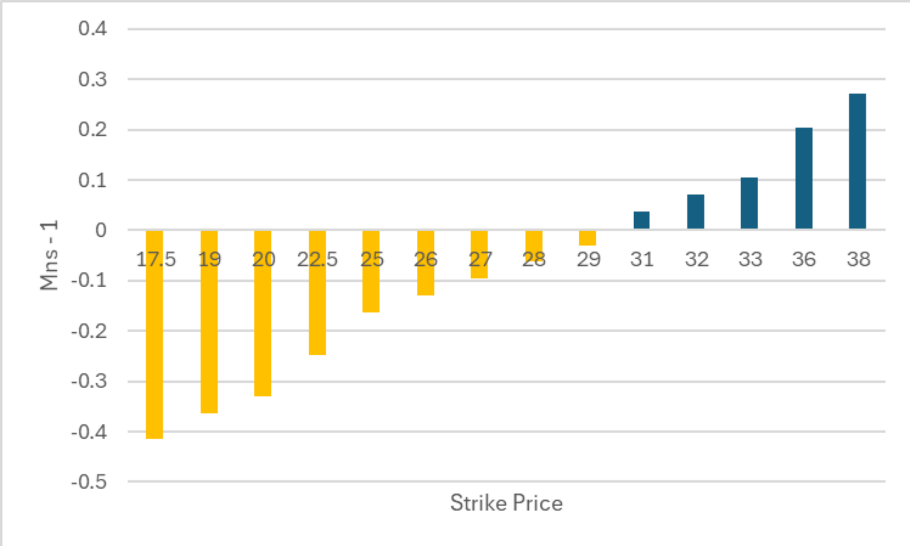


Figure 2.4: Construction of OTM Put Strike Asymmetry for Oracle Corporation

This figure shows the trading volume for each strike price traded in that day. The yellow bar charts are OTM put options, the blue bar charts are ITM put options.

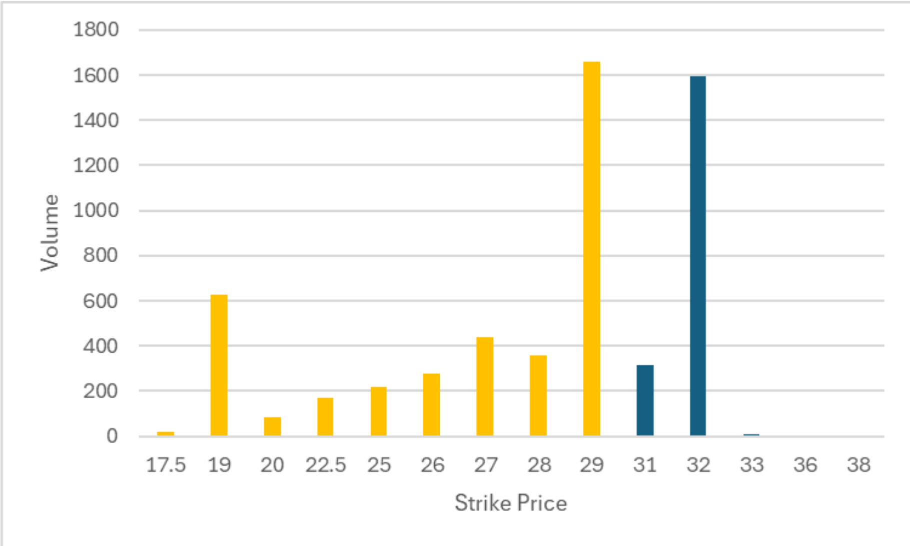
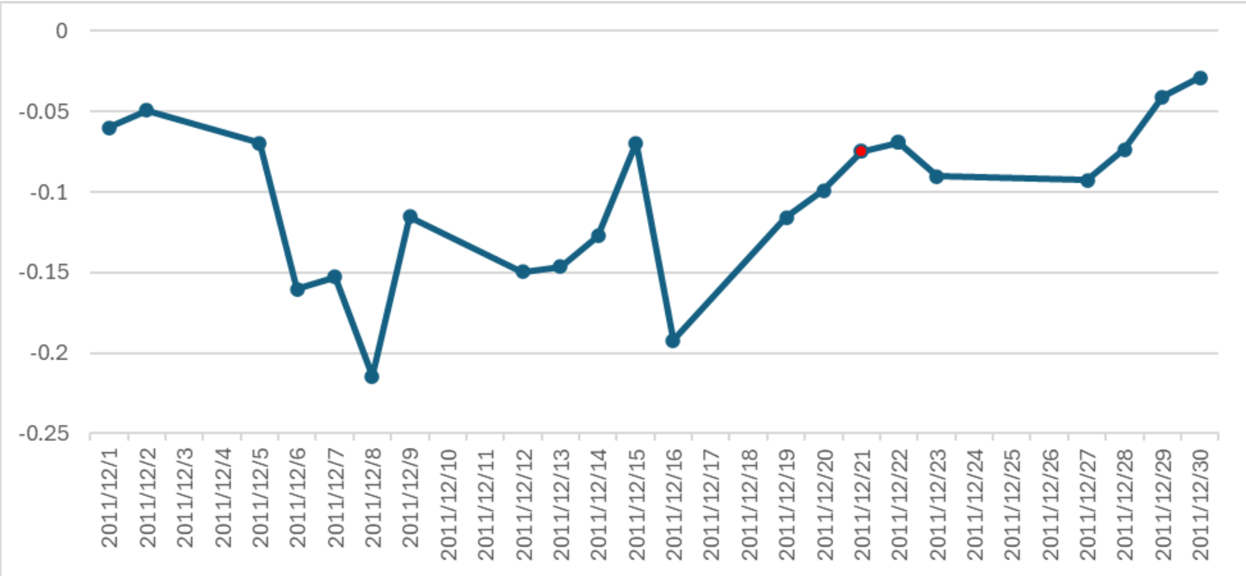


Figure 2.5: Construction of OTM Put Strike Asymmetry for Oracle Corporation

This figure shows the (moneyness level – 1) * volume for each strike price traded in that day. The yellow bar charts are OTM put options, the blue bar charts are ITM put options.

Figure 2.6: Daily evolution of Oracle's OTM Put Strike Asymmetry

This figure shows the daily OTM put strike asymmetry for Oracle stock from 2011-12-01 to 2011-12-31. The red dot is the actual stock price crash day, on that day, stock price dropped more than 11%.



3 Managerial discretion and Skewness risk premium

3.1 Introduction

It has been widely documented that managers hide bad news through earnings management practices. When previously accumulated bad news is released at once, it causes negative shocks in stock prices (Sloan, 1996; Jin and Myers, 2006; Hutton, Marcus, and Tehranian, 2009; Chi and Gupta, 2009; Zhu, 2016, among many others). Investors, on the other hand, dislike negative skewness because of the value destruction. Previous literature document that investors are willing to pay a high premium in the options market to protect themselves from negative skewness even though these options are never optimal to exercise (Bollen and Whaley, 2004; Driessen and Maenhout, 2007). Some studies focus on the skewness risk premium (SRP) (Kozhan, Neuberger, and Schneider, 2013; Schneider and Trojani, 2015; Pederzoli, 2021). In particular, Pederzoli (2021) measure the SRP at individual stock level. SRP is the difference between the risk-neutral skewness and realized skewness in the options market. Given that investors tend to hedge against downward movements to avoid losses, the SRP is generally positive (reflecting the compensation for bearing the downside risk), whereas SRP is negative when severe losses in stock price happen. Skewness swaps appear as the most appropriate vehicles for trading fear because it is a pure bet on the third moment and independent on first, second and fourth moment. Therefore, SRP reflects investors' fear for the sudden drop in the underlying stock price.

In this chapter, I study whether firms' managerial discretion, as reflected by discretionary accruals, determines the negative skewness, as reflected by firm level SRP. This study is motivated by previous studies which attempt to link earnings management practices with stock price crashes. (Hutton, Marcus, and Tehranian, 2009; Bradshaw, Hutton, Marcus, and Tehranian, 2010; Zhu 2016). These studies define crashes when the weekly return is 3 times standard deviation below its mean, representing an extreme downward movement in firm specific weekly returns. They argue that managers use income-increasing techniques to inflate accruals and hoard bad information. The bad news accumulates across time and managers release all bad news together at a tipping point, resulting in a crash in stock price. In addition, Benmelech, Kandel, and Veronesi (2010) develop a model and speculate that it is difficult for shareholders to separate bad news hoardings from the real increase of capitals. Investors fail to recognize earnings management practices and overestimate the value of these firms, eventually generate a negative return in the future. In addition to bad news hoarding, other mechanisms such as investor overreaction, liquidity shocks, or shifts in market sentiment may also contribute to crashes. However, these crashes are rare and extreme realization of risk. In this chapter, I use skewness as a measure of downward movement in stock price because it picks up not just crashes but also negative skew in the market. Previous literature document that on average SRP is very high, indicating a fear for negative skewness in the underlying asset price (Kozhan, Neuberger, and Schneider, 2013; Schneider and Trojani, 2015). Following Pederzoli (2021), I construct a skewness swap to measure SRP at individual stock level using out of the money options. Skewness swap is a portfolio of options which investors who would like to hedge against a negative skew in stock price buy at the start date of each month. Hence the price of the portfolio determines hedger's willingness to protect themselves against a negative skew and measures the risk-neutral skewness. Investors who want to protect themselves sell skewness swap (buy insurance), the buyer of skewness swap (sell insurance) get some compensation for bearing the skewness risk (sudden drop in realized skewness). The payoff of that portfolio is realized at maturity date and measures the realized skewness. Therefore, the return on skewness swap (SRP) is the difference between the payoff and the price of the options portfolio. SRP is more preferable than other crash risk premium variables. First, this chapter focuses on the individual stock level, previous risk premiums focus on index options (Kozhan, Neuberger, and Schneider, 2013). Risk premium from index options captures the market crash and ignores the crash risk at individual level. Second, SRP captures the downside tail risk. The variance risk premium captures both sides of risk, variance risk premium is positive when skewness is very high or very low. Although SRP is positively correlated with variance risk premium, they contain different information. Third, the skewness swap is model free and directly tradeable.

Based on the findings of previous research, this chapter predicts that discretionary accruals are negatively related to the SRP. I predict that if investors hold stocks with high earnings management practices, they believe these stocks are more likely to generate negative return in the future, they will go to options market to purchase insurance in the form of skewness swap (sell skewness, which means long OTM put options and short OTM call option). Firms engaging in high earnings management typically use income-increasing techniques to inflate reported earnings or smooth income over time (Jones, 1991), concealing adverse information until it is eventually released. When firms release accumulated bad news at once, the stock price goes down and the realized skewness is more negative than risk-neutral skewness, which leads us to observe a negative SRP.

Using 24385 firm-quarter observations from 1996 to 2021, this chapter finds that earnings management is significantly and negatively associated with the SRP. This finding is consistent with the prediction that firms who manage their earnings have higher skewness risk. When accumulated bad news is revealed at once, the realized skewness risk generates a negative SRP. This relation is robust after controlling for various control variables, including market to book, leverage, size, ROE, short interest, total volatility, stock return, stock turnover, earnings volatility, beta, and implied volatility smirk. It is possible that the negative relation between SRP and discretionary accruals is affected by the market crash. To alleviate this concern, the results are also checked by omitting the observations during the 2008 crisis period. Following Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2016), this chapter considers the crisis period from August 2007 to June 2009. The post-Covid-19 period is also considered as another crisis period. The negative relations between SRP and discretionary accruals still hold during non-crisis periods.

This chapter continues to examine when high discretionary accrual stocks generate negative SRP. A daily portfolio analysis is implemented around actual earnings announcement day, tracking the SRP from the next trading day until maturity based on the level of discretionary accruals. The same analysis is performed around pseudo earnings announcement day, which is randomly generated within the quarter and sufficiently far away from actual earnings announcement day. Consistent with the prediction, the findings show that firms with high discretionary accruals generate low SRP the next day after earnings announcement day, and no significant effect is observed around pseudo earnings announcement days. This finding is consistent with Van Buskirk (2011) and confirms the importance of earnings announcements as information-dense events affecting the SRP for firms that manage their earnings.

To further validate the negative relation between SRP and discretionary accruals around earnings announcement day, a portfolio analysis is conducted using the surprise indicator. Following Skinner and Sloan (2002), an indicator variable Good is constructed. Good equals 1 if the realized earnings per share (EPS) is greater than the median of analyst forecast EPS, and equals 0 if realized EPS is equal to or below the median. Portfolio analysis by discretionary accruals and Good indicator is then performed. Consistent with the prediction, firms who inflate earnings have significant negative SRP when their realized EPS does not meet analyst expectations. This finding is in line with the idea that negative earnings surprise serves as the tipping point above which it is no longer possible for firms with high discretionary accruals to keep hiding bad news. Hence, when realized earnings are below the expectation, all previously accumulated bad information is released at once, causing a significant decline in the realized skewness and a negative SRP. While discretionary accruals provide important information about earnings manipulation and bad news hoarding, they capture only one aspect of the information set reflected in the skewness risk premium. Hence, the relationship between discretionary accruals and SRP should be viewed as necessary but not sufficient: high discretionary accruals are likely to predict elevated SRP, but high SRP can also arise from other sources of downside risk such as market sentiment or macroeconomic uncertainty.

This chapter contributes to the literature in the following ways. First, it is the first to quantify the risk premium associated with firms with different levels of discretionary accruals. Hutton, Marcus, and Tehranian (2009) show that opacity increases the likelihood of future stock price crashes. This chapter extends theirs by focusing on the SRP, which can be seen as a measure of the premium that investors are willing to pay to protect themselves from crash risk. The expectation of crash from investors differs from the realized crashes. The measurement of realized crashes provides limited information for perceived ex-ante expectations of crashes (Santa-Clara and Yan 2010). Moreover, recent studies show that investors are willing to pay a large amount of premium (as measured by the SRP) to protect themselves from the crash (realized crash), although crash may not actually happen (Bollerslev and Todorov 2011; Pederzoli 2021). Thus, the impacts of managerial opportunism (as measured by discretionary accruals) on the expectation of crash and realized crash are both important.

Second, this chapter also contributes to the discretionary accruals literature on when to buy or sell stocks. Previous studies show how earnings management affects the future stock return. In the cross-section, firms who manipulate earnings show negative stock return in the future. However, these studies do not show the exact day that generates the negative return (e.g., Hutton, Marcus, and Tehranian, 2009; Chi and Gupta, 2009). In addition, some studies show that large price movement happens around earnings announcement day (e.g., Van Buskirk, 2011; Gao, Xing, and Zhang, 2018). Thus, it is reasonable to study whether crash happens for stocks with different levels of discretionary accruals. This chapter extends the literature by focusing on the performance of skewness swaps during a short period around actual earnings announcement day. The results suggest that firms who manipulate earnings are more likely to crash around earnings announcement day.

Third, this chapter explores how SRP reflects fundamental information from firms' financial statements. Pederzoli (2021) explains high SRP by short interest, a stock-level characteristic variable. This result suggests that stocks with high short selling constraints have higher demand for put options and hence push up the SRP. This chapter examines another possible source of the high premium by taking earnings quality into consideration. Moreover, the findings indicate that the options market does not fully reflect the information from discretionary accruals. This finding may help researchers to price options more accurately by including firm level accounting information such as discretionary accruals in option valuation models. This approach allows option pricing to better capture informational asymmetries that are not reflected in standard frameworks.

3.2 Data and Methodology

In this section, we introduce the empirical methodology including the sample selection, data filtering and measurement of the main and control variables.

3.2.1 Data

Our sample period is from January 1996 to December 2021. To compute the skewness swap payoffs and stock-related control characteristics, I obtain data on daily closing prices, trading volume, shares outstanding and returns for all individual stocks with listed options traded on US exchanges from CRSP. Further, I collect historical options data including volume, strike prices, best bid and ask prices, open interest, delta and implied volatilities from Ivy DB's OptionMetrics to construct implied volatility smirk and skewness swaps. Data required for the computation of discretionary accruals and accounting-based control variables are from quarterly Compustat file. Finally, I use Compustat Short Interest dataset to calculate a percentage of shares held short and I/B/E/S data file to estimate earnings surprises following quarterly announcement dates.

Next, I apply the following filters to the stock and options data. First, I exclude stocks if they do not have an exact match in daily close price provided by Compustat, CRSP, and OptionMetrics at the end of each year. Second, I exclude options if they have a zero or negative open interest, a negative bid-ask spread, a zero bid price and negative implied volatility. Further, I require at least two out-of-the-money (OTM) call options and two out-of-the-money put options to build skewness swaps. Finally, to take into account the special behaviour of stocks, I exclude the whole month’s observation if stock distributes special dividends during that monthly horizon and if stock experiences a split or repurchase during that month. The final sample consists of 4,938 firms and 24,385 firm-quarter observations.

I create a quarterly estimate of SRP using swaps constructed each month within a quarter. In particular, as options normally expire on the 3rd Friday of the month, we open the swap position for each stock on the first trading day after 3rd Friday (usually this is 4th Monday) of the first month in a quarter and close the swap position on the 3rd Friday of the next month. I then measure the return on a swap position over the first month in a quarter. Next, I build another swap contract on the first trading day after 3rd Friday of the second month in a quarter and close the swap position on the 3rd Friday of the next month. Lastly, I create the third swap contract within a quarter and measure the payoff over the next month. As a result, I obtain three monthly swap returns within the quarter and estimate the quarterly SRP as the average monthly swap return over three months. In the empirical analysis, we relate the current quarter's SRP to the discretionary accruals and control variables calculated using the information known up to and including the previous quarter.

3.2.2 Defining SRP

In this section, I detail the construction methodology of a monthly skewness swap and its return measurement. Following Pederzoli (2021), I define a skewness swap in a form of a trading strategy, where the fixed leg, settled at the start date of the swap, is exchanged with the floating leg at the maturity date of the swap. More specifically, on the first trading day after 3rd Friday of the month, an investor purchases the portfolio of OTM call and put options setting a fixed leg and the price of this portfolio measures the risk-neutral skewness of the asset. At the maturity date i.e. 3rd Friday of the next month, an investor obtains the final value of this option portfolio (that is also delta-hedged) which reflects the floating leg of the swap and measures the realized skewness of the asset. As a result, the difference between the final value (i.e. floating leg) and the price (i.e fixed leg) of the option portfolio determines the swap payoff and the risk premium demanded by investors for bearing negative skewness risk. All the payments of the swap constituting the payoff are made at maturity, when the investors exchange the fixed leg with the floating leg. The value of the swap on the first trading day after 3rd Friday of the month is zero.

Mathematically, the skewness swap is based on the strategy developed by Schneider and Trojani 2015 paper that proposes a Hellinger skew swap for trading skewness using options. The swap is a pure bet on the third moment of the return distribution and can be built with American-style options. The fixed $(\bar{S})$ and floating legs $(\tilde{S})$ of the swap have the following form:

$$\overline{Swap} = \frac{1}{B_{0,T}}\left(\int_0^{Fwd_{0,T}} \phi''(K) Price_{put}\, dK + \int_{F_{wd0,T}}^{\infty} \phi''(K) Price_{call}\, dK\right) \quad (3.1)$$

$$\widetilde{Swap} = \left(\int_0^{Fwd_{0,T}} \phi''(K)Pay_{put}\, \mathrm{d}K + \int_{Fwd_{0,T}}^{\infty} \phi''(K)Pay_{call}\, \mathrm{d}K\right) + \sum_{i=1}^{n-1}(\phi'(Fwd_{i-1,T}) - \phi'(Fwd_{i,T}))\,(Fwd_{T,T} - Fwd_{i,T}) \quad (3.2)$$

Where $\overline{Swap}$ is the fixed leg of the swap and $\widetilde{Swap}$ is the floating leg of the swap; and $Price_{put}$ and $Price_{call}$ are the price of European put and call options at time 0 with maturity T and strike price K; Pay_{put} and Pay_{call} are the payoff of the option at maturity; $Fwd_{i,T}$ is the forward price at time i with maturity T; $B_{0,T}$ is the price of zero-coupon bond at time 0 with maturity T, the face value of the bond is 1 dollar; K is the strike price for each option in the skewness swap; ϕ is the twice differentiable moment generating function, which defines the moment of the distributions in our skewness swap. This function has the following form.

$$\phi(x) = \phi\left(\frac{x}{Fwd_{0,T}}\right) = -24\left(\frac{x}{Fwd_{0,T}}\right)^{\frac{1}{2}} log\left(\frac{x}{Fwd_{0,T}}\right) + 24\left[\left(\frac{x}{Fwd_{0,T}}\right)^{\frac{1}{2}}\left(log\left(\frac{x}{Fwd_{0,T}}\right)^2 + 8\right) - 8\right] \quad (3.3)$$

At the beginning date of the swap, I use equation $\overline{Swap}$ with $\phi(x)$ to construct fixed leg. The equation $\overline{Swap}$ is written for options which have continuum strike price from 0 to +∞. In reality, I only have finite number of options. Therefore, I need to apply a discrete approximation for equation $\overline{Swap}$.

Suppose that at the start date of skewness swap, I have N put options and M call options, I can order the strike of these options in the following form.

$$\boldsymbol{K_1} < \cdots < \boldsymbol{K_{Put}} \leq Fwd_{0,T} < K_{Put+1} < \cdots < K_N$$

$$K_1 < \cdots < K_{call} \leq Fwd_{0,T} < \boldsymbol{K_{call+1}} < \cdots < \boldsymbol{K_M}$$

The skewness swap is constructed by out of the money options. Therefore, I select the following options only.

$$\boldsymbol{K_1} < \cdots < \boldsymbol{K_{Put}} \leq Fwd_{0,T} < \boldsymbol{K_{call+1}} < \cdots < \boldsymbol{K_M}$$

Then I can approximate the fixed leg $\overline{Swap}$ with the following formula

$$\overline{Swap} = \frac{1}{B_{0,T}}\left(\sum_{i=1}^{K_{Put}} \phi''(K_i)Price_{put}(K_i)\Delta K_i + \sum_{i=call+1}^{M} \phi''(K_i)Price_{call}(K_i)\Delta K_i\right) \tag{3.4}$$

Where

$$\Delta K_i \begin{cases} \dfrac{K_{i+1} - K_{i-1}}{2} & if\ 1 < i < M \\ K_2 - K_1 & if\ i = 1 \\ K_M - K_{M-1} & if\ i = M \end{cases}$$

$$\Delta K_i = \frac{K_{i+1} - K_{i-1}}{2} \qquad if\ 1 < i < M$$

$$\Delta K_i = K_2 - K_1 \qquad if\ i = 1$$

$$\Delta K_i = K_M - K_{M-1} \qquad if\ i = M$$

The floating leg $\widetilde{Swap}$ has two components: the payoff of the option portfolio plus delta hedge. Similar with the fixed leg, the same approximation is applied for the integral in the floating leg. I calculate the delta hedge from the next day of the beginning date until one day before the maturity of the skewness swap.

The dollar gain of risk premium for each stock is calculated by the difference between the floating leg of the swap and the fixed leg of the swap.

$$Risk\ Premium = \widetilde{Swap} - \overline{Swap}$$

The percentage gain of risk premium for each stock is the dollar gain divided by the cost I need to pay for the fixed leg of the swap.

$$Risk\ Premium\% = (\widetilde{Swap} - \overline{Swap})/cost$$

Where

$$cost = \frac{1}{B_{0,T}}\left(\sum_{i=1}^{K_{Put}} |\phi''(K_i)| Price_{put}(K_i)\Delta K_i + \sum_{i=call+1}^{M} |\phi''(K_i)| Price_{call}(K_i)\Delta K_i\right) \tag{3.5}$$

The equation $cost$ is similar with equation $\overline{Swap}$. The only difference is, when I compute cost, I take absolute value $|\phi''(K_i)|$.

Finally, I obtain the SRP, measured as a percentage gain of the swap, at the maturity as the difference between the floating leg and fixed leg of the swap, divided by the cost of the option portfolio (i.e. the absolute value of fixed leg). Intuitively, an investor buying (selling) the skewness swap takes a short (long) position in a fixed leg, a long (short) position in a floating leg and expects to earn a positive swap payoff when the realized skewness at the maturity does not exceed (exceeds) the risk-neutral skewness. Hence, a positive (negative) SRP indicates gains for swap buyers (sellers) who sell (buy) options forming a fixed leg and bet on no change or increase (decrease) in realized skewness, given in the floating leg. From the company perspective, a positive (negative) SRP is beneficial (detrimental) to shareholders as it generates gains (losses) for investors' equity option holdings. It is important to note that I do not measure a stock price crash *per se* using a popular ad-hoc approach of applying standard-deviation-based thresholds. Instead, a substantial downward movement in the stock price will be intrinsically reflected in the negative swap payoff only when the price falls down sufficiently to make out-of-money options worth exercising at the maturity and thus should only be considered as a crash when the realization of the third moment exceeds its *ex-ante* expectations by investors. Therefore, the SRP naturally combines both crash expectations (in a fixed leg) and crash realizations (in a floating leg).

[Insert Figure 3.1 here]

To examine the magnitude of SRP over time, I plot the monthly average swap return within a quarter across all stocks in our sample. Figure 1 clearly shows that the premium for bearing the negative skewness risk is mostly positive and exhibits significant declines during the periods of financial distress. This result is consistent with that documented by prior studies (see, for instance, Kozhan et al., 2013; Schneider and Trojani, 2015) and suggests that investors buying the swap and betting on positive skewness make gains on average, whereas those who sell a swap to hedge against a sudden decrease in skewness earn a positive return only when stocks experience a large downfall. For example, during the global financial crisis of 2007-2009, the SRP reaches an extremely high value of 350% on average implying substantial gains for skewness risk hedgers.

3.2.3 Defining Discretionary Accruals

Previous studies usually use annual data to estimate discretionary accruals. in this chapter, I construct skewness swap in a quarterly frequency. Therefore, I select quarterly data between 1990 to 2018 to estimate the discretionary accruals.

Following Chi and Gupta (2009), I measure the earnings management using the discretionary accruals obtained from a modified Jones (1991) model. More specifically, I run the following cross-sectional regressions for each quarter and each of the Fama-French 48 industry groups excluding financial and utility firms.

$$\frac{Total\ Accruals_{it}}{Total\ Asset_{it-1}} = \alpha \frac{1}{Total\ Asset_{it-1}} + \beta_1 \frac{\Delta Sales_{it} - \Delta Rect_{it}}{Total\ Asset_{it-1}} + \beta_2 \frac{PPEG_{it}}{Total\ Asset_{it-1}} + \beta_3 \frac{CFEE_{it}}{Total\ Asset_{it-1}} + \varepsilon_{it} \tag{3.6}$$

Where $Total\ Accruals_{it}$ is the total accruals at time t, we use the change in current asset (Compustat item 4) plus the the change in debt in current liabilities (Compustat item 34) plus the change in income taxes payable (Compustat item 71) minus the change in current liabilities (Compustat item 5) minus the change in cash and short-term investment (Compustat item 1) minus the depreciation and amortization item (Compustat item 14) to calculate the total accruals. $Total\ Asset_{it-1}$ is the total asset (Compustat item 6) at time t-1. $\Delta Sales_{it}$ is the change in sales (Compustat item 12). $\Delta Rect_{it}$ is the change in receivables (Compustat item 2). $PPEG_{it}$ is the gross property, plant and equipment (Compustat item 7). $CFEE_{it}$ is the income before extraordinary items (Compustat item 18) minus the $Total\ Accruals_{it}$. The quarterly discretionary accruals are the residuals from the above regression. The quarterly discretionary accruals are the residuals obtained from the above regression. In the main analysis, I use the discretionary accruals over one year estimated as the moving sum of quarterly discretionary accruals in the past four quarters (Disc. Accruals (4qtrs)). To examine the long-run effect of earnings management practices on SRP, I also estimate discretionary accruals over the previous two and three years as the moving sum of quarterly discretionary accruals over the past eight and twelve quarters (Disc. Accruals (8qtrs) and Disc. Accruals (12qtrs)), respectively. As shown by Dechow, Sloan and Sweeney (1996), increase in discretionary accruals is associated with earnings manipulation (i.e. inflated earnings), which typically follows by large negative discretionary accruals leading to correction in reported earnings.

3.2.4 Control variables

In the baseline regressions, this chapter controls for a wide array of previously documented stock price crash risk predictors (Hutton, Marcus, and Tehranian, 2009; Kim and Zhang, 2014). First, stock-related characteristics are included, such as firm's size (Size), the percentage of shares held short (Short Interest), stock return volatility (Total Volatility), quarterly stock return and its lagged values (Stock Return), turnover (Stock Turnover), and beta (Beta). Second, accounting-based control variables are added, such as market value to book equity ratio (Market to Book), financial leverage (Leverage), firm performance (ROE), and volatility of firm's business operations (Earnings Volatility) to verify the significance of discretionary accruals effects in the presence of firm fundamentals. Finally, to ensure that the relationship between earnings management and SRP is not driven by a perceived crash risk, implied volatility smirk (Implied Volatility Smirk) is included in all regression models.[1]

[1] To construct this measure, options data are obtained from OptionMetrics for all eligible stocks and subjected to a series of filters. First, only contracts with implied volatility between 0.03 and 2 are retained. Second, to ensure liquidity, contracts must exhibit positive open interest, trading volume, and bid price, along with a non-negative bid-ask spread. Third, options with absolute delta values below 0.02 or above 0.98 are excluded. Finally, open interest is used as weights to compute the daily weighted average of implied volatilities for at-the-money (ATM)

Consistent with Chen, Hong, and Stein (2001), Duan and Wei (2009), Hutton, Marcus, and Tehranian (2009), Van Buskirk (2011), Kim and L. Zhang (2014), and Callen and Fang (2015), this chapter expects a positive relationship between Leverage, Size, and SRP, whereas Short Interest, Total Volatility, Stock Return, Stock Turnover, and Beta are expected to be negatively associated with the SRP. In the Appendix, I provide a detailed definition of all control variables.

[Insert Table 3.1 here]

Table 3.1 presents the mean, standard deviation, first quartile, median, and third quartile for all variables used in this chapter. Consistent with Figure 1, the skewness swap return (SRP) is positive on average, with notable declines observed in the lower quartile, indicating the presence of significant downside tail events. The mean and median of Disc. Accruals (4 qtrs) are both close to zero, suggesting that the average firm in the sample does not engage in earnings management through unusually high or low accruals. The quartile statistics also indicate that Disc. Accruals (4 qtrs) are approximately symmetrically distributed across the sample. The summary statistics of control variables show mean and median values that are comparable to those reported in the existing literature.

3.3 Empirical analysis

This section presents the empirical findings of this chapter. First, the average skewness swap returns are examined across portfolios of firms sorted by different levels of Disc. Accruals (4 qtrs). Second, regression analysis is conducted to establish the effect of Disc. Accruals (4 qtrs) on swap returns after controlling for a wide array of well-known firm characteristics. The analysis then explores whether the negative relationship between Disc. Accruals (4 qtrs) and swap returns remains in the presence of perceived crash risk and further investigates the long-

call options (delta between 0.375 and 0.625) and out-of-the-money (OTM) put options (delta between –0.375 and –0.125). The quarterly estimate of the implied volatility smirk slope is calculated as the average daily difference between OTM put and ATM call implied volatilities over a three-month period.

run impact of earnings management practices on SRP. In addition, the empirical tests examine the association between Disc. Accruals (4 qtrs) and SRP around earnings announcement dates, including periods with different types of earnings surprises. Finally, a series of alternative regression specifications are estimated to verify the robustness of the results.

3.3.1 Portfolio-level analysis

This chapter begins the empirical analysis by explicitly exploring the economic price of crash risk for firms with various levels of Disc. Accruals (4 qtrs). Previous studies develop several firm-level indicators of earnings management and find that companies may be prone to significant declines in stock prices when firms' earnings significantly deviate from the net cash flow, due to managers' incentives to hide negative information and overstate accruals (see, for instance, Dechow, Sloan and Sweeney, 1996; Hutton, Marcus and Tehranian, 2009). While these papers establish a strong link between firm earnings manipulation and *ex post* realization of stock price crashes, there is a lack of direct evidence on the financial costs for firms that choose to accumulate bad news and their effect on investor performance. Applying the methodology recently developed by Pederzoli (2021), this chapter quantifies the crash risk premium via skewness swap returns, which directly reflect investors' monetary gains and losses from holding options on firms pursuing diverse earnings management practices.

To acquire first evidence of the Disc. Accruals (4 qtrs) effect on SRP and to discern any non-linear relations, a univariate portfolio-level analysis is conducted by sorting stocks based on Disc. Accruals (4 qtrs) estimated from the modified Jones model. At the end of each quarter, firms are allocated into five accrual-based portfolios. Portfolio 1 consists of firms with the lowest (understated) accruals, while Portfolio 5 consists of those with the highest (overstated) accruals over the past one year. At the beginning of the following quarter, for each firm in a given quintile portfolio, a skewness swap is implemented by taking a long position in the floating leg and a short position in the fixed leg. The swap return is measured over the next month as the difference between the floating and fixed legs. Once the first swap expires, two additional monthly swaps are executed, each starting and ending on the third Friday of the month. A quarterly estimate of SRP is then calculated as the average skewness swap return over the three-month period.

A time-series average of the quarterly mean SRP is reported for each quintile portfolio, as well as for Portfolio 5 minus Portfolio 1. This difference reflects the swap return spread between firms that inflate earnings (Portfolio 5) and those that deflate earnings (Portfolio 1). More specifically, Portfolios 5–1 constitute a trading strategy that buys a skewness swap on stocks with the highest levels of Disc. Accruals (4 qtrs) (Portfolio 5) and sells a skewness swap on stocks with the lowest levels of Disc. Accruals (4 qtrs) (Portfolio 1). Finally, risk-adjusted swap returns are documented by computing alphas from seven-factor model, which augments Fama-French 5 factor model with the momentum and Pástor and Stambaugh 2003 liquidity factors.

[Insert Table 3.2 here]

Table 3.2 presents the results. First, as the portfolio moves from stocks with the lowest levels of Disc. Accruals (4 qtrs) to those with the highest levels, skewness swap returns exhibit an inverse U-shape pattern, reaching the highest values for firms that tend to keep their Disc. Accruals (4 qtrs) near zero on average. A portfolio of stocks with the lowest (highest) Disc. Accruals (4 qtrs) over the past year generates an average monthly swap return of 13% (–3.6%) within a quarter, with the highest return of 18.7% observed for Portfolio 3. Intuitively, this pattern suggests that investors purchasing (selling) a skewness swap earn a considerably lower (higher) return on stocks that are more (less) exposed to sudden decreases in realized skewness, i.e., crashes caused by extreme (or zero) levels of Disc. Accruals (4 qtrs).

Second, focusing on portfolio differences, the systematic underperformance of portfolios with high levels of Disc. Accruals (4 qtrs) relative to firms that deflate earnings is tested. The results show that the swap returns on stocks in Portfolio 5 significantly differ from those in Portfolio 1, indicating that the premium for crash risk varies consistently across firms with extreme levels of earnings overstatement and understatement. Stocks with the highest levels of Disc. Accruals (4 qtrs) exhibit a substantial decline in realized skewness, generating significantly lower monthly average SRP within a quarter by 16.7% (t-statistic = 3.54), compared to stocks that deflate earnings. These results remain strong and largely unchanged after adjusting for risk using the seven-factor model. The monthly average alpha within a quarter equals –18.6% for Portfolio 5–1. Overall, the findings reveal a substantial premium of over 18% per month within a quarter, which crash-averse investors earn by selling a skewness swap on firms with high Disc. Accruals (4 qtrs) (i.e., betting on a sudden decrease in skewness) and buying a swap on firms with low Disc. Accruals (4 qtrs) (i.e., betting on no change in skewness). These findings can be illustrated through a simple trading strategy based on the empirical results. Each quarter, investors could go long on firms in the lowest discretionary accrual quintile (Q1) and short on those in the highest quintile (Q5), forming a zero-cost portfolio. This position effectively buys exposure to high-quality earnings firms and sells crash-prone firms, earning an average SRP spread of about 16–18% within a quarter as reported in Table 3.2. From a company perspective, this result provides evidence of managerial reporting opportunism, reflecting managers' willingness to inflate earnings through high Disc. Accruals (4 qtrs) in order to hide bad news. This practice ultimately imposes a significant cost on shareholders, amounting to a monthly loss of more than 18% within a quarter.

3.3.2 Fama-MacBeth regressions

The results from portfolio-level analysis elicit a strong negative relationship between Disc. Accruals (4 qtrs) and skewness swap returns (SRP), suggesting a significant gain for investors holding options on firms that inflate their earnings, and a sizeable loss to the firm's equity value. This section further investigates this relationship in a regression setting, controlling for previously documented crash-risk predictors. Specifically, quarterly Fama and MacBeth (1973) cross-sectional regressions are conducted using monthly average SRP within the current quarter, regressed on Disc. Accruals (4 qtrs) from the past year, along with a set of control variables measured at the end of the previous quarter. Following standard practice in the crash-risk literature (e.g., Kim, Li and Zhang, 2011; Kim and Zhang, 2014; Chen, Kim and Yao, 2017), the control variables are grouped into two categories. The first includes stock characteristics: Size, Short Interest, Total Volatility, Stock Return, Stock Turnover, and Beta. The second group contains accounting-based firm fundamentals: Market to Book, Leverage, ROE, and Earnings Volatility. Additionally, Implied Volatility Smirk is included as a proxy for perceived crash risk. To minimize the influence of extreme values, all independent variables are winsorized at the 1st and 99th percentiles. For interpretability, coefficients are standardized to reflect the effect of a one-standard-deviation increase in each regressor on SRP. Reported t-statistics are Newey-West adjusted with two lags.

[Insert Table 3.3 here]

Table 3.3 presents the baseline univariate (Model 1) and multivariate (Models 2 and 3) regression results. Starting with a two-variable model, a one-standard-deviation increase in Disc. Accruals (4 qtrs) over the past year leads to a 3.3% average monthly decline in SRP within the next quarter. This coefficient is statistically significant at the 1% level. After controlling for the full set of crash-risk predictors, the negative relationship between Disc. Accruals (4 qtrs) and SRP remains strong, robust, and statistically significant at the 1% level. These results imply a considerable return premium for crash-averse investors who sell swaps on firms with high Disc. Accruals (4 qtrs) (i.e., bet on crash occurrence) and buy swaps on firms with low Disc. Accruals (4 qtrs) (i.e., bet on no skewness change). Consistent with prior literature, the coefficients on Stock Return and Total Volatility are statistically significant and directionally expected: higher volatility and past return are associated with lower SRP (Callen and Fang, 2015; Chen, Hong, and Stein, 2001).

More interestingly, Implied Volatility Smirk shows a strong positive relation with SRP. A one-standard-deviation increase in this measure is associated with a 6.2% rise in monthly SRP, significant at the 1% level. Combined with the results on Disc. Accruals (4 qtrs), this finding highlights the distinct informational content of crash expectations (captured by Implied Volatility Smirk) versus realized crash exposure (captured by Disc. Accruals (4 qtrs)). A positive sign on Implied Volatility Smirk suggests that elevated crash fear increases the swap buyer's willingness to pay for downside protection, consistent with ex ante jump-risk models (e.g., Bates, 2008). In contrast, the negative coefficient on Disc. Accruals (4 qtrs) implies that earnings inflation driven by managerial opportunism benefits swap sellers—those who bet on realized skewness crashes.

In summary, the results provide further evidence that Disc. Accruals (4 qtrs) is a meaningful cross-sectional determinant of SRP, distinct from other stock crash predictors. These findings lend support to the interpretation that inflated accruals reflect bad-news hoarding, which erodes shareholder value and increases the cost of crash insurance priced into the options market.

3.3.3 Information content of implied volatility smirk

Prior literature (Hutton, Marcus, and Tehranian 2009; Bradshaw, Hutton, Marcus, and Tehranian, 2010; Kim and Zhang, 2014; Zhu, 2016) documents a positive and large impact of the earnings management on ex ante measures of crash risk and ex post measures of realized crashes. These crash risk proxies, however, are prone to several issues limiting our understanding of a true predictive power of firm's earnings manipulation for stock price crashes. For example, widely used measures of ex post crash incidence and magnitude such as weekly crash and jump indicators are unable to fully reflect risks anticipated by investors and thus may lead to spurious expectations of crash occurrence even when the ex post crash probability is high (Santa-Clara and Yan, 2010). Likewise, the ex-ante estimates of crash risk may only capture investors' crash expectations and fears, which do not necessarily materialize in the future, and thus mainly reflect an investors' demand for positive risk premium on stocks with a negative jump risk (Bollerslev and Todorov, 2011). More importantly, Kim and Zhang (2014) note that the effect of financial reporting opacity on ex ante and ex post indicators of crash risk and its magnitude vary dramatically due to differential pricing of the expected and realized jump risks and a large risk premium embedded in ex ante forecasts of crashes. Hence, for a deeper and unified understanding of earnings management effect on multifaceted nature of crash risks, this chapter employs a SRP as a natural way to combine both ex-ante crash expectations (in a fixed leg) and ex post crash realizations (in a floating leg) through a tradable portfolio of options. To ensure that the relationship between skewness swap returns and Disc. Accruals (4 qtrs) is not driven by perceived crash risk and is not due to the effect of Disc. Accruals (4 qtrs) on ex ante crash expectations only, a battery of regression tests is run with the Implied Volatility Smirk. Following Bradshaw, Hutton, Marcus, and Tehranian (2010) and Kim and Zhang (2014), the slope of implied volatility smile is exploited as a proxy for investors' ex ante expectations of future crash risk.

[Insert Table 3.4 here]

Table 3.4 presents the results from regression analysis when Implied Volatility Smirk is used as a dependent variable (Models 1 and 2) and as an independent variable to extract residual values of SRP (Model 3). The baseline model specification is identical to the one in Table 3. First, the relationship between Disc. Accruals (4 qtrs) and Implied Volatility Smirk is investigated using quarterly Fama-MacBeth cross-sectional regressions. Model 1 shows that Disc. Accruals (4 qtrs) are positively related to the slope of implied volatility smile, but this effect is weak and not statistically significant after including control variables in the regression model (as shown in Model 2). These findings may come surprising given the general consensus in the literature that earnings management proxies predict option-implied perceived crash risk indicators. However, Bradshaw, Hutton, Marcus, and Tehranian (2010) report significant results for put-based Implied Volatility Smirk, whereas Kim and Zhang (2014) do not examine the relationship between directional Disc. Accruals (4 qtrs) and Implied Volatility Smirk. Hence, the findings provide interesting evidence that a firm manager's proclivity to inflate earnings does not seem to engender high crash risk expectations among investors, suggestive of a minimal role fears play in explaining the Disc. Accruals (4 qtrs) effect on SRP.

Second, to shed more light on the robustness of the association between Disc. Accruals (4 qtrs) and SRP in the presence of Implied Volatility Smirk, the results from the cross-sectional regressions of residuals (from the regression of SRP on smirk) on Disc. Accruals (4 qtrs) and a list of other control variables are reported. This analysis shows that Implied Volatility Smirk is unlikely to explain the main findings, with the coefficient on Disc. Accruals (4 qtrs) retaining the statistical significance at 1% level. Overall, the obtained findings support the results from Table 3.3 and Table 3.4 further confirm that Implied Volatility Smirk and Disc. Accruals (4 qtrs) carry a distinct information content for crash risk premium. One possible reason is that accrual-based measures capture past financial reporting qualities, while the Implied Volatility Smirk reflects investors' forward-looking expectations of tail risk. These two variables therefore represent different information horizons, leading to a weak contemporaneous association.

3.3.4 Long-run effects

A significant premium for bearing a skewness risk is embedded in a portfolio of optionable stocks that are more prone to earnings manipulation via higher levels of Disc. Accruals (4 qtrs) accumulated over the past year. This finding relies on the notion that managers tend to hide bad news and report inflated earnings over a relatively short time horizon of one year. Dechow, Sloan, and Sweeney (1995) demonstrate that firms generally manipulate earnings from one to three years before being detected. Hence, to complement the previous findings, in this section we explore the long-run impact of earnings management on skewness swap returns when Disc. Accruals (8 qtrs) and Disc. Accruals (12 qtrs) are used. In particular, we measure the current quarter's Disc. Accruals (8 qtrs) and Disc. Accruals (12 qtrs) as the moving sum of quarterly accruals in the past eight and twelve quarters, respectively, and relate them to SRP measured over the next quarter.

[Insert Table 3.5 here]

Table 3.5 documents the results. Disc. Accruals (8 qtrs) are still negatively and significantly related to SRP. The magnitude of coefficients and their statistical significance are similar to those observed for Disc. Accruals (4 qtrs) in Table 3. However, when looking at the effect of earnings management using Disc. Accruals (12 qtrs), the coefficient loses its statistical significance. These findings are consistent with those documented by Dechow, Sloan, and Sweeney (1995) and show a clear decay in a long-run effect of inflated earnings on skewness swap returns. This suggests that managers' proclivity to manipulate earnings is unlikely to last long as it becomes more difficult to conceal negative information over long time horizons resulting in a less pronounced and weaker premium for investors betting on a drop in realized skewness for firms that report high Disc. Accruals (12 qtrs).

3.3.5 Evidence around earnings announcements

Our quarterly regression findings evince systematically low skewness swap returns for firms with high Disc. Accruals (4 qtrs). In this section, this chapter delves deeper into understanding of this quarterly effect by performing a more granular analysis of earnings management and subsequent swap returns around earnings announcement days. A vast and extensive literature documents a paramount importance of earnings announcements as information-dense events which provide fundamental information about the firm, drive stock prices (Lamont and Frazzini, 2007) and reduce uncertainty (Dubinsky and Johannes, 2006). Furthermore, a manager's willingness to keep inflating earnings via high Disc. Accruals (4 qtrs) and stockpiling bad news tends to be significantly affected by firm's ability to meet or beat analysts' earnings forecasts and its incentive to avoid negative earnings surprises (see, for example, Payne and Robb, 2000; Matsumoto, 2002; Burgstahler and Eames, 2006). Hence, we expect that a significantly negative SRP for firms that manipulate earnings will be more pronounced when earnings information is released and will be conditional on the type of information disclosed to investors on earnings announcement days. To test the earnings announcement effects, this chapter conducts the following empirical analysis.

First, a daily portfolio-level analysis is implemented around earnings announcements and the swap returns on Disc. Accruals (4 qtrs)-sorted portfolios are examined. In particular, the firms are sorted in ascending order into quintile portfolios (Q1, Q3 and Q5 have stocks with lowest, zero and highest Disc. Accruals (4 qtrs)) based on reported Disc. Accruals (4 qtrs) over the past year prior to the current quarter. Next, for each stock in each portfolio, skewness swaps are constructed 10 trading days prior to the current quarter's earnings announcement day (day 0) and held until 10 trading days after the earnings announcement day. The performance of skewness swaps is tracked (cumulated) each trading day, starting from day -10, to capture any abnormal changes in risk premium around earnings announcements. Finally, the average daily cumulative SRP for each quintile portfolio and portfolios 5-3 and 1-3 (which reflect the swap return differential between firms which inflate earnings (portfolio 5), deflate earnings (portfolio 1) and keep Disc. Accruals (4 qtrs) at a zero level on average (portfolio 3)) are computed. More specifically, portfolios 5-3 and 1-3 constitute a trading strategy that buys a skewness swap on stocks with the lowest and highest levels of Disc. Accruals (4 qtrs) (portfolios 1 and 5, respectively) and sells a skewness swap on stocks with zero levels of Disc. Accruals (4 qtrs) (portfolio 3). To preclude the possibility of any non-earnings-announcements-related effects on SRP, the same analysis is also performed around a pseudo date, which is randomly selected within the quarter and sufficiently distant from a real earnings announcement date. All t-statistics are Newey-West adjusted (with 2 lags).

Second, the swap returns on Disc. Accruals (4 qtrs)-sorted portfolios that are further split into two groups based on positive and negative or zero earnings surprises are investigated. Following Skinner and Sloan (2002), the earnings announcement data (with FPI=6) are first obtained from I/B/E/S summary file for all optionable stocks in the sample and then the earnings surprises are estimated by subtracting the median of forecasted earnings per share (EPS) in the last month of each quarter from the realized EPS in each quarter. When earnings forecasts exceed or equal to realized EPS, negative or zero earnings surprise is recorded and otherwise positive. Further, a dependent bivariate portfolio-level analysis is performed by sorting stocks first into quintile portfolios based on Disc. Accruals (4 qtrs) measured over the past year[2] prior to the current quarter and next, within each Disc. Accruals (4 qtrs)-sorted quintile portfolio, stocks are further divided into 2 groups on the basis of earnings surprises observed in current quarter. As a result, 10 portfolios are obtained. At the beginning of a current quarter, swaps are opened for each stock and quarterly SRP is computed as in univariate analysis in Table 3.2. Finally, a time-series average of the quarterly mean skewness swap returns for each of the 10 obtained portfolios and its Newey-West adjusted (with 2 lags) t-statistics is reported. The average level of Disc. Accruals (4 qtrs) for all 10 portfolios is also shown.

3.3.6 Effects around earnings announcements

[Insert Figure 3.2 and 3.3 here]

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[2] For earnings announcement analysis, I choose to report the results with Disc. Accruals (4 qtrs), however quantitatively similar findings are also documented with Disc. Accruals (8 qtrs) and Disc. Accruals (12 qtrs).

Figures 3.2 and 3.3 as well as Table 3.6 show the findings from a daily portfolio-level analysis around earnings announcements. First, this chapter studies the plot of daily skewness swap returns over 20 days around earnings announcement on portfolios of firms that understate (Q1), neither increase nor decrease (Q3) and overstate (Q5) Disc. Accruals (4 qtrs). Figure 3.2 illustrates a clear monotonic decay of skewness swap returns for all three portfolios from day –10 until day 10, with a more striking and substantial decline in skewness swap returns documented for portfolio 5 from day –1 to 1. This pattern suggests that earnings announcements convey fundamentally important (negative) information only for firms that choose to inflate earnings, leading to a significant monetary gain for those investors who sell swaps on such firms on day –10 and close the position on day 1. In contrast, there is no observed effect for stocks in portfolios 1 and 3 around earnings announcements. Second, a placebo test is conducted to ensure that earnings releases indeed determine the swap returns for firms with inflated earnings and other non-informational days within the quarter do not impact these results. As expected, Figure 3.3 demonstrates that the payoffs of skewness swaps do not systematically differ across three Disc. Accruals (4 qtrs) portfolios and do not exhibit substantial variations around pseudo earnings announcement day. This finding, consistent with Van Buskirk 2011, confirms the first-order importance of earnings announcements as information-dense events affecting the SRP for firms that manage their earnings.

[Insert Table 3.6 here]

Finally, Table 3.6 presents the average returns on portfolios that take a long position in a skewness swap on stocks with the lowest and highest levels of Disc. Accruals (4 qtrs) (portfolios 1 and 5, respectively) and a short position in a skewness swap on stocks with zero levels of Disc. Accruals (4 qtrs) (portfolio 3). The positions are held until day 10 and the daily returns are estimated. As it can be seen, the average swap return differential between portfolios 5 and 3 as well as 1 and 3 exhibits a small magnitude and is not highly statistically significant at any time up to one day prior to earnings announcement and jumps substantially on the day when earnings are released. For example, a strategy that buys a skewness swap on stocks with the highest levels of Disc. Accruals (4 qtrs) (portfolio 5) and sells a skewness swap on stocks with zero levels of Disc. Accruals (4 qtrs) (portfolio 3) generates a swap return of –19.2% on average from day –10 to day 1 (with a t-statistic of –1.98). Placebo test results further confirm that payoffs of skewness swaps for firms with various levels of Disc. Accruals (4 qtrs) are negligible and not statistically significant within a 20-day trading window around a pseudo-event date. In summary, these findings demonstrate that investors holding (selling) a swap on firms that manipulate earnings incur more significant portfolio losses (gains) when firm's fundamental information is disclosed. It suggests that earnings announcements may carry important negative information about the firms that prefer to hide bad news, thus representing a tipping point above which further bad news hoarding through manipulated accruals becomes unbearable resulting in large financial costs for company shareholders following an earnings announcement.

3.3.7 Heterogeneous effects from earnings surprises

[Insert Table 3.7 here]

Table 3.7 reports the average swap returns of the portfolios sorted on Disc. Accruals (4 qtrs) and further split into positive and negative/zero earnings surprises. The results are quite interesting. First, this chapter finds that firms reporting high Disc. Accruals (4 qtrs) (portfolio 5) generate an economically large and statistically significant negative monthly average swap return of 21.4% within the quarter after negative earnings surprises. This finding is in line with the idea that negative earnings surprises serve as a tipping point above which it is no longer possible for firms with high Disc. Accruals (4 qtrs) to keep hiding bad news and poor current performance. Hence, when earnings released are below the forecast, all previously accumulated bad news comes out to the market causing a significant decline in realized skewness and lower

SRP. Second, evidence is provided that high Disc. Accruals (4 qtrs) may also be associated with higher SRP and stock returns. It occurs when earnings surprises are positive. For example, a portfolio of firms that choose to report high Disc. Accruals (4 qtrs) (portfolio 5) earns a positive monthly average swap return of 11.9% within the quarter following positive earnings surprises. This result is consistent with the findings of several studies that high Disc. Accruals (4 qtrs) do not necessarily conceal bad news from investors, but can also be used as a signal of private information about positive firm's prospects to attract more capital via increased stock price in the short run (Sankar and Subramanyam, 2001; Linck, Netter, and Shu, 2013). Hence, the analysis reveals that both bad-news-hiding effect and private-information mechanism can co-exist in the options market. When managers signal private information to raise capital, high Disc. Accruals (4 qtrs) produce positive earnings surprises and become value-enhancing in the short run as investors buying the swap (i.e. bet on positive skewness) earn positive returns. However, when managers use high Disc. Accruals (4 qtrs) to stockpile negative information over the long run, there comes a certain point when further bad-news hiding is not possible resulting in poor realized earnings, a negative surprise and monetary gains for those investors who sell the swap (i.e. bet on negative skewness).

3.3.8 Robustness Checks

In this section, further robustness checks are conducted to verify that the negative relation between Disc. Accruals (4 qtrs) and SRP is not driven by econometric estimation techniques, adverse stock market movements, SRP and earnings management measurements.

3.3.8.1 Results from fixed effects regressions

First, the model specification as in Table 3.3 is run and control for firm, industry and time fixed effects in panel-data regression framework[3]. Kim and Zhang (2014) argue that that

[3] I use robust standard errors clustered at a firm and quarter level.

earnings management proxies may also capture unobserved business uncertainty or other unknown firm characteristics. To alleviate such concerns, firm fixed effects are added to the model. Further, McNichols and Stubben (2018) suggest that including time fixed effects is important to account for various time-series patterns in the dependent variable (i.e. SRP) that may lead to spurious relationship between Disc. Accruals (4 qtrs) and swap returns over time. Finally, to ensure that results are not driven by certain industries[4], industry dummies are included that are defined using the Fama-French 48-industry classification. The results in Table 3.8 confirm that the effect of Disc. Accruals (4 qtrs) on SRP remains largely unchanged and attains statistical significance after accounting for the firm, industry and quarter fixed effects.

[Insert Table 3.8 here]

3.3.8.2 Results from excluding the crisis periods

Second, the significant premium that investors earn by selling a swap on high-Disc. Accruals (4 qtrs) firms may not be engendered by firm-specific managerial reporting opportunism, but rather stem from the periods of exogenous market-wide shocks that hit the entire economy. To verify that the Disc. Accruals (4 qtrs) effect is not driven by big systematic events, the regression model as in Table 3.3 is run but the periods of global financial crisis of 2007–2009 and global Covid-19 pandemic of 2020 are excluded. Following Herskovic et al. 2016, the crisis period is defined from August 2007 to June 2009. The Covid-19 period is from January 2020 to April 2020. Table 3.9, Model 1 presents the results. Consistent with previous findings, the coefficient on our variable of interest is negative and statistically significant at 1% level affirming a clear firm-specific nature of the negative relationship between Disc. Accruals (4 qtrs) and swap returns, that is not driven by the negative economic shocks. The results are robust to excluding extreme market episodes such as the 2008–2009 Global Financial Crisis

[4] Dechow, Ge, Larson, and Sloan (2010) document that certain firm characteristics, such as accounting complexity and information asymmetry, increase the likelihood of earnings management, suggesting that the tendency to manipulate earnings may vary across firms.

and the early 2020 COVID-19 period, In addition, the key relationships remain significant in the more recent subsample period, suggesting that the main patterns are not driven by specific macroeconomic conditions.

[Insert Table 3.9 here]

3.3.8.3 Robustness results with idiosyncratic SRP measure

Third, Pederzoli (2021) decomposes total SRP into systematic and idiosyncratic components and finds that only firm-specific swap returns can be predicted. Since the manager's decision to report inflated earnings is unlikely to be systematically driven by market-wide shocks, the impact of high Disc. Accruals (4 qtrs) on the total gains of skewness swaps should be primarily reflected in the idiosyncratic component of swap returns. To test this prediction, for each stock the median regression of a firm's monthly total SRP on monthly SRP for S&P-500 index over the full sample period is first run. Next, the residuals from this regression are extracted and standardized by the price of fixed leg of the swap contract. The quarterly idiosyncratic SRP is the average monthly standardized residuals within a quarter. Finally, the quarterly Fama-MacBeth regressions as in Table 3.3 are conducted using the ratio of residuals over the price of fixed leg as a dependent variable. Table 3.9, Model 2 shows the regression output. The coefficient on Disc. Accruals (4 qtrs) is negative, highly statistically significant and has a similar magnitude as the coefficient estimate from the regressions in Table 3.3. These results provide supportive evidence for the negative Disc. Accruals (4 qtrs) effect on SRP, which mostly emerges from the idiosyncratic component of total skewness swap returns. While the SRP may serve as a firm-level fear gauge, it differs conceptually from the VIX, which reflects aggregate market-wide volatility expectations. VIX captures broad market uncertainty, whereas SRP isolates the compensation for downside asymmetry specific to individual firms. Using VIX instead of SRP would likely weaken the cross-sectional explanatory power, as market-wide volatility does not account for firm-specific information embedded in option skewness. In addition, the robustness test using the idiosyncratic SRP already controls for the systematic market component, effectively accounting for market-wide fear gauges such as the VIX.

3.3.8.4 Robustness results with real earnings management measure

Fourth, the robustness of Disc. Accruals (4 qtrs) effect in the presence of real earnings management is tested. To this end, the quarterly Fama-MacBeth regression analysis as in Table 3.3 is performed and firm's real earnings management is included as a control variable. Table 3.9, Model 3 illustrates the findings. The coefficient on Disc. Accruals (4 qtrs) remains mostly unchanged and retains its statistical significance at 1% level. These results further confirm that the negative relationship between Disc. Accruals (4 qtrs) and skewness swap payoff is unlikely to be explained by a firm's willingness to be engaged in real earnings management practices.

3.3.8.5 Other accruals models

[Insert Table 3.10 here]

Last, McNichols and Stubben (2018) argue that Disc. Accruals (4 qtrs) is a noisy proxy of earnings management and produce biased results. In addition, Larson, R. Sloan, and Zha Giedt 2018 document that the choice of accrual models may heavily affect the results of Disc. Accruals (4 qtrs). To alleviate this concern, the quarterly Fama-MacBeth regression analysis as in Table 3 is performed with Disc. Accruals (4 qtrs) from different models. Table 3.10, Model 1 shows the Disc. Accruals (4 qtrs) from (Barth and Hutton, 2004; Cohen and Lys, 2006; Kothari, Leone, and Wasley, 2005 among many others models). Model 2 presents the Disc. Accruals (4 qtrs) using Rees, Gill, and Gore (1996) model. Model 3 illustrates the Disc. Accruals (4 qtrs) from (Arif, Marshall, and Yohn, 2016; Fairfield, Whisenant, and Yohn, 2003)models. The coefficient of Disc. Accruals (4 qtrs) remains mostly unchanged and retains its statistical significance at 1% level. These results further confirm that the negative relationship between Disc. Accruals (4 qtrs) and SRP is robust across different accrual models.

3.4 Conclusion

In summary, our findings suggest that high Disc. Accruals (4 qtrs) stocks, as compared to near-zero Disc. Accruals (4 qtrs) stocks, are relatively crash-prone, on average generate negative return. Prior studies on the SRP have documented a high and significant return on skewness swaps. The skewness swaps are a portfolio of out of the money options. The high return on this portfolio indicate that investors are willing to pay a high premium to hedge against possible crashes. Therefore, this SRP reflect the investors' ex ante expectations on both likelihood and magnitude of future crashes. This paper examines whether the financial reporting quality or the Disc. Accruals (4 qtrs) increases the probability of crash and the return from skewness swaps. After controlling for various stock characteristic and fundamental control variables, this paper finds strong and robust evidence that the SRP decreases with Disc. Accruals (4 qtrs), indicating that realized crash happens are more likely to happen for high Disc. Accruals (4 qtrs) firms. This result is robust after controlling for the Implied Volatility Smirk, unknown firm or industry fixed effect, and systematic market crashes.

Overall, these findings highlight that financial reporting quality shapes investors' perceptions of downside risk. The relationship between discretionary accruals and SRP varies across market and governance environments. During optimistic periods, managers have stronger incentives to hide bad news, while investors influenced by behavioural biases such as cognitive dissonance (Antoniou, Doukas, and Subrahmanyam, 2013) are slower to process negative information. This pattern is consistent with psychological evidence that emotions affect risk perception (Lucey and Dowling, 2005). Waves of earnings manipulation may also appear during economic expansions when performance pressure is high and monitoring is weak, which strengthens the link between accruals and SRP. In contrast, periods of tighter regulation or stronger managerial discipline bring greater scrutiny and limit income-increasing discretion, thereby weakening this association.

Tables and Figure

Figure 3.1: Average quarterly Skewness Risk Premium

This figure plots the time-series average of skewness risk premium (SRP) for the whole sample from January 1996 to December 2021. The skewness swap starts on the 4th Monday of each month and matures on the 3rd Friday in the next month. The SRP is the quarterly average return of monthly skewness swaps. In each month, 1 dollar is invested in the skewness swap; the return is added to the previous gains without compounding.

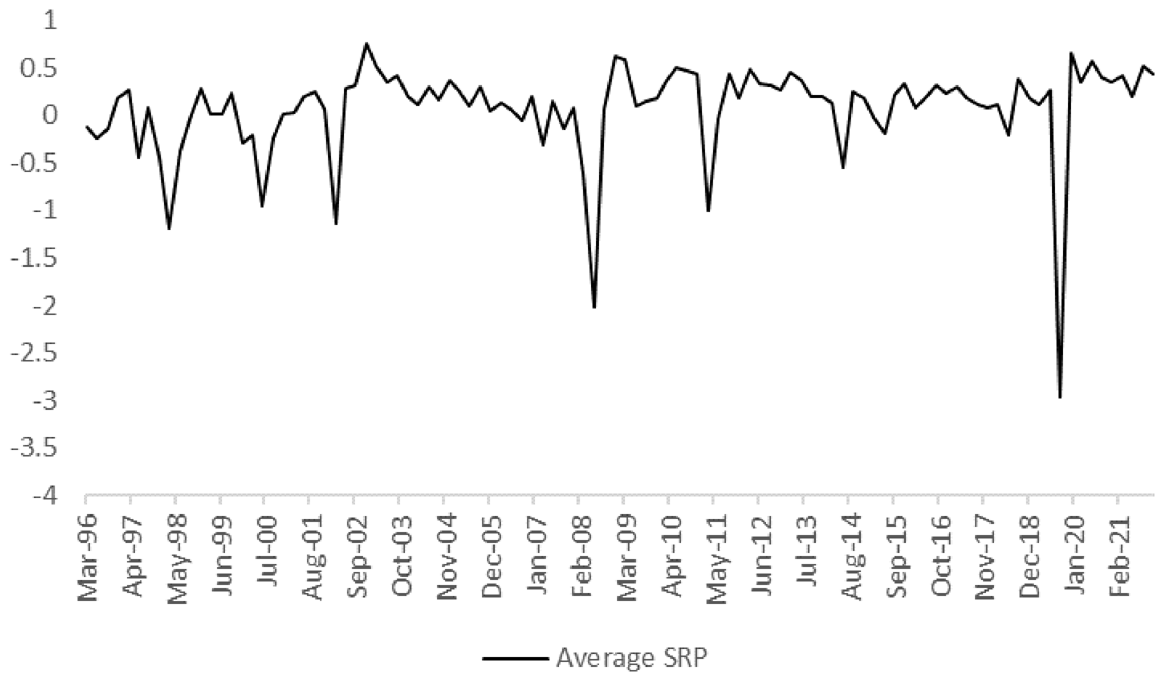


Figure 3.2: Earnings announcement day

This figure plots the daily cumulative returns for quintile portfolios around earnings announcement day. We sort the skewness risk premium (SRP) portfolio in ascending order based on Disc. Accruals (4 qtrs) into quintile portfolios over the sample period from January 1996 to December 2021. The Disc. Accruals (4 qtrs) is the sum of discretionary accruals over the past 4 quarters. The SRP portfolio is constructed 10 trading days before each firm's earnings announcement day. The investors buy skewness swaps 10 trading days prior to the earnings announcement day, hold it until 10 days after the earnings announcement day. The statistical significance is in Table 3.6.

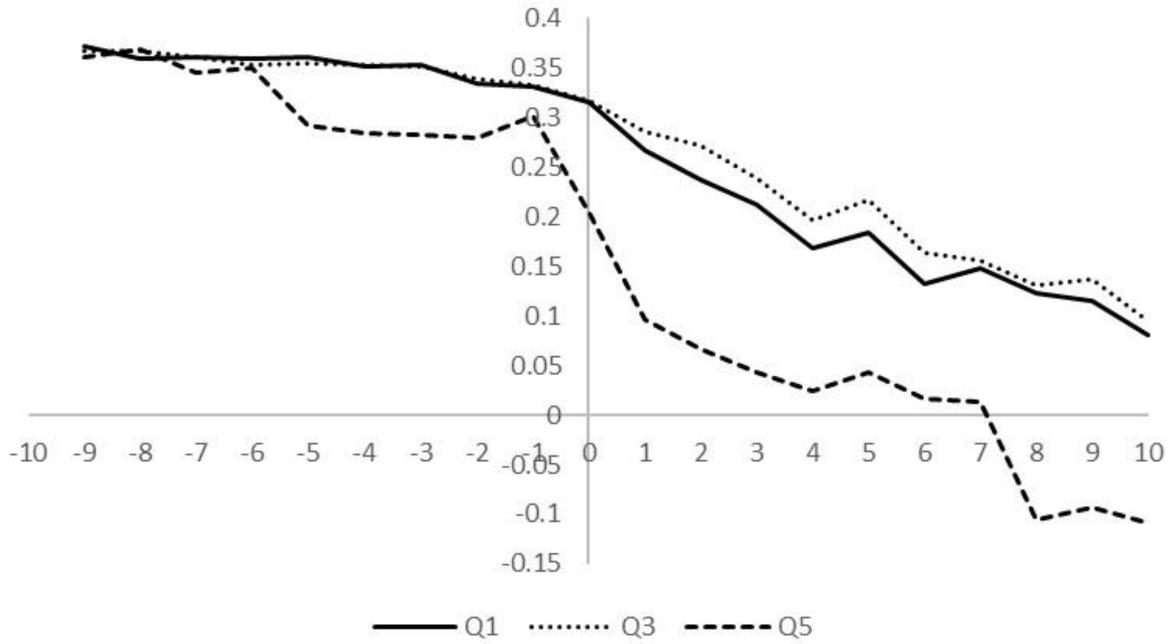


Figure 3.3: Placebo day

This figure plots the daily cumulative returns for quintile portfolios around pseudo earnings announcement day. We sort the skewness risk premium (SRP) portfolio in ascending order based on Disc. Accruals (4 qtrs) into quintile portfolios over the sample period from January 1996 to December 2021. The Disc. Accruals (4 qtrs) is the sum of discretionary accruals over the past 4 quarters. The SRP portfolio is constructed 10 trading days before each firm's pseudo earnings announcement day. The investors buy skewness swaps 10 trading days prior to the pseudo earnings announcement day, hold it until 10 days after the pseudo earnings announcement day.

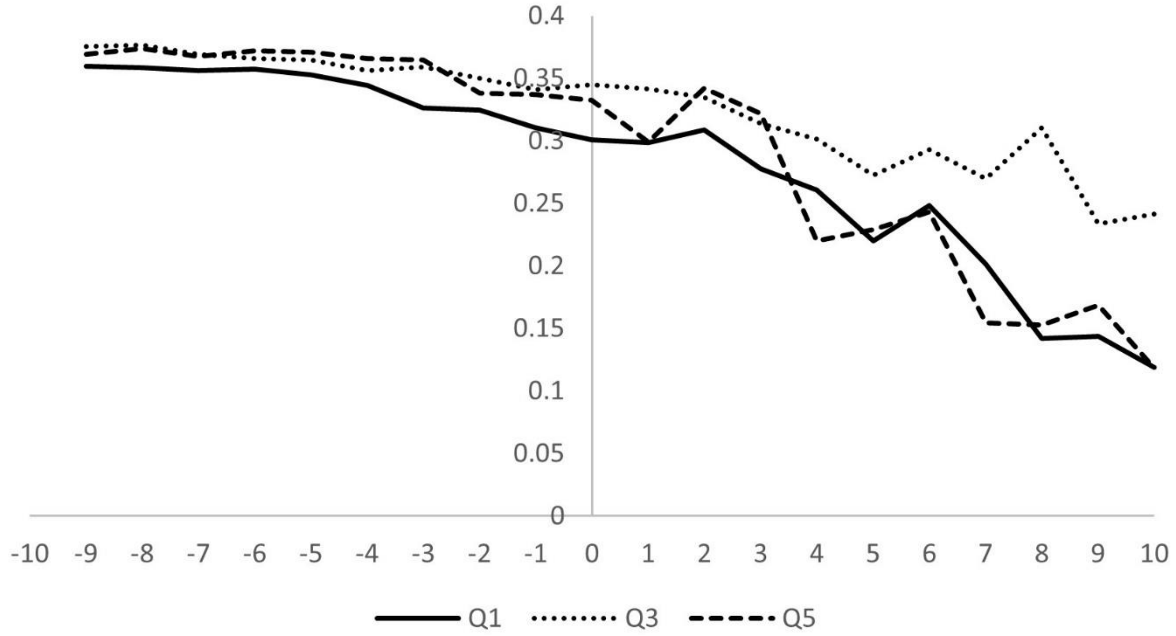


Table 3.1: Summary statistics for all variables in this study

This table reports the quarterly descriptive statistics for all the variables included in our study. The sample period starts from January 1996 and ends at December 2021. Skewness risk premium is the quarterly average of monthly skewness risk premium for each individual stock. The Disc. Accruals (4 qtrs) is the sum of discretionary accruals over the past 4 quarters. See Appendix for definition of all other variables.

	Mean	Std Dev	Q1	Median	Q3
SRP	0.057	5.005	-0.062	0.384	0.703
Disc. Accruals (4 qtrs)	-0.001	0.206	-0.083	-0.009	0.066
Implied Volatility Smirk	0.042	0.035	0.024	0.035	0.051
Market to Book	5.135	7.618	1.904	3.119	5.279
Leverage	0.251	0.171	0.125	0.242	0.355
Size	8.697	1.559	7.600	8.585	9.748
ROE	0.023	0.467	0.011	0.037	0.062
Short Interest	0.062	0.067	0.019	0.038	0.081
Total Volatility	0.419	0.229	0.272	0.369	0.506
Stock Return	0.020	0.131	-0.042	0.016	0.076
Stock Turnover	0.013	0.015	0.006	0.009	0.015
Beta	1.171	0.453	0.870	1.125	1.425
Earnings Volatility	0.027	0.138	0.008	0.014	0.026

Table 3.2: Profitability of SRP Portfolios

This table reports the profitability results of Disc. Accruals (4 qtrs) sorted quintile Skewness risk premium (SRP) portfolio (in ascending order from quintile 1, low Disc. Accruals (4 qtrs) to quintile 5, high Disc. Accruals (4 qtrs)) over the sample period from January 1996 to December 2021. The Disc. Accruals (4 qtrs) is the sum of discretionary accruals over the past 4 quarters. For each quintile portfolio, we report the average SRP, average Disc. Accruals (4 qtrs) and alphas from Fama-French 5 factor model augmented by the momentum factor and liquidity factor. The 5th -1st row reports the average SRP and alpha for the strategy that buys a high Disc. Accruals (4 qtrs) portfolio and sells a low Disc. Accruals (4 qtrs) portfolio. Newey-West adjusted (with 2 lags) t-statistics are reported in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5-Q1
Disc. Accruals (4 qtrs)	-0.236	-0.068	-0.005	0.058	0.281	
Raw SRP	0.13***	0.111	0.187***	0.031	-0.036	-0.167***
	(2.64)	(1.21)	(3.64)	(0.34)	(-0.62)	(-3.54)
Risk-adjusted SRP	0.138**	0.099	0.202***	0.006	-0.047	-0.186***
	(2.49)	(1.06)	(4.02)	(0.06)	(-0.71)	(-3.48)

Table 3.3: Fama-MacBeth Regressions

This table reports the results from Fama and MacBeth (1973) cross-sectional regressions of Skewness risk premium (SRP) over quarter t+1 on the Disc. Accruals (4 qtrs) and a list of stock related and fundamental characteristics control variables computed at the end of quarter t over our sample period from January 1996 to December 2021. The Disc. Accruals (4 qtrs) is the sum of discretionary accruals over the past 4 quarters. Newey-West adjusted (with 2 lags) t-statistics are reported in parentheses. Column (1) reports the univariate regression result. Column (2) reports the multivariate regression result. In Column (3), we include Implied volatility smirk as a control variable. *,**,*** denote statistical significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)
Disc. Accruals (4 qtrs)	-0.033***	-0.031***	-0.028***
	(-5.14)	(-4.05)	(-3.87)
Implied Volatility Smirk			0.062***
			(5.23)
Market to Book		0.009	0.012
		(0.70)	(0.96)
Leverage		0.001	-0.001
		(0.06)	(-0.15)
Size		-0.010	-0.016
		(-0.65)	(-1.08)
ROE		0.003	0.001
		(0.32)	(0.11)
Short Interest		0.015	-0.008
		(1.40)	(-0.73)
Total Volatility		-0.051*	-0.078***
		(-1.93)	(-2.75)
Stock Return$_{t-1}$		-0.025***	-0.021**
		(-3.12)	(-2.61)
Stock Return$_{t-2}$		-0.045***	-0.043***
		(-3.45)	(-3.27)
Stock Return$_{t-3}$		-0.018	-0.014
		(-1.47)	(-1.19)
Stock Turnover		-0.018	-0.005
		(-0.99)	(-0.26)
Beta		-0.001	0.002
		(-0.09)	(0.16)
Earnings Volatility		-0.011	-0.010
		(-0.65)	(-0.73)
Adj. R^2	0.011	0.121	0.134
Observations	24,385	24,385	23,524

Table 3.4: Robustness checks on the information content in SRP and implied volatility smirk

This table reports the results from Fama and MacBeth (1973) cross-sectional regressions. The dependent variable of column (1) and (2) are implied volatility smirk. In column (3), the dependent variable residual SRP is the residual of regressing SRP on implied volatility smirk. Column (1) reports the univariate regression result and columns (2) and (3) report the multivariate regression results. The sample period is from January 1996 to December 2021. The Disc. Accruals (4 qtrs) is the sum of discretionary accruals over the past 4 quarters. Newey-West adjusted (with 2 lags) t-statistics are reported in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

	Implied volatility smirk	Implied volatility smirk	Residual SRP
	(1)	(2)	(3)
Disc. Accruals (4 qtrs)	0.023*	-0.004	-0.029***
	(1.68)	(-0.43)	(-3.92)
Market to Book		0.043***	0.010
		(3.07)	(0.76)
Leverage		0.022**	-0.002
		(2.28)	(-0.25)
Size		-0.020	-0.011
		(-0.85)	(-0.76)
ROE		-0.025*	0.001
		(-1.87)	(0.14)
Short Interest		0.274***	-0.006
		(12.58)	(-0.54)
Total Volatility		0.317***	-0.070***
		(8.30)	(-2.67)
Stock Return$_{t-1}$		0.006	-0.022***
		(0.56)	(-2.78)
Stock Return$_{t-2}$		-0.023*	-0.042***
		(-1.91)	(-3.25)
Stock Return$_{t-3}$		-0.005	-0.015
		(-0.65)	(-1.22)
Stock Turnover		-0.124***	-0.005
		(-5.35)	(-0.29)
Beta		-0.013	-0.001
		(-0.67)	(-0.10)
Earnings Volatility		-0.052***	-0.010
		(-2.75)	(-0.71)
Adj. R^2	0.014	0.350	0.126
Observations	23,524	23,524	23,524

Table 3.5: Long-run effect

This table reports the results from Fama and MacBeth (1973) cross-sectional regressions of Skewness Risk Premium (SRP) over quarter t+1 on the Disc. Accruals (8 qtrs), Disc. Accruals (12 qtrs), and a list of stock related and fundamental characteristics control variables computed at the end of quarter t over our sample period from January 1996 to December 2021. The Disc. Accruals (8 qtrs) and Disc. Accruals (12 qtrs) are the sum of discretionary accruals over the past 8 and 12 quarters. Newey-West adjusted (with 2 lags) t-statistics are reported in parentheses. Column (1) and (4) report the univariate regression result. Column (2) and (5) reports the multivariate regression result. In Column (3) and (6), implied volatility smirk is included as a control variable. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Disc. Accruals (8 qtrs)	-0.025***	-0.021***	-0.019***			
	(-3.91)	(-2.81)	(-2.72)			
Disc. Accruals (12 qtrs)				-0.021***	-0.017*	-0.013
				(-2.63)	(-1.80)	(-1.38)
Implied Volatility Smirk			0.064***			0.070***
			(4.11)			(4.23)
Control variables	No	Yes	Yes	No	Yes	Yes
Adj. R^2	0.010	0.132	0.149	0.011	0.150	0.167
Observations	21,824	21,824	21,339	19,493	19,493	19,249

Table 3.6: Earnings announcement day

This table reports the difference between Disc. Accruals (4 qtrs) sorted quintile skewness risk premium (SRP) portfolio (in ascending order from quintile 1, low Disc. Accruals (4 qtrs) to quintile 5, high Disc. Accruals (4 qtrs)) over the sample period from January 1996 to December 2021. Columns (1) and (2) report the results from the actual earnings announcement day. The Q5-Q3 (Q1-Q3) columns reports the average SRP for the strategy that buys a high Disc. Accruals (4 qtrs) portfolio and sells a near-zero Disc. Accruals (4 qtrs) portfolio (buys low and sells near-zero). Columns (3) and (4) report the results using the same strategy from the placebo earnings announcement day. Newey-West adjusted (with 2 lags) t-statistics are reported in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. See Appendix for results excluding crisis periods.

	EA events		Placebo	
	Q5-Q3	Q1-Q3	Q5-Q3	Q1-Q3
Trading Day	(1)	(2)	(3)	(4)
-9	-0.007	-0.006	-0.003	0.014
-8	-0.078	-0.13*	-0.672	-0.31
-7	-0.139	-0.143	-0.746	-0.349
-6	-0.058	-0.125*	-0.685	-0.424
-5	-0.114	-0.107	-0.697	-0.336
-4	-0.107	-0.154*	-0.662	-0.358
-3	-0.098	-0.142*	-0.841	-0.49
-2	-0.102	-0.179*	-0.671	-0.392
-1	-0.107	-0.161*	-0.682	-0.387
0	-0.112	-0.179*	-0.721	-0.423
1	-0.192**	-0.281*	-0.741	-0.377
2	-0.187*	-0.305**	-0.635	-0.322
3	-0.181**	-0.274**	-0.66	-0.382
4	-0.198**	-0.271**	-0.627	-0.358
5	-0.169**	-0.256**	-0.867	-0.63
6	-0.194**	-0.264**	-0.872	-0.61
7	-0.201**	-0.279*	-0.515	-0.445
8	-0.192**	-0.267**	-0.488	-0.369
9	-0.188***	-0.22*	-0.513	-0.484
10	-0.191***	-0.218*	-0.465	-0.347

Table 3.7: Disc. Accruals (4 qtrs) and earnings surprise

This table reports the average monthly profitability of skewness risk premium (SRP) portfolios sorted on the Disc. Accruals (4 qtrs) and earnings surprise measure over the sample period from January 1996 to December 2021. The Disc. Accruals (4 qtrs) is the sum of discretionary accruals over the past 4 quarters. Following Skinner and Sloan 2002, the earnings surprise is the realized quarterly earnings per share (EPS) minus the median of analyst forecast EPS. In each quarter, we sort SRP portfolio in ascending order into quintile portfolios based on Disc. Accruals (4 qtrs). Next, within each quintile portfolio, we further split the stocks into 2 sub-samples based on earnings surprises. Finally, for each sub-sample portfolio, we compute the average SRP and average Disc. Accruals (4 qtrs). Newey-West adjusted (with 2 lags) t-statistics are reported in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. See Appendix for results excluding crisis periods.

	Earnings surprise	
	Negative or zero	Positive
	(1)	(2)
1 (low)	-0.04	0.27***
	(-0.5)	(5.44)
Average Disc. Accruals (4 qtrs)	-0.249	-0.229
2	-0.004	0.201***
	(-0.02)	(3.65)
Average Disc. Accruals (4 qtrs)	-0.069	-0.070
3	0.033	0.321***
	(0.49)	(5.08)
Average Disc. Accruals (4 qtrs)	-0.011	-0.008
4	-0.113	0.108
	(-1.00)	(1.24)
Average Disc. Accruals (4 qtrs)	0.058	0.055
5 (high)	-0.214**	0.119*
	(-2.15)	(1.95)
Average Disc. Accruals (4 qtrs)	0.272	0.270

Table 3.8: Panel regression with fixed effects

This table reports the results from panel regressions of skewness risk premium (SRP) over quarter t+1 on the Disc. Accruals (4 qtrs) and a list of stock related and fundamental characteristics control variables and implied volatility smirk computed at the end of quarter t over our sample period from January 1996 to December 2021. The Disc. Accruals (4 qtrs) is the sum of discretionary accruals over the past 4 quarters. Column (1) reports coefficient estimates from quarterly panel regressions with quarter and firm fixed effect, and report their R^2s. Column (2) reports coefficient estimates from quarterly panel regressions with quarter and industry fixed effect, and report their R^2s. t-statistics are reported in parentheses. We create industrial dummies based on Fama French 48 industry classifications. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

	(1)	(2)
Disc. Accruals (4 qtrs)	-0.029***	-0.030***
	(-3.95)	(-4.59)
Control variables	Yes	Yes
Firm fixed effects	Yes	
Industry fixed effects		Yes
Quarter fixed effects	Yes	Yes
Adj. R^2	0.233	0.167
Observations	23,337	23,523

Table 3.9: Fama-MacBeth Regression without crisis period

This table reports the results from Fama and MacBeth (1973) cross-sectional regressions of skewness risk premium (SRP) over quarter t+1 on the Disc. Accruals (4 qtrs) measures and a list of stock related and fundamental characteristics control variables and implied volatility smirk computed at the end of quarter t over our sample period from January 1996 to December 2021. In Column (1), we exclude 08 crisis period and covid period. In column (2), The dependent variable idio_SRP is the residual from a median regression of firm level SRP on S&P 500 index SRP. In column (3), real earnings management is included as a control variable. Following Roychowdhury (2006), the real earnings management is the sum of abnormal operating cashflow over the past 4 quarters. The Disc. Accruals (4 qtrs) is the sum of discretionary accruals over the past 4 quarters. Newey-West adjusted (with 2 lags) t-statistics are reported in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. See Appendix for Disc. Accruals (8 qtrs) and Disc. Accruals (12 qtrs) results.

	SRP (excluding crisis period)	idiosyncratic SRP	SRP (controlling for real EM)
	(1)	(2)	(3)
Disc. Accruals (4 qtrs)	-0.029***	-0.027***	-0.026***
	(-3.41)	(-2.76)	(-3.40)
Real Earnings Management			0.010
			(1.08)
Control variables	Yes	Yes	Yes
Adj. R^2	0.128	0.135	0.143
Observations	18,684	23,118	23,505

Table 3.10: Fama-MacBeth Regression from other accruals models

This table reports the results from Fama and MacBeth (1973) cross-sectional regressions of skewness risk premium (SRP) over quarter t+1 on the Disc. Accruals (4 qtrs) measures and a list of stock related and fundamental characteristics control variables and implied volatility smirk computed at the end of quarter t over our sample period from January 1996 to December 2021. In Column (1), Disc. Accruals (4 qtrs) is estimated following Barth and Hutton 2004 model. In column (2), Disc. Accruals (4 qtrs) is estimated following Rees, Gill, and Gore 1996 model. In column (3), Disc. Accruals (4 qtrs) is estimated following Arif, Marshall, and Yohn 2016 model. The Disc. Accruals (4 qtrs) is the sum of discretionary accruals over the past 4 quarters. Newey-West adjusted (with 2 lags) t-statistics are reported in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

	accruals model 1	accruals model 2	accruals model 3
	(1)	(2)	(3)
Disc. Accruals (4 qtrs)	-0.030***	-0.033***	-0.030***
	(-4.07)	(-4.14)	(-4.18)
Control variables	Yes	Yes	Yes
Adj. R^2	0.111	0.123	0.111
Observations	28,534	23,568	28,263

A Description of the Control Variables

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

Leverage is the long-term debt plus liability divided by firm's total assets. Source: COMPUSTAT.

Size is the natural log of firm's market value of equity at the end of each quarter. Source: COMPUSTAT.

ROE is the firm's net income divided by common equity. Source: COMPUSTAT.

Short Interest is the ratio of number of stocks shorted to share outstanding. Source: COMPUSTAT.

Total Volatility is the total volatility of stock i's daily stock return over the past year, including current month t. We require at least 225 observations over the past year. Source: CRSP.

Stock Return is the cumulative stock return of last month. Source: CRSP.

Stock Turnover is the average monthly stock turnover in each quarter. The stock turnover is the volume divided by share outstanding. Source: CRSP.

Beta is the market beta of firm i over the past year, including current month t. We run OLS regression of daily excess return on the market return and obtain the beta. We further require 225 observations during the past year. Source: CRSP.

Earnings Volatility is the standard deviation of earnings before extraordinary items divided by lagged total assets over the past 5 years. Source: COMPUSTAT.

Sales Volatility is the standard deviation of earnings divided by lagged total assets over the past 5 years. Source: COMPUSTAT

4 Crash and divergence in opinions

4.1 Introduction

Stock price crash often refers to a sudden, extreme drop in stock prices within a short period. Some studies define crashes as periods when firm-specific returns fall to three times below their mean (Hutton, Marcus, and Tehranian, 2009; Bradshaw, Hutton, Marcus, and Tehranian, 2010; Zhu 2016, among many others), capturing sharp downward movements within a week. Other studies use negative skewness in the distributions of firm-specific returns (Chen, Hong, and Stein, 2001; Kim and Zhang, 2014; Callen and Fang, 2015) to characterize crashes. Furthermore, existing literature shows that the divergence in investor opinions negatively predicts future stock returns (Diether, Malloy, and Scherbina, 2002; Hong and Stein, 2007). Similar phenomena have also been documented in the options market: when divergence in opinion is high, stocks tend to generate negative returns on average (Andreou, Kagkadis, Philip, and Tuneshev, 2018). More recent findings also suggest that analyst forecast-based disagreement and trading volume-based disagreement can predict future stock price crashes (Chang, Hsiao, Ljungqvist, and Tseng, 2022).

This study examines whether divergence in opinions, as captured by the dispersion in beliefs on individual stocks (IDISP), can predict subsequent stock price crashes, measured by firm-level extreme downward movements. This analysis is motivated by earlier research exploring the linkage between opinion divergence and future negative returns. Various disagreement proxies have been used in the literature, such as abnormal trading volume (Chen, Hong, and Stein, 2001; Hong and Stein, 2007), analyst forecast dispersion (Diether, Malloy, and Scherbina, 2002), and option-implied disagreement (Andreou, Kagkadis, Philip, and Tuneshev, 2018). These studies argue that high disagreement levels lead stock prices to reflect primarily the views of optimistic investors while suppressing the influence of pessimistic ones, particularly in markets with short-sale constraints. As a result, stocks may become overvalued and subsequently generate negative returns. More recently, Chang, Hsiao, Ljungqvist, and Tseng (2022) provide evidence that disagreement significantly predicts future stock price crashes across multiple proxies, such as analyst forecast range, abnormal short interest, and trading volume around earnings announcements. However, forecast-based proxies appear to have diminished predictive power in recent years, whereas disagreement derived from stock options remains robust, possibly due to the decline in analyst coverage and the faster incorporation of firm-specific information through derivative trading (Kelly and Ljungqvist, 2012)

The IDISP variable is adopted in this chapter as the primary proxy for divergence in investor opinions. IDISP is derived directly from observed options transactions and captures a wide spectrum of beliefs across investors. Unlike forecast-based or short-interest proxies, IDISP is free from short-sale constraints and reflects real-time belief dispersion observable on a daily basis. It is constructed as the trading volume-weighted average of the absolute difference between the moneyness level and the trading volume-weighted moneyness level. A value of zero implies that all investors concentrate trades on the same strike, reflecting consensus. In contrast, the maximum value occurs when investors are split between the most optimistic and most pessimistic strikes. This variable captures the divergence in opinion for several reasons: (1) it is based on actual market transactions; (2) it is not influenced by short-sale constraints; and (3) it is available at a high frequency and broadly applicable across all optionable stocks.

Based on prior empirical findings, it is hypothesized that IDISP is positively associated with the likelihood of future stock price crashes. When investors anticipate extreme downside risk, they are likely to hedge by purchasing out-of-the-money put options. Such trading behavior reveals private pessimistic signals and increases the IDISP value. Thus, elevated

IDISP is expected to precede stock price crashes. While IDISP captures the observable divergence in investors' beliefs, the underlying sources of disagreement may vary. Following Carlin, Longstaff, and Matoba (2014), disagreement can arise from differences in model assumptions, interpretations of public signals, or the persistence of biased beliefs. When investors interpret the same information through heterogeneous priors or learning speeds, belief updating becomes delayed or asymmetric, resulting in persistent dispersion. These mechanisms suggest that belief-persistence and biased learning are fundamental drivers of IDISP, particularly during periods of heightened uncertainty.

To test this hypothesis, this chapter employs a modified crash measure from Hutton, Marcus, and Tehranian (2009). Firm-specific weekly returns are calculated using CRSP data, and a crash week is identified if the weekly return is more than three standard deviations below the firm-specific mean return estimated over the prior 52-week rolling window. If any crash week occurs within a calendar month, that month is designated as a crash month. For the construction of IDISP, daily data from CRSP and OptionMetrics are used to calculate daily dispersion values, which are then averaged over the final week of each month to construct the monthly IDISP. Finally, the monthly IDISP is merged with crash indicators and relevant control variables. The empirical results are presented in the following sections.

Using 199,651 firm-month observations from 1996 to 2021 covering 15,567 unique firms, the analysis finds that the IDISP is significantly and positively associated with subsequent month stock price crashes. This finding is consistent with the prediction that firms with high divergence in opinions have higher crash probability. When firm-level pessimistic information is revealed in the options market, as reflected by higher values of IDISP, the subsequent stock price crash probability increases. This result remains robust after controlling for various factors including Size, Total Volatility, monthly Stock Return (lag1 to lag3), Market to Book, Leverage, and Ncskew. It is possible that the positive relation between IDISP and subsequent stock price crashes is influenced by the measurement of IDISP, divergence in opinions, or crash definitions. To address these concerns, robustness checks are conducted using options with different maturities to construct IDISP; alternative measures of divergence in opinions such as detrended turnover (Dturnover), Disagreement from Golez and Goyenko (2022), and analyst forecast dispersion (AFD); and alternative stock price crash definitions, including Pure Crash, Conservative Crash, model-free crashes like Monthly Crash 20 percent, Ncskew, and Duvol. The positive association holds across all these alternative measures and definitions. Furthermore, to ensure that IDISP is not simply capturing rare events rather than stock price crashes, the relation between IDISP and subsequent stock price Jumps is also examined. Similar to crash definitions, Jumps are identified when firm-specific weekly returns exceed the mean of the past 52 weeks by 3.25 times. A negative relation is observed between IDISP and subsequent Jumps, indicating that IDISP identifies crashes rather than merely high rate-of-return events.

To further explore potential explanations for why high IDISP predicts future stock price crashes, several channels are examined. First, the role of financial reporting quality is considered. A modified Jones (1991) model is employed, following Chi and Gupta (2009), to estimate quarterly firm-level discretionary accruals. These accruals, along with depreciation and R&D cut variables, are used to replicate the main analysis. The IDISP remains positively associated with subsequent stock price crashes. Second, short-sale constraints are evaluated by sorting the sample into five groups based on institutional ownership. Lower institutional ownership, indicating difficulty in shorting, is found to amplify the predictive power of IDISP across all groups. This suggests that IDISP captures information beyond general market disagreement. Third, market sentiment is considered by splitting the sample following Baker and Wurgler (2006)[5] into high- and low-sentiment subsamples. Results show that IDISP predicts stock price crashes regardless of sentiment regime. Finally, the earnings announcement effect is examined, motivated by literature showing that such announcements reduce firm-level uncertainty (Dubinsky and Johannes, 2006). A weekly-frequency approach is adopted. A ΔIDISP variable is constructed by comparing lag1 IDISP with earlier IDISP values (from lag2 to lag10). Dummy variables from two weeks before to two weeks after the announcement are introduced and interacted with ΔIDISP. Results indicate that when ΔIDISP significantly increases prior to announcements, crash probability rises during the announcement week.

To further understand firm-level characteristics driving crash events around announcements, the sample is split by discretionary accruals and the cumulative good index. Following Skinner and Sloan (2002), the index is set to one if realized EPS exceeds the analyst forecast median. Cumulative good index is defined as the sum of quarterly "good news" signals over the prior year. Results show that firms with both high discretionary accruals and high good index values have significantly higher crash probabilities during earnings announcement weeks. This finding aligns with bad news hoarding literature, where such firms are more likely to release previously concealed negative information during announcements, leading to crashes.

This study contributes to the literature in the following ways. First, this is the first to show the association between the divergence in opinions from the options market and subsequent stock price crashes. Previous studies focus on the divergence in opinions and subsequent negative stock returns. They use different disagreement measures like analyst forecast dispersion (Diether, Malloy, and Scherbina, 2002) and abnormal stock turnover (Chen, Hong, and Stein, 2001; Hong and Stein, 2007). Other study like Chang, Hsiao, Ljungqvist, and Tseng (2022) suggests that disagreement predicts crash, but they measure disagreement using

[5] Similar results are obtained when replacing the Baker and Wurgler (2006) sentiment measure with the alternative index of Huang, Jiang, Tu, and Zhou (2015), confirming that the predictive relation between IDISP and crash risk is robust across sentiment proxies.

analyst data, short interest and stock turnover. This study extends theirs by focusing on the IDISP, which is a divergence in opinion measure from the options market. The positive relationship between IDISP and subsequent stock price crashes indicate that IDISP shows some firm-level information over and above the stock the market.

Second, this research also contributes to the disagreement literature on when to buy or sell stocks. Previous studies show how disagreement affects the future stock return. In cross section, firms with high disagreement show negative stock return in the future. However, these studies do not show the exact day that generate negative return. In addition, some studies show that large stock price movement happens around earnings announcement (see for instance, Van Buskirk, 2011; Gao, Xing, and X. Zhang, 2018). Therefore, it is reasonable to study whether crash happens for stocks with different level of IDISP, different level of discretionary accruals and different level of cumulative earnings surprises. This study extends theirs by not only looking into the financial reporting quality but also linking stock price crashes with the divergence in opinions. The results of this chapter indicate that firms with high IDISP, high discretionary accruals and continuously reporting earnings above the expectations are more likely to crash around the earnings announcement.

Finally, previous studies on stock price crashes usually focus on yearly frequency (Hutton, Marcus, and Tehranian, 2009) or quarterly frequency (Chang, Hsiao, Ljungqvist, and Tseng, 2022). This study extends the literature on stock price crashes by conducting analysis at a higher frequency. Using monthly and weekly analysis, a more dynamic view of how the investor disagreement affects the subsequent stock price crash is provided. This approach provides a deeper insight to the short-term fluctuations and vulnerabilities in the stocks market.

4.2 Data and methodology

In this section, the data and key filter rule applied in the main analysis are first provided. Following this, the construction of crash measurements, the construction of dispersion of trading volume across different moneyness level measurements, alternative dispersion of belief measurements, and control variables are described. Finally, summary statistics in the sample are presented.

4.2.1 Data

For the main analysis, stocks data including stock price, stock return, and volume for individual stocks covering the period from January 1996 to December 2021 are obtained from the CRSP daily stock file. Options data including volume and strike price for individual stocks are collected from Ivy DB's OptionMetrics. Apart from estimating the main crash and dispersion measure, stocks data are used to estimate size, total volatility, monthly stock return, and Dturnover. Further, required data are collected from the Compustat fundamental quarterly file to calculate market-to-book ratio and leverage. Finally, I\B\E\S data are used to estimate the analyst forecast dispersion within each month.

Next, the following filters are applied to the stocks and options data. First, stocks with end-of-month price below 5 USD are excluded. Second, options with maturity between 10 days to 60 days, with at least 4 contracts in a day and at least 5 trading days within each month, are selected. Further, ordinary shares (with share code 10 and 11) and stocks listed in NYSE, AMEX, and NASDAQ (with exchange code 1 to 3) are selected. Finally, moneyness level is defined as strike price divided by spot price and options with moneyness level between 0.975 and 1.025 are excluded.

4.2.2 Construction of main variables

4.2.2.1 Construction of crash variables

Following Hutton, Marcus, and Tehranian (2009), crash is an indicative variable set equal to one if the firm-specific weekly log return is 3.25 times its standard deviation below its mean within each fiscal year. This crash is a yearly frequency variable. In this analysis, the relationship between divergence in opinions from options market and future crash probability is studied, which requires a higher frequency of crash. Therefore, the Hutton, Marcus, and Tehranian (2009) methodology is calibrated by estimating the mean and standard deviation of firm-specific weekly returns within a backward-looking 52-week rolling window, including the current week. At least 26 weekly observations are required in each 52-week window. If the current week's firm-specific return is 3.25 times its standard deviation below its mean, then the current week crash equals to one. If at least one crash week is detected within each month, then monthly crash equals to one. This crash measure allows the testing of relationships between crash and dispersion in beliefs at monthly frequency.

Chen, Hong, and Stein (2001) is followed to estimate the negative coefficient of skewness (Ncskew) and down-to-up volatility (Duvol) within each rolling window. Ncskew is defined as the negative value of the third moment of firm-specific weekly return divided by the third power of the standard deviation of firm-specific weekly return. Based on the 52-week rolling window, for any firm *i* and each week *t*, the Ncskew is computed as:

$$Ncskew_{i,t} = -\left(n(n-1)^{3/2}\Sigma Ret_{i,t}^{3}\right)/\left((n-1)(n-2)\left(\Sigma Ret_{i,t}^{2}\right)^{3/2}\right) \qquad (4.1)$$

where $Ret_{i,t}$ is the firm-specific weekly return of stock *i* over the 52-week rolling window and *n* is the number of weekly returns. At least 26 non-missing observations for each stock within each rolling window are required. The negative sign in the formula follows the convention that an increase in Ncskew implies that the stock has a higher crash probability.

Duvol is the ratio of down volatility to up volatility. Using a similar logic as for computing Ncskew, in each rolling window the weekly returns are separated into below-mean and above-mean return subsamples. The standard deviation for both subsamples is then calculated. Finally, the log ratio of the standard deviation of below-mean return subsample to the above-mean return subsample is taken:

$$Duvol_{i,t} = log\ (stdev_{down}(Ret_{i,t})/stdev_{up}(Ret_{i,t})) \tag{4.2}$$

where $Duvol_{i,t}$ represents the Duvol of stock i and each week t. The $stdev_{down}$ and $stdev_{up}$ denote the standard deviation of weekly return observations in the below-mean and above-mean return subsamples, respectively. The same convention is followed: a higher Duvol indicates a higher crash probability.

To reduce the concerns about this rolling window methodology, two slightly different crash measures and two different non-overlapping crash measures are constructed. First, a pure crash measure is constructed. Similar with crash measure, jump equals one if the firm-specific weekly log return is 3.25 times its standard deviation above its mean. Following the jump, price correction generates extremely low weekly returns in the future, resulting in a crash. To avoid this problem, if at least one jump is detected over the past 52 weeks, then crash is set equal to zero. Second, a more conservative crash measure is constructed. If a crash is detected, this extreme observation will largely affect the sample mean and standard deviation. Therefore, if a crash week is detected, the following 52 weeks' crash is set as missing. Third, the method of Andreou, Andreou, and Lambertides (2021) is followed, and crash week is defined as one where the market-adjusted weekly return is below 20% (results remain robust under other thresholds). If at least one crash week is detected within each month, then monthly crash is set to one. Finally, the method of Conrad, Kapadia, and Xing (2014) is calibrated by calculating the monthly firm-specific return. Monthly crash equals one if the monthly return is below 20%, and zero otherwise (results remain robust under other thresholds).

4.2.2.2 Divergence in beliefs measures

This study follows the methodology from Andreou, Kagkadis, Philip, and Tuneshev (2018) to measure the dispersion in beliefs on individual stocks (IDISP) using the trading volume of stock options across all moneyness levels. The IDISP is the volume-weighted average of the deviation of the moneyness level from the volume-weighted moneyness level. For each day and each individual stock, the current stock price is denoted as S, and a range of different strike prices of stock options K_i , where i=1, …, n. The moneyness level is defined as the ratio of strike price to stock price, $M_i=K_i / S$. The daily IDISP is then estimated using the following equation:

$$IDISP = \sum_{i=1}^{n} w_i |M_i - \sum_{i=1}^{n} w_i M_i| \tag{4.3}$$

where w_i is the weight of trading volume attached to option K_i , and n is the total number of strike prices of each stock option within each day. The IDISP equals zero if all investors focus on only one option. It reaches its maximum when investors trade both options with the lowest and highest strike prices.

Based on the construction of IDISP, the measure is comparable from daily frequency and onward. The weekly average of daily IDISP is calculated, and the last week's observation within each month is selected to construct the monthly IDISP. The last week is chosen for two reasons. First, new options are usually issued on the fourth Monday of each month, so selecting the last week helps avoid maturity effects. Second, to obtain the most recent information, we need the closest options before the next month.

The IDISP measures the divergence in opinions among option investors and reflects the investors' expectations of future price of underlying asset. Recent studies show a clear negative relation between divergence in opinions and cross-section of future stock returns (Diether, Malloy, and Scherbina, 2002; Andreou, Kagkadis, Philip, and Tuneshev, 2018). In addition, some studies argue that there is clear informed trading in options market, especially prior to some corporate events like earnings announcements, takeover, dividend change etc. (Chakravarty, Gulen, and Mayhew, 2004; Augustin, Brenner, and Subrahmanyam, 2019; Augustin and Subrahmanyam, 2020; Zhang, 2018). Moreover, Lakonishok,Lee, Pearson, and Poteshman (2007) show that most options investors make directional bets on the price on underlying assets. Within the above context, evidence is provided that our dispersion in beliefs (IDISP) measure contains informed trading prior to the stock price crashes. More specifically, the average weekly IDISP 12 weeks before and after crash weeks across all firms in our sample is plotted. As shown in Figure 4.1 Panel A, while there is a sharp increase at crash week and 1 week after crash, the IDISP also increases significantly before the crash. Therefore, based on the above framework, the IDISP is advocated as the predictor of future stock price crashes. While this empirical design reveals potential informed trading activity preceding crashes, it does not directly translate into a profitable trading strategy. In practice, transaction costs, timing uncertainty, and market frictions would likely offset the predictive gains. The purpose of this analysis is to capture the informational content of disagreement rather than to propose a tradable arbitrage rule.

[Insert Figure 4.1 here]

Although the increase in IDISP before crashes suggests the presence of informed trading in the options market, it is difficult to verify this directly. In future work, informed trading components could be isolated using probability-based measures such as PIN or VPIN. Nevertheless, disagreement may also arise from non-fundamental beliefs or sentiment-driven noise trading, as discussed in De Long, Shleifer, Summers, and Waldmann (1990), implying that IDISP reflects both informed and noise-related opinion divergence.

4.2.2.3 Other divergence in opinion measures

In addition to our main dispersion measure, two methodologies from stocks market and option market are also employed. A detrended stock turnover measure is formed following the spirit of Chen, Hong, and Stein, 2001 and Connolly, Stivers, and Sun, 2005. In particular, the weekly turnover for each individual stock is calculated. Next, for each week, a window from week -50 to week -1 is formed to calculate average turnover. Finally, the weekly detrended stock turnover is the difference between current week turnover and 50-week average turnover. Mathematically, the detrended stock turnover is constructed as follows,

$$DTURN_{i,t} = TURN_{i,t} - \frac{1}{50}\sum_{t=-50}^{-1} TURN_{i,t} \tag{4.4}$$

Where $TURN_{i,t}$ is the weekly average stock turnover. Daily stock trading volume divided by share outstanding (times 1000) is used to calculate the daily turnover, then the arithmetic mean of daily turnover is calculated to estimate the weekly turnover. Similar with the IDISP measure, the last week's detrended turnover within each month is selected to obtain the monthly detrended turnover.

The weekly detrended turnover is plotted around crash weeks. Figure 4.1 Panel B shows that detrended turnover remains the same until 2 weeks before the stock price crash and increases a lot from 1 week before the stock price crash. This plot is consistent with the findings that informed trading exists in both options market and stocks market (Chakravarty, Gulen, and Mayhew, 2004).

This chapter also follows Golez and Goyenko (2022) to construct a disagreement measure from the options market. Unlike the IDISP measure, this disagreement measure is the minimum between the delta-adjusted trading volume of bullish trading (long call options and short put options) and the delta-adjusted trading volume of bearish trading (long put options and short call options). More specifically, using the detailed trading volume data from the Chicago Board of Options Exchange (CBOE) and the International Securities Exchange (ISE), the disagreement is constructed as follows.

$$Disagreement = \frac{min(Bullish, Bearish)}{max(Bullish, Bearish)} \tag{4.5}$$

Where the

$$Bullish = \Sigma|\Delta_C|(OpenBuyCall + CloseBuyCall) + |\Delta_p|(OpenShortPut + CloseShortPut)$$
$$Bearish = \Sigma|\Delta_C|(CloseShortCall) + \left|\Delta_p\right| (OpenBuyPut + CloseBuyPut)$$

According to Lakonishok,Lee, Pearson, and Poteshman (2007), most option investors are directional investors; they usually do not combine options with individual stocks except for short call options. Investors usually combine individual stocks with short call options to construct a covered call strategy. Therefore, the open short call is not directional trading. Open short call options are excluded from the aggregated Bearish disagreement. Similar with other dispersion measures, the monthly disagreement measure is selected in the analysis.

The last divergence in opinion measure is analyst forecast dispersion (AFD). The AFD is defined as the standard deviation of analyst forecasts scaled by the median of analyst forecasts. Data is collected from I/B/E/S, and forecast period indicator (FPI) is required to equal 1. Other FPIs and alternative AFD definitions—such as the standard deviation of analyst forecast scaled by share price—are also tested. The results remain unchanged.

4.2.3 Control variables

This chapter employs two sets of control variables in the analysis. First set of controls are stock-related variables, including Size, Total Volatility, lag1 Stock Return, lag2 Stock Return, lag3 Stock Return, lag12 Ncskew and lag12 Duvol. The second set of controls are fundamental control variables, including Market to Book ratio and Leverage. The detailed descriptions of control variables are provided in Appendix.

4.2.4 Summary statistics

Table 4.1 reports the summary statistics of our sample. More specifically, this chapter reports the number of observations, mean, standard deviation, 25 percentile value, median and 75 percentile value of all variables across the sample. It is observed that the mean of stock price crash is 0.017. This is not surprising because the threshold selects 3.25 times its standard deviation, which is an extremely rare case. The mean of monthly IDISP is 0.087; compared with Figure 4.1 Panel A, the IDISP remains at average level 6 weeks before crash, but increases gradually since week -5. The mean of weekly detrended turnover is zero; compared with Figure 4.1 Panel B, it is also observed that the detrended turnover remains zero several weeks before the crash, but increases a lot from week -5 to week -2 and increases sharply at week -1. Overall, these figures clearly indicate that some informed investors take some action in both the stocks market and the options market before the crash. The informed trading increases the divergence in opinions, which increases the value of IDISP measure and detrended turnover. All other control variables are comparable with the existing literature.

[Insert Table 4.1 here]

4.3 Empirical analysis and robustness check

In this section, this chapter investigates the predictability of IDISP for the firm-level stock price crashes. The robustness of the predictability is further examined after controlling for detrended turnover, different versions of IDISP, different firm-level crash measures, and alternative divergence in opinion measures, including a wide range of stock-characteristic and fundamental-level control variables.

4.3.1 Predictability of IDISP on crash

The empirical analysis starts by examining the relationship between the lag values of IDISP and crash. In particular, pooled cross-sectional regression with industry and year-month fixed effects is applied as a linear proxy of logit models, with crash at month t as the dependent variable and IDISPs from month t-1 to t-4 as main independent variables. The following control variables are considered: log of market capitalization (Size) at t-1, total volatility of the past year (Total Volatility) at t-1, monthly stock return (Stock return) from t-1 to t-3, market to book ratio (Market to book) at t-1, and leverage (Leverage) at t-1. Table 4.2 presents the coefficients and corresponding t-statistics. Columns (1) – (4) report the results of IDISPs from month t-1 to month t-4, respectively. Columns (5) – (8) report the results after controlling for detrended turnover (Dturnover) from month t-1 to month t-4. It is observed that over the 4 lagged IDISP variables, IDISP at t-1 has the largest positive predictive power and is highly significant (t = 4.45). Lag2 IDISP also has positive coefficient but less significant (t = 2.08), while Lag3 and Lag4 are not significant. This result is consistent with the view that the options market is relatively short-term and the IDISP is constructed using short-term options (maturity between 10–60 days). Last month IDISP is positively associated with current month crashes, as also illustrated in Figure 4.1 Panel A. More notably, in column (5), the estimated coefficient of Dturnover is positive and significant (t = 2.50). This is consistent with existing evidence that detrended turnover correlates with the likelihood of extremely negative returns. In fact, Chen, Hong, and Stein (2001) show a positive relationship between Dturnover and Ncskew. A higher Ncskew reflects a more negatively skewed return or crash risk. After controlling for Dturnover, the coefficient of IDISP at t-1 remains positive and highly significant (t = 4.38), indicating that this measure reflects information beyond what Dturnover captures. Other control variables also show strong statistical significance, especially leverage and lag12 Ncskew. The R^2 is low but reasonable, consistent with the low occurrence of firm-level stock crashes.

[Insert Table 4.2 here]

Although this study does not explicitly test a trading strategy, the results suggest a conceptual implication for informed investors. A hypothetical strategy could involve shorting stocks with persistently high IDISP values or large increases in disagreement, as these firms exhibit elevated crash risk in subsequent months. Conversely, investors could go long in low-disagreement stocks that display stable opinion convergence. Such a strategy would exploit the predictive content of belief dispersion for downside tail events, although in practice transaction costs and market frictions would likely reduce its profitability. While IDISP partly reflects information inferred from informed traders' activities, it also embodies non-fundamental elements such as sentiment or belief heterogeneity. Hence, trading on IDISP would represent an information-based, rather than a purely fundamental, speculative strategy.

Next, this chapter examines the robustness of the relationship between IDISP and crash across various IDISP measures and crash measures. The robustness between IDISP and crash is first examined using different IDISP measures. In particular, four alternative IDISPs are constructed using options with different time to maturities. (2. IDISP with maturity between 10 to 180 days, 3. IDISP with maturity between 10 to 366 days, 4. IDISP with maturity between 60 to 366 days, and 5. IDISP with maturity between 60 to 180 days). Then, the same regression of crash on IDISPs plus all control variables and fixed effects is run. Table 4.3 Panel A reports the coefficients and corresponding t-statistics across all four alternative IDISP measures. Columns (1) to (4) report the results of all four alternative IDISPs at month t-1. Columns (5)-(8) report the results after controlling for detrended turnover (Dturnover) at month t-1. All coefficients remain positive and strongly significant, indicating that the IDISP measure is stable and persistent (Andreou, Kagkadis, Philip, and Tuneshev, 2018). Next, the robustness between IDISP and crash is examined using different crash measures. Pure crash, which is a subset of the crash measure, is set equal to missing if a jump is detected over the past 52 weeks. Conservative crash, which is also a subset of crash, is set equal to missing if a crash is detected over the past 52 weeks. The third type of crash is set equal to 1 if monthly cumulative return is below 20% and fourth type of crash is set equal to 1 if monthly cumulative log return is below 20%. The Ncskew and Duvol are also checked following the existing literature. Table 4.3 Panel B shows the results. Across columns (1) to columns (6), all coefficients of IDISP are positive and highly significant. The above findings establish a strong positive relation between IDISP at month t-1 and crash at month t and far from being random. Overall, these results indicate that the predictability of IDISP at t-1 on crash at t is robust across different alternative IDISP measures. Moreover, this finding is also robust to alternative definition of crash measures.

[Insert Table 4.3 here]

4.3.2 Predictability of other divergence in opinion measures

Our baseline results demonstrate that last month IDISP show a statistically and economically significant positive relationship with next month stock price crash. This positive relation is robust after controlling for a large set of control variables, alternative IDISP measures and alternative definition of crash measures. In this section, the Disagreement measure provided by Golez and Goyenko (2022) and analyst forecast dispersion (AFD) are selected as two other divergence in opinion measures to study the following two questions. First, whether the other divergence in opinion measures are positively related to next month crash. Second, whether the positive relationship between last month IDISP and next month crash persists after simultaneously controlling for other divergence in opinion measures. In particular, in each month, the pooled cross-sectional regression is first performed to assess the relationship between crash at month t and other divergence in opinion measures at month t-1. This analysis also include all control variables as well as industry and year-month fixed effects. Next, the same regression is repeated while ensuring the IDISP is not missing. Finally, IDISP and other divergence in opinion measure are incorporated simultaneously in the regression. The estimated coefficients of each divergence in opinion measure, the corresponding t-statistics, number of observations and R square are reported.

[Insert Table 4.4 here]

Table 4.4 presents the results. In column (1), regression of crash at month t on Disagreement at month t-1 plus all control variables along with industry and year-month fixed effects is run. The coefficient of Disagreement is positive (0.001) and statistically significant (with a t-statistic of 4.16). Comparing with Table 4.3, column (1), the economic magnitude of disagreement is lower than our IDISP measure. In column (2), the same regression is repeated and the IDISP is not missing. The coefficient of Disagreement retains a positive value (0.001) yet its significance level decreases (with a t-statistic of 2.42). In column (3), IDISP and Disagreement are included simultaneously in the regression. The coefficient of IDISP is positive (0.006) and highly significant (with a t-statistic of 6.40). On the other hand, the coefficient of Disagreement remains unchanged (0.001) but it is no longer significant (with a t-statistic of 1.33). Columns (4) to (6) present the outcomes when Disagreement is replaced with AFD, following the same approach as in columns (1) to (3). Regressions of crash on AFD only, crash on AFD when IDISP is not missing, and crash on AFD and IDISP simultaneously are run. In column (4) the coefficient of AFD is economically meaningless (-0.000) and statistically not significant. If IDISP is included in the model, then the coefficient of AFD becomes negative and highly significant. These results are not surprising because AFD loses its predictability power, especially after 2008 crisis. The negative and significant coefficient of AFD after controlling for IDISP may arise because the two measures capture different information horizons. IDISP reflects real-time option trading behavior that incorporates investors' private signals, whereas AFD is based on analysts' forecasts, which are updated less frequently and may contain backward-looking elements. Once the option-based disagreement absorbs the forward-looking component, the remaining variation in AFD could primarily reflect outdated or noisy forecasts, resulting in a negative association with crash risk. To summarize, these regression results indicate that last month IDISP has a strong prediction on current month stock price crash. The results remain robust after other divergence in opinion variables are included simultaneously. Moreover, the Disagreement does not exhibit predictability after the IDISP measure is included, and the AFD shows no predictability power and gives wrong information on next month crash. The correlations among the three disagreement measures are low (below 0.08), indicating that they capture distinct aspects of belief dispersion rather than overlapping information.

4.3.3 Predictability of IDISP on stock price jumps

So far, this chapter has established a strong and positive relationship between the last month divergence in opinion measures and next month stock price crashes. This chapter now tests whether or not the last month divergence in opinion measures predict next month extreme positive returns. As noted in section 2.2.1, the jump is set equal to one if an extreme positive weekly idiosyncratic return is detected. See Appendix for detailed variable definitions. Table 4.5 displays the results. Pooled cross-sectional regression of monthly stock price jumps on divergence in opinion measures is run. Each column represents a specific divergence in opinion measures. Notably, the coefficients of IDISP, Dturnover and Disagreement are negative and statistically significant, while the coefficient of AFD is negative and lack significance. These findings suggest that previous month divergence is negatively associated with next month stock price jumps. Moreover, the negative coefficient indicates that the divergence in opinion measures distinguish crashes from jumps, rather than simply pick up rare events.

[Insert Table 4.5 here]

4.3.4 Potential channels

In this section, I analyse the potential channels for the positive IDISP-crash relationship with various firm-level and market-level variables. The analysis begins by controlling for firm's financial reporting quality. Next, the effect of short sale constrains using institutional ownership data is explored. Then, the effect of investor sentiment is considered. Lastly, the effect of earnings announcement is discussed.

4.3.4.1 Financial reporting quality

Initial findings are tested for robustness after controlling for different financial reporting quality indicators. It has been widely documented that managers hide bad news through earnings management practices. When they are no longer able to hide bad news or it is too costly to do so, they release bad news at once. Resulting in a shock to stock prices (Sloan, 1996; Jin and Myers, 2006; Hutton, Marcus, and Tehranian, 2009; Chi and Gupta, 2009; Zhu, 2016, among many others). Additionally, existing literature document that depreciation is another tool to manipulate earnings (Bartov, 1993; Stolowy and Breton, 2004). Some researchers also suggest that managers reduce the R&D expenses to achieve certain earnings targets (Baber, Fairfield, and Haggard, 1991; Perry and Grinaker, 1994; Cheng, 2004). Therefore, certain proxies for earnings management are incorporated into the baseline models. The first set of these proxies are accrual-based variables measured using the modified Jones model. The Chi and Gupta (2009) methodology is followed to estimate the quarterly firm level discretionary accruals. The Disc. Accruals variables are the moving sum of discretionary accruals over the past 4, 8 and 12 quarters. Similarly, the Opacity variables are the moving sum of the absolute value of discretionary accruals over the past 4, 8 and 12 quarters. Next, firm depreciation value is included, which is the log value of firm's depreciation. Finally, the R&D cut is included, which is a binary variable set equal to one when R&D expenditure is lower than previous year. See Appendix for detailed definition of variables.

[Insert Table 4.6 here]

The results from Table 4.6 clearly show that the positive relation between crash and previous month IDISP remain unchanged after the inclusion of all financial reporting quality proxies. The coefficients of IDISP are positive and highly significant across all six models. While the accrual-based variables show a positive association, the significance level is marginal. Notably, the strongest result comes from Disc. Accruals (4 qtrs), with a t-statistics of 2.20. All Opacity variables are not significant. The lack of significance is not surprising because accrual-based earnings management has lost its predictability power post-Sarbanes-Oxley Act (Andreou, Lambertides, and Magidou, 2023). The above results indicate that the negative relation between crash and IDISP is a separate phenomenon from the earnings manipulation practices.

4.3.4.2 Short sale constraints

Following Miller (1977) theorem, when stock's divergence in opinions are high, these stocks are tend to be overvalued, generating in a negative future return or stock price crash risk. Diether, Malloy, and Scherbina, 2002; Chen, Hong, and Stein, 2001; Andreou, Kagkadis, Philip, and Tuneshev, 2018. This phenomenon is particularly pronounced for stocks facing high short-selling constraints. Intuitively, when stocks have lower institutional ownership, it means they are less owned by institutional investors. The lower supply from institutions makes these stocks more costly to borrow for short selling. Conversely, when short-selling costs and arbitrage frictions are high, institutional investors are also less willing to hold such stocks. Hence, the relationship between institutional ownership and short-sale constraints is likely to be two-way. In this analysis, the residual institutional ownership from Nagel (2005) is therefore used as a proxy for short-sale constraints rather than interpreted as a causal driver. Specifically, a lower value of residual institutional ownership indicates tighter short-sale constraints, implying that short-sellers must pay a higher premium to short these stocks.

For empirical implementation, stocks are sorted in ascending order into quintile sub-samples based on the residual institutional ownership value. Next, within each sub-sample, the pooled cross-sectional regression of monthly crash on each of all four divergence in opinion measures is performed, respectively.

[Insert Table 4.7 here]

Table 4.7 presents the results. In Panel A, it is found that IDISP shows significant results across all quintile subsamples. These results are surprising because following Miller (1977) theorem, significant results are expected for low institutional ownership sub-samples and insignificant results for high institutional ownership sub-samples. However, the IDISP shows significance for all sub-samples, indicating that the positive relationship between IDISP and next month crash is not driven by the institutional ownership. In Panel B, the Dturnover results are in line with the theoretical prediction of Miller (1977). The Dturnover is highly significant for quintile 1 (with coefficient 0.019 and t-statistics 2.81). Then, the t-statistics almost drops monotonically, from 1.89 in quintile 2 to 1.00 in quintile 5. These results indicate that the predictability of Dturnover and next month crash is driven by the short sale constraints. This is not surprising because the stock market data is used to construct the Dturnover, the institutional ownership data also comes from stocks market. In Panel C, the Disagreement results are in line with Miller (1977) prediction. However, these results are very weak given the quintile 1 is significant at 10% level, with t-statistics = 1.77. In addition, the coefficients of Disagreement are very low compared with the IDISP and Dturnover. A negative coefficient at quintile 4 is even observed. In Panel D, the coefficients of AFD are all negative and most of them are statistically not significant, with the exception of quintile 2. Again, these results indicate that AFD has lost its predictability power. In summary, Table 4.7 shows that the positive relation between IDISP and crash is not driven by the short sale constrains. As a robustness check, the analysis is re-estimated using short interest as an alternative proxy for short-sale constraints. The results remain qualitatively similar, with the positive and significant association between IDISP and crash risk unchanged.

4.3.4.3 Investor sentiment

Another potential channel to explain the positive relation between IDISP and crash is the overall market sentiment. Following Stambaugh, Yu, and Yuan (2012), when the overall market sentiment is high, the excessive buying and speculative trading push up the prices above the fundamental values. Investors tend to overvalue the stocks due to the wide-spread of optimism. When the overall market sentiment is low, the stock prices are close to the rational prices. This indicates that the overvaluation is more pronounced during the high sentiment period. Therefore, a stronger positive relationship between divergence in opinions and crash during high sentiment period is expected. On the other hand, when the overall market sentiment is low, the relationship between divergence in opinions and crash should be weaker. Whether the relationship between divergence in opinion is stronger during high-sentiment period is tested by splitting the whole sample into high-sentiment and low-sentiment subsamples. Baker and Wurgler 2006 sentiment index is followed and the high-sentiment (low-sentiment) period is defined when the sentiment value is above (below) the median of the whole sample. Then, within each sentiment subsample, pooled cross-sectional regression of crash on each of the divergence in opinion variables is run.

[Insert Table 4.8 here]

The results provided in Table 4.8 shed light on the relationship between divergence in opinions and the next month stock price crash, segregated into high and low sentiment periods. Firstly, columns (1) and (2) show positive and significant coefficients in both high and low-sentiment subsamples. These results indicate that a higher IDISP correlates with the higher crash risk. The positive relationship between IDISP and crash persists regardless of overall market optimism and or pessimism. It is also observed that this positive relation is stronger for high-sentiment subsample, with a higher coefficient and t-statistics compared with low-subsample. Secondly, columns (3) and (4) suggest that Dturnover is positively correlated with next month crash only during high-sentiment periods. These results indicate that when investors are overly optimistic and the stock prices are overvalued, an abnormally high trading volume prior to a stock price crash would be observed. Next, columns (5) and (6) show that similar with Dturnover, Disagreement also show a positive relationship with next month crash only during high-sentiment period. Lastly, columns (7) and (8) show that AFD is negatively correlated with next month crash, regardless of overall market sentiment. These results again indicate that AFD has lost its predictability power. In summary, results from Table 4.8 show that the positive relation between IDISP and next month crash persists regardless of market sentiment. Although this positive relation is stronger during high-sentiment periods. A strong and positive correlation between IDISP and next month crash during low-sentiment period is still observed. These results may also reflect the impact of sentiment reversals. When overall optimism fades, even firms without major hidden bad news may experience sharp price declines as investors collectively unwind positions. Thus, the high-sentiment effect likely captures both firm-level bad news release and market-wide shifts in sentiment.

4.3.4.4 Earnings announcement effect

The previous findings from this chapter evince a systematically positive relationship between IDISP and next month crash. In this section, a deeper understanding of this effect is obtained by performing a more granular analysis of weekly IDISP and subsequent weekly stock price crashes around earnings announcement weeks. It has been widely documented that earnings announcement is important to firm value by providing fundamental information and drives stock prices (Frazzini and Lamont, 2007), and reducing the uncertainty (Dubinsky and Johannes, 2006; Isakov and Perignon, 2001). In addition, a vast existing literature documents that the occurrence of stock price crash is higher during the earnings announcement periods versus non-earnings announcement periods (Van Buskirk, 2011; Zhu, 2016). Moreover, from Figure 4.2, a significant increase in IDISP before the crash is observed. Hence, a significant positive relationship between weekly incremental IDISP and weekly crashes around earnings announcement weeks is expected. To test the earnings announcement effects, the following empirical analysis is conducted.

First, the weekly incremental IDISP (ΔIDISP) is calculated by taking the difference between the weekly IDISP_{t-1} and earlier weekly IDISPs (from t-2 to t-10). This method helps to capture how much IDISP has increased compared with earlier weeks. Earlier weekly IDISPs are also controlled in the regression model. Next, to capture earnings announcement effect, dummy variables around earnings announcement weeks are set. More specifically, dummy variables from 2 weeks before the earnings announcement week until 2 weeks after the earnings announcement week are set, in total five weekly dummies. Then, interaction terms, which equal to the ΔIDISP times all five earnings announcement week dummies, are also set. The pooled cross-sectional regression at weekly level plus all control variables, weekly fixed effect and industry fixed effect is run.

[Insert Table 4.9 here]

Table 4.9 presents the results of the impact of the weekly IDISP on the subsequent stock price crashes, particularly around earnings announcements. The variable ΔIDISP measures the change in IDISP before the earnings announcement, providing insights on how the variation of IDISP influences crashes. The results suggest a statistically significant positive relationship between IDISP and future stock price crashes, consistent across multiple lags of IDISPs. The coefficient of ΔIDISP across from model (1) to model (5) are positive and statistically significant at 1% level, indicating that an increase in the weekly IDISP is associated with the higher probability of stock price crashes in the subsequent weeks. Similarly, coefficient of earnings announcement dummy EA_t across from model (1) to model (5) are positive and statistically significant, indicating a higher probability of stock price crash at earnings announcement week. More importantly, the interaction terms between ΔIDISP and earnings announcement weeks reveals that the effect of ΔIDISP and subsequent stock price crashes is more pronounced at the earnings announcement week. Specifically, the positive and significant coefficients on the interaction terms $EA_t \times \Delta IDISP$ across all columns, whereas the rest of the interaction terms are statistically not significant. This result highlights that the contemporaneous effects of earnings announcements amplify the impact of IDISP on crash risk.

In summary, the evidence from Table 4.9 suggests that weekly IDISP and the increase in the weekly IDISP predicts subsequent stock price crashes after controlling for various control variables and fixed effects. This effect is particularly pronounced during the earnings announcement periods.

4.3.4.5 Heterogeneous effects from financial reporting quality and earnings surprises

So far, it has been documented that weekly IDISP predicts the subsequent stock price crashes, especially around earnings announcement periods. Now the question is why this happens. Existing literature documents that managers are willing hold bad news through earnings management practises and tend to avoid negative earnings surprises (Matsumoto, 2002, Davis and García-Cestona, 2023). Therefore, a stronger positive relation between IDISP and subsequent stock price crashes for firms with higher earnings management practises and more positive earnings surprises is expected. The investigation of the relationship between the weekly IDISP and crashes is extended by considering the role of firm level discretionary accruals and cumulative earnings surprises. More specifically, first, the whole sample is split based on Disc. Accruals (4qtrs) into high discretionary accruals and low discretionary accruals subsamples. Next, within each discretionary accruals subsample, if the cumulative earnings surprises is equal to and greater than 3, this firm is categorized into high surprise group, otherwise this firm is categorized into low surprise group. Following Skinner and Sloan 2002, the earnings surprises are the differences between realized quarterly earnings per share (EPS) minus the median of foretasted EPS. Good is set equal to one if earnings surprises are positive and zero otherwise. The cumulative earnings surprises are the moving sum of the Good indicator over the past 4 quarters. A cumulative earnings surprises equal to 4 means that the firm reported 4 positive earnings surprises over the past 4 quarters. Finally, the same regression model as Table 4.9 is run for each discretionary accruals and cumulative earnings surprises group.

[Insert Table 4.10 here]

Table 4.10 Panel A focuses on firms with high discretionary accruals and cumulative earnings surprise equal to and greater than 3. Within this group, the results underscore the predictive power of IDISP for stock price crashes with the coefficients for ΔIDISP and its lags remaining positive and statistically significant across all models. The interaction term $EA_t \times \Delta IDISP$ remain positive and significant in all models except for column (2). However, even in that case, the interaction term is still positive and nearly reaches statistical significance, with a t-statistic of 1.48. This result indicate that earnings announcement week is crucial for the relationship between IDISP and future stock price crashes, especially for firms with high discretionary accruals and high cumulative earnings surprises. Panel B reports the results with high discretionary accruals but cumulative earnings surprise less than 3. Although the coefficients of ΔIDISP remain positive and significant, the lag values of weekly IDISP are statistically not significant. Notably, the interaction terms $EA_t \times \Delta IDISP$ are not significant in Panel B, the coefficients are very close to zero and even negative values in columns (2), (4) and (5) are observed. This result indicates that for firms with high discretionary accruals and less pronounced earnings surprises, the earnings announcement does not amplify the effect of IDISP and subsequent stock price crashes as it does for firms with high discretionary accruals and high surprises. The distinct results across panels A and B suggest that the combination of high discretionary accruals and high earnings surprises creates a unique environment where the dispersion of investor opinions has a more pronounced effect on crash risk. Additional checks excluding the 2008 Financial Crisis and COVID windows yield similar results, In addition, the key relationships remain significant in the more recent subsample period, indicating that the relationship between belief dispersion and crash risk is stable across market regimes.

4.4 Conclusion

This study extends the empirical finance literature by providing robust evidence on the predictive power of investor disagreement, measured as dispersion in beliefs on individual stocks (IDISP), for the likelihood of subsequent stock price crashes. Consistent with prior empirical findings, the results affirm a significant, positive association between investor disagreement and the stock price crashes, particularly around earnings announcement periods. This relationship is robust after controlling for various control variables, different versions of IDISP, different measurements of investor disagreement and different measurements of stock price crashes, highlighting the critical role of heterogeneous beliefs in exacerbating market volatility. Notably, these findings contribute to the broader discourse on market efficiency and the mechanisms through which investor psychology and sentiment divergence can precipitate significant market corrections.

The implications of this study are manifold. For individual investors, understanding the dynamics of investor disagreement offers a lens through which potential market downturns can be anticipated, allowing for more informed risk management and investment decision-making. For policymakers and regulators, these findings underscore the importance of monitoring investor disagreement as a barometer of market fragility, suggesting that measures to enhance transparency and information dissemination could mitigate the risks associated with high levels of disagreement among investors.

In summary, this study adds to the growing body of evidence that investor disagreement is not merely a reflection of diverse market views but a significant predictor of market instability, with profound implications for investors, regulators, and the finance community at large.

A Description of the control variables

Measures of stock price crash risk

I calculate the mean, and the standard deviation of firm i's current week market adjusted log return over the past 52 weeks, including current week t. Log market adjusted return is $\mathrm{Ret}_{i,t} = \log(1 + \epsilon_{i,t})$. Where $\epsilon_{(i,t)}$ is the residual obtained from the following regression.

$$r_{(i,t)} = \alpha_i + \beta_1 Rm_{t-2} + \beta_2 Rm_{t-1} + \beta_3 Rm_t + \beta_4 Rm_{t+1} + \beta_5 Rm_{t+2} + \epsilon_{(i,t)}$$

Where $r_{i,t}$ is firm i's cumulative daily return (CRSP variable ret) on week t, Rm_t is the cumulative CRSP value weighted return (CRSP variable vwret) on week t. See Hutton, Marcus, and Tehranian (2009) for detailed information. We select 3.25 times its standard deviation to generate the 0.1\% frequencies in the normal distribution.

Monthly Crash is an indicative variable which is set equal to one if firm i experiences at least one weekly crash within each month. The weekly crash is set equal to 1 if firm i's current week market adjusted log return falling 3.25 times its standard deviation below its mean. The log market adjusted return, the mean and the standard deviation are calculated above.

Monthly Jump is an indicative variable which is set equal to one if firm i experiences at least one weekly jump within each month. The weekly jump is set equal to 1 if firm i's current week market adjusted log return falling 3.25 times its standard deviation above its mean. The log market adjusted return, the mean and the standard deviation are calculated above.

Pure Crash is an indicative variable which is set equal to 1 if firm i experiences at least one pure weekly crash within each month. The pure weekly crash is set equal to 1 if firm i's current week market adjusted log return falling 3.25 times its standard deviation below its mean. The log market adjusted return, the mean and the standard deviation are calculated above. In addition, if we detect a Jump over the past 52 weeks, then pure weekly crash is set equal to zero. This adjustment is made to distinguish between a crash and a price correction resulting from previous extreme positive returns associated with Jumps.

Conservative Crash is an indicative variable which is set equal to 1 if firm i experiences at least one conservative weekly crash within each month. The conservative weekly crash is set equal to 1 if firm i's current week market adjusted log return falling 3.25 times its standard deviation below its mean. The log market adjusted return, the mean and the standard deviation are calculated above. If a weekly crash is detected over the past 52 weeks, the subsequent 51 weeks' conservative crash is set as missing. This adjustment aims to prevent the influence of previous crashes on the sample mean and standard deviation, ensuring that the weekly crash is not affected by prior crash occurrences.

Ncskew is the monthly average of weekly negative coefficient of skewness for firm i at week t. Weekly Ncskew is defined as the following equation.

$$Ncskew_{i,t} = -\left(n(n-1)^{3/2}\Sigma Ret_{i,t}^{3}\right)/\left((n-1)(n-2)\left(\Sigma Ret_{i,t}^{2}\right)^{3/2}\right)$$

The log market adjusted return, the mean and the standard deviation are calculated above. See Chen Hong and Stein (2001) for details.

Duvol is the monthly average of weekly down volatility to up volatility for firm i at week t. Weekly Duvol is defined as the following equation.

$$Duvol_{i,t} = log\ (stdev_{down}(Ret_{i,t})/stdev_{up}(Ret_{i,t}))$$

if $Ret_{i,t}$ < mean return over the past 52 weeks, then this weekly return is categorized as down group. Otherwise, it is categorized as up group. The log market adjusted return, the mean and the standard deviation are calculated above. See Chen Hong and Stein (2001) for details.

Monthly Crash 20 pct is an indicative variable which is set equal to one if firm i experiences at least one weekly crash 20 pct within each month. Weekly crash 20 pct is set equal to one if firm i's market adjusted weekly return is below 20\%. Market adjusted weekly return =$(r_{i,t} - Rm_t)$.

Where $r_{i,t}$ is firm i's cumulative daily return (CRSP variable ret) on week t, Rm_t is the cumulative CRSP value weighted return (CRSP variable vwret) on week t.

Monthly Crash 20 jack is an indicative variable which is set equal to one if firm i experiences at least one weekly crash 20 jack within each month. Weekly crash 20 jack is set equal to one if firm i's weekly log return is below 20\%. Weekly log return =$\log(1 + r_{i,t})$.

Where $r_{i,t}$ is firm i's cumulative daily return (CRSP variable ret) on week t.

Measures of divergence in opinions

IDISP is the dispersion in beliefs on individual stocks. Following Andreou, Kagkadis, Philip, and Tuneshev (2018), I measure the dispersion in beliefs on individual stocks (IDISP) using the trading volume of stock options across all moneyness levels. The IDISP is the volume weighted average of the deviation of the moneyness level on the volume weighted moneyness level. For each day and each individual stock, we have a current stock price S and a range of different strike prices of stock options $\mathrm{K_i}$, where $\mathrm{i} = 1, \dots, \mathrm{n}$. Then, we define the moneyness level as the ratio of strike price on stock price, ($\mathrm{M_i} = \frac{\mathrm{K_i}}{\mathrm{S}}$). Finally, I estimate the daily IDISP using the following equation.

$$IDISP = \sum_{i=1}^{n} w_i \left| M_i - \sum_{i=1}^{n} w_i M_i \right|$$

Where the $\mathrm{w_i}$ is the weight of trading volume attached to option $\mathrm{K_i}$, n is the total number of strike prices of each stock option within each day. I estimate the IDISP in daily frequency and we take weekly average in our analysis. I select different time to maturity to construct different versions of IDISP. In our main analysis, we use options with maturity between 10 to 60 days. I select last week IDISP within each month for two reasons. First, new options are usually issued at the 4th Monday in each month, I select last week's options to avoid maturing effect. Second, to obtain the most recent information, I need the closest options before next month.

Other versions of IDISPs I also use options with different time to maturity to construct different versions of IDISP.
(**$\mathbf{IDISP_2}$**) with option maturity between 10 to 180 days,
(**$\mathbf{IDISP_3}$**) with option maturity between 10 to 366 days,
(**$\mathbf{IDISP_4}$**) with option maturity between 60 to 366 days,
(**$\mathbf{IDISP_5}$**) with option maturity between 60 to 180 days.

Dturnover is the difference between the weekly turnover at week t and the average weekly turnover from week t-50 to t-1. Following Connolly, Stivers, and Sun 2005, we calculate the DTURN using the following equation.

$$DTURN_{i,t} = TURN_{i,t} - \frac{1}{50} \sum_{t=-50}^{-1} TURN_{i,t}$$

Where $TURN_{i,t}$ is the weekly average stock turnover, which equals to (CRSP variable vol) / (CRSP variable shrout × 1000).

Disagreement is the minimum between the delta adjusted trading volume of bullish trading (long call options and short put options) and the delta adjusted trading volume of bearish trading (long put options and short call options). Following Golez and Goyenko 2022, we construct the disagreement in the following way.

$$Disagreement = \frac{min(Bullish, Bearish)}{max(Bullish, Bearish)}$$

Where the

$$Bullish = \Sigma|\Delta_C|(OpenBuyCall + CloseBuyCall) + \left|\Delta_p\right|(OpenShortPut + CloseShortPut)$$

$$Bearish = \Sigma|\Delta_C|(CloseShortCall) + \left|\Delta_p\right| (OpenBuyPut + CloseBuyPut)$$

Analyst forecast dispersion (AFD) is the standard deviation of analyst forecasts scaled by the median of analyst forecasts. We collect data from I/B/E/S and require forecast period indicator (FPI) equals to 1.

Other variables

Size is the natural log of firm's market value of equity at the end of each quarter. Source: COMPUSTAT.

Total Volatility is the total volatility of stock i's daily stock return over the past year, including current month t. We require at least 225 observations over the past year. Source: CRSP.

Stock Return is the cumulative stock return of last month. Source: CRSP.

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

Leverage is the long-term debt plus liability divided by firm's total assets. Source: COMPUSTAT.

Disc. Accruals (4qtrs) is the moving sum of a firm's quarterly discretionary accruals over the past 4 quarters. The discretionary accruals are the residuals obtained from a modified Jones model. More specifically, we run the following cross-sectional regressions each quarter and each of the Fama-French 48 industry groups excluding financial and utility firms.

$$\frac{\text{Total Accruals}_{it}}{\text{Total Assets}_{\text{it-1}}} = \alpha \frac{1}{\text{Total Assets}_{\text{it-1}}} + \beta_1 \frac{\Delta\text{Sales}_{it} - \Delta\text{Rec}_{it}}{\text{Total Assets}_{\text{it-1}}} +$$

$$+\beta_2 \frac{\text{PPEG}_{it}}{\text{Total Assets}_{\text{it-1}}} + \beta_3 \frac{\text{CFEE}_{it}}{\text{Total Assets}_{\text{it-1}}} + \varepsilon_{it}$$

Where $\text{Total Accruals}_{it}$ is the total accruals for firm i at time t, $\text{Total Assets}_{\text{it-1}}$ is the total assets (Compustat item 6) at time t-1, ΔSales_{it} is the change in sales (Compustat item 12), ΔRec_{it} is the change in receivables (Compustat item 2), PPEG_{it} is the gross property, plant and equipment (Compustat item 7) and CFEE_{it} is the income before extraordinary items (Compustat item 18) minus the $\text{Total Accruals}_{it}$. We use the change in current assets (Compustat item 4) plus the change in debt in current liabilities (Compustat item 34) plus the change in income taxes payable (Compustat item 71) minus the change in current liabilities (Compustat item 5) minus the change in cash and short-term investment (Compustat item 1) minus the depreciation and amortization item (Compustat item 14) to calculate the total accruals. The quarterly discretionary accruals are the residuals obtained from the above regression.

Disc. Accruals (8qtrs) is the moving sum of a firm's quarterly discretionary accruals over the past 8 quarters.

Disc. Accruals (12qtrs) is the moving sum of a firm's quarterly discretionary accruals over the past 12 quarters.

Opacity (4qtrs) is the moving sum of absolute value of a firm's quarterly discretionary accruals over the past 4 quarters.

Opacity (8qtrs) is the moving sum of absolute value of a firm's quarterly discretionary accruals over the past 8 quarters.

Opacity (12qtrs) is the moving sum of absolute value of a firm's quarterly discretionary accruals over the past 12 quarters.

Depreciation is the log of firm i's Depreciation and Amortization (Compustat variable DPQ) at quarter t-1.

R&D cut is an indicative variable which is set equal to one if the change of Research and Development Expense (Compustat variable XRDQ) is negative. Otherwise, it is set equal to zero.

Residual Institutional ownership (I/O) is the residual of institutional ownership obtained from a cross-sectional regression of logit transformed institutional ownership on the log of firm size plus the log of firm size squared. See Nagel, 2005 for detailed information.

Sentiment is an overall market indicator. We calculate the median of sample sentiment and split the sample into the above median and below median subsamples. See Baker and Wugler 2006 for detailed information.

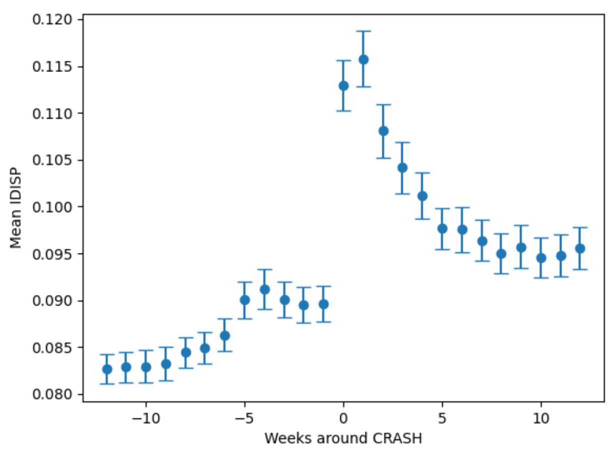
Cumulative Good is the sum of Good indicator over the past 4 quarters, including the current quarter. Following Skinner and Sloan (2002), in each quarterly earnings announcement, if the actual earnings per share (EPS) is above the median of analyst forecast EPS, the Good is set equal to one, otherwise it is set equal to zero. Cumulative Good takes the maximum value of 4 if we detect 4 positive earnings surprises and it takes the minimum value of 0 if we detect 4 negative earnings surprises.

Tables and Figure

Figure 4.1: Average weekly IDISP and Dturnover around crash weeks

These figures plot the cross-sectional average and 5% confidence interval of IDISP (in Panel A) and Dturnover (in Panel B) 12 weeks before and 12 weeks after the stock price crash week. The IDISP is the monthly divergence in opinions of individual stock options measured by volume weighted moneyness levels. Crashes are estimated using a cut-off point of 3.25 standard deviations below its mean idiosyncratic return to generate a frequency of 0.1% extreme left-tail events. Monthly crash is a binary variable which is set equal to 1 if at least 1 weekly crash is observed within each month. The Dturnover is the weekly detrended abnormal trading volume. The sample starts from January 1996 and ends on December 2021. See Appendix for the detailed definition of variables.

Panel A: Average weekly IDISP around crash weeks



Panel B: Average weekly Dturnover around crash weeks

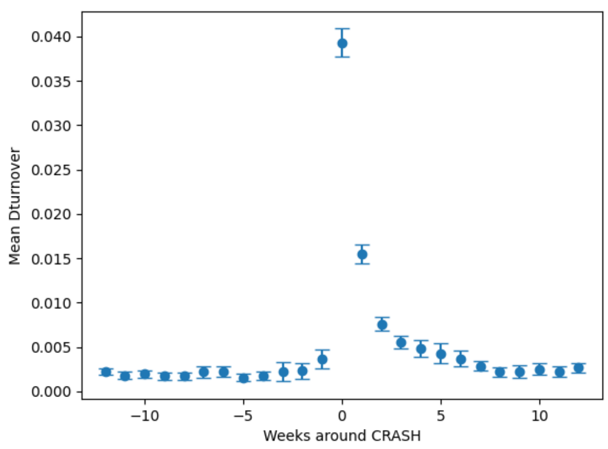


Table 4.1: Summary statistics

This table reports the monthly summary statistics of all variables included in the empirical analysis. The sample period starts from January 1996 and ends in December 2021. Crashes are estimated using a cut-off point of 3.25 standard deviations below its mean idiosyncratic return to generate a frequency of 0.1% extreme left-tail events. Monthly crash is a binary variable which is set equal to 1 if at least 1 weekly crash is observed within each month. The mean and standard deviation are calculated over the past 52 weeks. The IDISP is the monthly divergence in opinions of individual stock options measured by volume weighted moneyness levels. The crash variables (Crash, Pure Crash, Conservative Crash, Ncskew, Duvol, Monthly Crash 20 pct, and Monthly Crash 20 jack) are measured in month t, whereas the independent variables are measured in month t-1 unless specified. See Appendix for the definition of all other variables.

Variable	N	Mean	Std Dev	Q1	Median	Q3
Monthly Crash	1,455,401	0.017	0.130	0.000	0.000	0.000
Pure Crash	1,455,401	0.016	0.126	0	0	0
Conservative Crash	1,455,401	0.009	0.093	0	0	0
Ncskew	1,455,401	-0.018	0.883	-0.468	-0.047	0.380
Duvol	1,455,401	-0.072	0.380	-0.315	-0.083	0.157
Monthly Crash 20 pct	1673297	0.051	0.219	0.000	0.000	0.000
Monthly Crash 20 jack	1673297	0.087	0.282	0.000	0.000	0.000
IDISP	248,570	0.087	0.067	0.053	0.074	0.104
IDISP 2	338,664	0.100	0.079	0.061	0.085	0.120
IDISP 3	349,812	0.107	0.089	0.066	0.091	0.127
IDISP 4	262,647	0.136	0.099	0.080	0.114	0.163
IDISP 5	221,719	0.127	0.092	0.074	0.106	0.153
Dturnover	1,500,804	0.000	0.194	-0.002	-0.001	0.001
Disagreement	318,924	0.252	0.214	0.053	0.219	0.409
AFD	863,463	0.198	1.314	0.017	0.040	0.114
Size	1,502,758	5.691	2.170	4.105	5.572	7.148
Total Volatility	1,406,755	0.600	0.432	0.325	0.485	0.743
Stock Return$_{t-1}$	1,502,459	0.009	0.195	-0.071	0.000	0.071
Stock Return$_{t-2}$	1,493,829	0.009	0.194	-0.071	0.000	0.071
Stock Return$_{t-3}$	1,485,149	0.009	0.192	-0.070	0.000	0.071
Market to Book	1,333,396	3.437	5.695	1.198	1.950	3.515
Leverage	1,326,360	0.207	0.204	0.025	0.157	0.330
Ncskew$_{t-12}$	1,446,020	-0.010	0.863	-0.460	-0.045	0.378
Duvol$_{t-12}$	1,446,020	-0.069	0.375	-0.311	-0.081	0.156
Disc. Accruals (4 qtrs)	938,854	0.004	0.271	-0.066	-0.002	0.061
Disc. Accruals (8 qtrs)	969,215	0.008	0.398	-0.100	-0.002	0.093
Disc. Accruals (12 qtrs)	982,801	0.013	0.488	-0.125	-0.002	0.119
Opacity (4 qtrs)	938,854	0.158	0.252	0.034	0.086	0.189
Opacity (8 qtrs)	969,215	0.292	0.406	0.074	0.172	0.360
Opacity (12 qtrs)	982,801	0.414	0.531	0.113	0.254	0.521
Depreciation	1,128,894	33.018	195.109	0.435	2.247	12.023
R&D cut	635,254	0.296	0.456	0	0	1

Table 4.2: Baseline regression results

This table displays the pooled cross-sectional regression estimates of the effect of two lagged different divergence in opinions measures (IDISP and Dturnover) on the monthly stock price crash risk. The IDISP is the monthly divergence in opinions of individual stock options measured by volume weighted moneyness levels. The Dturnover is the weekly detrended abnormal trading volume. Crashes are estimated using a cut-off point of 3.25 standard deviations below its mean idiosyncratic return to generate a frequency of 0.1% extreme left-tail events. All models include control variables calculated at the end of previous month over the sample period from January 1996 to December 2021 as well as the month fixed effect and Fama-French 48 industry fixed effect. See Appendix for the definition of all other variables. Columns (1) to (4) report the regression results of IDISP on crash risk, with IDISP ranging from lag1 to lag4. Columns (5) to (8) present regression results when incorporating both IDISP and Dturnover as independent variables, with lags ranging from 1 to 4. t-statistics with standard errors clustered at the firm level are shown in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$IDISP_{t-1}$	0.003***				0.003***			
	(4.45)				(4.38)			
$IDISP_{t-2}$		0.001**				0.001**		
		(2.20)				(2.08)		
$IDISP_{t-3}$			0.001				0.001	
			(1.10)				(0.95)	
$IDISP_{t-4}$				-0.000				-0.000
				(-0.49)				(-0.40)
$Dturnover_{t-1}$					0.015**			
					(2.50)			
$Dturnover_{t-2}$						0.006***		
						(2.74)		
$Dturnover_{t-3}$							0.011***	
							(4.11)	
$Dturnover_{t-4}$								-0.004**
								(-2.53)
Size	-0.006***	-0.005***	-0.005***	-0.003***	-0.005***	-0.005***	-0.005***	-0.003***
	(-9.82)	(-8.75)	(-9.72)	(-6.44)	(-9.55)	(-8.66)	(-9.64)	(-6.44)
Total Volatility	-0.008***	-0.006***	-0.007***	-0.005***	-0.007***	-0.006***	-0.007***	-0.005***
	(-7.93)	(-7.52)	(-7.98)	(-6.13)	(-7.64)	(-7.41)	(-7.93)	(-6.06)
Stock $Return_{t-1}$	-0.004***	-0.005***	-0.005***	-0.005***	-0.004***	-0.005***	-0.005***	-0.005***
	(-5.30)	(-5.16)	(-5.30)	(-5.50)	(-6.38)	(-5.15)	(-5.34)	(-5.49)
Stock $Return_{t-2}$	-0.001**	-0.001***	-0.001***	-0.002***	-0.001**	-0.001***	-0.001***	-0.002***
	(-2.18)	(-3.21)	(-3.05)	(-3.37)	(-2.42)	(-3.48)	(-3.02)	(-3.36)
Stock $Return_{t-3}$	0.001*	0.000	0.000	0.000	0.001*	0.000	-0.000	0.000
	(1.80)	(1.30)	(0.57)	(0.04)	(1.69)	(1.21)	(-0.23)	(0.02)
Market to Book	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(5.40)	(6.05)	(5.87)	(5.80)	(5.40)	(6.05)	(5.87)	(5.81)
Leverage	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000
	(-0.41)	(0.10)	(-0.56)	(1.17)	(-0.44)	(0.08)	(-0.59)	(1.18)
$Ncskew_{t-12}$	0.000	-0.000	-0.000	0.000	0.000	-0.000	-0.000	0.000
	(0.22)	(-0.95)	(-0.50)	(0.36)	(0.22)	(-0.95)	(-0.49)	(0.35)
Fixed effect	Month, Industry	Month, Industry	Month, Industry	Month, Industry	Month, Industry	Month, Industry	Month, Industry	Month, Industry
Observations	199,651	199,506	199,322	198,284	199,651	199,506	199,322	198,284
R-squared	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013

Table 4.3: Robustness: alternative IDISP measures and crash risk measures

This table reports the robustness test in the form of the pooled cross-sectional regression estimates of the effect of divergence in opinions measures on monthly stock price crash risk. Panel A displays the regression results of monthly crash against different versions of IDISPs in the previous month, while Panel B shows the regression results of six alternative measures of monthly crash against IDISPs in the previous month. All models include control variables calculated at the end of previous month over the sample period from January 1996 to December 2021 as well as the month fixed effect and Fama-French 48 industry fixed effect. See Appendix for the definition of all other variables. Columns (1) to (4) report the regression results of all four different IDISPs on crash risk, all IDISPs are at lag1. Columns (5) to (8) present regression results when incorporating both IDISPs and Dturnover as independent variables, with both IDISPs and Dturnover at lag1. t-statistics with standard errors clustered at the firm level are shown in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

Panel A	Different version of IDISPs							
Variables	Crash (1)	Crash (2)	Crash (3)	Crash (4)	Crash (5)	Crash (6)	Crash (7)	Crash (8)
IDISP 2_{t-1}	0.002** (2.46)				0.002** (2.43)			
IDISP 3_{t-1}		0.001** (2.06)				0.001** (2.04)		
IDISP 4_{t-1}			0.003*** (6.06)				0.003*** (5.89)	
IDISP 5_{t-1}				0.003*** (5.50)				0.003*** (5.26)
Dturnover_{t-1}					0.015** (2.53)	0.015** (2.56)	0.015** (2.53)	0.016*** (2.58)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect	Month, Industry	Month, Industry	Month, Industry	Month, Industry	Month, Industry	Month, Industry	Month, Industry	Month, Industry
Observations	272,802	281,875	212,911	179,970	272,802	281,875	212,911	179,970
R-squared	0.012	0.012	0.013	0.013	0.012	0.012	0.013	0.014

Panel B	Different crash measures					
Variables	Pure Crash (1)	Conser -vative Crash (2)	Monthly Crash 20 pct (3)	Monthly Crash 20 jack (4)	Ncskew (5)	Duvol (6)
IDISP_{t-1}	0.003*** (4.39)	0.003*** (3.62)	0.011*** (4.92)	0.012*** (4.84)	0.026*** (3.73)	0.008*** (3.28)
Duvol_{t-12}						0.008*** (3.66)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect	Month, Industry	Month, Industry	Month, Industry	Month, Industry	Month, Industry	Month, Industry
Observations	199,651	160,703	199,684	199,684	199,651	199,651
R-squared	0.013	0.015	0.086	0.190	0.057	0.067

Table 4.4: Robustness: control for disagreement and analyst forecast dispersion

This table shows the robustness test in the form of the pooled cross-sectional regression estimates of the effect of divergence in opinions measures on monthly stock price crash risk using two alternative measures of divergence in opinions: Golez and Goyenko (2021) disagreement measure (Disagreement) and analyst forecast dispersion (AFD). All models include control variables calculated at the end of previous month over the sample period from January 1996 to December 2021 as well as the month fixed effect and Fama-French 48 industry fixed effect. See Appendix for the definition of all other variables. Columns (1) to (3) display regression results of disagreement measure on monthly crash, disagreement measure on monthly crash when IDISP is not missing, IDISP plus disagreement measure on monthly crash, respectively. Columns (4) to (6) display regression results of AFD on monthly crash, AFD on monthly crash when IDISP is not missing, IDISP plus AFD on monthly crash, respectively. All divergence in opinion measures are at lag1. t-statistics with standard errors clustered at the firm level are shown in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
IDISP_{t-1}			0.006***			0.003***
			(6.40)			(3.98)
$\text{Disagreement}_{t-1}$	0.001***	0.001**	0.001			
	(4.16)	(2.42)	(1.33)			
AFD_{t-1}				-0.000	-0.001***	-0.001***
				(-1.38)	(-2.69)	(-2.73)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect	Month, Industry	Month, Industry	Month, Industry	Month, Industry	Month, Industry	Month, Industry
Observations	257,597	117,515	117,515	669,750	181,865	181,865
R-squared	0.010	0.013	0.014	0.010	0.013	0.014

Table 4.5: Stock price jumps

This table displays the pooled cross-sectional regression estimates of the effect of all four divergence in opinions measures on the monthly stock price jumps. Similar with the crash measure, the jump is an extreme positive weekly idiosyncratic return. Jumps are estimated using a cut-off point of 3.25 standard deviations above its mean idiosyncratic return to generate a frequency of 0.1% extreme right-tail events. All models include control variables calculated at the end of previous month over the sample period from January 1996 to December 2021 as well as the month fixed effect and Fama-French 48 industry fixed effect. See Appendix for the definition of all other variables. t-statistics with standard errors clustered at the firm level are shown in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)
IDISP_{t-1}	-0.006***			
	(-3.25)			
Dturnover_{t-1}		-0.031**		
		(-2.47)		
$\text{Disagreement}_{t-1}$			-0.007***	
			(-2.76)	
AFD_{t-1}				-0.001
				(-0.99)
Control Variables	Yes	Yes	Yes	Yes
Fixed effect	Month, Industry	Month, Industry	Month, Industry	Month, Industry
Observations	199,651	199,651	117,515	181,865
R-squared	0.046	0.046	0.050	0.045

Table 4.6: The effect of financial reporting quality

This table displays the pooled cross-sectional regression estimates of the effect of divergence in opinions measure on the monthly stock price crash risk after controlling for firm's financial reporting quality, depreciation, and R&D cut. The methodology follows Chi and Gupta (2009) and estimates the quarterly discretionary accruals for each firm. The Disc. Accruals (4 qtrs), Disc. Accruals (8 qtrs) and Disc. Accruals (12 qtrs) are the moving sum of discretionary accruals over the past 4, 8 and 12 quarters. The Opacity (4 qtrs), Opacity (8 qtrs) and Opacity (12 qtrs) are the moving sum of absolute value of discretionary accruals over the past 4, 8 and 12 quarters. All models include control variables calculated at the end of previous month over the sample period from January 1996 to December 2021 as well as the month fixed effect and Fama-French 48 industry fixed effect. See Appendix for the definition of all other variables. t-statistics with standard errors clustered at the firm level are shown in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$IDISP_{t-1}$	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(5.15)	(5.24)	(5.24)	(5.14)	(5.22)	(5.22)
Disc. Accruals (4 qtrs)	0.001**					
	(2.20)					
Disc. Accruals (8 qtrs)		0.001				
		(1.41)				
Disc. Accruals (12 qtrs)			0.001*			
			(1.79)			
Opacity (4 qtrs)				0.000		
				(0.01)		
Opacity (8 qtrs)					0.001	
					(1.41)	
Opacity (12 qtrs)						0.001
						(1.38)
Depreciation	-0.004***	-0.004***	-0.003***	-0.004***	-0.004***	-0.004***
	(-2.84)	(-2.92)	(-2.60)	(-3.09)	(-3.11)	(-2.81)
R&D cut	-0.000	-0.000	-0.001	-0.000	-0.000	-0.001
	(-0.65)	(-0.78)	(-0.98)	(-0.68)	(-0.79)	(-0.99)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect	Month, Industry	Month, Industry	Month, Industry	Month, Industry	Month, Industry	Month, Industry
Observations	91,282	92,774	93,753	91,282	92,774	93,753
R-squared	0.015	0.015	0.015	0.015	0.015	0.014

Table 4.7: Short sale constrains, the effect of institutional ownership

This table displays the pooled cross-sectional regression estimates of the effect of all four divergence in opinions measure on the monthly stock price crash risk for the quintile subsamples sorted on the residual institutional ownership (in ascending order from quintile 1, low institutional ownership to quintile 5, high institutional ownership). See Nagel 2005 for detailed residual institutional ownership information. All models include control variables calculated at the end of previous month over the sample period from January 1996 to December 2021 as well as the month fixed effect and Fama-French 48 industry fixed effect. See Appendix for the definition of all other variables. t-statistics with standard errors clustered at the firm level are shown in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

Panel A					
	Q1 (1)	Q2 (2)	Q3 (3)	Q4 (4)	Q5 (5)
$IDISP_{t-1}$	0.002*	0.008***	0.004***	0.005***	0.002*
	(1.93)	(5.17)	(2.71)	(3.36)	(1.94)
Observations	40,543	39,776	39,273	38,955	38,126
R-squared	0.022	0.021	0.022	0.020	0.021
Panel B					
$Dturnover_{t-1}$	0.019***	0.019*	0.027	0.006*	0.020
	(2.81)	(1.89)	(1.50)	(1.71)	(1.00)
Observations	40,543	39,776	39,273	38,955	38,126
R-squared	0.022	0.019	0.022	0.019	0.021
Panel C					
$Disagreement_{t-1}$	0.002*	0.002	0.001	-0.000	0.001
	(1.77)	(1.41)	(0.96)	(-0.16)	(0.87)
Observations	23,853	23,534	23,295	23,086	22,827
R-squared	0.022	0.020	0.023	0.019	0.022
Panel D					
AFD_{t-1}	-0.001	-0.001***	-0.000	-0.001	-0.000
	(-0.71)	(-2.62)	(-0.82)	(-1.11)	(-1.64)
Observations	37,054	36,240	35,758	35,463	34,689
R-squared	0.023	0.020	0.024	0.021	0.021

Table 4.8: The effect of investor sentiment

This table displays the pooled cross-sectional regression estimates of the effect of all four divergence in opinions measure on the monthly stock price crash risk for the 2 subsamples sorted on the sentiment (in ascending order from low sentiment to high sentiment). The methodology follows Baker and Wurgler 2006 to obtain investor sentiment data. All models include control variables calculated at the end of previous month over the sample period from January 1996 to December 2021 as well as the month fixed effect and Fama-French 48 industry fixed effect. See Appendix for the definition of all other variables. t-statistics with standard errors clustered at the firm level are shown in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

	High (1)	Low (2)	High (3)	Low (4)	High (5)	Low (6)	High (7)	Low (8)
IDISP_{t-1}	0.005*** (5.16)	0.003*** (2.70)						
Dturnover_{t-1}			0.020*** (2.64)	0.004 (0.74)				
$\text{Disagreement}_{t-1}$					0.003** (2.51)	0.001 (1.21)		
AFD_{t-1}							-0.000* (-1.67)	-0.001*** (-3.15)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect	Month, Industry	Month, Industry	Month, Industry	Month, Industry	Month, Industry	Month, Industry	Month, Industry	Month, Industry
Observations	94,523	104,231	94,523	104,231	37,935	79,580	86,045	95,007
R-squared	0.013	0.015	0.012	0.014	0.012	0.014	0.012	0.015

Table 4.9: The effect of earnings announcement

This table reports the pooled cross-sectional regression estimates of the effect of weekly divergence in opinions measures (IDISP) on the weekly stock price crash risk. A ΔIDISP variable is constructed to estimate how much IDISP has increased by taking the difference between the lag1 IDISP and the earlier IDISPs (from lag2 to lag10). The earlier IDISPs are also controlled in the regression. To capture the earnings announcement effect, dummy variables are set from 2 weeks before until 2 weeks after the firm's actual earnings announcement week and ΔIDISP is interacted with the earnings announcement week dummies. All models include control variables calculated at the end of previous month over the sample period from January 1996 to December 2021 as well as the week fixed effect and Fama-French 48 industry fixed effect. See Appendix for the definition of all other variables. t-statistics with standard errors clustered at the firm level are shown in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

	ΔIDISP = IDISP$_{t-1}$ - X				
	X = IDISP$_{t-2}$ (1)	X = IDISP$_{t-4}$ (2)	X = IDISP$_{t-6}$ (3)	X = IDISP$_{t-8}$ (4)	X = IDISP$_{t-10}$ (5)
ΔIDISP	0.001***	0.001***	0.001***	0.001***	0.001***
	(4.60)	(4.71)	(5.66)	(5.00)	(5.43)
IDISP$_{t-2}$	0.001***				
	(7.84)				
IDISP$_{t-4}$		0.001***			
		(7.23)			
IDISP$_{t-6}$			0.001***		
			(6.13)		
IDISP$_{t-8}$				0.001***	
				(4.83)	
IDISP$_{t-10}$					0.001***
					(4.03)
EA$_{t-2}$	-0.000	0.000	-0.000	0.000	-0.000
	(-0.01)	(0.49)	(-0.03)	(0.09)	(-0.02)
EA$_{t-1}$	0.000	0.000	0.000	0.000	0.000
	(0.97)	(0.50)	(0.64)	(0.21)	(0.07)
EA$_t$	0.028***	0.028***	0.028***	0.028***	0.028***
	(33.68)	(32.66)	(31.67)	(33.10)	(33.41)
EA$_{t+1}$	-0.001***	-0.001***	-0.001***	-0.001***	-0.002***
	(-5.73)	(-4.96)	(-4.79)	(-5.46)	(-6.28)
EA$_{t+2}$	-0.002***	-0.001***	-0.001***	-0.002***	-0.002***
	(-7.08)	(-6.28)	(-5.78)	(-6.95)	(-7.71)
EA$_{t-2}$ × ΔIDISP	0.000	0.001	0.000	0.000	0.000
	(0.76)	(1.52)	(0.83)	(1.22)	(0.10)
EA$_{t-1}$ × ΔIDISP	-0.000	0.000	-0.000	-0.000	-0.000
	(-1.04)	(0.51)	(-0.65)	(-0.87)	(-1.27)
EA$_t$ × ΔIDISP	0.002*	0.001***	0.002***	0.001**	0.001**
	(1.81)	(2.94)	(3.07)	(2.47)	(2.18)
EA$_{t+1}$ × ΔIDISP	0.000*	0.000	-0.000	0.000	-0.000
	(1.90)	(0.50)	(-0.24)	(0.08)	(-0.83)
EA$_{t+2}$ × ΔIDISP	0.000	0.000	0.000	0.000	-0.000
	(0.09)	(0.78)	(0.33)	(0.42)	(-1.08)
Control Variables	Yes	Yes	Yes	Yes	Yes
Fixed effect	Week, Industry	Week, Industry	Week, Industry	Week, Industry	Week, Industry
Observations	811,995	780,875	753,720	787,163	780,743
R-squared	0.019	0.019	0.019	0.019	0.019

Table 4.10: The effect of earnings announcement and cumulative earnings surprises

This table reports the pooled cross-sectional regression estimates of the effect of weekly divergence in opinions measures (IDISP) on the weekly stock price crash risk. For the corresponding regression models, see Table 4.9. The sample is split based on the Disc. Accruals (4qtrs) and cumulative earnings surprises. Following Skinner and Sloan (2001), the earnings surprises are realized quarterly Earnings per Share (EPS) minus the median of analyst forecast EPS. Good indicator is set equal to 1 if earnings surprises are positive, otherwise Good indicator is set equal to 0. The cumulative earnings surprises are the moving sum of Good indicator over the past 4 quarters. In each week, the sample is split into 2 subsamples based on Disc. Accruals (4qtrs). Next, within each subsample, if cumulative earnings surprises is equal to and greater than 3, stocks are categorized into high surprise group, and low surprise group otherwise. Finally, for each group, pooled cross-sectional regression is run to identify the effect of weekly IDISP on the subsequent weekly stock price crash risk. All models include control variables calculated at the end of previous month over the sample period from January 1996 to December 2021 as well as the week fixed effect and Fama-French 48 industry fixed effect. Panel A represents results of high Disc. Accruals (4qtrs) and high surprise group. Panel B represents results of high Disc. Accruals (4qtrs) and low surprise group. See Appendix for the definition of all other variables. t-statistics with standard errors clustered at the firm level are shown in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

Panel A	High Discretionary accruals, cumulative good >= 3				
	ΔIDISP = IDISP$_{t-1}$ - X				
	X = IDISP$_{t-2}$ (1)	X = IDISP$_{t-4}$ (2)	X = IDISP$_{t-6}$ (3)	X = IDISP$_{t-8}$ (4)	X = IDISP$_{t-10}$ (5)
ΔIDISP	0.000*	0.001**	0.001*	0.001**	0.001**
	(1.80)	(1.99)	(1.92)	(2.49)	(2.32)
IDISP$_{t-2}$	0.001***				
	(3.26)				
IDISP$_{t-4}$		0.001***			
		(3.22)			
IDISP$_{t-6}$			0.001***		
			(2.65)		
IDISP$_{t-8}$				0.001**	
				(2.07)	
IDISP$_{t-10}$					0.001*
					(1.81)
EA$_t$ $\times$ ΔIDISP	0.006***	0.002	0.005**	0.005***	0.004**
	(3.17)	(1.48)	(2.30)	(2.64)	(2.02)
Observations	171,554	165,198	159,709	157,784	157,100
R-squared	0.028	0.028	0.030	0.030	0.029
Panel B	**High Discretionary accruals, cumulative good < 3**				
ΔIDISP	0.001*	0.000*	0.001**	0.001**	0.001*
	(1.81)	(1.87)	(2.37)	(2.02)	(1.77)
IDISP$_{t-2}$	0.000				
	(1.00)				
IDISP$_{t-4}$		0.000			
		(1.44)			
IDISP$_{t-6}$			0.000		
			(0.68)		
IDISP$_{t-8}$				0.000	
				(1.54)	
IDISP$_{t-10}$					-0.000
					(-0.36)
EA$_t$ $\times$ ΔIDISP	0.000	-0.000	0.001	-0.001	-0.000
	(0.10)	(-0.04)	(0.52)	(-0.66)	(-0.31)
Observations	129,110	123,521	118,695	117,223	116,636
R-squared	0.028	0.028	0.028	0.029	0.028

5 Crash and option strike price asymmetry

5.1 Introduction

Financial markets are often characterized by asymmetric information, where certain investors process their private information about future developments before they are revealed to the public. A growing body of research suggests that the options market serves as an important venue for such informed trading. Compared to the underlying stock market, options offer greater leverage, lower trading costs, and flexibility to bet on directional movements or hedge against risks. These features make them attractive to informed investors seeking to capitalize on non-public information or to avoid detection. Foundational studies such as Easley, O'Hara, and Srinivas (1998) argue that option trading activity embeds information about future price movements. Subsequent empirical evidence confirms that unusual option volume or pricing deviations can predict stock returns, corporate announcements, or even future volatility (Chakravarty, Gulen, and Mayhew, 2004; Pan and Poteshman, 2006; Augustin, Brenner, and Subrahmanyam, 2019).

This chapter examines whether options trading behaviour—potentially reflecting informed trading—predicts extreme downward movements in the stock market, namely stock price crashes. Specifically, it investigates whether the option strike asymmetry, a novel measure constructed from the traded option strikes and their volumes, helps forecast future crash risk. This analysis is motivated by previous studies that explore the predictive power of option-based information for future returns. For instance, Bergsma, Csapi, Diavatopoulos, and Fodor (2020) construct a strike concentration measure based on the volume-weighted deviation of traded strikes and find it predictive of future returns. Similarly, Ge, Lin, and Pearson (2016) and Gkionis, Kostakis, Skiadopoulos, and Stilger (2021) show that trading volume and implied information in out-of-the-money (OTM) options can contain directional insights about stock under- or over-valuation. However, these studies focus on future return predictability and do not directly address the prediction of extreme left-tail events. While some literature investigates the predictive power of simple volume-based measures (e.g., the option-to-stock volume ratio as in Johnson and So 2012, or buyer-initiated volume in Pan and Poteshman, 2006) for future returns, few studies systematically examine the informational content of option trading structures in the context of crash risk. Notably, Andreou, Kagkadis, Philip, and Tuneshev (2018) use an option-based disagreement measure to predict crashes, and Chang, Hsiao, Ljungqvist, and Tseng (2022) find that various disagreement proxies, including abnormal short interest and volume around earnings announcements, can signal future crash risk. However, to date, no prior work explores strike-based asymmetry in option trading as a crash predictor, even though preliminary evidence shows that OTM put volume tends to surge before crash days. This pattern, coupled with the failure of simple volume measures to predict crashes consistently, suggests that directional positioning, rather than sheer volume, is more relevant in detecting early warning signals. Therefore, this chapter proposes a new strike asymmetry measure that simultaneously incorporates option trading volume and relative moneyness.

By weighing traded options according to both volume and strike deviation from spot prices and introducing a directional adjustment via $(M_i - 1)$, where $M_i = K_i/S$ represents the moneyness of each option relative to the spot price, this measure is specifically designed to detect option positioning, which may reflect informed trading ahead of crash events. Future research could further examine this interpretation by comparing the strike asymmetry measure with established informed trading proxies such as PIN and VPIN to validate whether its predictive power originates from informed trading behavior. Compared to existing disagreement or volatility skew proxies, the proposed measure provides a more structured way to capture directional signals embedded in the option market, especially those driven by deep OTM put demand prior to tail-risk realizations. The option strike asymmetry takes the minimum value if all investors select the lowest strike price available on the market, and the maximum value if all investors trade the highest strike price available on the market. The option strike asymmetry is selected as the main proxy for informed positioning in the options market for the following reasons. First, it captures not only the intensity of trading via volume but also the directional intent by incorporating the strike distance from the spot price, offering a richer structure than traditional volume-based proxies. Second, it reflects investors' revealed beliefs through actual strike selection behaviour, which cannot be inferred from aggregate volume or price-based indicators alone. Third, the measure is constructed at a high frequency and is available for all optionable stocks, allowing for timely and firm-specific detection of extreme downside sentiment. Finally, unlike stock-based measures that may be distorted by short-sale constraints or institutional frictions, strike-level option activity remains a preferred channel for informed traders to position privately ahead of tail events.

Based on insights from prior literature and preliminary findings, the prediction is that option strike asymmetry, particularly OTM put strike asymmetry, is negatively associated with future stock price crashes. When investors anticipate extreme negative outcomes, they are more likely to trade in deep out-of-the-money put options to hedge or profit from such events. This behaviour concentrates volume on low strike puts, pulling the strike asymmetry downward. Therefore, a lower OTM put strike asymmetry signals an intensification of downside speculation and should precede future crash realizations. In this sense, the measure acts as a forward-looking indicator of crash risk, reflecting private pessimistic information embedded in option market structures.

The empirical analysis employs a modified crash measure from Hutton, Marcus, and Tehranian (2009). Using daily data from CRSP, firm-specific weekly returns are calculated and compared with the standard deviation over a past 52-week rolling window from 1996 to 2021. Then, it is identified whether the current week is a crash week. If at least one crash week occurs within a calendar month, this month is specified as a crash month. For option strike asymmetry estimation, daily data from CRSP and OptionMetrics are used to estimate the daily option strike asymmetry across different option subsets: (1) all available options, (2) put options only, (3) in-the-money (ITM) puts, and (4) out-of-the-money (OTM) puts. The average option strike asymmetry for the final week in the previous month is then calculated to construct the monthly option strike asymmetry. Following prior research, monthly stock price crashes are merged with the monthly option strike asymmetry and other control variables. The results are briefly revealed as follows.

Using a sample of 219,468 firm-month observations from 1996 to 2021, covering 15,567 unique firms, it is found that the volume-weighted average of option strike asymmetry (particularly from out-of-the-money put options) is significantly and negatively associated with the likelihood of subsequent stock price crashes. This result supports the hypothesis that option strike asymmetry reflects the ex-ante directional sentiment embedded in option traders' positioning and serves as a forward-looking indicator of crash risk. Specifically, when firm-level put options are traded at strike prices substantially below spot prices (i.e., lower strike asymmetry), it suggests early pessimistic sentiment that precedes extreme negative price movements. This early pessimistic sentiment may arise from two possible mechanisms. One interpretation is that it reflects the superior information of informed traders who foresee potential fundamental deterioration and position accordingly. Alternatively, it may stem from strategic behavior, whereby informed traders act preemptively to reduce their exposure or exploit the anticipated reactions of less-informed (noise) investors, as suggested by De Long et al. (1990a). Both interpretations are consistent with the view that option strike asymmetry embeds forward-looking information from the options market. The predictive power of option strike asymmetry remains significant after controlling for standard crash predictors, including firm Size, Total Volatility, past Stock Returns (lag1 to lag3), Market-to-Book, Leverage, and

Ncskew. To address potential concerns regarding the construction of the core measure, a series of robustness checks is conducted. First, the negative relation persists when using alternative definitions of strike asymmetry, such as restricting options with positive open interest. Second, the result is robust across various crash measures, including crash with different thresholds, crash based on forward return windows, and model-free crash definitions (e.g., monthly crash with 10% and 15% thresholds). Third, the possibility that the finding is driven by generic disagreement proxies is ruled out by controlling for measures such as detrended stock turnover (Dturnover), detrended option turnover (e.g., OTM Put Dturnover), and dispersion in beliefs on individual stocks (IDISP). Finally, the negative relation holds after controlling for VIX, suggesting that option strike asymmetry captures firm-specific downside information beyond aggregate market volatility.

Further analysis explores potential channels explaining why option strike asymmetry predicts future stock price crashes. The first channel relates to short-sale constraints, following the intuition of Miller's (1977) hypothesis. Firms are sorted into quintiles based on lagged short interest, and crash regressions are run within each group. Consistent with the theory, the predictive power of Total and ITM Put strike asymmetry becomes stronger in higher short interest quintiles, indicating greater crash sensitivity when pessimistic views are difficult to express through equity markets. However, OTM Put strike asymmetry exhibits a strikingly different pattern: it remains highly negative and statistically significant across all five groups, with stable magnitudes. This finding suggests that OTM put positioning captures informed downside speculation independent of short-sale frictions and embeds private crash-relevant signals that go beyond constraints in equity trading.

The second channel relates to financial reporting quality. Firms are first sorted by 12-quarter cumulative discretionary accruals, and crash regressions are repeated across these quintiles. It is found that while the predictive power of Total, Put, and ITM Put strike asymmetry weakens or disappears in most groups, OTM Put strike asymmetry remains negative and significant, indicating that it is not merely picking up accounting manipulation risks. The analysis is then extended by directly controlling for 12-quarter discretionary accruals, firm depreciation, and R&D cuts. Consistent with prior literature, it is found that firms with high accruals and low depreciation are more prone to crashes. However, OTM Put strike asymmetry retains its strong significance at the 1% level even after controlling for these variables, reinforcing that its predictive content reflects distinct informed positioning beyond traditional reporting quality indicators.

The third channel concerns investor sentiment. Using the sentiment index of Baker and Wurgler (2006), the sample is divided into high- and low-sentiment periods. While Total and ITM Put strike asymmetry exhibit some significance only in high-sentiment periods—consistent with overvaluation-driven crash risk—OTM Put strike asymmetry remains strongly negative and significant in both subsamples. This pattern contradicts a pure sentiment-based mispricing channel and instead points to firm-specific private information embedded in deep OTM put trading. Taken together, the evidence shows that while Total and ITM Put Strike Asymmetry may partially reflect mispricing under short-sale constraints or financial opacity, OTM Put strike asymmetry consistently captures directional downside positioning that reflects informed trading, regardless of these conditions. Its robustness across all subsamples highlights its unique role as a forward-looking crash predictor, offering firm-level early warning signals distinct from known theoretical channels.

This study contributes to the literature in several important ways. First, to the best of current knowledge, this is the first to investigate the predictive power of strike-based asymmetry in option trading for subsequent stock price crashes. While a growing body of research highlights the information content of option volume, implied volatility skew, or risk-neutral moments for future returns (e.g., Pan and Poteshman, 2006; Ge, Lin, and Pearson, 2016;

Gkionis, Kostakis, Skiadopoulos, and Stilger, 2021; Bergsma, Csapi, Diavatopoulos, and Fodor, 2020), these studies primarily focus on return predictability rather than extreme tail events. Although Chang, Hsiao, Ljungqvist, and Tseng (2022) examine various disagreement proxies and their relationship with crash risk, they do not explore directional signals embedded in strike selection. By constructing a novel option strike asymmetry measure that incorporates both traded strike deviation from spot and trading volume, this study adds a new dimension to the literature by capturing downside-oriented positioning patterns potentially indicative of informed trading prior to crash events.

Second, this paper advances the literature on the informational role of the options market by moving beyond the limitations of sheer volume-based metrics. Unlike option-to-stock volume ratios (Johnson and So, 2012) or buyer-initiated volume measures (Pan and Poteshman, 2006), which may fail to distinguish between directional intent and noise trading, the strike asymmetry measure integrates moneyness-weighted directional components and reveals early warning signs of left-tail risk. This improvement is particularly salient for OTM put asymmetry, which is shown to be significantly and negatively associated with future crash risk. The findings suggest that strike asymmetry captures refined information over and above existing option-based disagreement or volatility skew metrics, offering a more structured lens to detect downside risk anticipation.

Finally, the study contributes methodologically by introducing a directional and model-free measure of option-based crash risk anticipation. Unlike detrended turnover, option-to-stock volume ratios or implied volatility skew, the strike asymmetry measure is constructed directly from observable traded strikes and volumes, requiring no option pricing model or distributional assumption. It can be implemented at any frequency from daily onwards, making it suitable for real-time risk monitoring. Moreover, if signed option volume data are available, the measure can be further extended to isolate directional trades such as open buy OTM put asymmetry, providing even sharper identification of informed downside positioning.

5.2 Data and Methodology

In this section, the data and key filter rules applied in the main analysis are first provided. The construction of the monthly crash measures, the construction of option strike asymmetry measures across different option types or option moneyness levels, and control variables are then introduced. Finally, the summary statistics in the sample are presented.

5.2.1 Data

For the main analysis, stocks data including stock price, stock return, and volume for individual stocks covering the period from January 1996 to December 2021 are obtained from CRSP daily stock file. Options data including volume and strike price for individual stocks are collected from Ivy DB's OptionMetrics. Apart from estimating the main crash and option strike asymmetry measure, stocks data are used to estimate size, total volatility, monthly stock return, and Dturnover. Further, required data from Compustat fundamental quarterly files are collected to calculate market-to-book ratio, leverage, and firm-level discretionary accruals.

Next, the following filters are applied to the stocks and options data. First, stocks are excluded if the end-of-month price is below 5 USD. Second, options with maturity between 5 days to 60 days and with at least 4 contracts in a trading day are selected. Further, ordinary shares (with share code 10 and 11) and stocks listed in NYSE, AMEX, and NASDAQ (with exchange code 1 to 3) are retained. Finally, moneyness level is defined as strike price divided by spot price, and options with moneyness level between 0.975 and 1.025 are excluded. This range typically corresponds to at-the-money (ATM) options, which are primarily used for volatility trading rather than directional bets (Pan and Poteshman 2006; Bates 2000). Therefore, ATM options are excluded to focus on the informational content of out-of-the-money (OTM) options when constructing strike asymmetry measures.

5.2.2 Construction of main variables

5.2.1.1 Construction of crash variables

Following Hutton, Marcus, and Tehranian (2009), crash is defined as an indicative variable set equal to one if the firm-specific weekly log return is 3.25 times its standard deviation below its mean within each fiscal year. This crash is originally a yearly frequency variable. In this analysis, the relationship between the strike price asymmetry of the options market and the probability of future crashes is examined, which requires a higher frequency of crash identification. Therefore, the methodology of Hutton, Marcus, and Tehranian (2009) is calibrated by estimating the mean and standard deviation of firm-specific weekly returns within a backward-looking 52-week rolling window, including the current week. At least 26 weekly observations are required in each 52-week window. If the firm-specific return for the current week is 3.25 times its standard deviation below its mean, then the current week crash is equal to one. If at least one crash week is detected within a month, then the monthly crash indicator is set to one. This crash measure enables testing of the relationships between the monthly crash and option strike price asymmetry at monthly frequency.

To address potential concerns about the rolling window methodology in crash identification, four alternative crash measures are constructed to ensure the robustness of the results. First, the crash definition is modified by using different thresholds for extreme negative firm-specific returns, more specifically, 2.33 and 1.65 standard deviations below the mean idiosyncratic returns, corresponding approximately to the bottom 1% and 5% of the return distribution, respectively. Second, a forward-looking rolling window approach is adopted to estimate the mean and standard deviation of idiosyncratic returns, aiming to minimize the influence of past information. Crashes are defined as returns falling 3.25, 2.33, or 1.65 standard deviations below the estimated mean. Third, following Andreou, Andreou, and Lambertides (2021), a crash week is defined if the market-adjusted weekly return is below 10% or 15%. If at least one crash week occurs within a month, the monthly crash indicator is set to one. Finally, the methodology of Conrad, Kapadia, and Xing (2014) is calibrated by calculating monthly firm-specific returns, and a crash month is defined as one where the return falls below 10% or 15%. The main results are robust across these alternative crash definitions and thresholds.

5.2.1.2 Option strike price asymmetry measures

The option strike asymmetry measure is constructed to capture the directional skewness of trading activities across different option strike prices. This measure reflects the aggregated beliefs and positioning of option investors regarding future price movements. Specifically, for each day and each stock, the spot price S and a series of option strike prices K_i , where $i = 1, \dots, n$. The moneyness level is defined as $M_i = \frac{K_i}{S}$. To incorporate the directional feature of option trading, I calculate the asymmetry from the spot price using $M_i - 1$. The daily option strike asymmetry is constructed as the volume-weighted average of this asymmetry measure:

$$strike\ asymmetry = \sum_{i=1}^{n} w_i \cdot (M_i - 1) \tag{5.1}$$

where w_i denotes the trading volume weight of the i^{th} option contract. A positive (negative) value indicates that the trading volume is concentrated in higher (lower) strike options relative to the spot price, reflecting investors' bullish (bearish) expectation. When trading is symmetrically distributed around the spot price, the measure is close to zero.

To better capture the aggregated expectation in option investors' trading strategies, this measure is constructed across different option subsets: (1) all available options, (2) put options only, (3) in-the-money (ITM) puts, and (4) out-of-the-money (OTM) puts. The ITM and OTM classification is based on the relative position of the strike price to the spot price at the time of observation. For each subset, the daily strike asymmetry is calculated, aggregated to weekly averages, and the value from the last week of each month is used as the monthly observation to mitigate expiration effects and to capture the most recent information.

The construction of strike asymmetry is related to the recent study by Bergsma, Csapi, Diavatopoulos, and Fodor (2020), who examine the concentration of option trading across calls and puts to predict future stock returns. However, the present approach differs in several important aspects. First, the focus is on predicting stock price crashes rather than returns. Second, the strike distribution within put options is distinguished by further classifying options based on their moneyness levels, allowing for a more granular examination of investors' downside risk perception. Third, while Bergsma, Csapi, Diavatopoulos, and Fodor (2020) incorporate option price as a secondary weighting factor, this approach relies solely on trading volume and explicitly introduces a directional component through the $M_i - 1$ transformation, ensuring that the measure directly reflects the relative positioning of option investors.

This methodology also shares a conceptual similarity with Bernile, Gao, and Hu (2019), who propose a volume-weighted strike moneyness measure (VWKS) to predict future stock returns. However, the empirical focus and interpretation differ substantially. Their VWKS measure captures the distribution of investor expectations across strike levels and is shown to predict average stock returns in the cross-section. In contrast, the strike asymmetry measure is designed to identify informed trading related to extreme downside risk, specifically using OTM put strike asymmetry to predict firm-specific crash events. Moreover, it is emphasized that the occurrence of stock price crashes, while reflecting severe negative tail outcomes, does not necessarily imply lower expected returns across firms. Therefore, measures that predict crash risk may capture private downside information that is orthogonal to cross-sectional return predictions.

The option strike asymmetry measure captures trading concentration and directional positioning in the option market, which has been shown to reflect investors' private information or expectations of future downside risk (Lakonishok,Lee, Pearson, and Poteshman, 2007; Augustin, Brenner, and Subrahmanyam, 2019). The options market is a venue for informed trading, especially prior to firm-specific events or extreme price movements (Chakravarty, Gulen, and Mayhew, 2004; Augustin, Brenner, and Subrahmanyam, 2019; Zhang, 2018). Given that options markets are commonly used by informed traders to exploit private information, this strike asymmetry measure is expected to capture such positioning activities, particularly when investors anticipate large downside risks. To provide empirical support, the dynamics of the option strike asymmetry measure around crash events are examined. Specifically, the average weekly strike asymmetry for out-of-the-money (OTM) puts is plotted over a 6-week window surrounding identified crash weeks. As shown in Figure 5.1, the OTM put strike asymmetry begins to decline significantly five weeks prior to the crash. At the onset of the crash (week 0), the measure reverts toward its typical level, suggesting that informed traders had increased their OTM put activity in anticipation of the crash. This pattern provides additional evidence that the strike asymmetry measure captures informed trading behavior and serves as a leading indicator of stock price crashes.

[Insert Figure 5.1 here]

5.2.3 Control variables

Two sets of control variables are employed in the analysis. The first set of controls includes stock-related variables, such as size, total volatility, lag1 stock return, lag2 stock return, lag3 stock return, and lag12 Ncskew. The second set of controls consists of fundamental variables, including market-to-book ratio and leverage. The detailed descriptions of control variables are provided in the Appendix.

5.2.4 Summary statistics

Table 5.1 presents the summary statistics for all variables used in the empirical analysis. The number of observations, mean, standard deviation, 25th percentile (Q1), median, and 75th percentile (Q3) values across the sample period from January 1996 to December 2021 are reported. The dependent variable, Monthly Crash, has a mean of 0.017, consistent with the crash identification rule that uses a 3.25 standard deviation threshold of idiosyncratic returns, corresponding to approximately 0.1% of extreme left-tail events.

The mean value of Total strike asymmetry is 0.036, while the mean of Put strike asymmetry is slightly negative (-0.019), reflecting that trading volume is often skewed toward lower strikes in put options. The mean of ITM Put strike asymmetry is 0.150, whereas the OTM Put strike asymmetry exhibits a mean of -0.110, consistent with the option market structure where OTM puts are typically used for downside protection. The mean of monthly IDISP is 0.087, capturing the average level of dispersion in investor opinions based on option trading. Other control variables, including size, book-to-market ratio, leverage, and analyst forecast dispersion (AFD), are comparable to values reported in previous studies on crash risk (e.g., Hutton, Marcus, and Tehranian, 2009; Kim, Li, and Zhang, 2011; Andreou, Kagkadis, Philip, and Tuneshev, 2018). All variable definitions are provided in the Appendix.

[Insert Table 5.1 here]

5.2.5 Correlation matrix

Table 5.2 presents the pairwise Pearson correlation coefficients among the key variables used in the empirical analysis. The correlation between Monthly Crash and option strike asymmetry measures is weakly positive for Total strike asymmetry and Put strike asymmetry, and becomes more negative for OTM Put strike asymmetry, suggesting that skewed trading toward deep OTM puts may be associated with higher crash risk.

Among the strike asymmetry variables, ITM Put strike asymmetry and OTM Put strike asymmetry are negatively correlated (-0.263), reflecting distinct investor preferences in strike selection. Total strike asymmetry is highly correlated with its components—Put strike asymmetry (0.940) and ITM Put strike asymmetry (0.684)—as expected by construction. All control variables, including size, total volatility, past returns, and leverage, show low to moderate correlations, with no evidence of multicollinearity. Overall, the correlations support the validity of including these variables simultaneously in the regression analysis.

[Insert Table 5.2 here]

5.3 Empirical analysis and robustness check

This section examines the predictive power of option strike asymmetry for future stock price crashes. The robustness of the results is additionally tested by considering alternative constructions of the strike asymmetry measure, different crash definitions, various disagreement proxies (IDISP and Dturnover), and the VIX index. A comprehensive set of stock characteristics and firm fundamentals is also controlled for. Finally, potential channels are explored to explain the mechanism behind the predictive relation between strike asymmetry and crash risk. The same univariate and regression analysis is conducted for call-side strike asymmetry, where the results are generally weaker and statistically insignificant. Therefore, the main discussion focuses on put-side strike asymmetry measures, which exhibit stronger and more robust predictive power for future stock price crashes.

5.3.1 Predictability of Strike asymmetry on crash

The empirical analysis begins with examining the relationship between the lag values of option strike asymmetry and crash. Monthly crash events are sorted across quintile portfolios based on different measures of option strike asymmetry. In each month, firms are sorted into five groups based on the value of the corresponding strike asymmetry measure in ascending order. The number of monthly crash events within each quintile is then counted. Table 5.3 reports the results.

[Insert Table 5.3 here]

A clear monotonic pattern is observed for Total strike asymmetry, Put strike asymmetry, and ITM Put strike asymmetry, where firms in the highest quintile experience more frequent stock price crashes. In particular, the number of crash events increases from 1,042 in the lowest quintile to 1,755 in the highest quintile for Total strike asymmetry. For OTM Put strike asymmetry, the pattern is reversed, with a higher number of crash events observed in the lowest quintile, consistent with the prediction that a lower OTM put strike asymmetry reflects heavier trading in deep OTM puts, indicating a higher downside risk expectation. Although the sorting patterns are generally consistent across different option types, it is important to note that the predictive power of strike asymmetry measures is further examined in the multivariate regression analysis. As shown later, only the put-side asymmetry measures—particularly OTM Put strike asymmetry—exhibit robust and significant predictive power for future stock price crashes.

The empirical analysis proceeds by examining the predictive power of option strike asymmetry measures on future stock price crashes using pooled cross-sectional regressions with industry and year-month fixed effects. The dependent variable is a crash indicator at month t, and the main independent variables are different measures of strike asymmetry constructed at month $t-1$. The control variables include firm size (Size), total volatility over the past year (Total Volatility), stock returns from month $t-1$ to $t-3$, market-to-book ratio (Market to Book), leverage (Leverage), and 12-month skewness (Ncskew). Table 5.4 presents the regression results. Columns (1) to (4) report the results using Total strike asymmetry, Put strike asymmetry, ITM Put strike asymmetry, and OTM Put strike asymmetry, respectively. The coefficient on Total strike asymmetry is positive and significant at the 5% level (with a t-statistic of 2.00), suggesting that a higher strike asymmetry is associated with an increased likelihood of stock price crashes.

However, the predictive power varies substantially across option types. Specifically, the coefficient on Put strike asymmetry is positive but statistically insignificant, indicating that the overall put-side asymmetry is not a robust predictor once firm characteristics are controlled for. In contrast, ITM Put strike asymmetry shows a positive and significant coefficient (t-statistic of 2.27), while OTM Put strike asymmetry exhibits a negative and highly significant coefficient (t-statistic of -11.24). This finding supports the hypothesis that higher OTM put strike asymmetry (i.e., fewer trades in deep OTM puts) reflects lower crash risk, while lower OTM put strike asymmetry indicates more intensive trading in OTM puts, signaling elevated downside risk. Control variables show expected signs and strong statistical significance. Firm size and past returns are negatively associated with crash risk, while total volatility and market-to-book ratio have positive and significant effects. Leverage and Ncskew remain insignificant across all specifications. The R-squared values are relatively low but reasonable, given the rare occurrence of stock price crashes. Overall, the results suggest that option strike asymmetry, particularly OTM Put strike asymmetry, is a robust predictor of future stock price crashes.

The findings are broadly consistent with the existing literature on informed trading in the options market. Lakonishok,Lee, Pearson, and Poteshman (2007) show that options investors often take directional positions based on their expectations of future stock price movements. The results confirm that option strike asymmetry, particularly on the put side, captures investors' positioning for downside risk. Moreover, this study complements the findings of Augustin, Brenner, and Subrahmanyam (2019) and Augustin and Subrahmanyam (2020), who document that options markets contain valuable information about future stock returns, especially before firm-specific events such as earnings announcements. In this setting, the significant predictive power of OTM Put strike asymmetry indicates that option investors tend to increase their trading in deep OTM puts prior to stock price crashes, consistent with the presence of informed trading. This approach is also related to Bergsma, Csapi, Diavatopoulos, and Fodor (2020), who examine the concentration of option moneyness and its relation to future stock returns. While that study focuses on return predictability, the present analysis extends to the context of crash risk and provides additional evidence that the predictive power of strike asymmetry is driven primarily by put options, particularly those with OTM strikes. The insignificant results for call-side strike asymmetry further highlight the asymmetry of information and risk hedging activities in the options market. These findings also suggest a conceptual implication for investors. Firms with low or declining OTM Put strike asymmetry are more likely to experience subsequent price crashes, while those with relatively high asymmetry appear less exposed to downside risk. Based on this intuition, a theoretical long–short strategy could be designed by going long in high-asymmetry firms and short in low-asymmetry firms to capture the pricing effect associated with downside risk. Such a framework would conceptually link option-implied asymmetry to expected crash probability, even though the profitability of this strategy has not been empirically tested. Therefore, this discussion should be viewed as an illustrative interpretation rather than an investment recommendation.

[Insert Table 5.4 here]

5.3.2 Robustness Check

To ensure the robustness of the baseline results, a series of additional tests is conducted. Specifically, alternative constructions of the strike asymmetry measure, different crash definitions, different disagreement proxies, and control for market-wide uncertainty using the VIX index are considered. The results are reported in Tables 5.5 to 5.8, respectively. Overall, the main findings remain robust across all these tests.

As a robustness check, the baseline regressions are re-estimated using an alternative construction of the option strike asymmetry measures. Specifically, an additional filter is imposed that retains only options with strictly positive open interest when computing the asymmetry variables. This filter aims to remove illiquid options that may not reflect meaningful trading activity or investor expectations. Similar data cleaning approaches have been adopted in prior literature to ensure that option-based variables capture active market signals (e.g., Pan and Poteshman, 2006; Cremers and Weinbaum, 2010; Augustin, Brenner, and Subrahmanyam, 2019).

[Insert Table 5.5 here]

Table 5.5 reports the results using this refined specification. Consistent with the baseline findings, the coefficient on OTM Put strike asymmetry remains negative and highly significant (t-statistic of -11.06), confirming its strong predictive power for future stock price crashes. Total strike asymmetry and ITM Put strike asymmetry also remain significant at the 5% level. Put strike asymmetry continues to show an insignificant relation with crash risk. These results indicate that the findings are robust to alternative constructions of the asymmetry measure and are not driven by noise in illiquid or inactive options. The magnitudes and significance levels of the coefficients are highly consistent with those reported in Table 5.4, suggesting that the asymmetry measures capture meaningful trading signals rather than being sensitive to specific data filters.

In addition to testing the robustness of the strike asymmetry measure construction, further tests are conducted to assess whether the results are sensitive to alternative definitions of crash risk. Since the identification of extreme downside events may vary across studies, multiple crash definitions based on different thresholds, windowing schemes, and model dependencies are considered. These alternative specifications allow the evaluation of the stability of the findings across a broad spectrum of crash identification methods. Table 5.6

presents a comprehensive set of robustness tests that address these concerns. Four categories of crash definitions are examined: (i) threshold-based definitions using alternative standard deviation cutoffs, (ii) forward-looking return windows to mitigate backward-looking bias, (iii) model-free crash definitions based on raw weekly returns, and (iv) model-free crash definitions using log returns. Each panel is described in detail below.

[Insert Table 5.6 here]

In Table 5.6 Panel A, the robustness of the baseline findings is tested by modifying the threshold used to define stock price crashes. While the baseline definition uses 3.25 standard deviations below the mean idiosyncratic return (capturing approximately 0.1% of the left-tail distribution), more moderate thresholds of 2.33 and 1.65 standard deviations are adopted here, corresponding to the bottom 1% and 5% of the distribution, respectively. The regression results in columns (1) to (8) of Panel A show that the main findings remain robust under these alternative definitions. Notably, the coefficient on OTM Put strike asymmetry remains negative and highly significant across all specifications. This indicates that the predictive power of strike asymmetry is not driven by the extremity of the crash definition. The results for Total strike asymmetry and ITM Put strike asymmetry are also broadly consistent with the baseline, while Put strike asymmetry remains insignificant. These findings confirm that the asymmetry measures capture meaningful information regardless of the crash severity threshold.

Table 5.6 Panel B addresses a methodological concern related to the construction of crash indicators using past return distributions. In the baseline, the crash threshold is determined based on a backward-looking 52-week rolling window, which may be influenced by prior crash events and inflate the estimated standard deviation. To mitigate this potential bias, crash thresholds are recalculated using a forward-looking 52-week rolling window to estimate the mean and standard deviation of idiosyncratic returns. Despite this structural change, the results remain consistent with the baseline. OTM Put strike asymmetry continues to show strong negative and statistically significant coefficients, even under alternative crash thresholds of 0.1%, 1%, and 5%. This reinforces the robustness of the findings and suggests that the predictive signal embedded in option strike asymmetry is not sensitive to the windowing scheme used for crash identification. While this forward-looking specification is uncommon in the literature, it helps address look-back bias in high-volatility periods and strengthens the credibility of the crash proxy.

Table 5.6 Panel C further validates the findings using model-free crash measures based on extreme weekly raw returns, following the approach of Andreou, Andreou, and Lambertides (2021). A crash month is defined as one in which the firm experiences at least one week where the market-adjusted weekly return falls below 10% or 15%. Unlike idiosyncratic return-based crashes, this definition is free from model estimation and reflects large realized negative movements. Columns (1) to (8) in Panel C demonstrate that OTM Put strike asymmetry remains a strong and significant predictor of crash risk across both 10% and 15% thresholds. Moreover, other strike asymmetry measures, including Total strike asymmetry, Put strike asymmetry, and ITM Put strike asymmetry, also become significant under these more direct definitions of downside risk. These results are robust to the use of raw return shocks and provide further evidence that the core measure captures crash-related positioning in the options market.

Table 5.6 Panel D extends the model-free crash framework by computing crashes using log returns rather than raw returns, following the method in Conrad, Kapadia, and Xing (2014). As in Panel C, a monthly crash is defined if the firm experiences at least one week with a log market-adjusted return below 10% or 15%. This specification captures proportional return shocks and provides an alternative framing for large price drops. The results in Panel D are again highly consistent. OTM Put strike asymmetry remains strongly negative and statistically significant across all specifications, with t-statistics exceeding -12. Other asymmetry measures, including ITM Put strike asymmetry, also show significant coefficients, particularly at the 15% threshold. These findings further validate the main result and confirm that the predictive content of strike asymmetry is robust to alternative, model-free definitions of stock price crashes.

A large body of literature documents that investor disagreement predicts negative stock returns in the cross-section. For instance, Chen, Hong, and Stein (2001), Diether, Malloy, and Scherbina (2002), and more recently Chang, Hsiao, Ljungqvist, and Tseng (2022) all show that various proxies for disagreement, such as abnormal trading volume, analyst forecast dispersion, and short interest, are positively associated with future stock price crashes. In Chapter 2, this relationship is confirmed using a novel measure of option-implied belief dispersion (IDISP from Andreou, Kagkadis, Philip, and Tuneshev, 2018), further reinforcing the predictive power of disagreement for extreme downside risks. Given this well-established link, it is critical to demonstrate that the main results on option strike asymmetry are not simply a reflection of disagreement-related mechanisms. To this end, multiple alternative disagreement proxies are explicitly controlled for in the robustness tests.

[Insert Table 5.7 here]

Table 5.7 reports the results from the robustness tests after controlling for alternative disagreement measures. Table 5.7 Panel A focuses on Total strike asymmetry and Put strike asymmetry, while Table 5.7 Panel B presents results for ITM Put strike asymmetry and OTM Put strike asymmetry. For each asymmetry variable, additional controls are sequentially introduced: (i) Dturnover, (ii) OTM Put Dturnover, (iii) IDISP, and (iv) a full model that includes all three disagreement proxies simultaneously. Across both panels, OTM Put strike asymmetry remains consistently negative and highly significant, even after controlling for disagreement from both the stock and options markets. This finding supports the core hypothesis that trading concentration on deep out-of-the-money puts is often associated with downside speculation or informed positioning. Therefore, OTM Put strike asymmetry serves as a robust predictor of future stock price crashes. In contrast, ITM Put strike asymmetry is positively associated with crash likelihood, suggesting that trading activity in in-the-money puts may reflect speculative optimism or positioning for upside recovery, particularly among risk-tolerant investors. The Total strike asymmetry also exhibits positive and significant coefficients, likely reflecting the mix of both upward and downward views embedded in broader option trading. The results for Put strike asymmetry are more mixed and less stable, suggesting that aggregating all put trades without conditioning on moneyness may dilute the predictive signal.

Meanwhile, both Dturnover and IDISP retain their significance throughout the models, confirming their roles as strong and reliable predictors of stock price crashes. These findings are in line with previous literature (Chen, Hong, and Stein, 2001; Diether, Malloy, and Scherbina, 2002; Andreou, Kagkadis, Philip, and Tuneshev, 2018), which shows that investor disagreement—whether derived from the stock market or the options market—is a strong predictor of future crash risk. In contrast, OTM Put Dturnover is mostly insignificant, suggesting that disagreement captured solely through OTM put trading volume is not a robust predictor on its own. This highlights the necessity of incorporating both strike price and trading volume—as done in the strike asymmetry measure—to accurately detect directional positioning and information embedded in option markets. Overall, these results suggest that option strike asymmetry captures a distinct source of information, independent from traditional disagreement channels, and provides additional explanatory power for firm-level crash risk. While this approach is related in spirit to the option-implied dispersion measure (IDISP) proposed by Andreou, Kagkadis, Philip, and Tuneshev (2018), which captures the breadth of disagreement across strike levels, the strike asymmetry measure offers a complementary perspective by incorporating the directional skewness of investor positioning. This distinction allows detection of potential informed activity and crash anticipation more directly, particularly through the trading behavior in deep out-of-the-money puts.

Market-wide volatility and investor sentiment are widely recognized as key drivers of stock price dynamics, especially during periods of financial stress. The VIX index, often referred to as the "fear gauge," reflects market participants' expectations of future volatility based on S&P 500 index options. As such, it serves as a standard proxy for aggregate uncertainty and investor fear in the literature (e.g., Bloom, 2009; Bekaert, Hoerova, and Duca, 2013). Since sharp increases in VIX are typically associated with broad market sell-offs, it is essential to control for this factor to ensure that the results are not simply capturing systematic crash risk.

[Insert Table 5.8 here]

Table 5.8 presents the results after including the lagged value of the VIX index as an additional control variable in the baseline regressions. Across all specifications, the coefficient on VIX is consistently negative and highly significant, confirming its predictive power for crash events. This is consistent with prior findings that elevated levels of market volatility are associated with increased downside risk at the aggregate level.

Importantly, the coefficients on the strike asymmetry measures remain virtually unchanged compared to the baseline regressions in Table 5.4. In particular, OTM Put strike asymmetry continues to exhibit a strong and significant negative relationship with crash likelihood, even after controlling for market-wide volatility. This finding suggests that the measure is not merely capturing broad market stress, but rather reflects firm-specific positioning and potential informed trading activity that anticipates future crashes. These results reinforce the interpretation that option strike asymmetry—especially from the OTM put side—contains idiosyncratic information beyond macro-level volatility shocks. Thus, while VIX captures systematic uncertainty, the strike asymmetry variable complements it by highlighting micro-level signals embedded in the option market.

Taken together, the robustness analyses confirm the stability of the predictive relationship between option strike asymmetry and future stock price crashes. Across alternative strike asymmetry construction, multiple crash definitions—including both model-based and model-free measures, investor disagreement from both stock and option markets, and aggregate market volatility (VIX), the core findings remain consistent. In particular, the OTM Put strike asymmetry measure continues to demonstrate strong and statistically significant predictive power, reinforcing its role as a firm-specific crash risk indicator that is distinct from existing explanatory channels. These results provide compelling evidence that strike asymmetry captures meaningful signals related to downside risk, above and beyond known predictors.

5.3.3 Potential channels

So far, the robust predictive power of option strike asymmetry for future stock price crashes has been established. The next step is to explore the potential channels underlying this relationship. Specifically, the analysis examines whether the link between strike asymmetry and crash risk is consistent with key theoretical mechanisms proposed in the literature. The role of short-sale constraints is first investigated based on Miller's (1977) hypothesis. Next, the influence of firms' financial reporting quality is assessed, given its effect on information asymmetry and crash propensity. Finally, how the broader market sentiment environment may condition the predictive strength of strike asymmetry is analyzed.

5.3.3.1 Short sale constraints

Miller (1977) theory suggests that when short-sale constraints are binding, disagreement among investors is more likely to lead to stock overvaluation and subsequently higher crash risk. Intuitively, when short-selling is difficult, pessimistic investors are unable to express their negative views, resulting in prices that are overly reflective of optimistic beliefs. As a result, stocks with higher short interest are expected to be more prone to future crashes following divergence in opinions (Diether, Malloy, and Scherbina, 2002; Andreou, Kagkadis, Philip, and Tuneshev, 2018). To examine whether the option strike asymmetry measures are consistent with this mechanism, firms are sorted into quintiles based on their lagged short interest and baseline regressions are run separately within each quintile. Table 5.9 presents the results.

[Insert Table 5.9 here]

Looking at the Total strike asymmetry and ITM Put strike asymmetry columns, the observed patterns are broadly consistent with Miller's theory. Specifically, the coefficients increase in magnitude and significance from low short interest quintiles to high short interest quintiles, indicating that option strike asymmetry is a stronger predictor of crashes for firms with tighter short-sale constraints. This supports the idea that when pessimistic investors are constrained from trading on their views, options markets partially reflect the imbalance, and strike asymmetry becomes a more powerful signal. However, the results for Put strike asymmetry are less stable and generally insignificant across all quintiles, suggesting that aggregating across all put options without conditioning on moneyness likely dilutes the predictive power of the signal. Interestingly, the behavior of OTM Put strike asymmetry deviates from the classic Miller's framework. Across all five short interest quintiles, OTM Put strike asymmetry remains highly negative and statistically significant, with relatively stable magnitudes. This suggests that OTM Put strike asymmetry captures additional information beyond short-sale constraints. In particular, it likely reflects informed trading activity or early downside positioning by sophisticated investors, even in stocks where short-selling is less constrained. As deep out-of-the-money puts are especially sensitive to crash expectations, concentrated trading on these strikes embeds private information about future tail risks that is not solely explained by short-sale frictions. These findings imply that while traditional strike asymmetry measures partly align with Miller's theory, OTM Put strike asymmetry offers an independent and robust predictor of crash risk across different short interest environments.

5.3.3.2 Financial reporting quality

It has been widely documented that poor financial reporting quality increases firms' crash risk. Managers often engage in earnings management practices to conceal bad news, which ultimately leads to stock price crashes when the news is eventually released (Sloan, 1996; Jin and Myers, 2006; Hutton, Marcus, and Tehranian, 2009; Chi and Gupta, 2009; Zhu, 2016). To ensure that the findings on option strike asymmetry are not merely driven by earnings manipulation, the role of financial reporting quality is further investigated. Specifically, each month, firms are sorted based on their discretionary accruals aggregated over the past 12 quarters, in ascending order. The sample is divided into quintile portfolios and baseline crash regressions are performed separately within each quintile. Table 5.10 reports the results.

[Insert Table 5.10 here]

The results from Table 5.10 are quite informative. OTM Put strike asymmetry remains highly significant and negative across all quintiles, regardless of the firm's level of discretionary accruals. In contrast, the predictive power of Total strike asymmetry, Put strike asymmetry, and ITM Put strike asymmetry is weak and sporadic, with only a few coefficients reaching marginal significance. These patterns suggest that, while firms with higher discretionary accruals may indeed be more crash-prone, the predictive signal from OTM Put strike asymmetry operates independently and robustly, not merely capturing earnings management behavior. The consistent significance across all groups implies that deep out-of-the-money put trading embeds information beyond what is reflected through managerial accounting discretion.

In addition to discretionary accruals, existing literature documents that depreciation is another tool used by managers to manipulate earnings (Bartov 1993; Stolowy and Breton 2004). Some studies also suggest that firms may reduce R&D expenditures to meet earnings targets (Baber, Fairfield, and Haggard, 1991; Perry and Grinaker, 1994; Cheng, 2004). Therefore, to comprehensively control for earnings management activities, the baseline models are extended by including three variables: discretionary accruals (12 quarters), the log of firm depreciation, and an R&D cut dummy.

[Insert Table 5.11 here]

Table 5.11 presents the results after including these additional proxies of financial reporting quality. Consistent with expectations, higher discretionary accruals and lower depreciation are significantly associated with increased crash risk. Specifically, discretionary accruals show positive and significant coefficients, while depreciation shows a negative and significant relation with crashes, supporting the notion that aggressive earnings management elevates crash risk. R&D cut, however, is not significant, possibly reflecting its more nuanced role in earnings manipulation.

Importantly, after controlling for these financial reporting variables, OTM Put strike asymmetry continues to display a strong negative and highly significant relationship with crash risk at the 1% level. In contrast, the significance of Total strike asymmetry and ITM Put strike asymmetry weakens, with coefficients dropping to marginal levels. Put strike asymmetry remains largely insignificant. These findings further reinforce that OTM Put strike asymmetry captures early downside positioning that is distinct from traditional financial reporting quality issues. The information embedded in deep out-of-the-money put trading appears to be driven by sources beyond conventional accounting manipulations, offering robust predictive power for future firm-specific crash risks.

5.3.3.3 Investor sentiment

It has been widely documented that investor sentiment plays a critical role in explaining stock mispricing and crash risk. When the overall market sentiment is high, excessive optimism leads to speculative trading and overvaluation of stocks, making them more prone to sharp corrections once reality fails to meet inflated expectations (Stambaugh, Yu, and Yuan, 2012). In contrast, during periods of low sentiment, stock prices tend to be more closely aligned with fundamentals, reducing the likelihood of significant crashes driven by sentiment-related mispricing. To examine whether the predictive power of option strike asymmetry depends on the overall market sentiment, the sentiment index from Baker and Wurgler (2006) is used. Specifically, the full sample is split into high-sentiment and low-sentiment periods according to the median value of the sentiment index, and the baseline regressions are conducted separately within each subsample. This allows assessment of whether the informativeness of strike asymmetry varies with market-wide optimism or pessimism.

[Insert Table 5.12 here]

Table 5.12 presents the results. Total strike asymmetry and ITM Put strike asymmetry exhibit significantly positive coefficients during high-sentiment periods but become insignificant during low-sentiment periods. These results are consistent with the view that stocks are more likely to be overvalued when market sentiment is exuberant, leading to a stronger link between strike asymmetry and crash risk. Meanwhile, Put strike asymmetry remains insignificant across both subsamples, further suggesting that aggregating across all put options without conditioning on moneyness dilutes the predictive information. Similar to previous findings, OTM Put strike asymmetry remains strongly negative and statistically significant across both high- and low-sentiment periods. Moreover, the magnitude and significance of the coefficients are even stronger during low-sentiment periods, which is inconsistent with the overvaluation-based channel and suggests the presence of private information trading. These results imply that deep out-of-the-money put activity, as captured by OTM Put strike asymmetry, is less sensitive to market-wide optimism and more likely reflects informed positioning based on firm-specific negative information. These findings reinforce the unique role of OTM Put strike asymmetry in predicting crash risk, distinct from general sentiment-driven mispricing channels. The results suggest that this measure captures forward-looking private information embedded in option markets rather than merely reflecting broad market sentiment.

In this section, several potential channels are examined to explain the predictive power of option strike asymmetry for future stock price crashes. Specifically, the analysis tests whether the relation is driven by short-sale constraints (Miller, 1977), overall market sentiment (Baker and Wurgler, 2006), or firm-level financial reporting quality (Sloan, 1996; Hutton, Marcus, and Tehranian, 2009). Across these tests, Total strike asymmetry and ITM Put strike asymmetry generally conform to existing theories of overvaluation-driven crash risk. Their predictive power is stronger among firms facing high short-sale constraints, during periods of high investor sentiment, and becomes weaker or disappears after controlling for discretionary accruals, depreciation, and R&D manipulation proxies.

These patterns suggest that Total and ITM asymmetry primarily capture risks associated with inflated valuations and earnings management practices. In sharp contrast, OTM Put strike asymmetry remains strongly significant across all subsample splits and robustness tests. Its predictive power persists regardless of the level of short-sale constraints, market sentiment, or financial reporting quality. This robustness implies that OTM Put strike asymmetry captures a distinct source of information that is not attributable to market-wide mispricing or earnings manipulation.

Taken together, the findings suggest that OTM Put strike asymmetry likely reflects private information-based trading by informed investors, who anticipate firm-specific negative events and take positions in deep out-of-the-money put options well before bad news is reflected in stock prices. This directional and concentrated trading behavior provides valuable signals for forecasting extreme downside risks at the firm level. The predictive power of option strike asymmetry remains consistent when extreme events such as the 2008 Financial Crisis and the COVID crisis are removed from the sample. In addition, the key relationships remain significant in the more recent subsample period, confirming that the findings are not period-specific.

5.4 Conclusion

This paper extends the empirical literature on stock price crashes by introducing and validating a novel, model-free, directional measure derived from the options market—option strike asymmetry—as a significant predictor of future stock price crashes. Built from the traded strikes and volumes of equity options, especially those of out-of-the-money puts, the measure captures early downside positioning consistent with informed trading under asymmetric information. A robust and negative association is found between OTM Put Strike Asymmetry and subsequent crash risk, even after controlling for a wide range of firm-level characteristics, investor disagreement proxies, and aggregate volatility factors such as the VIX. The result holds across multiple crash definitions, strike asymmetry constructions, and remains consistent in cross-sectional and time-series analyses.

This chapter further investigates the mechanisms behind this predictive relationship. The results indicate that strike asymmetry embeds unique downside information that is not subsumed by short-sale constraints, financial reporting quality, or market sentiment. In particular, OTM Put Strike Asymmetry demonstrates persistent predictive power across firms with differing degrees of accounting opacity and investor disagreement, suggesting that informed investors may selectively use strike positioning to reveal private negative signals prior to crash events.

These findings contribute to the broader understanding of how derivatives markets reflect forward-looking information and play a role in price discovery under information asymmetry. For institutional investors and risk managers, monitoring strike-based option positioning provides a powerful tool to anticipate firm-level crash risk. For regulators, the results highlight the potential of strike-level option data as a real-time, high-frequency signal of market fragility.

In sum, the study demonstrates that option strike asymmetry—particularly from OTM puts—is not merely a structural feature of the options market, but a forward-looking and scalable measure that encapsulates private downside expectations. It offers new insights into how directional derivatives positioning can serve as an early warning indicator of market instability, with meaningful implications for financial risk management, regulatory oversight, and the understanding of informed trading dynamics.

A Description of the control variables

Measures of stock price crash risk

I calculate the mean, and the standard deviation of firm i's current week market adjusted log return over the past 52 weeks, including current week t. Log market adjusted return is $Ret_{i,t} = log(1 + \epsilon_{i,t})$. Where $\epsilon_{(i,t)}$ is the residual obtained from the following regression.

$$r_{(i,t)} = \alpha_i + \beta_1 Rm_{t-2} + \beta_2 Rm_{t-1} + \beta_3 Rm_t + \beta_4 Rm_{t+1} + \beta_5 Rm_{t+2} + \epsilon_{(i,t)}$$

Where $r_{i,t}$ is firm i's cumulative daily return (CRSP variable ret) on week t, Rm_t is the cumulative CRSP value weighted return (CRSP variable vwret) on week t. See Hutton, Marcus, and Tehranian (2009) for detailed information. We select 3.25 times its standard deviation to generate the 0.1\% frequencies in the normal distribution.

Monthly Crash is an indicative variable which is set equal to one if firm i experiences at least one weekly crash within each month. The weekly crash is set equal to 1 if firm i's current week market adjusted log return falling 3.25 times its standard deviation below its mean. The log market adjusted return, the mean and the standard deviation are calculated above.

Future Crash is an indicative variable which is set equal to 1 if firm i experiences at least one weekly crash within each month. The conservative weekly crash is set equal to 1 if firm i's current week market adjusted log return falling 3.25 times its standard deviation below its mean. The log market adjusted return, the mean and the standard deviation are calculated over the future 52-week rolling window, including the current week. This adjustment aims to prevent the influence of previous crashes on the sample mean and standard deviation, ensuring that the weekly crash is not affected by prior crash occurrences.

Ncskew is the monthly average of weekly negative coefficient of skewness for firm i at week t. Weekly Ncskew is defined as the following equation.

$$Ncskew_{i,t} = -\left(n(n-1)^{3/2}\Sigma Ret_{i,t}^3\right) / \left((n-1)(n-2)\left(\Sigma Ret_{i,t}^2\right)^{3/2}\right)$$

The log market adjusted return, the mean and the standard deviation are calculated above. See Chen Hong and Stein (2001) for details.

Monthly Crash 15 pct is an indicative variable which is set equal to one if firm i experiences at least one weekly crash 15 pct within each month. Weekly crash 15 pct is set equal to one if firm i's market adjusted weekly return is below 15\%. Market adjusted weekly return = $(r_{i,t} - Rm_t)$. Where $r_{i,t}$ is firm i's cumulative daily return (CRSP variable ret) on week t, Rm_t is the cumulative CRSP value weighted return (CRSP variable vwret) on week t. We also test alternative thresholds of 5\%, 10\%, and 20\% for the crash definition, and our results remain qualitatively unchanged.

Monthly Crash 15 jack is an indicative variable which is set equal to one if firm i experiences at least one weekly crash 15 jack within each month. Weekly crash 15 jack is set equal to one if firm i's weekly log return is below 15\%. Weekly log return = $log(1 + r_{i,t})$. Where $r_{i,t}$ is firm i's cumulative daily return (CRSP variable ret) on week t. We also test alternative thresholds of 5\%, 10\%, and 20\% for the crash definition, and our results remain qualitatively unchanged.

Measures of option strike asymmetry

Strike asymmetry} is the option strike price asymmetry, for each day and each stock, we observe the spot price \$S\$ and a series of option strike prices K_i , where $i = 1, \dots, n$. We define the moneyness level as $M_i = \frac{K_i}{S}$. To incorporate the directional feature of option trading, we calculate the deviation from the spot price using $M_i - 1$. The daily option strike asymmetry is constructed as the volume-weighted average of this deviation:

$$strike\ asymmetry = \sum_{i=1}^{n} w_i \cdot (M_i - 1)$$

where w_i denotes the trading volume weight of the i^{th} option contract. A positive (negative) value indicates that the trading volume is concentrated in higher (lower) strike options relative to the spot price, reflecting investors' bullish (bearish) expectations. When trading is symmetrically distributed around the spot price, the measure is close to zero.

Measures of divergence in opinions

IDISP is the dispersion in beliefs on individual stocks. Following Andreou, Kagkadis, Philip, and Tuneshev (2018), I measure the dispersion in beliefs on individual stocks (IDISP) using the trading volume of stock options across all moneyness levels. The IDISP is the volume weighted average of the deviation of the moneyness level on the volume weighted moneyness level. For each day and each individual stock, we have a current stock price S and a range of different strike prices of stock options K_i, where $i = 1, \dots, n$. Then, we define the moneyness level as the ratio of strike price on stock price, ($M_i = \frac{K_i}{S}$). Finally, I estimate the daily IDISP using the following equation.

$$IDISP = \sum_{i=1}^{n} w_i \left| M_i - \sum_{i=1}^{n} w_i M_i \right|$$

Where the w_i is the weight of trading volume attached to option K_i, n is the total number of strike prices of each stock option within each day. I estimate the IDISP in daily frequency and we take weekly average in our analysis. I select different time to maturity to construct different versions of IDISP. In our main analysis, we use options with maturity between 10 to 60 days. I select last week IDISP within each month for two reasons. First, new options are usually issued at the 4th Monday in each month, I select last week's options to avoid maturing effect. Second, to obtain the most recent information, I need the closest options before next month.

Dturnover is the difference between the weekly turnover at week t and the average weekly turnover from week t-50 to t-1. Following Connolly, Stivers, and Sun 2005, we calculate the DTURN using the following equation.

$$DTURN_{i,t} = TURN_{i,t} - \frac{1}{50} \sum_{t=-50}^{-1} TURN_{i,t}$$

Where $TURN_{i,t}$ is the weekly average stock turnover, which equals to (CRSP variable vol) / (CRSP variable shrout × 1000).

Other variables

Size is the natural log of firm's market value of equity at the end of each quarter. Source: COMPUSTAT.

Total Volatility is the total volatility of stock i's daily stock return over the past year, including current month t. We require at least 225 observations over the past year. Source: CRSP.

Stock Return is the cumulative stock return of last month. Source: CRSP.

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

Leverage is the long-term debt plus liability divided by firm's total assets. Source: COMPUSTAT.

Disc. Accruals (12 qtrs) is the moving sum of a firm's quarterly discretionary accruals over the past 12 quarters. The discretionary accruals are the residuals obtained from a modified Jones model. More specifically, we run the following cross-sectional regressions each quarter and each of the Fama-French 48 industry groups excluding financial and utility firms.

$$\frac{\text{Total Accruals}_{it}}{\text{Total Assets}_{\text{it-1}}} = \alpha \frac{1}{\text{Total}\sim\text{Assets}_{\text{it-1}}} + \beta_1 \frac{\Delta\text{Sales}_{it} - \Delta\text{Rec}_{it}}{\text{Total}\sim\text{Assets}_{\text{it-1}}} +$$

$$+\beta_2 \frac{\text{PPEG}_{it}}{\text{Total}\sim\text{Assets}_{\text{it-1}}} + \beta_3 \frac{\text{CFEE}_{it}}{\text{Total}\sim\text{Assets}_{\text{it-1}}} + \varepsilon_{it}$$

where $\text{Total Accruals}_{it}$ is the total accruals for firm i at time t, $\text{Total Assets}_{\text{it-1}}$ is the total assets (Compustat item 6) at time t-1, ΔSales_{it} is the change in sales (Compustat item 12), ΔRec_{it} is the change in receivables (Compustat item 2), PPEG_{it} is the gross property, plant and equipment (Compustat item 7) and CFEE_{it} is the income before extraordinary items (Compustat item 18) minus the $\text{Total Accruals}_{it}$. We use the change in current assets (Compustat item 4) plus the change in debt in current liabilities (Compustat item 34) plus the change in income taxes payable (Compustat item 71) minus the change in current liabilities (Compustat item 5) minus the change in cash and short-term investment (Compustat item 1) minus the depreciation and amortization item (Compustat item 14) to calculate the total accruals. The quarterly discretionary accruals are the residuals obtained from the above regression.

Depreciation is the log of firm i's Depreciation and Amortization (Compustat variable DPQ) at quarter t-1.

R&D cut is an indicative variable which is set equal to one if the change of Research and Development Expense (Compustat variable XRDQ) is negative. Otherwise, it is set equal to zero.

Residual Institutional ownership (I/O) is the residual of institutional ownership obtained from a cross-sectional regression of logit transformed institutional ownership on the log of firm size plus the log of firm size squared. See Nagel, 2005 for detailed information.

Sentiment is an overall market indicator. We calculate the median of sample sentiment and split the sample into the above median and below median subsamples. See Baker and Wugler 2006 for detailed information.

VIX is a widely used measure of market-wide uncertainty and investor fear. We obtain monthly VIX data from the CBOE and include the lagged value of VIX as a control variable in our regression models to account for market-wide volatility and aggregate risk sentiment. Following the literature (e.g., Bloom, 2009; Bekaert et al., 2013), a higher VIX level indicates elevated market uncertainty, which may influence stock price crash risk.

Tables and Figure

Figure 5.1: Average weekly OTM put strike asymmetry around crash weeks

This figure plots the cross-sectional average of out-of-the-money (OTM) Put Strike Asymmetry over a 13-week window centered around identified crash weeks (week 0). The strike asymmetry is calculated as the volume-weighted deviation of put option strikes from the spot price. I follow Hutton, Marcus, and Tehranian (2009) and estimate the frequency of stock price crash at 0.1\% level. The sample starts from January 1996 and ends on December 2021. See Appendix for the detailed definition of variables.

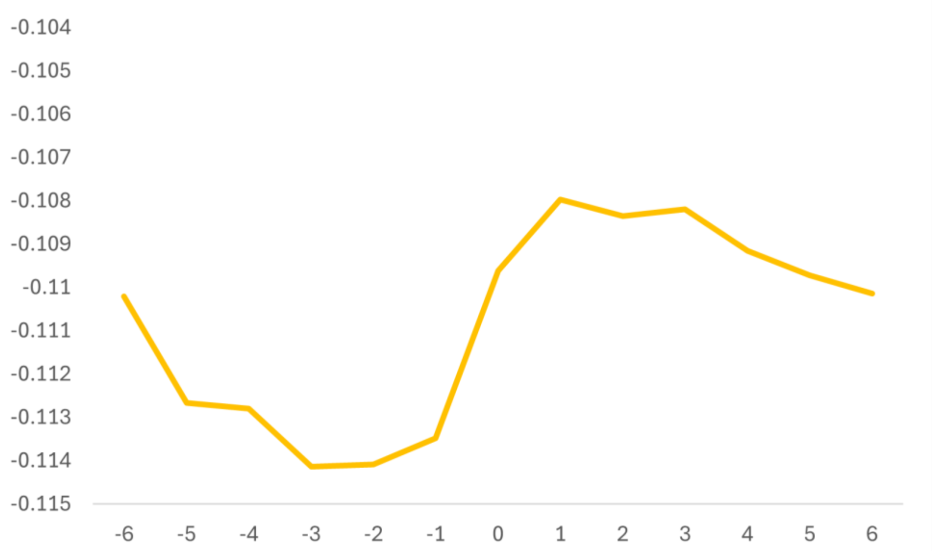


Table 5.1: Summary statistics

This table presents monthly summary statistics for all variables used in the empirical analysis. The sample covers the period from January 1996 to December 2021. The primary dependent variable, *Monthly Crash*, is a binary indicator equal to one if at least one weekly crash occurs within a given month. Crashes are identified using a threshold of 3.25 standard deviations below the mean of the firm's idiosyncratic return, corresponding to a frequency of 0.1% extreme left-tail events. Key explanatory variables include measures of option-implied strike price asymmetry, computed as volume-weighted averages across different option types: all options (*Total Strike Asym*), put options (*Put Strike Asym*), in-the-money puts (*ITM Put Strike Asym*), and out-of-the-money puts (*OTM Put Strike Asym*). All independent variables are lagged by one month unless otherwise noted. *IDISP* captures the monthly dispersion of investor opinions based on option information. Summary statistics include the number of observations (N), mean, standard deviation, and distributional percentiles (Q1, median, Q3). Variable definitions are provided in the Appendix.

Variable	N	Mean	Std Dev	Q1	Median	Q3
Monthly Crash	1,455,401	0.017	0.130	0.000	0.000	0.000
Total Strike Asym	355,598	0.036	0.390	-0.027	0.008	0.053
Put Strike Asym	340,216	-0.019	0.369	-0.084	-0.049	-0.003
ITM Put Strike Asym	248,404	0.150	0.435	0.060	0.090	0.148
OTM Put Strike Asym	304,873	-0.110	0.057	-0.130	-0.097	-0.073
Monthly Crash 15 pct	1673297	0.051	0.219	0.000	0.000	0.000
Monthly Crash 15 jack	1673297	0.087	0.282	0.000	0.000	0.000
IDISP	248,570	0.087	0.067	0.053	0.074	0.104
Dturnover	1,500,804	0.000	0.194	-0.002	-0.001	0.001
Disagreement	318,924	0.252	0.214	0.053	0.219	0.409
AFD	863,463	0.198	1.314	0.017	0.040	0.114
Size	1,502,758	5.691	2.170	4.105	5.572	7.148
Total Volatility	1,406,755	0.600	0.432	0.325	0.485	0.743
Stock Return$_{t-1}$	1,502,459	0.009	0.195	-0.071	0.000	0.071
Stock Return$_{t-2}$	1,493,829	0.009	0.194	-0.071	0.000	0.071
Stock Return$_{t-3}$	1,485,149	0.009	0.192	-0.070	0.000	0.071
Market to Book	1,333,396	3.437	5.695	1.198	1.950	3.515
Leverage	1,326,360	0.207	0.204	0.025	0.157	0.330
Ncskew$_{t-12}$	1,446,020	-0.010	0.863	-0.460	-0.045	0.378
Disc. Accruals (12 qtrs)	982,801	0.013	0.488	-0.125	-0.002	0.119
Depreciation	1,128,894	33.018	195.109	0.435	2.247	12.023
R&D cut	635,254	0.296	0.456	0	0	1

Table 5.2: Correlation matrix of key variables

This table presents the pairwise Pearson correlation coefficients among the key variables used in the empirical analysis. The dependent variable is *Monthly Crash*, a binary indicator equal to one if at least one weekly crash occurs within a given month. Crashes are identified using a threshold of 3.25 standard deviations below the mean of the firm's idiosyncratic return, corresponding to a frequency of 0.1% extreme left-tail events. The table also includes option-based asymmetry measures—*Total Strike Asym*, *Put Strike Asym*, *ITM Put Strike Asym*, and *OTM Put Strike Asym*—as well as firm characteristics such as size, volatility, lagged stock returns, market-to-book ratio, leverage, and other control variables. Correlations are computed based on monthly observations over the sample period from January 1996 to December 2021.

	Monthly Crash	Total Strike Asym	Put Strike Asym	ITM Put Strike Asym	OTM Put Strike Asym	Size	Total Volatility	Stock Return$_{t-1}$	Stock Return$_{t-2}$	Stock Return$_{t-3}$	Market to Book	Leverage	Ncskew$_{t-12}$	Dturnover
Monthly Crash	1.000	0.048	0.053	0.057	-0.019	0.007	0.008	-0.028	-0.017	-0.012	0.010	0.007	0.185	0.010
Total Strike Asym		1.000	0.840	0.828	-0.074	-0.116	0.160	-0.059	-0.029	-0.025	0.009	0.002	0.053	0.031
Put Strike Asym			1.000	0.961	0.165	-0.114	0.125	-0.076	-0.046	-0.042	-0.020	0.005	0.064	0.035
ITM Put Strike Asym				1.000	-0.239	-0.185	0.225	-0.074	-0.047	-0.044	-0.006	0.011	0.073	0.049
OTM Put Strike Asym					1.000	0.344	-0.468	-0.040	-0.031	-0.027	-0.051	0.009	-0.004	-0.073
Size						1.000	-0.501	0.060	0.059	0.059	0.165	0.120	0.071	-0.005
Total Volatility							1.000	0.035	0.026	0.019	0.048	-0.016	-0.012	0.007
Stock Return$_{t-1}$								1.000	0.004	-0.007	0.009	-0.004	-0.100	0.005
Stock Return$_{t-2}$									1.000	0.003	0.039	-0.006	-0.091	0.000
Stock Return$_{t-3}$										1.000	0.069	-0.008	-0.084	0.000
Market to Book											1.000	0.083	-0.010	-0.010
Leverage												1.000	0.009	0.001
Ncskew$_{t-12}$													1.000	-0.001
Dturnover														1.000

Table 5.3: Univariate sorting of monthly crash by option strike asymmetry measures

This table reports the number of monthly crash events across quintile portfolios sorted by different option-implied strike price asymmetry measures. In each month, the sample is sorted into five groups based on the value of the corresponding asymmetry measure in ascending order. *Crash* is a binary indicator equal to one if at least one weekly crash occurs within a given month. Crashes are identified using a threshold of 3.25 standard deviations below the mean of the firm's idiosyncratic return, corresponding to a frequency of 0.1% extreme left-tail events.

	Quintile 1	**Quintile 2**	**Quintile 3**	**Quintile 4**	**Quintile 5**
Total Strike Asym	1,042	1,035	1,215	1,335	1,755
Put Strike Asym	1,253	1,042	1,126	1,272	1,475
ITM Put Strike Asym	723	809	879	1,034	1,232
OTM Put Strike Asym	1,390	1,119	1,039	1,043	950

Table 5.4: Baseline regression results – Option-implied asymmetry and crash risk

This table presents baseline regression results examining the relationship between option-implied strike price asymmetry measures and the likelihood of monthly stock price crashes. The dependent variable is *Monthly Crash*, a binary indicator equal to one if at least one extreme negative idiosyncratic return occurs within a given month. Crash events are defined using a cutoff of 3.25 standard deviations below the mean firm-specific residual return, corresponding to approximately 0.1% of the left-tail distribution. The key independent variables include four volume-weighted asymmetry measures based on different subsets of put options: *Total Strike Asym*, *Put Strike Asym*, *ITM Put Strike Asym*, and *OTM Put Strike Asym*. All regressions include a standard set of control variables measured at the end of the prior month, as well as year-month fixed effects and Fama-French 48 industry fixed effects. Standard errors are clustered at the firm level (permno). Columns (1) to (4) report regression results where each asymmetry measure is included separately. *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Monthly Crash	**(2)** Monthly Crash	**(3)** Monthly Crash	**(4)** Monthly Crash
Total Strike Asym	0.0014**			
	(2.00)			
Put Strike Asym		0.0001		
		(0.28)		
ITM Put Strike Asym			0.0017**	
			(2.27)	
OTM Put Strike Asym				-0.0053***
				(-11.24)
Size	-0.0050***	-0.0053***	-0.0057***	-0.0050***
	(-11.38)	(-11.73)	(-10.82)	(-9.92)
Total Volatility	-0.0055***	-0.0051***	-0.0058***	-0.0080***
	(-9.85)	(-9.27)	(-9.02)	(-10.99)
Stock Return$_{t-1}$	-0.0043***	-0.0046***	-0.0044***	-0.0051***
	(-8.18)	(-8.30)	(-6.66)	(-8.15)
Stock Return$_{t-2}$	-0.0009***	-0.0011***	-0.0008**	-0.0012***
	(-2.81)	(-3.22)	(-2.06)	(-3.17)
Stock Return$_{t-3}$	0.0003	0.0002	0.0001	0.0001
	(0.98)	(0.71)	(0.18)	(0.36)
Market to Book	0.0014***	0.0014***	0.0017***	0.0015***
	(5.07)	(5.17)	(5.09)	(5.01)
Leverage	-0.0000	0.0000	-0.0001	-0.0002
	(-0.08)	(0.02)	(-0.21)	(-0.53)
Ncskew$_{t-12}$	-0.0000	0.0000	0.0001	-0.0000
	(-0.12)	(0.11)	(0.34)	(-0.14)
Constant	0.0251***	0.0258***	0.0271***	0.0252***
	(45.59)	(44.83)	(38.03)	(39.64)
Observations	281,374	269,566	197,476	242,413
R-squared	0.012	0.012	0.014	0.013

Table 5.5: Robustness check – Alternative construction of option-implied asymmetry measures

This table reports robustness tests using an alternative specification of the option-implied strike price asymmetry measures. Unlike the baseline results in Table 5.4, we impose an additional filter that restricts options to those with strictly positive open interest when constructing the asymmetry variables. The dependent variable is *Monthly Crash*, defined as a binary indicator equal to one if at least one extreme negative idiosyncratic return occurs within a given month. All regressions include control variables, month fixed effects, and Fama-French 48 industry fixed effects. Standard errors are clustered at the firm level. Columns (1) to (4) present results for the four asymmetry measures, respectively. *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Monthly Crash	**(2)** Monthly Crash	**(3)** Monthly Crash	**(4)** Monthly Crash
Total Strike Asym	0.0017**			
	(2.02)			
Put Strike Asym		0.0006		
		(1.07)		
ITM Put Strike Asym			0.0026**	
			(2.49)	
OTM Put Strike Asym				-0.0054***
				(-11.06)
Controls	Yes	Yes	Yes	Yes
Monthly fixed effect	Yes	Yes	Yes	Yes
FF48 industry fixed effect	Yes	Yes	Yes	Yes
Observations	281,206	264,900	186,695	236,590
R-squared	0.012	0.012	0.014	0.013

Table 5.6: Robustness checks – Alternative crash risk definitions

This table presents robustness checks of the baseline results using alternative definitions of crash risk. In Panel A, we modify the crash definition by using different thresholds for extreme negative firm-specific returns—2.33 and 1.65 standard deviations below the mean—corresponding approximately to the bottom 1% and 5% of the distribution, respectively. Panel B further adopts a forward-looking rolling window to estimate the mean and standard deviation of idiosyncratic returns, aiming to minimize the influence of past information in crash identification. Across all specifications, *OTM Put Strike Asym* consistently exhibits a significant and negative relationship with crash likelihood, confirming the robustness of our baseline findings. All regressions include standard control variables, month fixed effects, and Fama-French 48 industry fixed effects. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Crash definitions with different standard deviation thresholds

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Crash (1%)				Crash (5%)			
Total Strike Asym	0.0024**				0.0021*			
	(1.97)				(1.66)			
Put Strike Asym		-0.0005				-0.0011		
		(-0.79)				(-1.16)		
ITM Put Strike Asym			0.0005				-0.0005	
			(0.54)				(-0.40)	
OTM Put Strike Asym				-0.0051***				-0.0070***
				(-7.00)				(-6.43)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	260,177	249,416	183,454	224,315	260,177	249,416	183,454	224,315
R-squared	0.019	0.019	0.020	0.020	0.030	0.030	0.031	0.031

Panel B: Crash definitions based on future rolling window

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Future Crash				Future Crash (1%)				Future Crash (5%)			
Total Strike Asym	0.0010*				0.0015*				0.0015			
	(1.78)				(1.65)				(1.41)			
Put Strike Asym		-0.0002				-0.0004				-0.0006		
		(-0.43)				(-0.55)				(-0.54)		
ITM Put Strike Asym			0.0006				0.0006				0.0003	
			(1.07)				(0.70)				(0.24)	
OTM Put Strike Asym				-0.0035***				-0.0053***				-0.0069***
				(-8.07)				(-7.61)				(-6.61)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	274,589	263,125	193,079	236,586	274,589	263,125	193,079	236,586	274,589	263,125	193,079	236,586
R-squared	0.010	0.010	0.011	0.011	0.018	0.018	0.020	0.020	0.029	0.029	0.030	0.030

continued on the next page

Table 5.6 (continued): Robustness checks – Model-free crash definitions

Panel C presents regression results using alternative model-free crash definitions based on extreme weekly returns. We define Monthly Crash 10 pct (15 pct) as a binary indicator equal to one if a firm experiences at least one week in a given month where the market-adjusted return is below 10% (15%). Panel D defines Monthly Crash 10 jack (15 jack) similarly but using log weekly returns. We also tested thresholds at the 5% and 20% levels and results remain unaffected. All models control for standard firm characteristics, month fixed effects, and Fama-French 48 industry fixed effects. Standard errors are clustered at the firm level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel C: Model-Free Crash based on raw returns (Crash 10% and 15%)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Monthly Crash 10 pct				Monthly Crash 15 pct			
Total Strike Asym	0.0111***				0.0102**			
	(3.03)				(2.49)			
Put Strike Asym		0.0087***				0.0103***		
		(4.11)				(5.45)		
ITM Put Strike Asym			0.0161***				0.0157***	
			(4.19)				(5.12)	
OTM Put Strike Asym				-0.0238***				-0.0166***
				(-15.26)				(-15.21)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	281,436	269,625	197,520	242,461	281,436	269,625	197,520	242,461
R-squared	0.198	0.198	0.209	0.197	0.131	0.132	0.142	0.130

Panel D: Model-Free Crash based on log returns (Crash 10 jack and 15 jack)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Monthly Crash 10 jack				Monthly Crash 15 jack			
Total Strike Asym	0.0026**				0.0035***			
	(2.38)				(2.80)			
Put Strike Asym		-0.0007				0.0015		
		(-0.72)				(1.31)		
ITM Put Strike Asym			0.0032**				0.0059***	
			(2.08)				(2.92)	
OTM Put Strike Asym				-0.0148***				-0.0148***
				(-12.70)				(-13.29)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	281,436	269,625	197,520	242,461	281,436	269,625	197,520	242,461
R-squared	0.204	0.206	0.215	0.206	0.195	0.196	0.207	0.196

Table 5.7: Robustness – Controlling for alternative disagreement measures

This table presents robustness tests addressing alternative explanations based on investor disagreement. We augment the baseline regressions by including two additional proxies for divergence in beliefs: IDISP, which captures dispersion in the moneyness of traded options, and Dturnover, which measures abnormal weekly turnover relative to the past 50 weeks. Panel A focuses on Total Strike Asym and Put Strike Asym. Columns (1)–(4) report regressions using Total Strike Asym with each disagreement proxy included either individually or jointly. Columns (5)–(8) repeat the same structure for Put Strike Asym. Panel B reports similar results using more refined asymmetry measures. Columns (1)–(4) use ITM Put Strike Asym, while Columns (5)–(8) focus on OTM Put Strike Asym, again with various combinations of Dturnover and IDISP included. All regressions include standard firm-level controls, month fixed effects, and Fama-French 48 industry fixed effects. Standard errors are clustered at the firm level. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1) CRASH	(2) CRASH	(3) CRASH	(4) CRASH	(5) CRASH	(6) CRASH	(7) CRASH	(8) CRASH
Panel A: Total and Put strike asymmetry								
Total Strike Asym	0.0014**	0.0081***	0.0111***	0.0110***				
	(1.99)	(2.76)	(4.70)	(4.68)				
Put Strike Asym					0.0001	0.0009	-0.0044**	-0.0042**
					(0.12)	(0.84)	(-2.52)	(-2.46)
Dturnover	0.0096***			0.0135**	0.0097***			0.0136**
	(2.63)			(2.03)	(2.61)			(2.00)
OTM Put Dturnover		0.0002		0.0163		0.0001		0.0149
		(0.79)		(1.13)		(0.64)		(1.10)
IDISP			0.0027***	0.0026***			0.0037***	0.0036***
			(3.67)	(3.57)			(4.30)	(4.22)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	281,374	279,412	199,637	199,551	269,566	267,761	196,252	196,172
R-squared	0.012	0.012	0.013	0.014	0.012	0.012	0.013	0.014
Panel B: ITM and OTM Put strike asymmetry								
ITM Put Strike Asym	0.0016**	0.0046***	0.0060***	0.0057***				
	(2.22)	(2.64)	(2.78)	(2.72)				
OTM Put Strike Asym					-0.0053***	-0.0053***	-0.0060***	-0.0059***
					(-11.14)	(-11.17)	(-9.22)	(-9.11)
Dturnover	0.0098**			0.0139**	0.0072**			0.0117*
	(2.57)			(2.01)	(2.00)			(1.74)
OTM Put Dturnover		0.0001		0.0154		0.0044*		0.0138
		(0.48)		(1.01)		(1.92)		(1.07)
IDISP			0.0028***	0.0027***			0.0025***	0.0023***
			(3.09)	(3.03)			(3.56)	(3.48)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	197,476	195,888	156,826	156,772	242,413	242,004	187,625	187,560
R-squared	0.014	0.014	0.015	0.015	0.013	0.013	0.015	0.015

Table 5.8: Controlling for market volatility (VIX) – Robustness of strike asymmetry and crash risk

This table presents the regression results of monthly stock price crash risk on various measures of option-implied strike price asymmetry, controlling for market-wide volatility. We include the lag 1 of the VIX index as an additional control variable to account for investor fear and expected volatility in the market. The dependent variable is Monthly Crash, a binary indicator equal to one if the stock experiences at least one crash-level return in the month. Columns (1)–(4) report results for Total Strike Asym, Put Strike Asym, ITM Put Strike Asym, and OTM Put Strike Asym, respectively. All independent variables are lagged by one month unless otherwise noted. All regressions include month fixed effects and Fama-French 48 industry fixed effects. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)
Total Strike Asym	0.0014**			
	(2.00)			
Put Strike Asym		0.0001		
		(0.28)		
ITM Put Strike Asym			0.0017**	
			(2.27)	
OTM Put Strike Asym				-0.0053***
				(-11.24)
VIX	-0.0324***	-0.0311***	-0.0407***	-0.0383***
	(-2.78)	(-2.63)	(-4.07)	(-3.16)
Controls	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	281,374	269,566	197,476	242,413
R-squared	0.012	0.012	0.014	0.013

Table 5.9: Testing Miller's Theorem via short interest

This table presents robustness tests examining whether the relationship between option-implied strike price asymmetry and crash risk is consistent with Miller's (1977) hypothesis. Miller's theorem suggests that in the presence of short-selling constraints, disagreement among investors is more likely to generate overvaluation and subsequent crash risk. To test this, I sort the sample into quintiles based on firms' lagged short interest, from lowest (Column 1) to highest (Column 5), and estimate the baseline regressions within each subsample. All regressions include control variables, month fixed effects, and Fama-French 48 industry fixed effects. Standard errors are clustered at the firm level and t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1) Q1 (Low SI)	**(2)** Q2	**(3)** Q3	**(4)** Q4	**(5)** Q5 (High SI)
Total Strike Asym	0.0001	0.0013	0.0048**	0.0019	0.0082***
	(0.19)	(1.02)	(2.15)	(1.03)	(3.03)
Observations	53,006	52,162	50,696	48,211	47,693
R-squared	0.018	0.019	0.021	0.018	0.019
Put Strike Asym	-0.0006	-0.0006	-0.0008	0.0009	0.0012
	(-1.65)	(-0.75)	(-0.66)	(0.62)	(0.69)
Observations	51,180	50,379	48,966	46,560	46,023
R-squared	0.019	0.019	0.021	0.019	0.018
ITM Put Strike Asym	-0.0001	0.0018	0.0067*	0.0002	0.0068***
	(-0.48)	(1.09)	(1.92)	(0.20)	(3.20)
Observations	37,751	37,065	35,921	34,436	33,945
R-squared	0.022	0.023	0.026	0.021	0.021
OTM Put Strike Asym	-0.0034***	-0.0031***	-0.0049***	-0.0049***	-0.0085***
	(-2.93)	(-2.89)	(-4.84)	(-5.21)	(-7.71)
Observations	46,591	45,848	44,602	42,299	41,695
R-squared	0.020	0.021	0.022	0.020	0.023

All regressions include control variables, month fixed effects, and Fama-French 48 industry fixed effects.

Table 5.10: Robustness – Sorting by Disc. Accruals (12 qtrs)

This table presents crash risk regression results across quintile portfolios sorted by firms' discretionary accruals, calculated over the past 12 quarters. Firms are sorted from low to high values of *Disc. Accruals (12 qtrs)*. Columns (1) to (5) report baseline regressions estimated within each quintile. All regressions control for firm characteristics and include month fixed effects and Fama-French 48 industry fixed effects. Standard errors are clustered at the firm level. T-statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Q1 (Low)	(2) Q2	(3) Q3	(4) Q4	(5) Q5 (High)
Total Strike Asym	0.0027	0.0051**	0.0024	0.0009	0.0005
	(1.18)	(1.99)	(1.52)	(1.02)	(0.93)
Observations	35,728	49,783	52,422	45,920	37,878
R-squared	0.022	0.016	0.019	0.020	0.020
Put Strike Asym	0.0014	-0.0011	0.0002	-0.0020*	0.0002
	(0.91)	(-0.64)	(0.18)	(-1.79)	(0.16)
Observations	33,959	47,985	50,565	44,016	35,732
R-squared	0.022	0.016	0.019	0.021	0.021
ITM Put Strike Asym	0.0020	0.0028	0.0016	-0.0004	0.0025*
	(1.02)	(1.28)	(1.38)	(-0.36)	(1.66)
Observations	25,286	35,956	36,888	32,131	25,845
R-squared	0.026	0.019	0.023	0.025	0.025
OTM Put Strike Asym	-0.0062***	-0.0047***	-0.0048***	-0.0051***	-0.0063***
	(-4.62)	(-4.87)	(-4.45)	(-4.43)	(-5.28)
Observations	30,073	43,587	45,937	39,459	30,885
R-squared	0.024	0.018	0.021	0.023	0.023

All regressions include control variables, month fixed effects, and Fama-French 48 industry fixed effects.

Table 5.11: Regression icluding Disc. Accruals (12 qtrs), Depreciation, and R&D Cut

This table reports the regression results of crash risk on option-implied strike price asymmetry measures, controlling for discretionary accruals, depreciation, and R&D cut. Discretionary Accruals (12 qtrs) is the signed abnormal accruals aggregated over 12 quarters. Depreciation is the log of the firm's Depreciation and Amortization (Compustat variable DPQ) at quarter t−1. R&D cut is an indicator variable equal to one if the change in Research and Development expense (Compustat variable XRDQ) is negative, and zero otherwise. All regressions include standard controls, month and Fama-French 48 industry fixed effects. t-statistics are in parentheses, and standard errors are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) CRASH	(2) CRASH	(3) CRASH	(4) CRASH
Total Strike Asym	0.0033*			
	(1.67)			
Put Strike Asym		0.0005		
		(0.49)		
ITM Put Strike Asym			0.0023*	
			(1.68)	
OTM Put Strike Asym				-0.0058***
				(-8.15)
Disc. Accruals (12 qtrs)	0.0007*	0.0008*	0.0004	0.0012***
	(1.81)	(1.82)	(0.85)	(2.61)
Depreciation	-0.0034***	-0.0035***	-0.0040***	-0.0032***
	(-3.28)	(-3.22)	(-3.11)	(-2.67)
R&D Cut	-0.0007	-0.0006	-0.0004	-0.0004
	(-1.59)	(-1.29)	(-0.69)	(-0.87)
Controls	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	131,810	126,252	94,705	112,818
R-squared	0.013	0.013	0.015	0.014

Table 5.12: Impact of market sentiment

This table reports the pooled cross-sectional regression results examining the impact of different option-implied strike price asymmetry measures on stock crash risk, conditional on market sentiment. We divide the full sample into two subsamples based on the monthly average investor sentiment index and estimate regressions separately for High Sentiment (Columns 1, 3, 5, 7) and Low Sentiment (Columns 2, 4, 6, 8) periods. *Sentiment* is an overall market indicator. We calculate the median of sample sentiment and split the sample into above- and below-median subsamples. See Baker and Wurgler (2006) for detailed information. The dependent variable is *Monthly Crash*, and key independent variables include *Total Strike Asym*, *Put Strike Asym*, *ITM Put Strike Asym*, and *OTM Put Strike Asym*, with one-month lags. All regressions control for *Disc. Accruals (12 qtrs)*, *Depreciation*, and *R&D cut*, along with month and Fama-French 48 industry fixed effects. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Total K Asym		**Put K Asym**		**ITM Put K Asym**		**OTM Put K Asym**	
	H Sent	L Sent	H Sent	L Sent	H Sent	L Sent	H Sent	L Sent
Total Strike Asym	0.0044***	0.0030						
	(2.95)	(1.21)						
Put Strike Asym			0.0008	0.0005				
			(0.74)	(0.34)				
ITM Put Strike Asym					0.0030**	0.0021		
					(2.39)	(1.10)		
OTM Put Strike Asym							-0.0048***	-0.0067***
							(-5.23)	(-6.24)
Disc. Accruals (12 qtrs)	0.0010*	0.0001	0.0010*	0.0002	0.0009	-0.0005	0.0014**	0.0009
	(1.96)	(0.08)	(1.96)	(0.18)	(1.45)	(-0.46)	(2.25)	(1.27)
Depreciation	-0.0040***	-0.0034**	-0.0038***	-0.0037**	-0.0046***	-0.0037*	-0.0032**	-0.0035**
	(-2.92)	(-2.21)	(-2.66)	(-2.34)	(-2.80)	(-1.96)	(-2.07)	(-2.04)
R&D Cut	-0.0009	-0.0004	-0.0007	-0.0003	-0.0004	-0.0002	-0.0005	-0.0002
	(-1.36)	(-0.63)	(-1.05)	(-0.50)	(-0.47)	(-0.28)	(-0.68)	(-0.25)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	64,085	67,143	60,685	65,008	46,177	48,129	52,915	59,377
R-squared	0.012	0.015	0.012	0.015	0.014	0.018	0.013	0.017

6 Conclusion

This chapter investigates the determinants and mechanisms of crash risk in equity markets by exploring three distinct, yet complementary, option-based approaches. Through the lens of the skewness risk premium, divergence in investor beliefs, and strike asymmetry in options markets, the research provides novel insights into how early signals embedded in option pricing can predict extreme downside risk. Each empirical chapter develops a tradable or observable measure rooted in investor expectations, contributing to both the academic understanding of crash risk formation and the practical frameworks for risk management and policy design.

The first study introduces a firm-level measure of the skewness risk premium (SRP), capturing the ex-ante compensation demanded by investors to bear the risk of severe negative returns. Using a model-free approach based on out-of-the-money options, the study shows that firms engaging in earnings manipulation—proxied by high discretionary accruals—exhibit significantly negative SRP. This implies that investors anticipate a higher likelihood of downward price shocks for such firms and price these risks accordingly in the options market. The analysis further demonstrates that the negative SRP is especially concentrated around earnings announcement dates and among firms that miss analyst expectations. A key contribution lies in bridging the literature on earnings management and crash risk through an options-based perspective, highlighting the pricing implications of opacity in financial reporting. For investors and regulators, the findings underscore the importance of monitoring SRP dynamics as a forward-looking indicator of crash-prone firms, particularly during periods of concentrated information disclosure.

Building upon this investor-expectation-based foundation, the second chapter constructs a model-free proxy of divergence in investor beliefs—termed IDISP—from the cross-sectional distribution of option trading volume across strike prices. The study finds that higher IDISP values strongly predict future stock price crashes, suggesting that extreme opinion dispersion in the options market, particularly driven by OTM put trading, reflects underlying disagreement and pessimistic expectations. The robustness of this relationship holds across multiple crash definitions and alternative belief dispersion proxies. Importantly, the chapter explores potential channels behind this predictive power, including financial reporting quality, short-sale constraints, investor sentiment, and earnings announcement timing. The results show that IDISP predicts crashes beyond what can be explained by other traditional variables, and that its effects are most pronounced during earnings announcements—especially for firms with sustained earnings surprises and aggressive accruals. These findings suggest that options market-based disagreement metrics capture nuanced, real-time sentiment shifts that precede extreme price declines. Policymakers and risk managers can benefit from incorporating IDISP as a supplementary tool for systemic risk surveillance and firm-level fragility assessment.

The third chapter develops and empirically tests a novel measure of option strike asymmetry to capture directional skew in investor positioning. By constructing a volume-weighted average of the moneyness deviation of put options, the study focuses on the asymmetry of strike selection—particularly among OTM puts—as a predictor of future crash risk. The findings reveal that higher levels of strike asymmetry, especially for firm-level OTM puts, are associated with elevated crash probabilities in the subsequent period. This predictive power remains robust after controlling for market-wide volatility (e.g., VIX), belief dispersion (e.g., IDISP), and other crash risk proxies. The chapter also examines potential mechanisms by testing the link between strike asymmetry and informed trading behaviors, such as short interest, financial opacity, and investor sentiment. The results suggest that strike asymmetry may reflect early positioning by informed traders anticipating downside events, making it a powerful signal of insider-informed crash risk. This measure offers a forward-looking, high-frequency, and model-independent tool that can complement traditional volatility or skewness metrics. Its application is particularly relevant for regulators and institutional investors seeking to detect signs of latent market stress not yet reflected in realized returns.

Taken together, the three chapters advance the understanding of crash risk through an options market perspective, highlighting the rich informational content embedded in non-price option characteristics. By focusing on skewness pricing, belief heterogeneity, and strike structure, the thesis develops a cohesive framework for measuring and predicting downside tail risk in equities. These contributions are timely and actionable: they enable earlier detection of risk buildup, promote transparency in market-based expectations, and offer novel tools for policymakers, investors, and researchers interested in systemic risk monitoring and portfolio insurance strategies.

While the thesis offers valuable insights, it also presents limitations that open avenues for future research. First, although the option-based measures are largely model-free, they still depend on the availability and liquidity of option markets, which may constrain generalizability to less-developed financial environments. Second, this research focuses primarily on U.S.-listed firms; applying the methodology to international contexts could uncover cross-market differences in crash dynamics. Third, although the studies document strong predictive relationships, establishing causality remains challenging due to potential endogeneity and information asymmetry concerns. Finally, integrating textual analysis or machine learning-based option order flow classification may enrich future iterations of belief or asymmetry measures.

The findings of this chapter have several practical implications for different stakeholders. For investors, the option-based predictors developed in this research, such as skewness risk premium, belief dispersion, and strike asymmetry, can serve as early warning signals of future crash risk. Incorporating these indicators into portfolio risk management may help mitigate extreme downside exposure. For regulators and policymakers, the results highlight that market-implied information contains valuable forward-looking signals that complement accounting- or sentiment-based measures. Monitoring firm-level option indicators could assist in detecting accumulations of tail risk before they materialize into market stress. For academics, this chapter contributes to the literature on downside risk by integrating behavioural and option-based mechanisms, providing a foundation for future studies that explore the interaction between informed trading, investor sentiment, and crash dynamics across different markets.

In conclusion, this chapter contributes to the growing literature on forward-looking crash risk indicators by designing empirically grounded, option-based measures that are both theoretically sound and practically relevant. Through detailed investigations of SRP, IDISP, and strike asymmetry, it demonstrates that investor expectations, as revealed in the options market, offer powerful predictive signals of extreme downside events. These findings have significant implications for financial regulation, portfolio management, and our broader understanding of market fragility in complex financial systems.

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