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Essays on Stock Price Crash Risk

Ensaios sobre Stock Price Crash Risk

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1. Risco de *crash* 2. Assembleias gerais de acionistas evasivas 3. Analistas financeiros. .

Este trabalho é dedicado ao meu pai, um cidadão do mundo que, desde a minha infância, me ensinou a enxergar o mundo com os olhos de um cientista. In Memoriam.

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"Some of the best theorizing comes after collecting data because then you become aware of another reality."

Robert J. Shiller

Louise Banks: *If you could see your whole life from start to finish, would you change things?*

Ian Donnelly : *Maybe I'd say what I felt more often. I-I don't know.*

Arrival (2016)

ABSTRACT

Schwarz, L. A. D. (2023). *Essays on Stock Price Crash Risk* (Ph.D. Dissertation). School of Economics, Business Administration and Accounting at Ribeirão Preto, University of São Paulo, Ribeirão Preto.

Firm-specific stock crashes could be devastating for investors, with significant wealth implications. The economic significance of stock crashes has attracted increasing attention from academia to stock price crash risk' potential drivers. This dissertation comprises two related but different essays on potential stock price crash risk' drivers unexplored by literature, to my knowledge. In the first essay, I extend the existing literature by examining the relationship between evasive shareholder meetings and stock price crash risk, an unexplored question. I argue that evasive shareholder meetings could increase stock price crash risk through two potential mechanisms, namely *Deterrence* and *Attention*. To test my hypotheses, I construct a hand-collected dataset on annual shareholder meetings scheduling' characteristics. In the second essay, I extend the existing literature by examining the relationship between sell-side analysts' busyness and stock price crash risk. Mainly grounded on the busy directors' literature, I argue that the relationship between analysts' busyness and stock price crash risk reflects the net effect of two opposing perspectives: *Busyness* and *Networking*.

Keywords: Crash Risk, Shareholder Meetings, Financial Analysts.

RESUMO

Schwarz, L. A. D. (2023). *Ensaios sobre Stock Price Crash Risk* (Tese de Doutorado). Faculdade de Economia, Administração e Contabilidade de Ribeirão Preto, Universidade de São Paulo, Ribeirão Preto.

Uma queda acentuada no preço de uma ação em particular (i.e., um *crash* individual) pode ser devastadora para os acionistas, com implicações patrimoniais significantes. A relevância econômica de *crashes* individuais tem atraído a atenção da academia para os potenciais fatores que podem vir a aumentar ou diminur o risco de *crash* de uma determinada ação. Essa tese compreende dois ensaios relacionados, mas separados, sobre dois potenciais fatores ainda não explorados pela literatura, para o meu conhecimento. No primeiro ensaio, procuro expandir a literatura existente ao examinar a relação entre assembleias gerais de acionistas evasivas e o risco de *crash* individual por meio de dois potenciais mecanismos, nomeados *Dissuasão* e *Atenção*. Para testar as minhas hipóteses, construí uma base de dados manual com informações sobre localização e horário para assembleias gerais de acionistas de firmas norte-americanas. No segundo ensaio, eu procuro expandir a literatura existente ao avaliar a relação entre o grau de ocupação de analistas *sell-side* e o risco de *crash* de uma determinada ação. Alicerçando-se na literatura sobre conselheiros com participação em múltiplas diretorias, eu argumento que a relação entre o grau de ocupação de analistas e o risco de *crash* reflete o efeito líquido de duas perspectivas opostas: *Busyness* e *Networking*.

Keywords: Risco de *crash*, Assembleias gerais de acionistas evasivas, Analistas financeiros.

SUMÁRIO

1 A GENERAL INTRODUCTION

Since they have numerous incentives to maximize investors' perception of a company's value theoretically reflected in the share price, managers can hoard bad news as long as possible as a way of not harming their career or their executive compensation, for example (Kim et al., 2019a; Park and Jung, 2017). When this accumulation of bad news reaches a critical level and the cost of keeping it covered becomes extreme, managers choose to make it public. This dissemination of accumulated bad news alters the perception of firms' fundamentals and tends to generate long left tails in the stock returns distribution. In other words, it tends to generate stock price crashes. Given the relevance that crashes play in financial markets, there is a growing interest, especially after Jin and Myers (2006), in understanding stock price crash risk. Stock price crash risk, or firm-specific crash risk, refers to the probability of observing extremely negative returns for a given stock, even after controlling for systemic risk. In this dissertation, I extend the literature by investigating two unexplored questions.

Are evasive firms associated with higher stock price crash risk? In my first essay, "Evasive shareholder meetings, meeting announcement lag, and stock price crash risk", I empirically investigate the unexplored relationship between evasive shareholder meetings and stock price crash risk. I argue that evasive shareholder meetings could increase crash risk via two non-mutually exclusive potential mechanisms, namely *Deterrence* and *Attention*. Additionally, I investigate if firms strategically announce annual general meetings closer to event dates as an evasiveness mechanism.

Using hand-collected data on annual shareholder meeting scheduling' characteristics for 9,086 meetings held by 1,486 public U.S. firms between 2012 and 2020, I fail to find evidence consistent with my *deterrence hypothesis*. I initially find a puzzling strong negative relationship between evasive timing-based strategies and crash risk. However, this puzzling negative relationship disappears in alternative empirical specifications. I also find no evidence that firms are strategically announcing meetings closer to annual meeting dates to withhold bad news from investors. Collectively, I find no evidence that evasive shareholder meetings practices (distance-based or timing-based) affect future stock price crash risk.

Are busy analysts less effective monitors? In my second essay, "Are busy analysts detrimental? Evidence from stock price crash risk", I empirically investigate the relationship between firm-level analyst busyness and stock price crash risk. On the one hand, sell-side analysts' busyness could facilitate bad news hoarding due to poor monitoring. On the other hand, busy analysts are more likely to enjoy benefits from a wider network of contacts. To test these two competing views, namely *Busyness* and *Networking*, I use a large sample of U.S. firms from 2000 to 2021 (35,526 firm-year observations). I argue that the relationship between firm-level analyst busyness and stock price crash risk reflects the net effect of these two opposing perspectives.

I find that firms followed by analysts with larger portfolios (based on the number of firms followed) and by analysts with a high average number of reports issuance are associated with higher stock price crash risk. However, in my baseline results, I fail to find evidence of a statistically significant relationship between the average number of industries covered and stock price crash risk. My further analysis shows that the positive relation between firm-level analyst busyness and crash risk is more pronounced for firms with higher information asymmetry. Overall, these findings provide support to the notion that firm-level analyst busyness appears to deteriorate firm monitoring, increasing bad news hoarding.

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2 EVASIVE SHAREHOLDER MEETINGS, MEETING ANNOUNCEMENT LAG, AND STOCK PRICE CRASH RISK

Abstract

I investigate the relationship between evasive shareholder meetings and stock price crash risk. Using hand-collected data on annual shareholder meeting scheduling characteristics for 9,086 meetings held by 1,486 public U.S. firms between 2012 and 2020, I fail to find evidence consistent with managers deterring shareholders and stakeholders' attendance at meetings to hoard bad news (i.e., my *deterrence hypothesis*). Nonetheless, I initially find a puzzling strong negative relationship between evasive timing strategies and stock price crash risk. However, in robustness checks, this effect virtually disappears. I also find no evidence that firms are strategically announcing meetings closer to annual meeting dates to withhold bad news from investors. To alleviate a potential self-selection bias, I employ an entropy balance approach. Collectively, I find no evidence that evasive shareholder meetings practices (distance-based or timing-based) affect future stock price crash risk.

Keywords: Evasive shareholder meetings, Crash Risk, Annual meetings

JEL Codes: G12, G30, M40.

2.1 Introduction

Shareholders and stakeholders rely on a variety of corporate communication channels to interact with firm management, such as earnings conference calls, analyst days, investor days, broker-hosted investors conferences, and annual shareholder meetings (Kirk and Markov, 2016; Price et al., 2012; Li and Yermack, 2016). Researchers have only recently begun to focus on specific, and seemingly important, peculiarity of these interactions: *evasiveness*, or the strategic evasion from potential firm monitoring through events' location and scheduling characteristics (Li and Yermack, 2016; Gam et al., 2021). Li and Yermack (2016) find that companies tend to underperform market benchmarks over six months after scheduling annual shareholder meetings in remote locations (i.e., away from firm's headquarters), suggesting that managers strategically schedule meetings when they possess adverse information about future firm performance. More recently, Gam et al. (2021) show that a firm is more likely to commit corporate fraud when scheduling the annual shareholders meeting on certain busy dates to avoid attention, supporting the Li and Yermack (2016)' suppression of bad news view of evasiveness.

This sparse (and unique) evidence on evasive shareholder meetings illustrates how little we know about its impacts on corporate outcomes. To shed light on this incipient debate, I investigate the relationship between evasive shareholder meetings and stock price crash risk. Crash risk refers to the likelihood of observing extreme negative in firm-specific return distributions, that is, the likelihood of stock price crashes (Hutton et al., 2009; Jin and Myers, 2006; Chen et al., 2001). Given the devastating effects of stock price crashes on investor welfare, and its important implications in the fields of asset pricing and risk management, the topic has attracted the attention of academics, practitioners and policy-makers (Callen and Fang, 2015a; Kim and Zhang, 2016; Xu et al., 2013). The last decade has witnessed a plethora of studies of stock price crash risk' determinants.

Stock price crash risk literature is largely based upon the agency theoretical framework of Jin and Myers (2006), also defined as the bad news hoarding framework, which suggest that crashes are caused by the existence of information asymmetries between firms' insiders and outsiders. Under Jin and Myers (2006)' bad news hoarding framework, managers have incentives (e.g., compensation, career concerns) to withhold bad news from investors for extended periods. However, when the accumulation of bad news reaches a critical threshold level, managers have to give up and release accumulated bad news all at once, leading to abrupt, large declines in stock prices (Jin and Myers, 2006). Empirical evidence supports the view that managers tend to systematically withhold bad news (Kothari et al., 2009). Whether evasive shareholder meetings could affect stock price crash risk, and what are the potential mechanisms underlying this relationship, is unclear, *ex ante*.

Previous literature has suggested a possible nexus between different investor communication' choices and stock price crash risk. In more "traditional" (paper-based) corporate disclosure' channels, accruals-based earnings management, real-activity earnings management and earnings smoothing has been shown to increase stock price crash risk by increasing bad news hoarding (Khurana et al., 2018; Hutton et al., 2009; Francis et al., 2016; Chen et al., 2017), while accounting conservatism has been shown to mitigate bad news hoarding (Kim and Zhang, 2016). Both Ertugrul et al. (2017) and Kim et al. (2019a) find a greater likelihood of stock price crashes among firms with less readable 10-Ks filings due increased opacity.

Beyond financial reporting mechanisms, Firth et al. (2019) show reduced bad news hoarding among more accessible firms. Firth et al. (2019) argue that accessibility reduces stock price crash risk by increasing private communications between firms and investors through in-house visits, private meetings or investor days, for example. Empirical evidence on the relationship between corporate site visits and stock price crash risk show that crash risk increases with site visits. (Gao et al., 2017) find a positive relation between institutional investors' site visits and crash risk, while (Lu et al., 2018) find a positive relation between general (e.g., individuals, investment management companies) corporate site visits and crash risk.

I conjecture a positive relationship between evasive shareholder meetings and stock price crash risk through two not necessarily mutually exclusive channels which, for lack of better terms, I call *deterrence* and *attention*. First, previous evidence suggests that managers move annual shareholders' meetings to remote locations to discourage scrutiny, imposing additional constraints (e.g., geographical, financial) to analysts, investors, and media. If managers successfully avoid monitoring by strategically scheduling annual shareholders' meetings in remote locations, managers may withhold bad news longer than non-evasive or less evasive firms. Second, since attention is a scarce resource and it is physically impossible for some monitors to attend overlapping events, managers may rely on timing' strategies to shift attention away from annual meetings, which, in turn, deteriorate monitoring quality, increasing managers' capabilities to withhold bad news. In both cases, when the long run of bad news accumulates to a critical threshold, accumulated bad news is released all at once, leading to a firm-specific stock crash.

I test the above conjecture using hand-collected data on annual shareholder meetings scheduling' characteristics for 9,086 meetings held by 1,486 public U.S. firms between 2012 and 2020. Based on prior research (Li and Yermack, 2016; Gam et al., 2021), I employ four distance-based and two timing-based proxies for evasive shareholder meetings. Distance-based proxies (*HEADQUARTERS*, *DISTANCE*, *REMOTE*, and *TRAVEL*) are mainly grounded on the distance between meeting locations and firm headquarters. Timing-based proxies (*CLUSTER* and *FIRST*) are mainly grounded on the concept of clustering, the scheduling of meetings on "busy" dates. Also following prior literature (Chen et al., 2001; Kim et al., 2011a), I employ three well-known proxies for stock price crash risk: the negative conditional firm-specific daily returns skewness (*NCSKEW*), the down-to-up volatility of firm-specific daily returns (*DUVOL*), and the number of crashes minus the number of jumps over the fiscal year (*COUNT*).

I fail to find evidence consistent with my *deterrence hypothesis*. I initially find a puzzling strong negative relationship between evasive shareholder meetings timing-based strategies and stock price crash risk. However, this effect disappears in alternative empirical specifications. In an additional analysis, I test if firms are strategically announcing their annual general meeting closer to event dates as a potential evasiveness mechanism but find no evidence consistent with this conjecture. Collectively, I find no evidence that evasive shareholder meetings are significantly associated with stock price crash risk. These findings seem to challenge the "hidden information hypothesis" proposed by Li and Yermack (2016), which argues that managers move annual shareholders meetings away from firm headquarters to suppress negative news for long as possible.

My contribution is threefold. First, this is first study to investigate the relationship between evasive shareholder meetings and stock price crash risk. To my knowledge, no empirical studies have addressed this relationship. Second, I contribute to the literature on evasive shareholder meetings and evasive management practices, an emerging field of research. By focusing on the effect of evasive shareholder meetings on the incidence of abrupt declines in stock prices (the third moment of the return distribution), I was able to investigate whether managers rely on evasive' annual shareholder meetings to systematically hoard bad news from investors, controlling for well-known factors that may increase or curb bad news hoarding behavior. This approach differs from the one used in Li and Yermack (2016) that focuses on mean cumulative abnormal stock returns (thus, the central tendency of the return distribution) and is based on a limited number of subsamples. Third, I extend the vast and fast-growing literature on stock price crash risk, broadening our understanding of the implications of evasive shareholder meetings on shareholders' wealth.

This paper proceeds as follows. Section 2.2 reviews prior literature on evasive shareholder meetings and stock price crash risk, and develops my research hypotheses. Section 2.3 describes data sources, sample, variable measurement and identification strategies. Section 2.4 reports empirical results. Section 2.5 addresses endogeneity issues. Section 2.6 concludes the paper.

2.2 Related literature and hypothesis development

2.2.1 Evasive shareholder meetings

Traditionally, annual shareholder meetings are mandatory face-to-face events that provide shareholders an opportunity to elect the board of directors, to vote on corporate governance proposals, and to express their concerns with corporate performance, executive compensation, and other related topics through Q&A (Questions-and-Answers) sessions, where they can use a microphone to ask unscripted questions to the management and the directors (Li and Yermack, 2016; Dimitrov and Jain, 2011)[1]. Despite not being legally mandatory in the U.S., few firms skip the Q&A session, and firms that do so may suffer heavy scrutiny. Dimitrov and Jain (2011) highlight the Home Depot case, in 2006, when the Home Depot's CEO decision to refuse to answer questions and skip the Q&A session faced heavy scrutiny. However, annual shareholder meetings are often viewed as old-fashioned, monotonous, largely pro forma events, with low shareholder attendance (Brochet et al., 2020; Li and Yermack, 2016). Using a sample of annual shareholders meetings held in the Netherlands, De Jong et al. (2006) find that these meetings do not provide shareholders any significant influence on management. Additionally, numerous studies find insignificant market reactions around shareholder meetings, supporting the anecdotes that annual meetings are irrelevant (Denes et al., 2017).

In contrast, Holland et al. (2021) argues that previous literature fails to find significant market reactions around shareholder meetings because investors constantly update their beliefs on meeting outcomes over a long horizon, in a way that short window stock return event studies cannot fully capture market reactions. Using option implied volatility to assess the information content of annual shareholder meetings, Holland et al. (2021) document that implied volatility gradually declines from record date for an annual meeting until the meeting date, suggesting that shareholders anticipate meeting outcomes. The gradual declines reflect the reduced uncertainty around meeting outcomes. Dimitrov and Jain (2011) find positive average cumulative abnormal returns during the forty days prior to the annual shareholder meeting date, suggesting that managers attempt to influence the market's perception about the firm and

[1]Due to COVID-19 pandemic, many firms were forced to hold virtual shareholder meetings in 2020 and 2021 (Brochet et al., 2020).

reduce shareholder discontent at the annual meeting through the opportunistic release of positive news. They also find that firms with poor past stock price performance tend to exhibit higher pre-meeting returns when shareholder scrutiny is likely to be higher, i.e., for firms with high institutional ownership, high CEO compensation, and more shareholder-sponsored proposals.

Assuming that firms are more likely to have investors concentrated in their local communities, and that local analysts outperform distant analysts, Li and Yermack (2016) introduce a new approach to evaluate the information content of annual shareholder meetings. Li and Yermack (2016) examine whether managers signal firms' future performance when strategically scheduling a meeting far away from firm's headquarters, since scheduling a meeting far away from the firm's headquarters provides an opportunity for managers to deter shareholders and stakeholders' attendance at these meetings. They find that firms that hold meetings far from headquarters underperform the market in the six months following the evasive shareholder meeting[2]. Overall, these findings are consistent with the idea that managers strategically schedule evasive shareholder meetings to hide bad news from investors and stakeholders, as a way to prevent scrutiny by reducing attendance. Therefore, according to Li and Yermack (2016), an evasive shareholder meeting can be used as a proxy for the evasiveness of management.

Using managers decisions' to hold an annual shareholder meeting on busy dates as a proxy for the evasiveness of management, Gam et al. (2021) examine whether evasive shareholder meetings increase the likelihood of committing corporate fraud. Unlike Li and Yermack (2016), Gam et al. (2021) emphasize timing particularities of annual shareholder meetings, instead of location, as a way to assess evasive management practices. They find that a sudden change in corporate policy to hold an annual shareholder meeting on a busy date is associated with a greater likelihood of committing corporate fraud. They also find that this relationship is exacerbated for firms that hold annual shareholder meetings far away from firms' headquarters and whose meetings' agendas include audit election or dismissal, and for firms managed by professional CEOs, i.e., when the CEO is a hired CEO.

2.2.2 Stock price crash risk

Stock price crash risk refers to the likelihood of stock price crashes - sudden, abrupt but infrequent large stock price decreases (Jin and Myers, 2006; Hutton et al., 2009). Crash risk is also understood as the conditional skewness, i.e., the third moment, of the return distribution (Chen et al., 2001). While the first and the second moments are the mean (central tendency) and variance (deviation) of the return distribution, respectively, the third moment (conditional skewness) captures the return distribution's asymmetry – a distribution skewed to left indicates a negative skewness (increasing the frequency of

[2]Specifically, Li and Yermack (2016) examine the mean cumulative abnormal returns for four subsamples: firms with annual meetings held in firm's headquarters, firms with annual shareholders meetings held 1 to 10 miles away from firm's headquarters, firms with annual meetings held 10 to 100 miles away from firm's headquarters and, lastly, firms with annual meetings held more than 100 miles away from firm's headquarters. Six months after the annual shareholder meeting, the first, second, third, and fourth subsample experienced an underperformance of approximately 2.5%, 4%, 4.5%, and 6.5%, respectively, apparently worsening with distance increases.

extreme negative returns), and a distribution skewed to right indicates a positive skewness (decreasing the frequency of extreme negative returns).

Anecdotal and empirical evidence show that crashes plays a key role on investor welfare, portfolio management and asset pricing. Firm-specific stock crashes often make financial media headlines[3] and such sudden decline of stock prices could be devastating for investors, as an extreme collapse in stock prices could significantly destroy shareholders' wealth, imposing losses (Li and Zeng, 2019; Dang et al., 2018). Anecdotal evidence, such as the collapse of Enron Corporation, illustrates how crashes could be a serious concern for investors. Many Enron's employees were also Enron's shareholders, and when the company shares plunged from more than $90 per share to almost $0, many saw investment accounts totally destroyed. Hutton et al. (2009) argue that the importance of left tails in portfolio management and risk management is reflected in the interest of investors and portfolio managers in tail risk measures, such as value at-risk, and the effect of (negative) skewness on pricing and implied volatility in options markets. Empirically, Harvey and Siddique (2000) find that conditional skewness is a priced-risk factor in the cross-section of stock returns, indicating that investors demand a higher risk premium for more crash-prone stocks.

There are two main streams of research in the literature that explain stock price crash risk through two different perspectives: the market mechanisms and participants framework and the management bad news hoarding framework. Earlier literature based on financial market mechanisms and market participants framework posits that crashes derive from broad financial market mechanisms, such as volatility feedback and stochastic bubbles (Kim et al., 2016b), or from market participants' characteristics (Chen et al., 2001; Hong and Stein, 2003). Hong and Stein (2003) theoretical model suggests that differences of opinion among investors plays a relevant role in explaining why some stocks are more likely to crash. They argue that short-sale constraints keep bearish investors partially out of markets when disagreement among investors is large, keeping fundamental information away from stock prices, inflating price bubbles. Chen et al. (2001) provides empirical support for Hong and Stein (2003) model, by showing a positive relationship between differences of opinion among investors and crash risk.

In contrast, a large part of the recent literature is encapsulated in the bad news hoarding theoretical framework presented by Jin and Myers (2006). Their theoretical analysis uses the agency theory to provide a link between bad news hoarding and stock price crash risk, suggesting that agency conflicts between management and shareholders promote bad news hoarding since an opaque information environment allows self-interested corporate managers to better capture a firm's operating cash flows through ways not perceived by shareholders (Jin and Myers, 2006; Kubick and Lockhart, 2021). However, when the accumulation of bad news reaches a critical point, i.e., when it becomes too costly or infeasible to hoard more negative information, the accumulated bad news is released all at once, triggering a stock

[3] E.g., "DiDi shares crash as China tightens the regulatory screws", *CNN*, July 6, 2021, "Shares in China's Evergrande plunge again as fears of contagion grow", *The Guardian*, September 20, 2021.

crash. Hutton et al. (2009) provide empirical evidence consistent with this argument, by showing that opaque firms are more crash-prone than non-opaque firms. Additionally, this argument is in line with Kothari et al. (2009), who show that managers have a tendency to delay disclosure of bad news relative to good news.

Incentives to withhold bad news, which, in turn, should increase crash risk, stem from a variety of sources, such as compensation (Kim et al., 2011a) and career concerns (Kubick and Lockhart, 2021). For instance, Kim et al. (2011a) find a positive relation between chief financial officer's (CFO) option portfolio sensitivity on the market value of equity and a one-year ahead stock price crash risk. Kubick and Lockhart (2021) findings suggest that managerial labor market incentives increase bad news hoarding and, consequently, crash risk. The vast and growing crash risk literature that has focused on identifying crash risk potential determinants, based on Jin and Myers (2006) framework, has shown how firm-level, management-level, market-level, and institutional-level characteristics can increase or mitigate crash risk (Habib et al., 2018)[4].

Most studies at the firm-level examine how financial reporting quality and disclosure attributes are associated with crash risk. The main underlying rationale is how the decrease (increase) of information transparency could increase (decrease) crash risk by enabling the managerial ability and opportunities to hide and accumulate bad news. Kim et al. (2011b) find that tax avoidance is positively associated with crash risk. Hutton et al. (2009) and Francis et al. (2016) findings suggest a greater likelihood of stock crashes among firms that engage in accrual-based and real-activities earnings management. Chen et al. (2017) show that earnings smoothness is associated with higher crash risk. Kim et al. (2019a) and Ertugrul et al. (2017) find that less readable 10-Ks fillings are associated with higher crash risk. Kim and Zhang (2016) find that accounting conservatism is associated with a lower likelihood of stock price crashes, curbing bad news hoarding behavior.

At the management-level, most prior research focus on understanding how CEOs and CFOs personal traits and characteristics affect stock price crash risk. The traits examined include CEO and/or CFOs overconfidence (Kim et al., 2016b; Lee et al., 2019), power (Al Mamun et al., 2020; Shahab et al., 2020; Harper et al., 2020), trustworthiness (Gu et al., 2020), age (Andreou et al., 2017), gender (Li and Zeng, 2019), political orientation (Chen et al., 2020), cultural background (Fu and Zhang, 2019), and early-life experience (Long et al., 2020). Additionally, some studies focus on the relation between crash risk and board and directors' characteristics, such as reforms (Hu et al., 2020), hierarchy (Jebran et al., 2019), board diversity (Jebran et al., 2020), coalition (Xu et al., 2020a), director's and officers' liability insurance (Yuan et al., 2016), and director's foreign experience (Cao et al., 2019) and external social networks (Fang et al., 2021).

[4] Habib et al. (2018) synthesize the literature into five groups: i) financial reporting and corporate disclosures; ii) managerial incentives and managerial characteristics; iii) capital market transactions; iv) corporate governance mechanisms, and; v) informal institutional mechanisms.

At the market-level, studies are heterogeneous. Following the well documented idea that institutional and large shareholders have greater incentives to monitor management since they extract greater benefits from monitoring than smaller retail investors, several studies have shown that institutional and large investors' characteristics may increase (or mitigate) stock price crash risk by allowing or reducing managers ability to hoard bad news. Investors' characteristics examined include institutional investor stability (Callen and Fang, 2013), institutional investor attention (Ni et al., 2020; Xiang et al., 2020), and information interaction among large shareholders (Li et al., 2021). The role of financial analysts has also been a topic of interest among market-level determinants of crash risk, with mixed results. While Kim et al. (2019b) conclude that financial analysts are perceived in the options market as relevant external monitors by documenting that a reduction in analyst coverage increases expected crash risk, Xu et al. (2013) show that an increase in analyst coverage increases stock price crash risk through optimistic earnings forecasts, which hinder the reveal of bad news in a timely way to the market. Finally, some studies suggest that short sellers, as sophisticated investors, play a relevant role in monitoring and curbing bad news hoarding behavior (Callen and Fang, 2015b; Ni and Zhu, 2016; Deng et al., 2020).

A smaller fraction of the literature on crash risk examines how institutions (both informal and formal) could explain stock price crash risk. Callen and Fang (2015a) find that U.S. firms headquartered in counties with higher religiosity levels face lower stock price crash risk. Similarly, Li and Cai (2016) show that Chinese firms registered in areas with higher levels of religiosity exhibit lower crash risk. Cao et al. (2016) and Li et al. (2017) find that Chinese firms headquartered in regions of high social trust tend to exhibit lower crash risk levels. Some more specific traits, as attitudes towards gambling and superstitious beliefs, increases crash risk. Ji et al. (2021) provide evidence that firms located in gambling-prone regions are more likely to experience a higher crash risk. Bai et al. (2020) find that firms with unlucky ticker symbols have higher stock price crash risk, showing the role of superstition. Overall, these findings suggest how social/moral norms and cultural forces (informal institutions) could curb (increase) opportunistic managerial behavior.

In contrast, analyzing changes in laws, other studies find a relationship between shareholders rights, takeover protection, and crash risk (Bhargava et al., 2017; Obaydin et al., 2021). Using the staggered adoption of universal demand laws in some U.S. states, Obaydin et al. (2021) examined the impact of the reduction in shareholders' litigation rights on crash risk. They find that lower shareholder litigation rights increase crash risk. Using the passage of state antitakeover laws in the U.S., Bhargava et al. (2017) suggest a negative relationship between takeover protection and crash risk. Overall, evidence suggests that both informal and formal institutions affect stock price crash risk to a certain degree.

2.2.3 Hypotheses development

Institutional investors, retail investors, activist shareholders, media and analysts could unveil bad news through annual shareholders meetings by directly inquiring managers and firms' representatives about firms' operations and activities (Li and Yermack, 2016; Han et al., 2018). Annual shareholders meetings, unlike 10-Ks and other regulatory filings, allow shareholders to ask unscripted questions through an open microphone period (Li and Yermack, 2016; Carrington and Johed, 2007). By moving annual shareholder meetings to a remote location, i.e., extremely distant from firm headquarters (HQ), managers impose additional monitoring costs, deterring potential firm monitoring. Lower attendances levels and, consequently, less scrutiny, would increase managerial capabilities and incentives to withhold bad news, due to poorer monitoring. This can consequently increase the stock price crash risk of firms strategically scheduling annual shareholder meetings' location for evasiveness. Contrarily, bad news is less likely to be accumulated in less evasive firms. I call this *deterrence hypothesis*[5].

Hypothesis 1. All else being equal, firms' choice to hold annual shareholders meetings away from firms' headquarters is positively associated with stock price crash risk.

In addition, previous literature suggests that managers attempt to hide bad news by opportunistically timing the disclosure of earnings announcements or annual reports (DeHaan et al., 2015; Li et al., 2020b). For example, Li et al. (2020b) investigate whether firms conceal bad news by disclosing annual reports during periods of reduced market attention and find that firms strategically timing the disclosure of their annual reports have greater stock price crash risk. Because attention is a scarce cognitive resource and it is physically impossible for media, institutional investors (with limited professionals), activist shareholders and retail investors to attend annual shareholders meetings simultaneously, it is possible that managers may strategically schedule annual shareholder meetings on busy dates, i.e., when many firms' annual shareholders' meetings overlap, to evade potential external monitoring (Gam et al., 2021; Kahneman, 1973). Looser monitoring due to lower attention would increase managerial capabilities to withhold bad news, thus increasing stock price crash risk. I call this *attention hypothesis*[6].

Hypothesis 2. All else being equal, firms' choice to schedule annual shareholders meetings on busy days is positively associated with stock price crash risk.

[5] I test this hypothesis using the distance between meetings and firms' headquarters locations as a proxy for the evasiveness of management.

[6] I test this hypothesis using meetings timing' decisions as a proxy for the evasiveness of management. It is important to note that I do not discuss, in this paper, an alternative explanation of the relationship between evasiveness of management and stock price crash risk. Based on prior studies (Denes et al., 2017; De Jong et al., 2006), one could argue that the information flow between management and institutional investors, retail investors, analysts and media through annual shareholders meetings is irrelevant. If the information flow is irrelevant and I find a positive significant relationship between the evasiveness of management and stock price crash risk, my results may be driven by signalling. Evasive shareholder meetings may function only as a "signal" of evasiveness, signalling a "last resort" in the search for evasiveness by firm' management. In this explanation, a firms' decision to schedule an evasive meeting is likely to be associated with previous, and perhaps unobservable, attempts to adopt lesser extreme mechanisms to avoid scrutiny.

2.3 Data and methodology

2.3.1 Data sources and sample

My initial sample comprise U.S. firms that are listed, headquartered and incorporated in the United States between 2012–2020[7]. Using a sample of U.S. headquartered and incorporated firms is necessary to calculate the distance between firm headquarters and annual shareholders meeting locations, one of my evasiveness' measures, through *zipcodeR* package[8], built based on a 5-digit ZIP code format. Financial institutions (Standard Industrial Classification [SIC] codes from 6000 to 6999) and utilities companies (Standard Industrial Classification [SIC] codes from 4000-4999) are excluded from my initial sample, following the convention. To mitigate the impact of extreme outliers, I winsorize continuous variables at the 1% level in both tails.

I obtain data on annual shareholders meetings scheduling characteristics, such as shareholder meetings locations, dates, and times, by downloading proxy statements (SEC DEF 14A) distributed specifically to announce annual shareholder meetings from the Electronic Data Gathering, Analysis and Retrieval (*EDGAR*) system[9]. I read downloaded forms to find annual meeting scheduling characteristics. In some specific cases, the annual meeting location address is disclosed incompletely, with missing ZIP code information. In these cases, I retrieve ZIP code data from United States Postal Service (*USPS*) *ZIP Code™ Lookup* platform[10]. I retrieve firm-level annual accounting data and other data on firm characteristics, including headquarters ZIP codes[11], from *COMPUSTAT*. To compute stock price crash risk measures and some control variables, I use daily (and monthly) stock data from Center for Research in Security Prices (*CRSP*).

2.3.2 Crash risk measures

Following existing literature (e.g., Azevedo et al., 2023; Kim et al., 2011a), I employ three measures of well-known *ex post*[12] firm-specific stock price crash risk measures: the negative conditional firm-specific daily returns skewness (*NCSKEW*), the down-to-up volatility of firm-specific daily returns (*DUVOL*), and the number of crashes minus the number of jumps over the fiscal year (*COUNT*). Also following previous literature, to ensure that my three stock price crash risk measures represent only firm-specific factors rather than general market conditions and economic shocks, such as the 2020 stock market crash or the 2007-2008 Global Financial Crisis, these three measures are based on firm-specific daily returns.

[7] My sample begin in 2012, one year after the changes promoted by the Dodd-Frank Wall Street Reform and Consumer Protection Act on shareholder meetings (Li and Yermack, 2016). Public health restrictions (e.g., social distance measures and lockdowns) due to COVID-19 resulted in canceled corporate in-person events, forcing some firms to adopt a virtual format after 2019 (Brochet et al., 2020), reducing the number of observations for 2020.

[8] https://cran.r-project.org/web/packages/zipcodeR/index.html

[9] Unlike Li and Yermack (2016), I do not obtain data on special shareholder meetings.

[10] https://tools.usps.com/zip-code-lookup.htm

[11] In my empirical analyses I use headquarters addresses from DEF 14-A forms, allowing me to capture potential changes in company headquarters locations over the years.

[12] *Ex post* crash risk measures are based on the realized distributions of returns (i.e., historical crash risk), while *ex ante* crash risk measures are based on the crash risk perceived by investors (i.e., expected crash risk) (Kim and Zhang, 2014).

To calculate my stock price crash risk measures, I first obtain the firm-specific residual daily returns from the following model, estimated for each firm in each year, based on Kim et al. (2011a).

$$r_{i,t} = \beta_0 + \beta_1 r_{mkt,t-2} + \beta_1 r_{mkt,t-1} + \beta_3 r_{mkt,t} + \beta_5 r_{mkt,t+1} + \beta_1 r_{mkt,t+2} + \varepsilon_{i,t} \tag{2.1}$$

$r_{i,t}$ is the return on stock i in day t. $r_{mkt,t}$ is the CRSP value-weighted[13] market index return in day t. I employ $r_{mkt,t}$ leads and lags terms to correct for potential nonsynchronous trading (Kim et al., 2011a). The firm-specific daily stock return ($W_{i,t}$) is calculated as $ln(1 + \varepsilon_{i,t})$, where $\varepsilon_{i,t}$ is the residual obtained from Equation 3.1.

My first crash risk measure is the conditional firm-specific daily returns skewness - *NCSKEW*. *NCSKEW* is calculated as the negative of the third central moment of the firm-specific daily returns over a year, normalized by the standard deviation of the firm-specific daily returns (sample variance) raised to the third power (Chen et al., 2001; Kim et al., 2011a). Precisely, I calculate *NCSKEW* as:

$$NCSKEW_{i,t} = -\left[n(n-1)^{\frac{3}{2}} \sum W_{i,t}^3\right] / \left[(n-1)(n-2)\left(\sum W_{i,t}^2\right)^{3/2}\right] \tag{2.2}$$

n is the number of daily returns over a year t. As I employ the absolute value, multiplying the construct by negative one, a higher *NCSKEW* value indicates a higher stock price crash risk.

The second crash risk measure is the down-to-up volatility of firm-specific daily returns (*DUVOL*). For each firm i in a given year t, the firm-specific daily returns are classified into two groups: "*Down*", when the returns are below the annual average, and "*Up*", when the return are above the annual average. I then calculate the standard deviation of firm-specific daily returns separately for each of these two groups ("*Down*" days and "*Up*" days). *DUVOL* is calculated as the natural logarithm of ratio between the standard deviation in "*Down*" to the standard deviation of "*Up*" (Chen et al., 2001; Kim et al., 2011a). Specifically:

$$DUVOL_{i,t} = \log\left\{(n_b - 1)\sum_{Down} W_{i,t}^2 / (n_a - 1)\sum_{Up} W_{i,t}^2\right\} \tag{2.3}$$

n_b and n_a represents the number of "*Up*" and "*Down*" days, respectively, over a year t. A higher *DUVOL* indicates a higher stock price crash risk.

Based on Kim et al. (2011b), The third crash risk measure is the number of crashes minus the number of jumps over the fiscal year (*COUNT*). A crash (jump) occurs when the firm-specific daily return is 3.09 standard deviations below (above) its mean over the fiscal year.

2.3.3 Evasive shareholder meetings

I construct two classes of evasive shareholder meeting measures based on two dimensions - distance (i.e., annual shareholders meeting and HQ locations) and scheduling (i.e., annual shareholders meeting timing),

[13] My results remain qualitatively unchanged when I use CRSP equal-weighted as market index.

following previous studies that take into account annual meetings' distance and scheduling characteristics to assess whether a firm is trying to discourage shareholders and stakeholders' scrutiny (Li and Yermack, 2016; Gam et al., 2021). I employ distance-based measures to test my *deterrence hypothesis* and timing-based measures to test my *attention hypothesis*.

2.3.3.1 Distance-based measures

I construct four distance-based measures of evasive shareholder meetings based upon Li and Yermack (2016) and Gam et al. (2021). My first proxy, *HEADQUARTERS*, is an indicator variable that equals one if the annual meeting takes place at the company's headquarters in a given year and zero otherwise. *DISTANCE* is my second proxy for evasive shareholder meetings. *DISTANCE* is the natural logarithm of one plus the distance, in miles, between company headquarters and the annual meeting location, based upon ZIP code data. My third proxy, *REMOTE*, is an indicator variable that equals one if the annual shareholder meeting takes place at a remote location. Following Li and Yermack (2016), I define an annual shareholder meeting as remote if it takes place 50 miles (approximately 80,46 kilometers) away from company headquarters and also more than 50 miles away from a large hub airport[14]. Federal Aviation Administration (FAA) defines an airport as a large hub airport if it receives 1% or more of the annual U.S. commercial enplanements, i.e., annual passenger boardings.

TRAVEL, my fourth evasive shareholder meeting proxy, relies on estimated travel time between firm headquarters and annual shareholders meeting location. I estimate travel time in a way similar to that suggested by Li and Yermack (2016). When a meeting is located on firm headquarters or less than a mile away (about 1,61 kilometer), I assume a travel time of 0.05 hour (3 minutes). When a meeting is located 1 to 2 miles (3,22 kilometers) away from firm HQ, I assume a travel time of 0.10 hour (6 minutes). For distances longer than 2 miles and lower than or equal 250 miles (about 402 kilometers), I use driving time calculations from Google Maps to estimate travel time. I hand-collect driving time calculations data from Google Maps.

A more sophisticated way is adopted to determine the travel time when an annual meeting is held in a distance longer than 250 miles away from company headquarters. In these cases, I compute travel time as the sum of: i) the estimated flight time between the nearest large hub airport closest to headquarters and the meeting location[15]; ii) the estimated Google Maps' driving time calculation from firm headquarters to the nearest airport and from the destination airport nearest to the meeting location and the annual meeting location, and; iii) 1.5 hour to take into account baggage claim, check-in, and logistics' time[16]. Finally, *TRAVEL* is the natural logarithm of travel time, in hours, from firm

[14] `https://airport.globefeed.com/US_Nearest_Airport.asp`. The IATA code of the nearest large airport is identified based upon the HQ and the annual meeting ZIP codes.

[15] `https://www.flighttimecalculator.org/`, based on firm headquarters and annual meeting nearest large airports IATA codes.

[16] For example, Chevron Corporation held its 2017 Annual Shareholder Meeting at Midland, Texas, 1189 miles away from Chevron's headquarters, located in San Ramon, California. The closest airport to Chevron's headquarters is the Oakland

headquarters to the meeting site based on these estimates.

It is important to note that *HEADQUARTERS*, *DISTANCE* and *TRAVEL* rely on the assumption that shareholders and stakeholders are located near firms' headquarters (Li and Yermack, 2016). On the other hand, *REMOTE* overcome this limitation by also taking into account the distance to large airports. For example, a Los Angeles-based company with an annual shareholder meeting in New York would not be considered evasive given its proximity to a large hub airport.

2.3.3.2 Timing-based measures

I construct two timing-based measures of evasive shareholder meetings based upon Gam et al. (2021), that consider the annual shareholder meeting's timing to detect evasive behavior by management. These measures rely on the concept of clustering - the strategically scheduling of annual shareholder meetings on busy ("popular") days. My first timing-based proxy, *CLUSTER*, is an indicator variable that equals one if a firm held their annual general meeting on clustering dates, and zero otherwise. *CLUSTER* allows me to better explore variations of clustering decisions by management. My second timing-based proxy, *FIRST*, is an indicator variable that equals one if a firm that never held their annual shareholder meeting on clustering dates in all previous years announced their annual meeting on clustering dates, and zero otherwise. Initially, I employ two different clustering dates thresholds - 1% and 2%. A clustering date threshold 1% (2%) implies that a date is considered busy when at least 1% (2%) of sample firms' annual shareholder meetings are scheduled to that date.

2.3.4 Firm-level control variables

I control for well-known determinants of stock price crash risk documented in prior literature (Chowdhury et al., 2020; Chang et al., 2017; Xu et al., 2020b; An et al., 2020). This set of control variables include changes in stock turnover (*DTURN*), average idiosyncratic daily return (*RET*), standard deviation of firm-specific daily returns (*SIGMA*), firm size (*SIZE*), calculated as the natural logarithm of total assets, firm performance (*ROA*), calculated as the ratio between income before extraordinary items and total assets, market-to-book ratio (*MTB*), calculated as the ratio between market value of equity and book value of equity, firm leverage (*LEV*), calculated as the ratio between total debt and total assets, R&D intensity (*R&D*), calculated as research and development expenditure scaled by total assets[17], and one-year lagged *NCSKEW*[18].

International Airport, while the closest airport to Chevron 2017 Annual Meeting location was the Midland International Airport. I estimate: i) a flight time of 2.86 hours between Oakland International Airport and the Midland International Airport; ii) 0.97 hour of driving time (26 minutes between Chevron HQ and Oakland airport and 32 minutes between Midland airport and the meeting location), and; iii) 1.5 hour. The estimated total travel time is 5.33 hours.

[17] Following previous studies, I set missing R&D spending to zero to avoid losing many observations (Lewis and Tan, 2016; Nguyen and Qiu, 2022; Huang and Ritter, 2009). R&D is missing for about 30% of firm-years.

[18] Regressing *NCSKEW* on one-year lagged *NCSKEW* will likely result in biased estimates (Keele and Kelly, 2006). For this reason, I do not include one-year lagged *NCSKEW* as a control variable when $NCSKEW_{t+1}$ is the dependent variable.

2.3.5 Model specification

To examine the relationship between evasive shareholder meetings and stock price crash risk, I estimate several specifications of the following baseline regression model:

$$CRASH_{i,t+1} = \alpha + \beta EVASIVE_{i,t} + \lambda' Firm_{i,t} + Year_t + Industry_j + \varepsilon_{i,t} \tag{2.4}$$

CRASH is a placeholder for stock price crash risk measures: *NCSKEW*, *DUVOL*, or *COUNT*, as detailed in Section 3.2.2. *EVASIVE* is a placeholder for distance-based measures (i.e., *HEADQUATERS, DISTANCE, REMOTE, or TRAVEL*) or timing-based measures (i.e., *FIRST or CLUSTER*) of evasive shareholder meetings, depending on which hypothesis is being tested, as detailed in Section 3.2.3. $\lambda' Firm$ is the set of one-year-lagged firm-level control variables for stock price crash risk specified in Section 3.2.4. I also control for year and industry (based on two-digit SIC codes) fixed effects, in all regressions, to capture the unobserved heterogeneity across industry and time. All variables are defined and detailed in Appendix A.

2.4 Results

2.4.1 Descriptive statistics

Table 2.1 presents the sample distribution by industry and year in Panel A and Panel B, respectively. Panel A shows that the most represented industry in my sample is Chemical & Allied Products (SIC = 28; 1,421 observations), followed by Business Services (SIC = 73; 1,289 observations) and Electronic & Other Electric Equipment (SIC = 36; 835 observations). Those three industries represent 39.02% of my sample. Panel B shows that the number of firm-year observations increases (decreases) from 2012 (2019) to 2019 (2020). A decrease from 2019 to 2020 was expected, since public health restrictions, such as social distance measures and lockdowns, resulted in canceled corporate in-person events, leading some firms to switch to virtual events.

Table 2.2 presents summary statistics for key variables used in my regression models from 2012 to 2020 for my sample firms. There are 9,086 firm-year observations, and all the continuous variables are winsorized at the top and bottom one-percentiles, following Xu et al. (2014). The mean (median) values of stock price crash risk measures $NCSKEW_{t+1}$, $DUVOL_{t+1}$, and $COUNT_{t+1}$ are 0.112 (−0.069), −0.002 (−0.035), and −0.216 (0.000), respectively. The mean value of *HEADQUARTERS* is 0.667, showing that most shareholder meetings (66.7%) take place in firms' headquarters, comparable with Li and Yermack (2016). The mean value of REMOTE is 0.010, suggesting that only 1% of shareholder meetings were held in a remote location[19]. The mean value of *DISTANCE* is 1.076, indicating that the

[19] In untabulated results, I employ a more restrictive threshold to define if an event is remote or not. Specifically, I consider a threshold of 25 miles instead of 50 miles. The results remain qualitatively similar.

Table 2.1. Sample distribution by industry and year

Panel A: Sample distribution by industry			
SIC Code	Industry	Obs.	Percentage
28	Chemical & Allied Products	1,421	15.64%
73	Business Services	1,289	14.19%
36	Electronic & Other Electric Equipment	835	9.19%
38	Instruments & Related Products	724	7.97%
35	Industrial Machinery & Equipment	571	6.28%
13	Oil & Gas Extraction	359	3.95%
37	Transportation Equipment	307	3.38%
20	Food & Kindred Products	288	3.17%
50	Wholesale Trade – Durable Goods	261	2.87%
80	Health Services	222	2.44%
87	Engineering & Management Services	208	2.29%
34	Fabricated Metal Products	204	2.25%
58	Eating & Drinking Places	179	1.97%
51	Wholesale Trade – Nondurable Goods	143	1.57%
56	Apparel & Accessory Stores	139	1.53%
33	Primary Metal Industries	134	1.47%
59	Miscellaneous Retail	133	1.46%
55	Automative Dealers & Service Stations	116	1.28%
15	General Building Contractors	107	1.18%
79	Amusement & Recreation Services	103	1.13%
23	Apparel & Other Textile Products	102	1.12%
30	Rubber & Miscellaneous Plastics Products	99	1.09%
-	Other	1,142	12.57%

Panel B: Sample distribution by year		
Year	Number of Obs.	Percentage
2012	842	9.27%
2013	906	9.97%
2014	956	10.52%
2015	963	10.60%
2016	1066	11.73%
2017	1142	12.57%
2018	1186	13.05%
2019	1244	13.69%
2020	781	8.60%

Notes. This table reports the number of observations per industry (based on two-digit SIC codes) and year.

mean log distance between a firm's headquarters and meeting location is 1.076, while the mean value for *TRAVEL*, the estimated travel time between a firm headquarters and the meeting location, is 0.051 hour (3.06 minutes). The mean values of *CLUSTER* at 1% and *CLUSTER* at 2% are 0.587 and 0.375, respectively, while the mean values of *FIRST* at 1% and *FIRST* at 2% are 0.675 and 0.520, respectively. The average firm in my sample has a natural logarithm of total assets of 15.939, a market-to-book ratio of 3.719, a leverage of 0.194, a return on assets of -0.040, a volatility of firm-specific daily returns over the fiscal-year period of 0.025, an average idiosyncratic daily return of −0.042, a R&D intensity of 0.067, and a detrended stock trading volume of 0.028.

Table 2.3 reports Pearson (Spearman) correlations below (above) the diagonal among all continuous variables. The three crash risk measures ($NCSKEW_{t+1}$, $DUVOL_{t+1}$, and $COUNT_{t+1}$) are highly correlated with each other. The Pearson (Spearman) correlation coefficient between $NCSKEW_{t+1}$ and

Table 2.2. Summary statistics

Panel A: Summary statistics						
Variables	Obs.	Mean	Std. Dev.	25th Pctl.	Median	75th Pctl.
Panel A.1.: Crash risk proxies						
$NCSKEW_{t+1}$	9,086	0.112	1.856	−0.761	−0.069	0.735
$DUVOL_{t+1}$	9,086	−0.002	0.507	−0.316	−0.035	0.274
$COUNT_{t+1}$	9,086	−0.216	1.784	−1	0	1
Panel A.2.: Distance-based evasiveness proxies						
HEADQUARTERS	9,086	0.667	0.471	0	1	1
REMOTE	9,086	0.010	0.098	0	0	0
DISTANCE	9,086	1.076	1.927	0.000	0.000	1.681
TRAVEL	9,086	0.051	0.008	0.050	0.050	0.050
Panel A.3.: Timing-based evasiveness proxies						
CLUSTER at 1%	9,086	0.587	0.492	0	1	1
CLUSTER at 2%	9,086	0.375	0.484	0	0	1
FIRST at 1%	9,086	0.675	0.469	0	1	1
FIRST at 2%	9,086	0.520	0.500	0	1	1
Panel A.4.: Firm-level control variables						
SIZE	9,086	15.939	2.098	14.481	16.034	17.364
MTB	9,086	3.719	6.905	1.400	2.396	4.229
LEV	9,086	0.194	0.191	0.00000	0.161	0.319
ROA	9,086	−0.040	0.271	−0.033	0.038	0.078
SIGMA	9,086	0.025	0.015	0.015	0.021	0.031
RET	9,086	−0.042	0.059	−0.048	−0.022	−0.011
R&D	9,086	0.067	0.141	0.000	0.008	0.072
DTURN	9,086	0.028	0.991	−0.301	−0.014	0.291
Panel A.5.: Other variables						
COMMIT	9,086	41.774	7.351	39	42	46

Notes. This table reports the summary statistics for the variables used in the baseline empirical analyses. My sample consists of 9,086 firm-year observations for 1,486 public U.S. firms over the period 2012-2020. All variables are defined in Appendix A. Continuous variables are winsorized at the 1st and 99th percentile to mitigate the effect of outliers.

$DUVOL_{t+1}$, $NCSKEW_{t+1}$ and $COUNT_{t+1}$, and $DUVOL_{t+1}$ and $COUNT_{t+1}$ are 0.926 (0.936), 0.533 (0.669), and 0.684 (0.724), respectively, indicating that these measures seem to be picking up the same construct, as suggested by Callen and Fang (2013).

Figure 2.1 presents the geographical distribution of annual shareholders' meetings in the United States, based on a choropleth map. The state of California hosted the highest number of meetings (1,796), followed by Texas (1,065), New York (847), Massachusetts (736), and Illinois (511), which together accounted for nearly 55% of all meetings in my sample. In contrast, states such as Montana, New Mexico, Wyoming, North Dakota, and Alaska had a significantly lower number of meetings, with West Virginia having none recorded in my sample. The *Delaware Hypothesis* suggests that firms may choose to hold meetings in Wilmington, Delaware, due to the state's favorable incorporation laws and tax benefits. However, in my sample of 9,086 meetings, only 25 were held in Delaware. The most distant event in my sample was held by Par Pacific Holdings, which is headquartered in Houston, Texas, and held its 2017 meeting in Honolulu, Hawaii, 3,892 miles (7,208 kilometers) away. For firms headquartered and whose annual meetings occur within conterminous states (48 adjoining states and the District of Columbia), the most distant event was held by Nuance Communications, which is headquartered in Burlington,

Table 2.3. Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) NCSKEW	1	0.936	0.669	0.009	-0.00002	0.137	0.091	0.016	0.104	-0.089	0.089	0.015	-0.029
(2) DUVOL	0.926	1	0.724	0.008	-0.002	0.175	0.120	0.023	0.135	-0.114	0.114	0.025	-0.041
(3) COUNT	0.533	0.684	1	0.001	-0.003	0.177	0.116	0.017	0.145	-0.129	0.129	0.012	-0.043
(4) DISTANCE	0.005	0.004	0.002	1	0.350	-0.020	0.002	0.046	-0.020	0.021	-0.021	-0.015	-0.006
(5) TRAVEL	-0.007	-0.005	0.001	0.559	1	0.006	-0.013	0.046	-0.030	-0.004	0.004	-0.014	-0.024
(6) SIZE	0.123	0.171	0.182	0.001	0.005	1	0.436	0.341	0.468	-0.699	0.699	-0.025	-0.128
(7) MTB	0.036	0.057	0.062	0.015	0.004	0.198	1	0.029	0.246	-0.240	0.239	0.033	0.219
(8) LEV	0.011	0.017	0.011	0.061	0.043	0.275	0.052	1	0.003	-0.220	0.221	0.017	-0.240
(9) ROA	0.057	0.103	0.121	-0.022	-0.004	0.397	-0.033	0.062	1	-0.571	0.571	-0.005	-0.307
(10) SIGMA	-0.094	-0.132	-0.145	0.022	0.006	-0.626	-0.049	-0.130	-0.593	1	-1.000	0.161	0.262
(11) RET	0.098	0.129	0.131	-0.033	-0.015	0.499	0.030	0.103	0.560	-0.941	1	-0.160	-0.263
(12) DTURN	0.003	0.012	0.004	-0.008	-0.014	-0.041	-0.004	0.008	-0.055	0.287	-0.343	1	0.007
(13) R&D	-0.016	-0.056	-0.067	-0.022	-0.028	-0.224	0.121	-0.149	-0.743	0.449	-0.409	0.036	1

Notes. This table reports correlations for the full sample. Pearson (Spearman) correlations are presented below (above) the diagonal. All variables are defined in Appendix A. Continuous variables are winsorized at the 1st and 99th percentile.

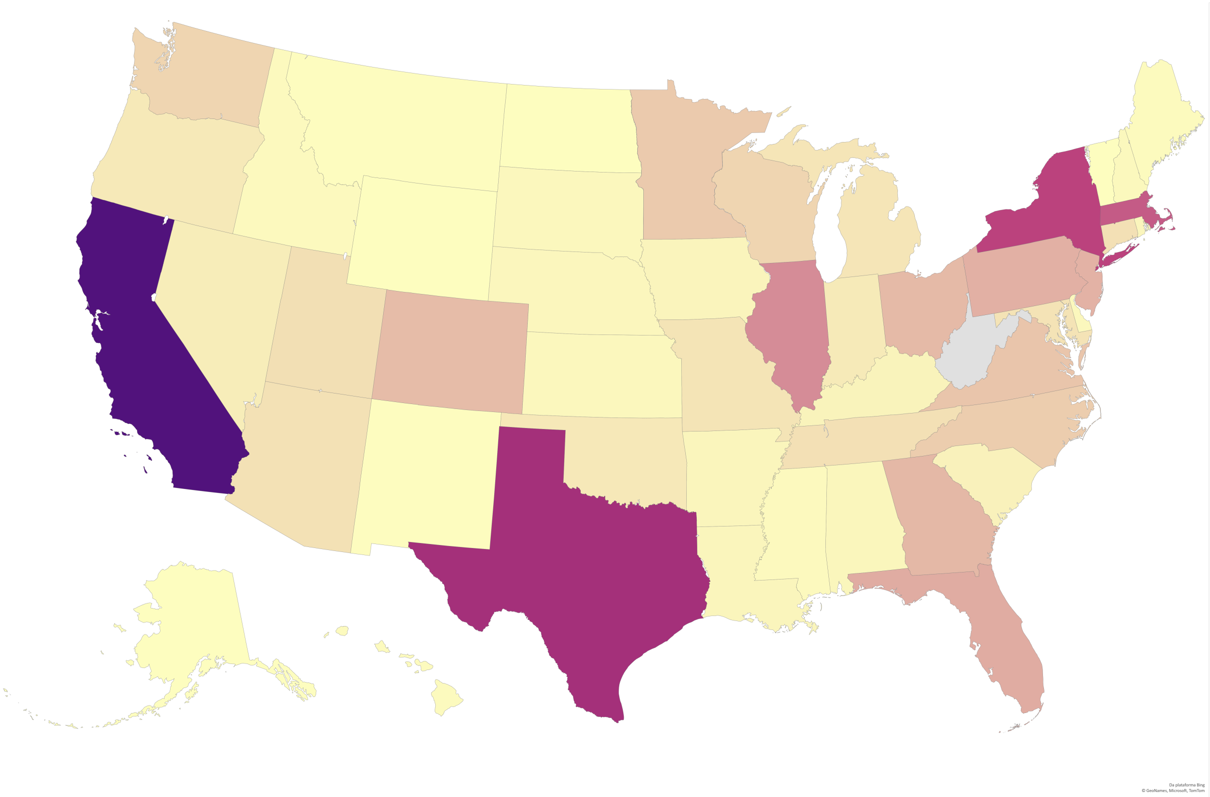

Figure 2.1. The Geography of Annual Shareholder Meetings

Notes. This figure shows the concentration of meetings by state using a choropleth map. Darker (lighter) tones indicates a greater (lower) number of meetings. None of the firms in my sample held meetings in unincorporated territories of the United States.

Massachusetts, and held its 2012 meeting in Sunnyvale, California, 2,681 miles (4,965 kilometers) away.

Figure 2.2 shows the dates of annual shareholder meetings between 2012 and 2020 for the firms in my sample. Most meetings are concentrated between May and July. The busiest day in my sample was May 22$^{\text{nd}}$, 2014, with 47 events taking place on the same day. This represents 4.9% of the 956 annual shareholders' meetings held in 2014. The annual shareholder meetings in my sample are more dispersed than those studied by Gam et al. (2021), who focused on the extreme case of clustering dates in South Korea. Gam et al. (2021) found that more than three-quarters of all firms in their sample scheduled their annual shareholder meetings on the three busiest dates[20].

2.4.2 Test of Hypothesis 1

Table 2.4 reports regression results of the relationship between distance-based measures of evasiveness and stock price crash risk, where stock price crash risk is proxied by negative conditional skewness ($NCSKEW_{t+1}$). Distance-based evasiveness is proxied by *HEADQUARTERS*, *DISTANCE*, *REMOTE*, and *TRAVEL* in columns (1), (2), (3), and (4), respectively. I control for a set of stock crash risk determinants (discussed in Section 2.3.5), industry, and year fixed effects. Coefficient estimates on *HEADQUARTERS* ($p = 0.243$, t-value = -1.167), *DISTANCE* ($p = 0.171$, t-value = 1.369), *REMOTE* ($p =$

[20] For this reason, I could not use the same thresholds employed by Gam et al. (2021). For instance, no particular day accounted for more than 5% or 10% of all meetings in a given year.

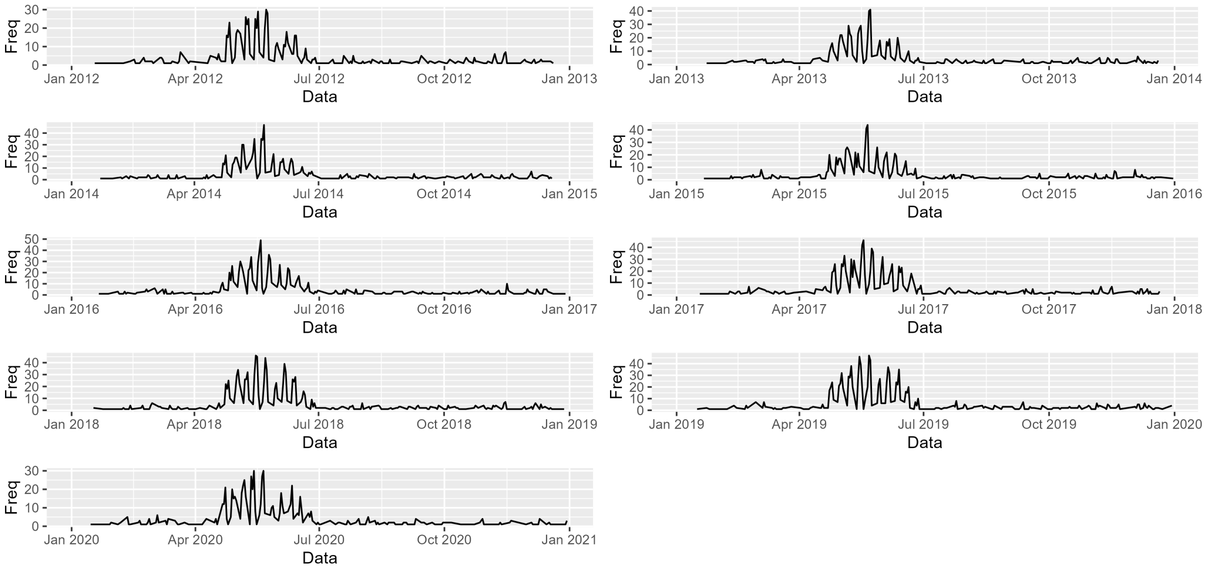

Figure 2.2. Dates of Annual Shareholder Meetings

Notes. This figure shows the dates concentration of 9,086 annual shareholders meetings between 2012 and 2020.

0.730, t-value = 0.345), and *TRAVEL* (p-value = 0.685, t-value = -0.406) are not statistically significant at the conventional levels.

Table 2.4. The effect of distance-based evasiveness on negative conditional skewness

	Dependent variable: NCSKEW$_{t+1}$			
	(1)	(2)	(3)	(4)
HEADQUARTERS	−0.048			
	(0.041)			
DISTANCE		0.014		
		(0.010)		
REMOTE			0.064	
			(0.185)	
TRAVEL				−0.916
				(2.255)
SIGMA	16.808***	16.961***	16.909***	16.851***
	(5.404)	(5.404)	(5.405)	(5.406)
RET	5.651***	5.686***	5.654***	5.637***
	(1.234)	(1.235)	(1.235)	(1.236)
ROA	0.059	0.059	0.054	0.052
	(0.132)	(0.133)	(0.133)	(0.133)
SIZE	0.111***	0.111***	0.111***	0.111***
	(0.014)	(0.014)	(0.014)	(0.014)
MTB	0.002	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
LEV	−0.157	−0.160	−0.152	−0.151
	(0.117)	(0.117)	(0.117)	(0.117)
DTURN	0.054**	0.054**	0.053**	0.053**
	(0.024)	(0.024)	(0.024)	(0.024)
R&D	0.193	0.200	0.184	0.177
	(0.275)	(0.275)	(0.274)	(0.274)
Constant	−1.543***	−1.605***	−1.581***	−1.526***
	(0.320)	(0.318)	(0.318)	(0.342)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.030	0.030	0.029	0.029
F Statistic	5.266***	5.274***	5.247***	5.248***
Observations	9,086	9,086	9,086	9,086

Notes. This table presents the regression results of the effect of distance-based measures of evasiveness on stock price crash risk. The dependent variable, crash risk, is proxied by negative conditional skewness (*NCSKEW*) in year $t+1$. In Column (1) distance-based evasiveness is proxied by an indicator variable (*HEADQUARTERS*) that takes one if the annual meeting takes place at company headquarters in a given year and zero otherwise. In Column (2) distance-based evasiveness is proxied by the natural logarithm of one plus the distance, in miles, between company headquarters and the annual meeting location (*DISTANCE*). In column (3) distance-based evasiveness is proxied by an indicator variable (*REMOTE*) that equals one if the annual shareholder meeting takes place at a remote location in a given year and zero otherwise. In Column (4) distance-based evasiveness is proxied by the estimated travel time between firm headquarters and annual shareholders meeting location (*TRAVEL*). See Appendix A for other variable definitions. I also include industry and year dummies to control for industry and time (year) fixed effects. Robust standard errors to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.5 reports results from the regression analysis of the relationship between distance-based measures of evasiveness and stock price crash risk, where stock price crash risk is proxied by the down-to-up volatility of firm-specific daily returns ($DUVOL_{t+1}$). Distance-based evasiveness is proxied by *HEADQUARTERS*, *DISTANCE*, *REMOTE*, and *TRAVEL* in columns (1), (2), (3), and (4), respectively. I control for the same set of variables as in the previous model. While coefficient estimates on *HEADQUARTERS* (p = 0.109, t-value = -1.601),*DISTANCE* (p = 0.152, t-value = 1.433), and *REMOTE* (p = 0.569, t-value = 0.570) are in the expected directions, they are not statistically significant at conventional levels. The coefficient estimate on *TRAVEL* (p = 0.867, t-value = -0.167) is also not statistically significant.

Table 2.5. The effect of distance-based evasiveness on down-to-up volatility of firm-specific daily returns

	Dependent variable:			
	$DUVOL_{t+1}$			
	(1)	(2)	(3)	(4)
HEADQUARTERS	-0.018			
	(0.011)			
DISTANCE		0.004		
		(0.003)		
REMOTE			0.028	
			(0.050)	
TRAVEL				-0.101
				(0.602)
SIGMA	4.321^{***}	4.375^{***}	4.363^{***}	4.350^{***}
	(1.404)	(1.404)	(1.405)	(1.405)
RET	1.468^{***}	1.479^{***}	1.470^{***}	1.467^{***}
	(0.311)	(0.311)	(0.311)	(0.311)
ROA	0.058^{*}	0.057^{*}	0.056	0.055
	(0.035)	(0.035)	(0.035)	(0.035)
SIZE	0.038^{***}	0.038^{***}	0.038^{***}	0.038^{***}
	(0.004)	(0.004)	(0.004)	(0.004)
MTB	0.002^{**}	0.002^{**}	0.002^{**}	0.002^{**}
	(0.001)	(0.001)	(0.001)	(0.001)
LEV	-0.071^{**}	-0.072^{**}	-0.069^{**}	-0.069^{**}
	(0.031)	(0.031)	(0.031)	(0.031)
DTURN	0.019^{***}	0.019^{***}	0.019^{***}	0.018^{***}
	(0.006)	(0.006)	(0.006)	(0.006)
R&D	-0.021	-0.020	-0.024	-0.026
	(0.069)	(0.069)	(0.069)	(0.069)
NCSKEW	-0.004	-0.004	-0.004	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)
Constant	-0.536^{***}	-0.557^{***}	-0.551^{***}	-0.544^{***}
	(0.091)	(0.090)	(0.090)	(0.096)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.055	0.055	0.055	0.055
F Statistic	9.035^{***}	9.026^{***}	8.999^{***}	8.995^{***}
Observations	9,086	9,086	9,086	9,086

Notes. This table presents the regression results of the effect of distance-based measures of evasiveness on stock price crash risk. The dependent variable, crash risk, is proxied by the down-to-up volatility of firm-specific daily returns (*DUVOL*) in year $t + 1$. In Column (1) distance-based evasiveness is proxied by an indicator variable (*HEADQUARTERS*) that takes one if the annual meeting takes place at company headquarters in a given year and zero otherwise. In Column (2) distance-based evasiveness is proxied by the natural logarithm of one plus the distance, in miles, between company headquarters and the annual meeting location (*DISTANCE*). In Column (3) distance-based evasiveness is proxied by an indicator variable (*REMOTE*) that equals one if the annual shareholder meeting takes place at a remote location in a given year and zero otherwise. In Column (4) distance-based evasiveness is proxied by the estimated travel time between firm headquarters and annual shareholders meeting location (*TRAVEL*). See Appendix A for other variable definitions. I also include industry and year dummies to control for industry and time (year) fixed effects. Robust standard errors to account for heteroskedasticity are displayed in parenthesess. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Finally, Table 2.6 reports regression results of the relationship between distance-based measures of evasiveness and crash risk, where crash risk is proxied by the number of crashes minus the number of jumps over the fiscal year ($COUNT_{t+1}$). Distance-based evasiveness is proxied by *HEADQUARTERS*, *DISTANCE*, *REMOTE*, and *TRAVEL* in columns (1), (2), (3), and (4), respectively. I control for the same set of variables as in the previous models. Coefficient estimates on *HEADQUARTERS* (p = 0.150, t-value = -1.440), *DISTANCE* (p = 0.186, t-value = 1.323), *REMOTE* (p = 0.996, t-value = 0.005), and *TRAVEL* (p = 0.556, t-value = 0.588) are in the expected directions, but they are not statistically significant at conventional levels.

Table 2.6. The effect of distance-based evasiveness on the number of crashes minus the number of jumps over the fiscal year

	Dependent variable:			
	COUNT_{t+1}			
	(1)	(2)	(3)	(4)
HEADQUARTERS	−0.057			
	(0.040)			
DISTANCE		0.013		
		(0.010)		
REMOTE			0.001	
			(0.192)	
TRAVEL				1.340
				(2.277)
SIGMA	4.177	4.353	4.282	4.333
	(4.923)	(4.921)	(4.924)	(4.922)
RET	2.233**	2.268**	2.232**	2.249**
	(1.084)	(1.084)	(1.085)	(1.084)
ROA	0.374***	0.373***	0.367***	0.368***
	(0.118)	(0.118)	(0.118)	(0.118)
SIZE	0.129***	0.129***	0.129***	0.129***
	(0.014)	(0.014)	(0.014)	(0.014)
MTB	0.008***	0.008***	0.008***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)
LEV	−0.339***	−0.342***	−0.334***	−0.336***
	(0.108)	(0.109)	(0.108)	(0.108)
DTURN	0.044**	0.044**	0.043**	0.043**
	(0.021)	(0.021)	(0.021)	(0.021)
R&D	0.217	0.221	0.203	0.208
	(0.223)	(0.223)	(0.222)	(0.223)
NCSKEW	−0.012	−0.012	−0.012	−0.012
	(0.009)	(0.009)	(0.009)	(0.009)
Constant	−1.928***	−1.995***	−1.970***	−2.046***
	(0.350)	(0.350)	(0.349)	(0.373)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.048	0.048	0.048	0.048
F Statistic	7.948***	7.944***	7.915***	7.921***
Observations	9,086	9,086	9,086	9,086

Notes. This table presents the regression results of the effect of distance-based measures of evasiveness on stock price crash risk. The dependent variable, crash risk, is proxied by the number of crashes minus jumps over a fiscal year (*COUNT*) in year $t + 1$. In Column (1) distance-based evasiveness is proxied by an indicator variable (*HEADQUARTERS*) that takes one if the annual meeting takes place at company headquarters in a given year and zero otherwise. In Column (2) distance-based evasiveness is proxied by the natural logarithm of one plus the distance, in miles, between company headquarters and the annual meeting location (*DISTANCE*). In Column (3) distance-based evasiveness is proxied by an indicator variable (*REMOTE*) that equals one if the annual shareholder meeting takes place at a remote location in a given year and zero otherwise. In Column (4) distance-based evasiveness is proxied by the estimated travel time between firm headquarters and annual shareholders meeting location (*TRAVEL*). See Appendix A for other variable definitions. I also include industry and year dummies to control for industry and time (year) fixed effects. Robust standard errors to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Collectively, I fail to find evidence consistent with my *deterrence hypothesis*. In fact, 12 out of 12 models show no relation between distance-based evasiveness and stock price crash risk. The coefficient estimates on control variables (except for *R&D* and lagged *NCSKEW*) are statistically significant for at least one proxy of stock price crash risk. Specifically, I find that the standard deviation of firm-specific daily returns (*SIGMA*), average idiosyncratic daily return (*RET*), firm size (*SIZE*), market-to-book ratio (*MTB*), and the detrended stock trading volume (*DTURN*) are positively associated with stock price crash risk, consistent with Callen and Fang (2015a) and Hasan et al. (2022). Additionally, I find that leverage (*LEV*) and lagged *NCSKEW* are negatively associated with crash risk, consistent with prior findings (Callen and Fang, 2015a; Hasan et al., 2022; Wu and Lai, 2020). Finally, I find that return on assets (ROA) is positively associated with crash risk, consistent with the findings of Wen et al. (2019) and Hasan et al. (2022).

2.4.3 Test of Hypothesis 2

Tables 2.7 and 2.8 present results from the regression analysis examining the relationship between timing-based measures of evasiveness and crash risk. In Table 2.7, timing-based evasiveness is proxied by *CLUSTER* at 1% in columns (1)-(3) and by *CLUSTER* at 2% in columns (4)-(6). Crash risk is proxied by $NCSKEW_{t+1}$ in columns (1) and (3), by $DUVOL_{t+1}$ in columns (2) and (4), and by $COUNT_{t+1}$ in columns (4) and (6). *A puzzle?* Surprisingly, I find evidence of a negative relation between *CLUSTER* and stock price crash risk measures, i.e., firms holding annual shareholder meetings on "busy" dates exhibit lower stock price crash risk. *CLUSTER* is statistically significant at conventional levels in 4 out of 6 specifications. The coefficient estimates on *CLUSTER* at 1% are statistically significant in columns (2) and (3) at the 5% level (p = 0.047, t-value = -1.986; p = 0.010, t-value = -2.563). The coefficient estimates on *CLUSTER* at 2% are statistically significant in columns (5) and (6) at the 5% level (p = 0.047, t-value = -1.986; p = 0.010, t-value = -2.563).

In Table 2.8, timing-based evasiveness is proxied by *FIRST* at 1% in columns (1)-(3) and by *FIRST* at 2% in columns (4)-(6). Crash risk is proxied by $NCSKEW_{t+1}$ in columns (1) and (3), by $DUVOL_{t+1}$ in columns (2) and (4), and by $COUNT_{t+1}$ in columns (4) and (6). Overall, the results are mixed. Contrary to my *attention hypothesis* prediction, firms that never held annual general meetings on clustering dates in previous years, but then change and hold annual general meetings on "busy" dates exhibit lower stock price crash risk, as shown in columns (1)-(3). However, coefficient estimates on *FIRST* at 2% are not statistically significant at the conventional levels.

2.4.4 The Announcement-Annual Shareholder Meeting lag

Under the U.S. Securities and Exchange Commission Notice and Access rule, which became effective on July 1st, 2007, firms are required to post proxy and annual general meeting materials on a website and notify shareholders of their availability electronically, allowing firms to send shareholders a one-page notice instead of a full set of proxy materials[21]. Specifically, under the Notice and Access rule, a firm is required to send the notice of the electronic availability of the proxy materials at least 40 calendar days prior to the meeting (SEC, 2020). *Are firms strategically choosing to announce their annual general meetings closer to event dates as an evasiveness mechanism?*

[21] Firms are also allowed to deliver a traditional full set of paper proxy materials, also known as the *full set delivery option*, as long as firms inform shareholders that proxy materials are publicly available online.

Table 2.7. The effect of clustering on stock price crash risk

	Dependent variable:					
	NCSKEW_{t+1}	DUVOL_{t+1}	COUNT_{t+1}	NCSKEW_{t+1}	DUVOL_{t+1}	COUNT_{t+1}
	(1)	(2)	(3)	(4)	(5)	(6)
CLUSTER at 1%	−0.037	-0.022^{**}	-0.099^{**}			
	(0.041)	(0.011)	(0.039)			
CLUSTER at 2%				−0.037	-0.022^{**}	-0.099^{**}
				(0.041)	(0.011)	(0.039)
SIGMA	17.231^{***}	4.567^{***}	5.196	17.231^{***}	4.567^{***}	5.196
	(5.424)	(1.410)	(4.931)	(5.424)	(1.410)	(4.931)
RET	5.722^{***}	1.514^{***}	2.426^{**}	5.722^{***}	1.514^{***}	2.426^{**}
	(1.239)	(0.312)	(1.085)	(1.239)	(0.312)	(1.085)
ROA	0.050	0.054	0.359^{***}	0.050	0.054	0.359^{***}
	(0.133)	(0.035)	(0.118)	(0.133)	(0.035)	(0.118)
SIZE	0.113^{***}	0.039^{***}	0.133^{***}	0.113^{***}	0.039^{***}	0.133^{***}
	(0.014)	(0.004)	(0.014)	(0.014)	(0.004)	(0.014)
MTB	0.002	0.002^{**}	0.008^{***}	0.002	0.002^{**}	0.008^{***}
	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)
LEV	−0.147	-0.066^{**}	-0.319^{***}	−0.147	-0.066^{**}	-0.319^{***}
	(0.117)	(0.031)	(0.109)	(0.117)	(0.031)	(0.109)
DTURN	0.053^{**}	0.019^{***}	0.044^{**}	0.053^{**}	0.019^{***}	0.044^{**}
	(0.024)	(0.006)	(0.021)	(0.024)	(0.006)	(0.021)
R&D	0.181	−0.026	0.203	0.181	−0.026	0.203
	(0.274)	(0.069)	(0.222)	(0.274)	(0.069)	(0.222)
NCSKEW		−0.005	−0.013		−0.005	−0.013
		(0.003)	(0.010)		(0.003)	(0.010)
Constant	-1.591^{***}	-0.557^{***}	-2.005^{***}	-1.591^{***}	-0.557^{***}	-2.005^{***}
	(0.319)	(0.090)	(0.348)	(0.319)	(0.090)	(0.348)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.030	0.055	0.049	0.030	0.055	0.049
F Statistic	5.258^{***}	9.059^{***}	8.021^{***}	5.258^{***}	9.059^{***}	8.021^{***}
Observations	9,086	9,086	9,086	9,086	9,086	9,086

Notes. This table presents the regression results of the effect of clustering on stock price crash risk on stock price crash risk. In columns (1) and (4) crash risk is proxied by negative conditional skewness ($NCSKEW$) in year $t + 1$. In columns (2) and (5) crash risk is proxied by the down-to-up volatility ($DUVOL$) in year $t + 1$. In columns (3) and (6) crash risk is proxied by the number of crashes minus jumps ($COUNT$) in year $t + 1$. In columns (1)-(6) timing-based evasiveness is proxied by $CLUSTER$, an indicator variable that equals one if a firm held their annual general meeting on clustering dates. A date is considered busy when at least 1% of sample firms' annual shareholder meetings are scheduled to that date in columns (1)-(3). A date is considered busy when at least 2% of sample firms' annual shareholder meetings are scheduled to that date in columns (4)-(6). See Appendix A for other variable definitions. I also include industry and year dummies to control for industry and time (year) fixed effects. Robust standard errors to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Firms may strategically announce annual shareholder meetings with shorter advance notice to discourage attendance and engagement from institutional investors, retail investors, activist investors, media, and analysts due to time constraints for planning (e.g., to check for availability, booking tickets, accommodation), in a similar way as my *deterrence hypothesis*. If firms are successfully using closer announcement dates to reduce monitoring and scrutiny in annual shareholder meetings, it would be easier for managers to withhold bad news, thus increasing stock price crash risk. While most firms in my sample disclosed their meeting dates approximately 40 calendar days before the annual shareholders meeting, some firms announced their annual shareholders meeting only 10 calendar days before the annual shareholders meeting took place. By contrast, firms announcing annual shareholder meetings in advance would facilitate potential participants' planning and participation, potentially increasing monitoring quality,

Table 2.8. The effect of switching to clustering dates on stock price crash risk

	Dependent variable:					
	NCSKEW_{t+1}	DUVOL_{t+1}	COUNT_{t+1}	NCSKEW_{t+1}	DUVOL_{t+1}	COUNT_{t+1}
	(1)	(2)	(3)	(4)	(5)	(6)
FIRST at 1%	-0.082^{*}	-0.032^{***}	-0.108^{***}			
	(0.043)	(0.012)	(0.041)			
FIRST at 2%				-0.034	-0.015	-0.045
				(0.040)	(0.011)	(0.039)
SIGMA	17.756^{***}	4.724^{***}	5.474	17.118^{***}	4.464^{***}	4.562
	(5.436)	(1.413)	(4.942)	(5.414)	(1.407)	(4.925)
RET	5.807^{***}	1.536^{***}	2.449^{**}	5.692^{***}	1.489^{***}	2.283^{**}
	(1.239)	(0.312)	(1.087)	(1.236)	(0.312)	(1.084)
ROA	0.049	0.054	0.362^{***}	0.051	0.055	0.365^{***}
	(0.133)	(0.035)	(0.118)	(0.133)	(0.035)	(0.118)
SIZE	0.115^{***}	0.040^{***}	0.134^{***}	0.112^{***}	0.039^{***}	0.131^{***}
	(0.014)	(0.004)	(0.014)	(0.014)	(0.004)	(0.014)
MTB	0.002	0.002^{**}	0.008^{***}	0.002	0.002^{**}	0.008^{***}
	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)
LEV	-0.142	-0.066^{**}	-0.321^{***}	-0.145	-0.066^{**}	-0.325^{***}
	(0.117)	(0.031)	(0.108)	(0.117)	(0.031)	(0.109)
DTURN	0.053^{**}	0.019^{***}	0.043^{**}	0.053^{**}	0.019^{***}	0.043^{**}
	(0.024)	(0.006)	(0.021)	(0.024)	(0.006)	(0.021)
R&D	0.184	-0.025	0.206	0.181	-0.026	0.202
	(0.275)	(0.069)	(0.222)	(0.274)	(0.069)	(0.223)
NCSKEW		-0.005	-0.014		-0.005	-0.013
		(0.003)	(0.010)		(0.003)	(0.010)
Constant	-1.603^{***}	-0.560^{***}	-2.006^{***}	-1.598^{***}	-0.558^{***}	-1.997^{***}
	(0.319)	(0.090)	(0.349)	(0.320)	(0.091)	(0.350)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.030	0.056	0.049	0.030	0.055	0.048
F Statistic	5.303^{***}	9.120^{***}	8.028^{***}	5.256^{***}	9.025^{***}	7.938^{***}
Observations	9,086	9,086	9,086	9,086	9,086	9,086

Notes. This table presents the regression results of the effect of switching to clustering dates on stock price crash risk. In columns (1) and (4) crash risk is proxied by negative conditional skewness (*NCSKEW*) in year $t+1$. In columns (2) and (5) crash risk is proxied by the down-to-up volatility (*DUVOL*) in year $t+1$. In columns (3) and (6) crash risk is proxied by the number of crashes minus jumps (*COUNT*) in year $t+1$. In columns (1)-(6) timing-based evasiveness is proxied by *FIRST*, an indicator variable that equals one if a firm that never held their annual shareholder meeting on clustering dates in all previous years announced their annual meeting on clustering dates, zero otherwise. A date is considered busy when at least 1% of sample firms' annual shareholder meetings are scheduled to that date in columns (1)-(3). A date is considered busy when at least 2% of sample firms' annual shareholder meetings are scheduled to that date in columns (4)-(6). See Appendix A for other variable definitions. I also include industry and year dummies to control for industry and time (year) fixed effects. Robust standard errors to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

and thus reducing stock price crash risk.

To test this potential (and unexplored, to my knowledge) evasiveness mechanism, I regress stock price crash risk measures on *COMMIT*. *COMMIT* is the number of days between an annual shareholder meeting date announcement, i.e., the date when the proxy is made publicly available online, and the actual annual shareholder meeting date. Greater *COMMIT* values indicate a longer interval between the meeting announcement and the meeting date, while lower *COMMIT* values indicate a shorter interval. Table 2.9 reports regression results of the relationship between the announcement-annual shareholder meeting lag, proxied by *COMMIT*, and stock price crash risk. Crash risk is proxied by *NCSKEW* in Column (1), by *DUVOL* in Column (2), and by *COUNT* in Column (3). I find no evidence that firms are strategically announcing meetings closer to annual meeting dates to withhold bad news from investors.

Table 2.9. The effect of Announcement-Annual Shareholder Meeting lag on stock price crash risk

	Dependent variable:		
	$NCSKEW_{t+1}$	$DUVOL_{t+1}$	$COUNT_{t+1}$
	(1)	(2)	(3)
COMMIT	0.004	0.0003	−0.0001
	(0.003)	(0.001)	(0.003)
SIGMA	16.738***	4.344***	4.236
	(5.407)	(1.405)	(4.913)
RET	5.628***	1.467***	2.221**
	(1.236)	(0.311)	(1.082)
ROA	0.053	0.056	0.367***
	(0.133)	(0.035)	(0.118)
SIZE	0.108***	0.038***	0.129***
	(0.014)	(0.004)	(0.014)
MTB	0.002	0.002**	0.008***
	(0.003)	(0.001)	(0.003)
LEV	−0.140	−0.069**	−0.335***
	(0.117)	(0.031)	(0.109)
DTURN	0.053**	0.019***	0.043**
	(0.024)	(0.006)	(0.021)
R&D	0.177	−0.026	0.203
	(0.274)	(0.069)	(0.222)
NCSKEW		−0.004	−0.013
		(0.003)	(0.010)
Constant	−1.714***	−0.560***	−1.966***
	(0.329)	(0.093)	(0.360)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Adjusted R^2	0.030	0.055	0.048
F Statistic	5.283***	8.998***	7.916***
Observations	9,086	9,086	9,086

Notes. This table presents the regression results of the effect of annual meeting commitment lag on stock price crash risk. Annual meeting commitment lag is proxied by the number of days between annual shareholder meeting date and commitment date based on proxy statements (*COMMIT*). In column (1) crash risk is proxied by negative conditional skewness (*NCSKEW*) in year $t+1$. In column (2) crash risk is proxied by negative conditional skewness (*NCSKEW*) in year $t+1$. In column (3) crash risk is proxied by the number of crashes minus jumps over a fiscal year (*COUNT*) in year $t+1$, in which a crash (jump) event occurs when a firm-specific daily return is 3.09 standard deviations below (above) its mean over a fiscal year. See Appendix A for other variable definitions. I also include industry and year dummies to control for industry and time (year) fixed effects. Robust standard errors to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

2.5 Sensitivity checks

In this section, I conduct additional tests to check the sensitivity of my main findings[22]. As sensitivity checks, I employ: i) different sub-samples to address potential effects that may arise from different fiscal-year end among firms in my original sample, and; ii) an entropy balancing approach to address a potential self-selection bias.

[22]Controlling for analyst coverage, based on the total number of analysts (as recorded in I/B/E/S) following a firm, does not change my results (untabulated).

2.5.1 Eliminating firms with a fiscal year-end different than the last day of December

Although most U.S. public firms have a fiscal year that begins on January 1st and ends on December 31st, not all fiscal years coincide with the calendar year. For this reason, even though I observe a concentration of annual shareholder meetings between April and June in my sample (with most "busy" dates concentrated in May), there are events held outside of this timeframe, such as in December. One could argue that a company that held its annual general meeting in May of a given year, for example, may have more time to accumulate bad news until the end of the following year than a company that held its annual general meeting in December, given that my analyses consider lagged independent variables to reduce the problem of simultaneity or reverse causality. To address potential concerns about significant differences in fiscal years among firms in my original sample, I re-estimate all main regressions using a subsample of firms whose fiscal year ends on December 31st.

Table 2.10 reports regression results of the relationship between distance-based measures (*HEADQUARTERS*, *DISTANCE*, *REMOTE*, and *TRAVEL*) and stock price crash risk based on the subsample of firms whose fiscal years ends on December 31st. Crash risk is proxied by *NCSKEW* in columns (1), (3), and (6), by *DUVOL* in columns (2), (4), and (7), and by *COUNT* in columns (7), (5), and (8). Table 2.11 presents regression results of the relationship between timing-based measures of evasiveness (*CLUSTER* and *FIRST*) and stock price crash risk based on the subsample of firms whose fiscal years end on December 31st. Crash risk is proxied by *NCSKEW* in columns (1), (4), (7), and (10), by *DUVOL* in columns (2), (5), (8), and (11), and by *COUNT* in columns (3), (6), (8), and (12). The results remain qualitatively the same in Table 2.10. On the other hand, as shown in Table 2.11, the relationship between timing-based evasiveness and stock price crash risk measures is weakened using a subsample of firms whose fiscal years ends on December 31st.

2.5.2 Entropy Balancing

To address a potential self-selection bias, reducing pre-existing category differences between firms holding annual shareholder meetings in firms' headquarters and firms holding annual shareholder meetings outside headquarters, we employ an entropy balancing approach[23]. For example, smaller companies may systematically choose to hold their annual general meetings away from their headquarters to increase firm visibility. Introduced by Hainmueller (2012), entropy balancing is a method for matching treatment and control observations that assign weights to the control group based on the matching variables (covariates). The goal is to ensure that the post-weighting matching variables have similar means, variances, and skewness between the control and treatment groups. I first divide my sample into two groups: treatment and control groups. I consider firm-year observations for firms holding annual general meetings outside

[23]Entropy Balancing offers several advantages over Propensity Score Matching: i) the entropy balancing approach retains all firm-year observations; ii) the entropy balancing approach ensures that the distributions of the covariates are similar between the treatment and control groups not only in terms of means, but also in terms of variance and skewness, and; iii) PSM might be less effective when dealing with categorical matching variables (Hainmueller, 2012).

Table 2.10. The effect of distance-based measures of evasiveness on stock price crash risk for firms with fiscal years ending in December

	Dependent variable:											
	$NCSKEW_{t+1}$				$DUVOL_{t+1}$				$COUNT_{t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
HQ	−0.058				−0.021				−0.024			
	(0.050)				(0.013)				(0.047)			
DISTANCE		0.018				0.004				0.005		
		(0.012)				(0.003)				(0.011)		
REMOTE			0.058				0.010				−0.257	
			(0.211)				(0.054)				(0.208)	
TRAVEL				0.175				−0.084				−1.061
				(2.627)								(2.611)
Constant	−1.619***	−1.691***	−1.665***	−1.674***	−0.648***	−0.671***	−0.664***	−0.659	−2.579***	−2.606***	−2.594***	−2.536***
	(0.407)	(0.405)	(0.405)	(0.432)	(0.111)	(0.111)	(0.111)	(0.422)	(0.422)	(0.422)	(0.421)	(0.451)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.026	0.026	0.026	0.026	0.055	0.055	0.055	0.055	0.049	0.049	0.049	0.049
Observations	6,435	6,435	6,435	6,435	6,435	6,435	6,435	6,435	6,435	6,435	6,435	6,435

Notes. This table presents the regression results of the effect of distance-based measures of evasiveness on stock price crash risk based on a subsample of firms with fiscal years ending in December. Controls ommited for brevity. F Statitics ommited for brevity. In columns (1)-(4) crash risk is proxied by negative conditional skewness (*NCSKEW*) in year $t+1$. In columns (5)-(8) crash risk is proxied by negative conditional skewness (*NCSKEW*) in year $t+1$. In columns (9)-(12) crash risk is proxied by the number of crashes minus jumps over a fiscal year (*COUNT*) in year $t+1$, in which a crash (jump) event occurs when a firm-specific daily return is 3.09 standard deviations below (above) its mean over a fiscal year. *HEADQUARTERS* is an indicator variable that equals one if the annual meeting takes place at company headquarters in a given year and zero otherwise, *DISTANCE* is the natural logarithm of one plus the distance, in miles, between company headquarters and the annual meeting location, based upon ZIP code data, *REMOTE* is an indicator variable that equals one if the annual shareholder meeting takes place at a remote location, and *TRAVEL* is the estimated travel time between firm headquarters and annual shareholders meeting location. See Appendix A for other variable definitions. I also include industry and year dummies to control for industry and time (year) fixed effects. Robust standard errors to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.11. The effect of timing-based measures of evasiveness on stock price crash risk for firms with fiscal years ending in December

	Dependent variable:											
	NCSKEW	DUVOL	COUNT	NCSKEW	DUVOL	COUNT	NCSKEW	DUVOL	COUNT	NCSKEW	DUVOL	COUNT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CLUSTER at 1%	−0.028	−0.020	−0.137**									
	(0.064)	(0.017)	(0.059)									
CLUSTER at 2%				−0.028	−0.020	−0.137**						
				(0.064)	(0.017)	(0.059)						
FIRST at 1%							−0.097	−0.043*	−0.185**			
							(0.091)	(0.024)	(0.082)			
FIRST at 2%										−0.006	−0.006	−0.054
										(0.064)	(0.017)	(0.060)
Constant	−1.649***	−0.654***	−2.527***	−1.649***	−0.654***	−2.527***	−1.595***	−0.634***	−2.469***	−1.660***	−0.660***	−2.564***
	(0.404)	(0.111)	(0.420)	(0.404)	(0.111)	(0.420)	(0.406)	(0.112)	(0.424)	(0.404)	(0.111)	(0.422)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.026	0.055	0.050	0.026	0.055	0.050	0.026	0.055	0.050	0.026	0.055	0.049
Observations	6,435	6,435	6,435	6,435	6,435	6,435	6,435	6,435	6,435	6,435	6,435	6,435

Notes. This table presents the regression results of the effect of timing-based measures of evasiveness on stock price crash risk based on a subsample of firms with fiscal years ending in December. Controls omitted for brevity. F Statitics omitted for brevity. In columns (1)-(4) crash risk is proxied by negative conditional skewness (*NCSKEW*) in year $t+1$. In columns (5)-(8) crash risk is proxied by negative conditional skewness (*NCSKEW*) in year $t+1$. In columns (9)-(12) crash risk is proxied by the number of crashes minus jumps over a fiscal year (*COUNT*) in year $t+1$, in which a crash (jump) event occurs when a firm-specific daily return is 3.09 standard deviations below (above) its mean over a fiscal year. In columns (1)-(6) timing-based evasiveness is proxied by *CLUSTER*, an indicator variable that equals one if a firm held their annual general meeting on clustering dates. In columns (7)-(12) timing-based evasiveness is proxied by *FIRST*, an indicator variable that equals one if a firm that never held their annual shareholder meeting on clustering dates in all previous years announced their annual meeting on clustering dates, zero otherwise. A date is considered busy when at least 1% of sample firms' annual shareholder meetings are scheduled to that date in columns (1)-(3) and (7-9). A date is considered busy when at least 2% of sample firms' annual shareholder meetings are scheduled to that date in columns (4)-(6) and (10)-(12). See Appendix A for other variable definitions. I also include industry and year dummies to control for industry and time (year) fixed effects. Robust standard errors to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.12. The distribution of the control variables before and after entropy balancing

Panel A: before entropy balancing						
	Treatment firms			Control firms		
	Mean	Variance	Skewness	Mean	Variance	Skewness
	(1)	(2)	(3)	(4)	(5)	(6)
SIGMA	0.025	0.000	1.825	0.026	0.000	1.727
RET	-0.040	0.003	-4.149	-0.046	0.004	-3.660
ROA	-0.030	0.060	-3.568	-0.059	0.098	-3.168
SIZE	15.960	4.234	-0.136	15.900	4.731	0.142
MTB	3.646	45.390	2.783	3.867	52.250	2.719
LEV	0.189	0.035	0.923	0.204	0.039	0.793
DTURN	0.034	0.916	0.829	0.017	1.116	0.884
R&D	0.067	0.017	3.255	0.072	0.025	3.359
Panel B: after entropy balancing						
	Treatment firms			Control firms		
	Mean	Variance	Skewness	Mean	Variance	Skewness
	(1)	(2)	(3)	(4)	(5)	(6)
SIGMA	0.025	0.000	1.825	0.025	0.000	1.825
RET	-0.040	0.003	-4.149	-0.04	0.003	-4.148
ROA	-0.030	0.060	-3.568	-0.030	0.060	-3.569
SIZE	15.960	4.234	-0.136	15.960	4.235	-0.135
MTB	3.646	45.39	2.783	3.646	45.4	2.783
LEV	0.189	0.035	0.923	0.189	0.035	0.923
DTURN	0.034	0.916	0.829	0.034	0.917	0.829
R&D	0.067	0.017	3.255	0.067	0.017	3.256

Notes. This table presents the distribution of the control variables before and after entropy balancing. Panel A presents the distribution of the control variables before entropy balancing and Panel B presents the distribution of the control variables after entropy balancing. *SIGMA* is the standard deviation of firm-specific daily returns, *RET* is the average idiosyncratic daily return, *SIZE* is the natural logarithm of total assets, *MTB* is the ratio between market value of equity and book value of equity, *LEV* is the ratio between total debt and total assets, *DTURN* is the detrended stock trading volume, and *R&D* is the R&D intensity.

firms' headquarters as my treatment group (*TREAT*). I denote all other firm-year observations as the control group with TREAT equal to 0. Table 2.12 reports the summary statistics of the covariates before and after entropy balancing. After the entropy balancing, my matching variables of treatment and control firms are nearly equal in terms of mean, variance, and skewness.

I re-estimate my main distance-based regressions using the balanced (re-weighted) sample and report the results in Table 2.13. I find no evidence that distance-based evasiveness (proxied by *HEADQUARTERS*) affects future stock price crash risk using a re-weighted sample. Coefficient estimate on *HEADQUARTEES* is not statistically significant at the conventional levels in column 1 (p = 0.346, t-value = -0.94), column 2 (p = 0.124, t-value = -1.54), and column 3 (p = 0.208, t-value = -1.26), although the directions were as expected.

2.6 Concluding Remarks

This study investigates the impact of evasive shareholder meetings on stock price crash risk. Using hand-collected data on annual shareholder meeting scheduling characteristics for 9,086 meetings held by

Table 2.13. Entropy balancing approach

	Dependent variable:		
	NCSKEW$_{t+1}$	DUVOL$_{t+1}$	COUNT$_{t+1}$
	(1)	(2)	(3)
HEADQUARTERS	-0.040	-0.0177	-0.051
	-0.043	(0.012)	(0.040)
SIGMA	18.86***	4.699***	8.087
	(5.901)	(1.536)	(5.265)
RET	6.114***	1.581***	3.285***
	(1.288)	(0.330)	(1.157)
ROA	0.119	0.071*	0.407***
	(0.138)	(0.037)	(0.126)
SIZE	0.120***	0.040***	0.132***
	(0.015)	(0.004)	(0.015)
MTB	0.003	0.002	0.007**
	(0.004)	(0.001)	(0.003)
LEV	-0.176	-0.083**	-0.369***
	(0.131)	(0.035)	(0.115)
DTURN	0.058**	0.020***	0.053**
	(0.026)	(0.007)	(0.022)
R&D	0.296	-0.008	0.229
	(0.292)	(0.076)	(0.239)
NCSKEW		-0.003	-0.016
		(0.004)	(0.011)
Constant	-1.779***	-0.590***	-2.114***
	(0.351)	(0.097)	(0.367)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
R^2	0.039	0.063	0.054
F Statistic	7.490***	9.000***	12.720***
Observations	9,086	9,086	9,086

Notes. This table presents the regression results of the effect of *HEADQUARTERS* on stock price crash risk using the entropy balancing approach. In column (1) crash risk is proxied by negative conditional skewness (*NCSKEW*) in year $t + 1$. In column (2) crash risk is proxied by negative conditional skewness (*NCSKEW*) in year $t + 1$. In column (3) crash risk is proxied by the number of crashes minus jumps over a fiscal year (*COUNT*) in year $t + 1$, in which a crash (jump) event occurs when a firm-specific daily return is 3.09 standard deviations below (above) its mean over a fiscal year. See Appendix A for other variable definitions. I also include industry and year dummies to control for industry and time (year) fixed effects. Linearized standard errors are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

1,486 public U.S. firms between 2012 and 2020, I fail to find evidence consistent with my *deterrence hypothesis*. I initially find a puzzling strong negative relationship between evasive timing strategies and crash risk. However, the puzzling strong negative relationship virtually disappears in robustness checks. Additionally, I find no evidence that firms are strategically announcing meetings closer to annual shareholder meetings dates to withhold bad news from investors. Collectively, I find no evidence that evasiveness (distance-based or timing-based) affect stock price crash risk.

These findings challenge the "hidden information hypothesis" proposed by Li and Yermack (2016), which argues that managers move annual shareholders meetings away from firm headquarters to suppress negative news for long as possible. It is important to highlight that instead of focusing on stock price crash risk, i.e., the likelihood of stock price crashes, Li and Yermack (2016) focuses on stock performance based on cumulative abnormal stock returns. My study also has implications for securities regulators and policymakers, indicating if firms are relying on evasive shareholder meeting practices to hoard bad news from investors. Annual meetings play a crucial role in corporate governance, being one of the only occasions for most investors to directly meet and interact with firm management and raise concerns regarding firm operations (Schwartz-Ziv, 2021)[24]. However, most studies focuses on shareholder voting, and little attention has been paid to meetings' scheduling characteristics, such as location and timing, and their potential effects on corporate outcomes, an emerging field of research.

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[24]Schwartz-Ziv (2021) cites a statement by a shareholder in the 2019 JPMorgan Chase & Company Shareholder Meeting that convey this view: "I appreciate the access I have to management of the company, but I'm here today as a shareholder of JPMorgan shares. And the reason I do this is because this is the only chance, one time per year, when I can ask questions of the general Board and have them be held publicly accountable".

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3 ARE BUSY ANALYSTS DETRIMENTAL? EVIDENCE FROM STOCK PRICE CRASH RISK

Abstract

I examine the impact of firm-level analyst busyness on stock price crash risk. I argue that the relationship between firm-level analyst busyness and stock price crash risk reflects the net effect of two opposing perspectives: *busyness* and *networking*. Using a large sample of U.S. firms for the period 2000-2021, I find a positive relation between the average number of firms followed by sell-side financial analysts and crash risk. I also find a significant and positive relationship between the average number of reports issuance and stock price crash risk. Collectively, these results support the idea that the *busyness perspective* dominates the relationship between busyness and crash risk, overshadowing the potential benefits of higher busyness. However, I find conflicting results when busyness is proxied by the average number of industries covered by analysts, as the relation is sensitive to model specification. My main findings are robust to a battery of sensitivity tests, including alternative proxies to reduce potential measurement error and an entropy balancing approach to take into account potential self-selection bias. Additional tests reveal that the positive relationship between firm-level analyst busyness (proxied by the average number of reports issuance or by the average number of firms followed) and crash risk is more pronounced in firms with higher information asymmetry.

Keywords: Crash Risk, Busyness, Analysts.

JEL Codes: G30, G24, G12.

3.1 Introduction

On March 19, 2021, The Financial Times reported that a group of first-year investment banking analysts of Goldman Sachs called for reforms to reduce workload. These professionals raised concerns over “arduous working conditions” claiming an average workweek of up to 100 hours. Some years ago, Andrew Sorkin, a financial columnist for The New York Times, wrote an article titled “Reflections on Stress and Long Hours on Wall Street”, discussing the strong pressure and workload that financial services professionals face and raising attention over the death of Sarvshreshth Gupta, a 22-year-old analyst at the Goldman Sachs who committed suicide whom told his father before his death that “This job is not for me. Too much work and too little time”. However, despite the relevance of busyness among financial services professionals, most studies focus instead on multiple directorships and the consequences of busyness among board and committee members on corporate outcomes, such as firm value (Ferris et al., 2003; Field et al., 2013; Andres et al., 2013; Daniliuc et al., 2020; Fich and Shivdasani, 2006; Falato et al., 2014), and CEO compensation (Pathan et al., 2019), for example. Whether the busyness of financial services professionals matters for corporate outcomes is still an under-researched topic, with sparse recent evidence (Kini et al., 2020).

In this paper, I examine whether sell-side financial analysts' busyness influences their ability to curb bad news hoarding behavior by firms. A key component of Wall Street's labor force, sell-side financial analysts are industry experts with private knowledge and advanced analytical skills who engage in firm-level and market-level information search to perform forecasts and issue stock recommendations for investors (Luo and Zheng, 2018; To et al., 2018). It is well-known that financial analysts' monitoring activities play a crucial role in financial markets, reducing agency costs (Jensen and Meckling, 1976), and improving firms' information environment (Ellul and Panayides, 2018). Based on the rationale that analysts act as external monitors, previous literature show that analyst coverage have a substantial role on curbing earnings management (Yu, 2008; Degeorge et al., 2013) and corporate fraud (Chen et al., 2016), increasing corporate disclosure quality (Irani and Oesch, 2013), firm value (Chung and Jo, 1996), and improving firms investments' decisions (To et al., 2018). While a large body of literature has sought to explain the determinants and consequences of analyst coverage, the academic attention to analysts' busyness has been confined to the effects of their busyness on earnings forecasts' properties, mainly analyst forecast accuracy (Clement, 1999; Kini et al., 2009), largely ignoring the analysts' busyness consequences on monitoring quality.

The literature on busy directors has identified two distinct effects through which busyness influences monitoring quality, with mixed results. Some studies posit that busyness weakens corporate governance since directors might shirk their responsibilities, suggesting that busy directors may have less time and energy (i.e., resources) to monitor management effectively (Falato et al., 2014). Contrarily, other studies posit that busy directors might enjoy the increased experience and knowledge (Elyasiani and Zhang, 2015). Ferris et al. (2003) find no evidence that firms with busy boards present poor future performance or a higher likelihood of being named in a securities fraud lawsuit. In contrast, Fich and Shivdasani (2006) find that companies with busy boards exhibit weak corporate governance, with lower market-to-book ratios, lower sensitivity of CEO turnover to firm performance, and weaker profitability. Using a sample of German firms, Andres et al. (2013) show that firms with intensely connected supervisory boards exhibit lower firm performance and higher executive compensation. Using the death of directors and CEOs as exogenous shocks to board busyness, Falato et al. (2014) find that busy directors are detrimental to monitoring quality and shareholder value. They find a decrease in earnings quality and an increase in CEO rent extraction when there is an increase in directors' busyness.

Based on the earlier discussion, I argue that the relationship between sell-side analysts' busyness and stock price crash risk reflects the net effect of two different opposing perspectives: the *busyness perspective* and the *network perspective*[1]. To properly perform their external monitoring activities on

[1] *Ex ante*, it is unclear which effect prevails.

covered firms, sell-side financial analysts need to devote a significant amount of time and effort (i.e., resources) to read 10-K and 10-Q reports and to attend conference calls, non-deal roadshow days, investor days, industry conferences, company or plant visits, and private meetings with management (Cheng et al., 2016, 2019; Soltes, 2014; Bowen et al., 2002; Brown et al., 2015)[2]. Time constraints may limit analysts' ability to engage or attend such activities, preventing analysts from effectively monitoring and scrutinizing all firms they follow adequately. A looser monitoring, in turn, facilitates opportunistic behavior and makes it easier for firms to hide bad news from investors for an extended period, since managers have a general (documented) tendency to withhold bad news (Kothari et al., 2009). When the accumulated bad news reaches a critical point, the sudden release of the long-run of bad news may cause a stock price crash. Overall, these arguments suggest that analysts' busyness can facilitate bad news hoarding by firms, thus increasing stock price crash risk. I call this *busyness perspective*.

An alternative hypothesis is that busy analysts are more likely to enjoy an informational advantage through increased connections and experiences resulting from a wider network of contacts (Phua et al., 2018; Bradley et al., 2020; Cohen et al., 2010)[3]. First, Phua et al. (2018) suggest that connections among sell-side analysts who work at the same brokerage, as a way to exchange knowledge with well-informed colleagues, are a valuable resource in "producing high-quality research", improving the collection of information used to create a "mosaic of firm's business operations". Second, some studies highlight the role of external social and professional ties and connections on improving analysts' forecasting quality and monitoring intensity (Bradley et al., 2020; Cohen et al., 2010; Li et al., 2020a). For example, Bradley et al. (2020) show that analysts with professional connections with executives are more likely to ask more questions during conference calls and investor/analyst days. If a busy analyst takes advantage of such informational advantages to improve monitoring quality, managers will face greater constraints to withhold bad news. Therefore, analysts' busyness may reduce bad news hoarding behavior due to increased access to information and better monitoring skills, thus decreasing stock price crash risk. I call this *network perspective*[4].

I test these opposing views by examining a sample of U.S. public firms for the period of 2000-2021 (35,526 firm-year observations). Based on prior studies (Kini et al., 2020; Kim et al., 2021), I employ three proxies to capture firm-level analyst busyness: the average number of firms followed by analysts ($BUSY\_FIRMS$), the average number of reports issuance ($BUSY\_REPORTS$), and the average number of industries covered ($BUSY\_IND$)[5]. Following prior studies (Kim et al., 2011a; Wu and Lai, 2020), I employ three measures of firm-specific stock price crash risk: the negative skewness of firm-specific daily

[2]In a recent study, Hirshleifer et al. (2019) show how the lack of enough cognitive resources affects analysts' judgments and, subsequently, forecast quality. They find that fatigued sell-side financial analysts provide less accurate Earnings Per Share (EPS) forecasts and are more likely to herd towards the consensus forecast than their less fatigued peers.

[3]Intuitively, I assume that busy analysts are likely to be more connected than non-busy analysts. Field et al. (2013) and Chen and Guay (2020) present a similar reasoning regarding busy directors.

[4]It is not my intention to disentangle what is a "technical skill" (e.g., skills acquired through the CFA program) from skills generated by the network itself (e.g., greater capability to build a "mosaic").

[5]I measure analyst busyness at the firm-level, calculating the average busyness across analysts following a firm.

returns ($NCSKEW$), the down-to-up volatility of firm-specific daily returns ($DUVOL$), and the number of crashes minus the number of jumps ($COUNT$). My baseline results suggest: i) a significant and positive relationship between the average number of firms followed by analysts and stock price crash risk; ii) a significant and positive relationship between the average number of reports issuance and stock price crash risk, and; iii) a non-statistically significant relationship between the average number of industries followed and stock price crash risk. Additional analysis suggests that the positive relationship between firm-level analyst busyness (proxied by $BUSY\_FIRMS$ and $BUSY\_FIRMS$) is stronger in firms with higher information asymmetry. Next, I perform robustness checks to examine the sensitivity of my results, including alternative proxies for firm-level analyst busyness, the inclusion of a potential omitted variable, and an entropy balancing approach to take potential self-selection bias into account. Overall, the evidence in my study supports the notion that busyness is harmful, potentially deteriorating monitoring quality.

This paper contributes to the current literature in three ways. First, my study adds to the scarce literature on the consequences of analyst busyness for firms and their managers. Kini et al. (2020) studies the impact of analyst busyness on firm monitoring and finds that firms with busiest analysts are associated with lower operating performance, higher cost of capital, greater earnings management, and excessive CEO compensation. Another related paper is Bradley et al. (2017). Bradley et al. (2017) examines whether analysts' prior industry experience influences their ability to serve as effective external firm monitors, focusing on financial disclosure quality, earnings management, executive compensation, and CEO turnover. However, my study differs from these papers since I focus on stock price crash risk, based on the bad news hoarding agency-based framework of Jin and Myers (2006). To the best of my knowledge, this is the first paper to empirically investigate the link between firm-level analyst busyness and stock price crash risk.

Second, I contribute to the vast literature on the determinants of stock price crash risk (e.g., Kim et al., 2014; Dumitrescu and Zakriya, 2021; Kubick and Lockhart, 2021; Hasan et al., 2022; An et al., 2020; Al Mamun et al., 2020; Xu et al., 2020b; Gu et al., 2020; Harper et al., 2020; Long et al., 2020; Fu and Zhang, 2019). Within this literature, a line of studies explores the impact of analyst coverage on stock price crash risk with mixed results (Xu et al., 2013; Kim et al., 2019b; He et al., 2019). However, this particular literature focuses on levels of analyst coverage as a measure of firm monitoring and little attention has been paid to analysts' characteristics, such as analyst busyness.

Third, my findings offer important insights for investment practitioners since understanding stock price crashes determinants is relevant for portfolio management and asset pricing (Harlow, 1991). Additionally, my findings add to the current debate on strong pressure and high workloads among financial services professionals, including sell-side financial analysts.

The remainder of this study is organized as follows. Section 3.2 describes the research design, including data sources, sample selection, variable measurement, and model specification. The baseline empirical results and additional analysis are discussed in Section 3.3. Section 3.4 provides robustness checks. Finally, Section 3.5 concludes the paper.

3.2 Data and methodology

3.2.1 Data sources and sample

My sample includes publicly listed U.S. firms for the period 2000–2021. Following previous literature, I exclude financial institutions (SIC codes between 6000 and 6999) and public utility firms (SIC codes between 4000 and 4999). My data are obtained from three different sources: Institutional Brokers' Estimate System (I/B/E/S), Center for Research in Security Prices (CRSP), and COMPUSTAT. I use the I/B/E/S Detail File, from I/B/E/S, to retrieve data on individual analysts' earnings forecasts for my sample firms. This database provides detailed information on individual analysts' earnings estimates. Each broker and analyst has a unique identifier, which I use to identify the firms followed by an analyst in a given year. I obtain firm-level annual accounting data and other data on firm characteristics from COMPUSTAT. Finally, I collect daily (and monthly) stock data from CRSP to compute stock price crash risk measures and some control variables. After further excluding observations without complete data, my main sample consists of 35,526 firm-year observations for 4,763 unique firms. To lessen the influence of extreme outliers, I winsorize all financial continuous variables at the 1st and 99th percentiles.

3.2.2 Measuring stock price crash risk

Following existing literature (e.g., Azevedo et al., 2023; Kim et al., 2011a), I employ three measures of well-known *ex post*[6] firm-specific stock price crash risk measures: the negative conditional firm-specific daily returns skewness ($NCSKEW$), the down-to-up volatility of firm-specific daily returns ($DUVOL$), and the number of crashes minus the number of jumps over the fiscal year ($COUNT$). Also following existing literature, to ensure that my three stock price crash risk measures represent only firm-specific factors, rather than general market conditions, these three measures are based on firm-specific daily returns. To calculate the stock price crash risk measures, I first obtain the firm-specific residual daily returns from the following model, estimated for each firm in each year, based on Kim et al. (2011a).

$$r_{i,t} = \beta_0 + \beta_1 r_{mkt,t-2} + \beta_1 r_{mkt,t-1} + \beta_3 r_{mkt,t} + \beta_5 r_{mkt,t+1} + \beta_1 r_{mkt,t+2} + \varepsilon_{i,t} \tag{3.1}$$

$r_{i,t}$ is the return on stock i in day t. $r_{mkt,t}$ is the CRSP value-weighted market index return in day t. I employ $r_{mkt,t}$ leads and lags terms to correct for potential nonsynchronous trading (Kim et al., 2011a). The firm-specific daily stock return ($W_{i,t}$) is calculated as $ln(1 + \varepsilon_{i,t})$, where $\varepsilon_{i,t}$ is the residual obtained from Equation 3.1.

[6] *Ex post* crash risk measures are based on the realized distributions of returns (i.e., historical crash risk), while *ex ante* crash risk measures are based on the crash risk perceived by investors (i.e., expected crash risk) (Kim and Zhang, 2014).

My first crash risk measure is the conditional firm-specific daily returns skewness - *NCSKEW*. *NCSKEW* is calculated as the negative of the third central moment of the firm-specific daily returns over a year, normalized by the standard deviation of the firm-specific daily returns (sample variance) raised to the third power (Chen et al., 2001; Kim et al., 2011a). Precisely, I calculate *NCSKEW* as:

$$NCSKEW_{i,t} = -\left[n(n-1)^{\frac{3}{2}} \sum W_{i,t}^{3}\right] / \left[(n-1)(n-2)\left(\sum W_{i,t}^{2}\right)^{3/2}\right] \tag{3.2}$$

n is the number of daily returns over a year t. As I employ the absolute value, multiplying the construct by negative one, a higher *NCSKEW* value indicates a higher stock price crash risk.

The second crash risk measure is the down-to-up volatility of firm-specific daily returns (*DUVOL*). For each firm i in a given year t, the firm-specific daily returns are classified into two groups: "*Down*", when the returns are below the annual average, and "*Up*", when the return are above the annual average. Next, I calculate the standard deviation of firm-specific daily returns separately for each of these two groups ("*Down*" days and "*Up*" days). *DUVOL* is calculated as the natural logarithm of ratio between the standard deviation in "*Down*" to the standard deviation of "*Up*" (Chen et al., 2001; Kim et al., 2011a). Specifically:

$$DUVOL_{i,t} = \log\left\{(n_b - 1)\sum_{Down} W_{i,t}^{2} / \, (n_a - 1)\sum_{Up} W_{i,t}^{2}\right\} \tag{3.3}$$

n_b and n_a represents the number of "*Up*" and "*Down*" days, respectively, over a year t. A higher *DUVOL* indicates a higher stock price crash risk.

Based on Wu and Lai (2020), my third crash risk measure is the number of crashes minus the number of jumps over the fiscal year (*COUNT*). A crash (jump) event occurs when a firm-specific daily return is 3.09 standard deviations below (above) its mean over a fiscal year. A high value of *COUNT* indicates a great number of realized stock price crashes.

3.2.3 Measuring analyst busyness

I construct three firm-year measures of analyst busyness based on the average level of busyness across analysts covering a firm in a given year. First, *BUSY_FIRMS* represents the average number of firms covered by the analysts of a given firm in a given year (Kini et al., 2020). Additionally, I employ two other measures to gauge the average level of busyness across analysts for a given firm-year: *BUSY_IND* and *BUSY_REPORTS*. *BUSY_IND* is the average number of industries covered by the analysts of a given firm in a given year, while *BUSY_REPORTS* is calculated as the average number of reports issued by the analysts of a given firm in a given year, similar to Kim et al. (2021). However, unlike Kim et al. (2021) who calculate busyness measures at the analyst-level, both *BUSY_IND* and *BUSY_REPORTS* are calculated at the firm-level allowing me to match firm-level data with these measures of analyst busyness. Higher values of *BUSY_FIRMS*, *BUSY_IND*, and *BUSY_REPORTS* indicate greater busyness.

Suppose that company i was followed by four analysts in a given year. Two of these four analysts covered five companies, while the other two covered six companies. In this case, the average number of firms covered by these analysts (*BUSY_FIRMS*) would be equal to 5.5. If two of them covered three industries each, while the other two covered four, the average number of industries covered by the analysts following the company (*BUSY_IND*) would be 3.5. Similarly, suppose two analysts issued fifteen reports each, and the other two issued ten reports each. *BUSY_REPORTS* would be equal to 12.5, which represents the average number of reports issued by the analysts covering the company. The average analyst following company i covered 5.5 firms, 3.5 industries, and issued 12.5 reports.

3.2.4 Firm-level control variables

In line with prior literature (Chowdhury et al., 2020; Chang et al., 2017; Xu et al., 2020b; An et al., 2020), I control for changes in stock turnover (*DTURN*), calculated as the average monthly share turnover over the current year t minus the average monthly share turnover over the previous year (*t-1*), average idiosyncratic daily return (*RET*), calculated as the mean of firm-specific daily returns over the fiscal year t times 100, the standard deviation of firm-specific daily returns (*SIGMA*), firm size (*SIZE*), calculated as the natural logarithm of total assets, firm performance (*ROA*), calculated as the ratio between income before extraordinary items and total assets, market-to-book ratio (*MTB*), calculated as the ratio between market value of equity and book value of equity, firm leverage (*LEV*), calculated as the ratio between total debt and total assets, R&D intensity (*R&D*), calculated as research and development (*R&D*) expenditure scaled by total assets[7], and one-year lagged *NCSKEW*[8].

3.2.5 Model specification

I estimate the following baseline regression model using ordinary least squares (OLS) to investigate the effect of firm-level analyst busyness on crash risk:

$$CRASH_{i,t+1} = \alpha + \beta BUSYNESS_{i,t} + \lambda' Controls_{i,t} + Year_t + Industry_j + \varepsilon_{i,t} \tag{3.4}$$

where *CRASH* is a placeholder for stock price crash risk measures (i.e., *NCSKEW*, *DUVOL*, and *COUNT*), as detailed in Section 3.2.2, *BUSYNESS* is a placeholder for analyst busyness measures (i.e., *BUSY_FIRMS*, *BUSY_IND*, and *BUSY_REPORTS*), and $\lambda' Controls$ is the set of one-year-lagged firm-level control variables for stock price crash risk specified in Section 3.2.4. The baseline model and all other specifications derived from the baseline model include industry ($Industry_j$) and fiscal year

[7] Following previous studies, I set missing R&D spending to zero to avoid losing many observations (Lewis and Tan, 2016; Nguyen and Qiu, 2022; Huang and Ritter, 2009).

[8] Regressing *NCSKEW* on one-year lagged *NCSKEW* will likely result in biased estimates (Keele and Kelly, 2006). For this reason, I do not include one-year lagged *NCSKEW* as a control variable when $NCSKEW_{t+1}$ is the dependent variable.

($Year_t$) fixed effects to account for industry-specific time-invariant characteristics and business cycles. All variables are defined and detailed in Appendix C.

3.3 Results

3.3.1 Descriptive statistics

Table 3.1 presents the sample distribution by industry and year in Panel A and Panel B, respectively. The sample distribution by industry is based on two-digit SIC codes. Table 3.1, Panel A, shows that Business Services have the largest number of observations, with 5,477 observations, approximately 15.42% of my sample, followed by Chemical & Allied Products (SIC = 28; 4,567 observations), Electronic & Other Electric Equipment (SIC = 36; 3,493 observations), Instruments & Related Products (SIC = 38; 2,711 observations), and Industrial Machinery & Equipment (SIC = 35; 2,468 observations). Combined, those five industries represent approximately 52.69% of my sample. No single industry accounted for more than 20% of the full sample and only two accounted for more than 10%. Table 3.1, Panel B, shows an average of 1,615 observations per year.

Table 3.2 presents summary statistics for key variables used in my regression models from 2000 to 2021 for my sample firms. Table 3.2, Panel A.1., reports the aggregate summary statistics for stock price crash risk proxies, namely *NCSKEW*, *DUVOL*, and *COUNT*. The mean (median) values of stock price crash risk measures *NCSKEW*, *DUVOL*, and *COUNT* are 0.111 (-0.055), -0.015 (0.041), and -0.245 (0.000), respectively. Table 3.2, Panel A.2., reports the aggregate summary statistics for analyst busyness proxies, namely *BUSY_FIRMS*, *BUSY_REP*, and *BUSY_IND*. The mean (median) values of the three proxies for analyst busyness, *BUSY_FIRMS*, *BUSY_REP*, and *BUSY_IND*, are 2.756 (2.825), 4.074 (4.162), and 1.781 (1.872), respectively. Finally, Table 3.2, Panel A.3., shows the aggregate summary statistics for firm-level control variables. The average firm in my sample has a natural logarithm of total assets of 6.758, a market-to-book ratio of 3.447, a leverage of 0.186, a return on assets of -0.007, a volatility of firm-specific daily returns over the fiscal-year period of 0.028, an average idiosyncratic return of -0.001, a R&D intensity of 0.058, and a detrended stock trading volume of 0.064.

Figure 3.1 shows the means of *BUSY_FIRMS*, *BUSY_REP*, and *BUSY_IND* across the sample years 2000-2021. All three measures exhibit an increasing pattern since 2003, coinciding with the end of Dot-com bubble. One potential explanation for the reduction in the average number of firms and industries covered, as well as reports issuance by financial analysts, between 2000-2002, is that the Dot-com bubble led to a significant increase in corporate bankruptcies, reducing the average analyst's portfolio size. By the end of 2002, most publicly-traded Dot-com companies had already failed. A similar trend is observed in 2009-2011, after the 2007–2008 Financial Crisis, and coinciding with a notable increase in bankruptcy filings[9].

[9] According to Bloomberg, based on a sample of filings for public and private companies with liabilities greater than

Table 3.1. Sample distribution by industry and year

Panel A: Sample distribution by industry			
SIC Code	Industry	Obs.	Percentage
73	Business Services	5,477	15.4169%
28	Chemical & Allied Products	4,567	12.8554%
36	Electronic & Other Electric Equipment	3,493	9.8322%
38	Instruments & Related Products	2,711	7.6310%
35	Industrial Machinery & Equipment	2,468	6.9470%
37	Transportation Equipment	1,281	3.6058%
13	Oil & Gas Extraction	1,271	3.5777%
20	Food & Kindred Products	1,121	3.1554%
50	Wholesale Trade - Durable Goods	836	2.3532%
87	Engineering & Management Services	811	2.2828%
80	Health Services	720	2.0267%
33	Primary Metal Industries	671	1.8888%
58	Eating & Drinking Places	653	1.8381%
59	Miscellaneous Retail	653	1.8381%
51	Wholesale Trade - Nondurable Goods	561	1.5791%
56	Apparel & Accessory Stores	527	1.4834%
79	Amusement & Recreational Services	515	1.4496%
10	Metal, Mining	492	1.3849%
34	Fabricated Metal Products	487	1.3708%
26	Paper & Allied Products	388	1.0922%
23	Apparel & Other Textile Products	386	1.0865%
27	Printing & Publishing	368	1.0359%
-	Other	5,069	14.2684%

Panel B: Sample distribution by year		
Year	Number of Obs.	Percentage
2000	1,554	4.3743%
2001	1,448	4.0759%
2002	1,496	4.2110%
2003	1,580	4.4474%
2004	1,615	4.5460%
2005	1,609	4.5460%
2006	1,545	4.3489%
2007	1,560	4.3912%
2008	1,542	4.3912%
2009	1,570	4.3912%
2010	1,627	4.5797%
2011	1,566	4.4080%
2012	1,566	4.4080%
2013	1,599	4.5009%
2014	1,594	4.4869%
2015	1,567	4.4109%
2016	1,589	4.4728%
2017	1,649	4.6417%
2018	1,690	4.7571%
2019	1,743	4.9063%
2020	1,835	5.1652%
2021	1,982	5.5790%

Notes. This table reports the number of observations per industry (based on two-digit SIC codes) and year.

Table 3.2. Summary statistics

Panel A: Summary statistics						
Variables	Obs.	Mean	Std. Dev.	25th Pctl.	Median	75th Pctl.
Panel A.1.: Crash risk proxies						
NCSKEW	35,526	0.110	1.566	−0.607	−0.055	0.578
DUVOL	35,526	−0.015	0.452	−0.293	−0.041	0.229
COUNT	35,526	−0.245	1.711	−1	0	1
Panel A.2.: Busyness measures						
BUSY_FIRMS	35,526	2.756	0.441	2.630	2.825	2.993
BUSY_REP	35,526	4.074	0.574	3.867	4.162	4.394
BUSY_IND	35,526	1.781	0.547	1.438	1.872	2.175
Panel A.3.: Firm-level control variables						
SIGMA	35,526	0.028	0.015	0.017	0.024	0.035
RET	35,526	−0.001	0.001	−0.001	−0.0003	−0.0001
ROA	35,526	−0.007	0.186	−0.016	0.039	0.080
SIZE	35,526	6.758	1.877	5.406	6.653	7.973
MTB	35,526	3.447	4.926	1.366	2.299	3.979
LEV	35,526	0.186	0.192	0.003	0.145	0.300
DTURN	35,526	0.064	1.050	−0.318	0.012	0.377
R&D	35,526	0.058	0.105	0.000	0.010	0.074

Notes. This table reports the summary statistics for the variables used in the baseline empirical analyses. My sample consists of 35,526 firm-year observations for 4,763 public U.S. firms over the period 2000-2021. All variables are defined in Appendix C. Continuous independent variables are winsorized at the 1st and 99th percentile to mitigate the effect of outliers.

Table 3.3 presents the correlation matrix for the key variables. Pearson correlations appear below the diagonal, and Spearman correlations correlations above. As expected, all stock price crash risk variables are significantly and positively correlated with each other, suggesting that they successfully capture the same construct[10]. Both Pearson and Spearman correlation coefficients between stock price crash risk proxies and analyst busyness proxies are positive and statistically significant with a p-value of less than 0.05. These results suggest that firms covered by busy analysts are more likely to experience a higher stock price crash risk, providing some preliminary evidence supporting the *busyness perspective* mechanism.

US$50 million, 225 companies filed for bankruptcy in 2008, while 293 filed for bankruptcy in 2009, and 158 in 2010.

[10]However, since *COUNT* is a discrete variable, smaller Pearson and Speerman correlation coefficients for *NCSKEW* and *COUNT* and *DUVOL* and *COUNT* are expected.

Table 3.3. Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) NCSKEW	1	0.928	0.680	-0.003	-0.006	-0.004	-0.054	0.055	0.097	0.067	0.081	-0.0002	0.030	-0.024
(2) DUVOL	0.918	1	0.709	0.015	0.016	0.008	-0.084	0.084	0.115	0.091	0.094	0.013	0.034	-0.041
(3) COUNT	0.534	0.672	1	0.017	0.024	0.014	-0.091	0.091	0.120	0.102	0.094	0.010	0.030	-0.033
(4) BUSY_FIRMS	0.009	0.020	0.018	1	0.808	0.390	-0.043	0.043	-0.092	0.091	0.064	0.149	0.025	0.021
(5) BUSY_REP	0.002	0.021	0.027	0.870	1	0.327	-0.129	0.129	-0.037	0.255	0.011	0.216	0.025	-0.113
(6) BUSY_IND	0.001	0.013	0.019	0.503	0.410	1	-0.205	0.205	0.148	0.071	-0.039	0.134	0.004	-0.210
(7) SIGMA	-0.059	-0.096	-0.108	-0.011	-0.108	-0.174	1	-1.000	-0.446	-0.586	-0.181	-0.155	0.141	0.212
(8) RET	0.066	0.098	0.105	0.001	0.092	0.150	-0.960	1	0.447	0.587	0.180	0.155	-0.140	-0.213
(9) ROA	0.064	0.100	0.115	-0.085	-0.018	0.195	-0.488	0.480	1	0.264	0.267	-0.092	0.048	-0.244
(10) SIZE	0.044	0.083	0.108	0.010	0.198	0.025	-0.536	0.455	0.363	1	0.042	0.437	0.020	-0.283
(11) MTB	0.043	0.062	0.064	0.063	0.029	-0.029	-0.036	0.020	-0.013	0.001	1	-0.074	0.078	0.238
(12) LEV	-0.010	0.002	0.005	0.117	0.173	0.078	-0.066	0.050	-0.029	0.317	-0.015	1	0.053	-0.307
(13) DTURN	0.018	0.019	0.021	0.020	0.022	-0.005	0.213	-0.229	-0.004	-0.005	0.046	0.041	1	-0.026
(14) R&D	-0.022	-0.056	-0.060	0.088	-0.013	-0.271	0.344	-0.325	-0.652	-0.374	0.163	-0.172	0.010	1

Notes. This table reports correlations for the full sample. Pearson (Spearman) correlations are presented below (above) the diagonal. All variables are defined in Appendix C. Continuous variables are winsorized at the 1st and 99th percentile.

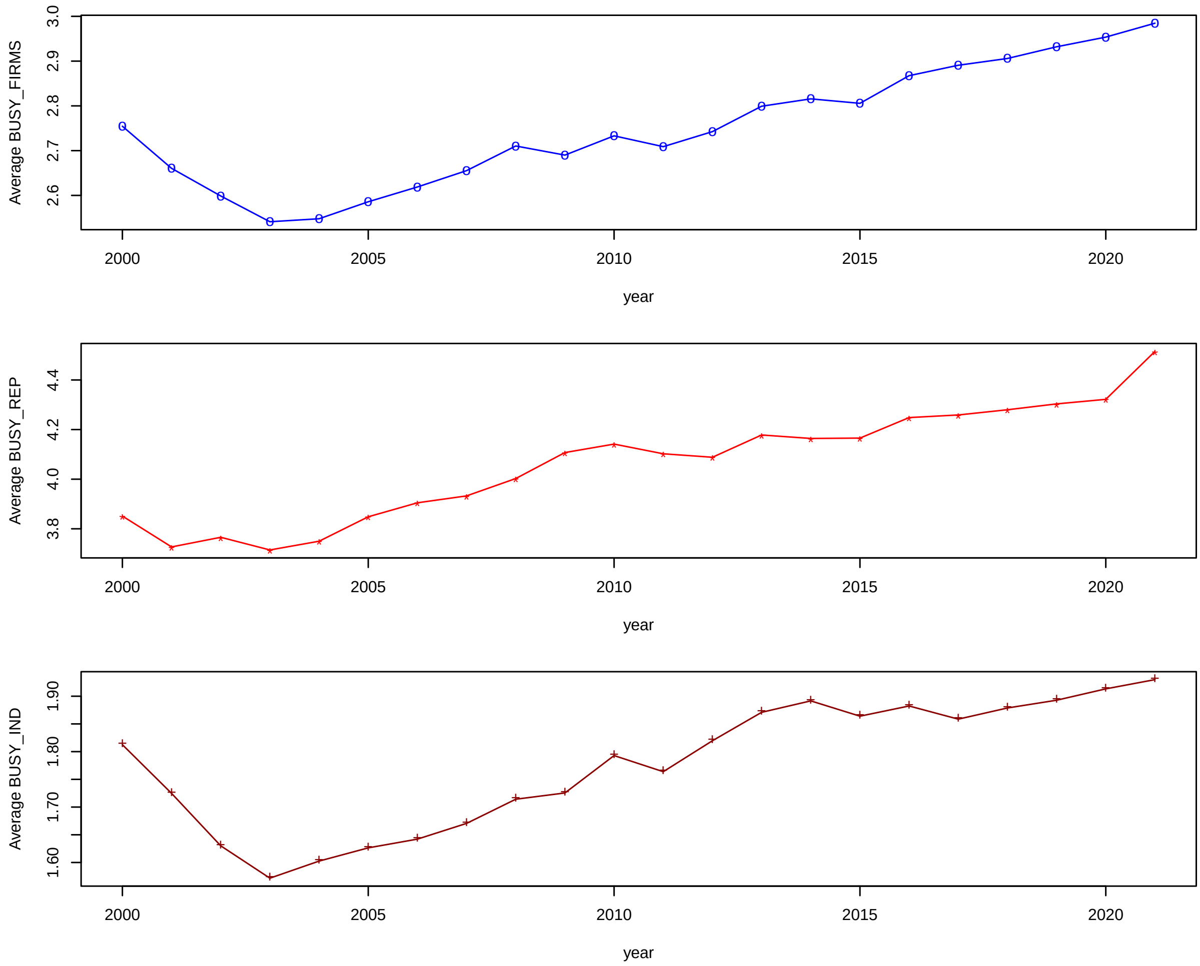

Figure 3.1. The Evolution of Analyst Busyness (2000-2021)

Notes. Time-series distribution of analyst busyness. This figure reports the yearly mean value (log) for analyst busyness measures across the sample years 2000-2021.

3.3.2 Baseline regression analysis

I begin the regression analysis by investigating the effect of firm-level analyst busyness, proxied by the average number of firms covered by analysts of a given firm in a given year (*BUSY_FIRMS*), on stock price crash risk, proxied by negative conditional skewness ($NCSKEW_{t+1}$), down-to-up volatility of firm-specific daily returns ($DUVOL_{t+1}$), and the number of crashes minus the number of jumps over the fiscal year ($COUNT_{t+1}$). Table 3.4 reports the baseline regression results based on Eq. 3.4 where *BUSY_FIRMS* is my main variable of interest. Columns (1) and (2) show the results when I use $NCSKEW_{t+1}$ as the dependent variable, while columns (3)-(4) and (5)-(6) use $DUVOL_{t+1}$ and $COUNT_{t+1}$ as the dependent variable, respectively. In all regressions in Table 3.4, I control for year and industry fixed effects.

I start with a parsimonious model in column (1) that only includes the main variable of interest *BUSY_FIRMS* as well as industry and year fixed effects. In column 1 the coefficient on *BUSY_FIRMS* is positive (0.053), and it is statistically significant at the 1% level (p-value = 0.001, t-statistic = 3.240). When I control for firm-level characteristics in column (2), the coefficient on *BUSY_FIRMS* remains positive (0.062) and statistically significant (p-value = 0.000, t-statistic = 3.776). Columns (3) and (4) present the results when *DUVOL* is used as the dependent variable. The coefficient estimates on *BUSY_FIRMS* are 0.017 and 0.021 in columns (3) and (4), respectively, and both coefficients are statistically significant at the 1% level (p-value = 0.001, t-statistic = 3.417; p-value = 0.000, t-statistic = 4.210), suggesting a positive relationship between $DUVOL_{t+1}$ and *BUSY_FIRMS* even after controlling for a number of firm characteristics. Finally, columns (5) and (6) report the results with $COUNT_{t+1}$ as the dependent variable, without controlling for firm-level characteristics and after controlling for firm-level characteristics, respectively. In column (5), the coefficient of *BUSY_FIRMS* is positive (0.057) and statistically significant at the 1% level (p-value = 0.008, t-statistic = 2.653). In column (6), the coefficient of *BUSY_FIRMS* is 0.073, statistically significant at the 1% level (p-value = 0.001, t-statistic = 3.435).

Overall, the results suggest that stock price crash risk is significantly and positively related to the average number of firms covered by analysts (*BUSY_FIRMS*), even after controlling for several firm-level characteristics, industry and year fixed effects, i.e., firms followed by analysts with larger portfolios (on average) are more likely to experience stock price crashes. As shown in Table 3.4, the coefficients on *BUSY_FIRMS* are all significantly positive, regardless of firm-specific crash risk measures. Results in Table 3.4 support the idea that the *busyness perspective* dominates the relationship between firm-level analyst busyness and future crash risk, overshadowing potential benefits of higher busyness levels expected by the *network perspective*. The coefficient estimates on the control variables are statistically significant for at least one proxy of stock price crash risk and are generally consistent with prior studies (Callen and Fang, 2015a; Hasan et al., 2022; Wu and Lai, 2020; Wen et al., 2019). Larger firms (*SIZE*), firms with a higher average idiosyncratic daily return (*RET*), market-to-book ratio (*MTB*), stock turnover (*DTURN*), return on assets (*ROA*), R&D intensity (*R&D*) and standard deviation of firm-specific daily returns (*SIGMA*) are associated with higher future crash risk. On the other hand, firms that have a higher leverage ratio (*LEV*) and lagged (*NCSKEW*) values are associated with a lower future crash risk.

Table 3.4. The effect of firm-level analyst busyness, measured by *BUSY_FIRMS*, on stock price crash risk

	Dependent variable:					
	$NCSKEW_{t+1}$		$DUVOL_{t+1}$		$COUNT_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
BUSY_FIRMS	0.053***	0.062***	0.017***	0.021***	0.057***	0.073***
	(0.016)	(0.016)	(0.005)	(0.005)	(0.021)	(0.021)
SIGMA		11.490***		2.106***		2.948
		(2.347)		(0.679)		(2.607)
RET		3.866***		1.006***		2.552***
		(0.521)		(0.151)		(0.588)
ROA		0.397***		0.148***		0.732***
		(0.069)		(0.019)		(0.074)
SIZE		0.037***		0.013***		0.062***
		(0.006)		(0.002)		(0.007)
MTB		0.011***		0.005***		0.018***
		(0.002)		(0.001)		(0.002)
LEV		−0.076		−0.029**		−0.155***
		(0.053)		(0.015)		(0.055)
DTURN		0.042***		0.013***		0.055***
		(0.009)		(0.002)		(0.009)
R&D		0.262*		0.018		0.388***
		(0.145)		(0.039)		(0.134)
NCSKEW				−0.001		−0.011*
				(0.002)		(0.006)
Constant	−0.109*	−0.508***	−0.086***	−0.180***	−0.703***	−1.058***
	(0.062)	(0.105)	(0.021)	(0.032)	(0.096)	(0.134)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.012	0.021	0.029	0.048	0.018	0.041
F Statistic	7.099***	10.975***	16.362***	23.824***	10.116***	20.444***
Observations	35,526	35,526	35,526	35,526	35,526	35,526

Notes. This table presents the regression results of the effect of firm-level analyst busyness, measured by *BUSY_FIRMS*, on stock price crash risk. In columns (1)-(2) crash risk is proxied by negative conditional skewness (*NCSKEW*) in year $t + 1$. In columns (3)-(4) crash risk is proxied by the down-to-up volatility (*DUVOL*) in year $t + 1$. In columns (5)-(6) crash risk is proxied by the number of crashes minus jumps (*COUNT*) in year $t + 1$. In all columns firm-level analyst busyness is measured by *BUSY_FIRMS*, the average number of firms covered by analysts of a given firm in a given year. I also include industry and year dummies to control for industry and time (year) fixed effects. See Appendix C for other variable definitions. Robust standard errors to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

In Table 3.5 I examine the relationship between firm-level analyst busyness, proxied by the average number of reports issued by the analysts of a given firm in a given year (*BUSY_REP*), and stock price crash risk, proxied by negative conditional skewness ($NCSKEW_{t+1}$), down-to-up volatility of firm-specific daily returns ($DUVOL_{t+1}$), and the number of crashes minus the number of jumps over the fiscal year ($COUNT_{t+1}$). Columns (1)-(2) show the results when I use $NCSKEW_{t+1}$ as the dependent variable, while columns (3)-(4) and (5)-(6) use $DUVOL_{t+1}$ and $COUNT_{t+1}$ as the dependent variable, respectively. All regressions include industry and year fixed effects to control for unobserved industry invariant specific factors and unobservable heterogeneity across years.

In column (1), using $NCSKEW_{t+1}$ as the dependent variable and without controlling for firm-level characteristics, the coefficient estimate on *BUSY_REP* is positive (0.059) and statistically significant at the 1% level (p-value = 0.000, t-statistic = 4.409). Column (2) shows the regression results for the influence of $BUSY\_REP$ on $NCSKEW_{t+1}$ after adding firm-level control variables. Similarly, there is a positive (0.039) and statistically significant relationship at the 1% level (p-value = 0.003, t-statistic = 2.950). Columns (3)-(4) present the results when $DUVOL_{t+1}$ is adopted to measure stock price crash risk. In column (3), the positive coefficient estimate on $BUSY\_REP$ is statistically significant at the 1% level (p-value = 0.000, t-statistic = 5.822). In column (4), controlling for firm-level characteristics, the coefficient on $BUSY\_REP$ remains positive (0.016) and statistically significant (p-value = 0.0002, t-statistic = 3.957). Columns (5)-(6) report the results using $COUNT_{t+1}$ as the dependent variable, without controlling for firm-level characteristics and after controlling, respectively. The coefficient estimates on $BUSY\_REP$ are 0.090 and 0.054 in columns (5) and (6), respectively, and both are statistically significant at the 1% level (p-value = 0.000, t-statistic = 5.118; p-value = 0.002, t-statistic = 3.106).

Using the average number of reports issued by the analysts of a given firm in a given year ($BUSY\_REP$) as a measure of firm-level analyst busyness yields similar conclusions for the relationship between firm-level analyst busyness and stock price crash risk. The coefficient estimates on $BUSY\_REP$ are positive and significant at the 1% level across all model specifications, i.e., a higher average number of reports issuance is positively related to a higher future crash risk. These findings support the *busyness perspective* and are consistent with my first results in Table 3.4. Coefficient estimates on firm-level controls are qualitatively similar to those in Table 3.4.

Table 3.5. The effect of firm-level analyst busyness, measured by *BUSY_REP*, on stock price crash risk

	Dependent variable:					
	$NCSKEW_{t+1}$		$DUVOL_{t+1}$		$COUNT_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
BUSY_REP	0.059***	0.039***	0.024***	0.016***	0.090***	0.054***
	(0.013)	(0.013)	(0.004)	(0.004)	(0.018)	(0.018)
SIGMA		11.286***		2.039***		2.714
		(2.343)		(0.678)		(2.605)
RET		3.826***		0.992***		2.503***
		(0.520)		(0.151)		(0.588)
ROA		0.396***		0.148***		0.732***
		(0.069)		(0.019)		(0.074)
SIZE		0.035***		0.012***		0.059***
		(0.006)		(0.002)		(0.007)
MTB		0.011***		0.005***		0.018***
		(0.002)		(0.001)		(0.002)
LEV		−0.072		−0.029*		−0.152***
		(0.053)		(0.015)		(0.055)
DTURN		0.042***		0.013***		0.055***
		(0.009)		(0.002)		(0.009)
R&D		0.268*		0.019		0.392***
		(0.145)		(0.039)		(0.134)
NCSKEW				−0.001		−0.010*
				(0.002)		(0.006)
Constant	−0.194***	−0.485***	−0.132***	−0.181***	−0.893***	−1.058***
	(0.068)	(0.106)	(0.022)	(0.033)	(0.103)	(0.137)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.012	0.021	0.030	0.048	0.018	0.041
F Statistic	7.183***	10.927***	16.619***	23.801***	10.388***	20.417***
Observations	35,526	35,526	35,526	35,526	35,526	35,526

Notes. This table presents the regression results of the effect of firm-level analyst busyness, measured by *BUSY_REP*, on stock price crash risk. In columns (1)-(2) crash risk is proxied by negative conditional skewness (*NCSKEW*) in year $t + 1$. In columns (3)-(4) crash risk is proxied by the down-to-up volatility (*DUVOL*) in year $t + 1$. In columns (5)-(6) crash risk is proxied by the number of crashes minus jumps (*COUNT*) in year $t + 1$. In all columns firm-level analyst busyness is measured by *BUSY_REP*, the average number of reports issued by the analysts of a given firm in a given year. I also include industry and year dummies to control for industry and time (year) fixed effects. See Appendix C for other variable definitions. Robust standard errors to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Next, I explore the relation between firm-level analyst busyness, proxied by the average number of industries covered by the analysts of a given firm in a given year (*BUSY_IND*), and stock price crash risk, proxied by negative conditional skewness ($NCSKEW_{t+1}$), down-to-up volatility of firm-specific daily returns ($DUVOL_{t+1}$), and the number of crashes minus the number of jumps over the fiscal year ($COUNT_{t+1}$). If the *busyness perspective* dominates the relationship between firm-level analyst busyness (based on the number of industries covered) and stock price crash risk, a positive and statistically significant coefficient estimate on *BUSY_IND* is expected. Otherwise, if the *network perspective* dominates the relationship, a negative and statistically significant coefficient estimate on *BUSY_IND* shall prevail. A non-statistically significant coefficient estimate indicates that neither the *busyness perspective* nor the *network perspective* prevails. Table 3.6 reports the baseline regression results based on Eq. 3.4, where

$BUSY\_IND$ is the main variable of interest.

Columns (1) and (2) show the results using $NCSKEW_{t+1}$ as the dependent variable, without firm-level controls and after controlling for firm-level characteristics, respectively. The impact of $BUSY\_IND$ on stock price crash risk, proxied by $NCSKEW_{t+1}$, is not statistically significant (p-value = 0.918, t-statistic = -0.103; p-value = 0.622, t-statistic = -0.493). Columns (3) and (4) present the results when I use $DUVOL_{t+1}$ as the dependent variable. In both estimations, before and after firm-level control variables, the coefficient estimates on $BUSY\_IND$ are not statistically significant at the conventional levels (p-value = 0.813, t-statistic = 0.237; p-value = 0.829, t-statistic = -0.216). Finally, columns (5) and (6) show the estimation results using $COUNT_{t+1}$ to measure crash risk. Similarly, the relationship between the average number of industries covered by the analysts of a given firm and stock price crash risk remains not statistically significant (p-value = 0.210, t-statistic = 1.254; p-value = 0.926, t-statistic = -0.093). Collectively, I find no evidence that firms with analysts following a higher number of industries (on average) increase or decrease stock price crash risk.

Table 3.6. The effect of firm-level analyst busyness, measured by *BUSY_IND*, on stock price crash risk

	Dependent variable:					
	NCSKEW$_{t+1}$		DUVOL$_{t+1}$		COUNT$_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
BUSY_IND	−0.002	−0.010	0.005	−0.004	0.025	−0.002
	(0.016)	(0.017)	(0.005)	(0.005)	(0.019)	(0.020)
SIGMA		11.023***		1.907***		2.514
		(2.368)		(0.686)		(2.635)
RET		3.797***		0.975***		2.485***
		(0.523)		(0.152)		(0.591)
ROA		0.394***		0.147***		0.730***
		(0.069)		(0.019)		(0.074)
SIZE		0.035***		0.012***		0.061***
		(0.006)		(0.002)		(0.007)
MTB		0.011***		0.005***		0.018***
		(0.002)		(0.001)		(0.002)
LEV		−0.061		−0.024		−0.140**
		(0.053)		(0.015)		(0.055)
DTURN		0.043***		0.014***		0.055***
		(0.009)		(0.002)		(0.009)
R&D		0.268*		0.019		0.409***
		(0.148)		(0.040)		(0.137)
NCSKEW				−0.001		−0.010*
				(0.002)		(0.006)
Constant	0.020	−0.328***	−0.050***	−0.115***	−0.595***	−0.863***
	(0.051)	(0.101)	(0.017)	(0.031)	(0.084)	(0.130)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.012	0.021	0.029	0.048	0.018	0.041
F Statistic	6.999***	10.857***	16.240***	23.649***	10.043***	20.295***
Observations	35,526	35,526	35,526	35,526	35,526	35,526

Notes. This table presents the regression results of the effect of firm-level analyst busyness, measured by *BUSY_IND*, on stock price crash risk. In columns (1)-(2) crash risk is proxied by negative conditional skewness (*NCSKEW*) in year $t+1$. In columns (3)-(4) crash risk is proxied by the down-to-up volatility (*DUVOL*) in year $t+1$. In columns (5)-(6) crash risk is proxied by the number of crashes minus jumps (*COUNT*) in year $t+1$. In all columns firm-level analyst busyness is measured by *BUSY_IND*, the average number of industries covered by the analysts of a given firm in a given year. I also include industry and year dummies to control for industry and time (year) fixed effects. See Appendix C for other variable definitions. Robust standard errors to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Overall, these findings indicate that firms followed either by analysts following a higher number of companies or with a higher number of reports issuance are positively associated with stock price crash risk. Consistent with the *busyness perspective* prediction, increased busyness could deteriorate monitoring quality, thus enhancing managers' capabilities to withhold bad news. First, analysts following a higher number of firms may face more time constraints to properly perform their external monitoring activities on covered firms, such as attending investor days and private meetings with firm management. Second, producing more reports could lead to increased fatigue due to the higher workload for analysts (Kim et al., 2021), which, in turn, may hinder their ability to effectively monitor all the firms they follow adequately. As shown in Table 3.4 and 3.5, the *busyness perspective* outweighs the *network perspective* when I use *BUSY_FIRMS* and *BUSY_REP* as proxies for firm-level analyst busyness. However, using *BUSY_IND* to measure firm-level analyst busyness, I fail to find a statistically significant relationship (positive or negative) between firm-level analyst busyness and all three measures of stock price crash risk, i.e., neither the *busyness perspective* or the *network perspective* seems to prevail.

3.3.3 Additional analysis

3.3.4 Cross-sectional analysis: the impact of information asymmetry

Next, I investigate whether the relationship between firm-level analyst busyness and stock price crash risk is more pronounced among firms with a poor information environment. As agency problems arise when the interests of managers (agents) are not aligned with the interests of shareholders (principals) and information asymmetry between the principals and agents exists, firms with higher information asymmetry between managers and shareholders are more likely to experience severe agency conflicts than those with lower information asymmetry (Jensen and Meckling, 1976; Callen and Fang, 2015b). Following this line of reasoning and based on the Jin and Myers (2006) bad news hoarding framework, I expect that managers' abilities to hoard bad news will be stronger in firms with higher information asymmetry (Fu and Zhang, 2019). For instance, Kim and Zhang (2016) finds that the relation between conservatism and crash risk is more pronounced for firms with higher information asymmetry. Empirically, I use the median of R&D intensity, calculated as R&D expenditure divided by total assets, to divide my sample into *Higher R&D* (High Information Asymmetry) and *Lower R&D* (Low Information Asymmetry) subsamples. Prior studies find that R&D intensity increases information asymmetry (Aboody and Lev, 2000), leading to a more opaque information environment. Vorst (2017) suggest that the information asymmetry for firms with significant investments in R&D is likely higher due the difficulty of attaching a value to R&D investments and the uncertainty of pay-offs.

Table 3.7 presents results of subsample analysis of the impact of firm-level analyst busyness, measured by *BUSY_FIRMS*, on stock price crash risk. Columns (1), (3), and (5) reports results of stock price crash risk proxies regressed on *BUSY_FIRMS* for firms with higher R&D intensity (higher information asymmetry levels). Columns (2), (4), and (6) reports results of stock price crash risk proxies regressed on *BUSY_FIRMS* for firms with lower R&D intensity (lower information asymmetry levels). In columns (1)-(2) crash risk is proxied by $NCSKEW_{t+1}$. In columns (3)-(4) crash risk is proxied by $DUVOL_{t+1}$. In columns (5)-(6) crash risk is proxied by $COUNT_{t+1}$. Overall, the results suggest that the effect of firm-level analyst busyness (proxied by *BUSY_FIRMS*) on stock price crash risk is more pronnounced in R&D-intensive firms. For example, Models 1 and 2 of Table 3.7 show that the coefficient estimate on *BUSY_FIRMS* is statistically signfiicant at the 1% level in the subsample of R&D-intensive firms, while not statistically significant at the conventional levels in the subsample of non R&D-intensive firms.

Table 3.7. Sample partitions: firm-level analyst busyness, measured by *BUSY_FIRMS*, and stock price crash risk conditional on information asymmetry

	Dependent variable:					
	$NCSKEW_{t+1}$		$DUVOL_{t+1}$		$COUNT_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
	Higher R&D	*Lower R&D*	*Higher R&D*	*LowerR&D*	*Higher R&D*	*Lower R&D*
BUSY_ FIRMS	0.086***	0.018	0.029***	0.006	0.112***	0.025
	(0.028)	(0.022)	(0.008)	(0.007)	(0.033)	(0.031)
SIGMA	10.801***	3.862	2.976***	−0.261	5.676	−4.188
	(3.663)	(3.384)	(1.031)	(1.024)	(3.802)	(4.068)
RET	4.082***	2.248***	1.260***	0.522**	3.208***	1.280
	(0.763)	(0.748)	(0.214)	(0.232)	(0.805)	(0.945)
ROA	0.352***	0.404***	0.121***	0.186***	0.576***	0.975***
	(0.090)	(0.116)	(0.025)	(0.034)	(0.092)	(0.141)
SIZE	0.040***	0.032***	0.018***	0.010***	0.087***	0.045***
	(0.010)	(0.009)	(0.003)	(0.003)	(0.010)	(0.011)
MTB	0.012***	0.009***	0.005***	0.004***	0.021***	0.015***
	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(0.004)
LEV	−0.030	−0.056	−0.034	−0.008	−0.170**	−0.080
	(0.092)	(0.071)	(0.025)	(0.021)	(0.085)	(0.083)
DTURN	0.046***	0.049***	0.015***	0.014***	0.070***	0.039***
	(0.012)	(0.011)	(0.003)	(0.003)	(0.012)	(0.014)
R&D	0.024	5.913	−0.032	1.151	0.232	−10.237
	(0.195)	(6.505)	(0.052)	(1.846)	(0.173)	(7.104)
NCSKEW			−0.007***	0.002	−0.028***	0.001
			(0.002)	(0.003)	(0.007)	(0.009)
Constant	−0.890***	0.022	−0.380***	−0.007	−1.876***	−0.418*
	(0.205)	(0.217)	(0.063)	(0.067)	(0.355)	(0.252)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.026	0.028	0.054	0.051	0.051	0.042
F Statistic	3.046***	2.444***	5.449***	3.709***	5.154***	3.204***
Observations	17,763	17,763	17,763	17,763	17,763	17,763

Notes. This table presents results of subsample analysis of the impact of firm-level analyst busyness, measured by *BUSY_FIRMS*, on stock price crash risk. Columns (1), (3), and (5) reports results of stock price crash risk regressed on firm-level analyst busyness for firms with higher R&D intensity (higher information asymmetry levels). Columns (2), (4), and (6) reports results of stock price crash risk regressed on firm-level analyst busyness for firms with lower R&D intensity (lower information asymmetry levels). In all columns firm-level analyst busyness is measured by *BUSY_FIRMS*, the average number of firms covered by analysts of a given firm in a given year. In columns (1)-(2) crash risk is proxied by negative conditional skewness (*NCSKEW*) in year $t + 1$. In columns (3)-(4) crash risk is proxied by the down-to-up volatility (*DUVOL*) in year $t + 1$. In columns (5)-(6) crash risk is proxied by the number of crashes minus jumps (*COUNT*) in year $t + 1$. I also include industry and year dummies to control for industry and time (year) fixed effects. See Appendix C for other variable definitions. Robust standard errors to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3.8 reports regression results when firm-level analyst busyness is proxied by *BUSY_ REPORTS*. Columns (1), (3), and (5) reports results of stock price crash risk proxies regressed on *BUSY_REPORTS* for firms with higher R&D intensity (higher information asymmetry levels). Columns (2), (4), and (6) reports results of stock price crash risk proxies regressed on *BUSY_REPORTS* for firms with lower R&D intensity (lower information asymmetry levels). The results reported in columns (1), (3), and (5) show that the coefficient estimates on *BUSY_REPORTS* are higher in the subsample of R&D-intensive firms and statistically significant at the 1% level, suggesting that the effect of firm-level analyst busyness (proxied by *BUSY_REPORTS*) on stock price crash risk is more pronounced in firms with a high degree of R&D-intensity.

Table 3.8. Sample partitions: firm-level analyst busyness, measured by *BUSY_REPORTS*, and stock price crash risk conditional on information asymmetry

	Dependent variable:					
	$NCSKEW_{t+1}$		$DUVOL_{t+1}$		$COUNT_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
	Higher R&D	*Lower R&D*	*Higher R&D*	*LowerR&D*	*Higher R&D*	*Lower R&D*
BUSY_ REP	0.079***	0.009	0.027***	0.006	0.093***	0.022
	(0.023)	(0.018)	(0.007)	(0.006)	(0.027)	(0.025)
SIGMA	10.662***	3.782	2.933***	−0.280	5.509	−4.265
	(3.661)	(3.378)	(1.030)	(1.023)	(3.803)	(4.065)
RET	4.045***	2.234***	1.249***	0.517**	3.164***	1.262
	(0.762)	(0.747)	(0.214)	(0.232)	(0.805)	(0.945)
ROA	0.353***	0.403***	0.121***	0.186***	0.577***	0.975***
	(0.090)	(0.116)	(0.025)	(0.034)	(0.092)	(0.141)
SIZE	0.037***	0.032***	0.017***	0.010***	0.082***	0.044***
	(0.010)	(0.009)	(0.003)	(0.003)	(0.010)	(0.011)
MTB	0.012***	0.009***	0.005***	0.004***	0.021***	0.015***
	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(0.004)
LEV	−0.030	−0.054	−0.035	−0.008	−0.168**	−0.080
	(0.092)	(0.071)	(0.025)	(0.021)	(0.085)	(0.083)
DTURN	0.046***	0.049***	0.015***	0.014***	0.070***	0.039***
	(0.012)	(0.011)	(0.003)	(0.003)	(0.012)	(0.014)
R&D	0.012	5.910	−0.036	1.166	0.221	−10.181
	(0.195)	(6.507)	(0.052)	(1.846)	(0.173)	(7.105)
NCSKEW			−0.007***	0.002	−0.028***	0.001
			(0.002)	(0.003)	(0.007)	(0.009)
Constant	−0.932***	0.041	−0.396***	−0.009	−1.895***	−0.423*
	(0.206)	(0.215)	(0.064)	(0.066)	(0.357)	(0.251)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.026	0.028	0.055	0.051	0.051	0.042
F Statistic	3.053***	2.443***	5.461***	3.709***	5.154***	3.204***
Observations	17,763	17,763	17,763	17,763	17,763	17,763

Notes. This table presents results of subsample analysis of the impact of firm-level analyst busyness, measured by BUSY_reports, on stock price crash risk. Columns (1), (3), and (5) reports results of stock price crash risk regressed on firm-level analyst busyness for firms with higher R&D intensity (higher information asymmetry levels). Columns (2), (4), and (6) reports results of stock price crash risk regressed on firm-level analyst busyness for firms with lower R&D intensity (lower information asymmetry levels). In all columns firm-level analyst busyness is measured by *BUSY_REPORTS*, the average number of reports issued by the analysts of a given firm in agiven year. In columns (1)-(2) crash risk is proxied by negative conditional skewness (*NCSKEW*) in year $t+1$. In columns (3)-(4) crash risk is proxied by the down-to-up volatility (*DUVOL*) in year $t+1$. In columns (5)-(6) crash risk is proxied by the number of crashes minus jumps (*COUNT*) in year $t+1$. I also include industry and year dummies to control for industry and time (year) fixed effects. See Appendix C for other variable definitions. Robust standard errors to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3.9 reports regression results when firm-level analyst busyness is proxied by *BUSY_IND*. Columns (1), (3), and (5) reports results of stock price crash risk proxies regressed on *BUSY_IND* for firms with higher R&D intensity (higher information asymmetry levels). Columns (2), (4), and (6) reports results of stock price crash risk proxies regressed on *BUSY_IND* for firms with lower R&D intensity (lower information asymmetry levels). Coefficient estimates on *BUSY_IND* are not statistically significant at the conventional levels across all specifications.

Table 3.9. Sample partitions: firm-level analyst busyness, measured by *BUSY_IND*, and stock price crash risk conditional on information asymmetry

	Dependent variable:					
	$NCSKEW_{t+1}$		$DUVOL_{t+1}$		$COUNT_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
	Higher R&D	*Lower R&D*	*Higher R&D*	*LowerR&D*	*Higher R&D*	*Lower R&D*
BUSY_IND	0.011	0.0001	0.003	−0.003	0.050	0.004
	(0.029)	(0.025)	(0.008)	(0.008)	(0.033)	(0.033)
SIGMA	10.828***	3.754	2.964***	−0.340	6.071	−4.318
	(3.680)	(3.394)	(1.036)	(1.026)	(3.821)	(4.076)
RET	4.087***	2.232***	1.259***	0.510**	3.264***	1.261
	(0.765)	(0.750)	(0.215)	(0.232)	(0.807)	(0.946)
ROA	0.351***	0.402***	0.121***	0.185***	0.573***	0.973***
	(0.090)	(0.116)	(0.025)	(0.034)	(0.092)	(0.141)
SIZE	0.040***	0.032***	0.018***	0.010***	0.089***	0.045***
	(0.010)	(0.009)	(0.003)	(0.003)	(0.011)	(0.011)
MTB	0.012***	0.009***	0.005***	0.004***	0.021***	0.015***
	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(0.004)
LEV	−0.017	−0.052	−0.030	−0.006	−0.158*	−0.075
	(0.092)	(0.071)	(0.025)	(0.021)	(0.085)	(0.083)
DTURN	0.046***	0.049***	0.015***	0.014***	0.070***	0.039***
	(0.012)	(0.011)	(0.003)	(0.003)	(0.012)	(0.014)
R&D	0.047	5.856	−0.025	1.140	0.279	−10.328
	(0.196)	(6.503)	(0.052)	(1.845)	(0.174)	(7.108)
NCSKEW			−0.007***	0.002	−0.028***	0.001
			(0.002)	(0.003)	(0.007)	(0.009)
Constant	−0.669***	0.071	−0.303***	0.018	−1.695***	−0.358
	(0.206)	(0.216)	(0.063)	(0.066)	(0.356)	(0.250)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.025	0.028	0.054	0.051	0.051	0.042
F Statistic	3.017***	2.443***	5.406***	3.707***	5.114***	3.202***
Observations	17,763	17,763	17,763	17,763	17,763	17,763

Notes. This table presents results of subsample analysis of the impact of firm-level analyst busyness, measured by BUSY_IND, on stock price crash risk. Columns (1), (3), and (5) reports results of stock price crash risk regressed on firm-level analyst busyness for firms with higher R&D intensity (higher information asymmetry levels). Columns (2), (4), and (6) reports results of stock price crash risk regressed on firm-level analyst busyness for firms with lower R&D intensity (lower information asymmetry levels). In all columns firm-level analyst busyness is measured by *BUSY_IND*, the average number of industries covered by the analysts of a given firm in a given year. In columns (1)-(2) crash risk is proxied by negative conditional skewness (*NCSKEW*) in year $t + 1$. In columns (3)-(4) crash risk is proxied by the down-to-up volatility (*DUVOL*) in year $t + 1$. In columns (5)-(6) crash risk is proxied by the number of crashes minus jumps (*COUNT*) in year $t + 1$. I also include industry and year dummies to control for industry and time (year) fixed effects. Robust standard errors to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Collectively, I find evidence that the impact of firm-level analyst busyness (proxied *BUSY_FIRMS* and *BUSY_REPORTS*) is more pronounced for firms with greater information asymmetry. However, the relation between *BUSY_IND* remains not statistically significant at the conventional levels in *Higher R&D* and *Lower R&D* subsamples.

3.4 Robustness checks

In this section I perform several robustness checks to examine the sensitivity of my results. First, I use alternative measures of firm-level analyst busyness to take into account potential measurement error.

Second, we include a potential omitted variable. Third, I employ an entropy balancing approach, a method for matching treatment and control observations that assign weights to the control group based on the matching variables (covariates), ensuring that the post-weighting matching variables are virtually identical between the control and treatment groups in terms of mean, variance, and skewness (Zuo et al., 2022).

3.4.1 Excluding analysts that are likely to be an analyst team rather than an individual analyst

One could argue that my firm-level analyst busyness measures are also capturing, by design, the busyness of analyst teams rather than the busyness of individual (sell-side) analysts. For instance, some analysts in my sample cover more than 50 companies. As an analyst team is more likely to maintain such a high level of coverage, I employ different thresholds on the maximum number of firms followed by a single analyst to test the sensitivity of my results. Specifically, to partially alleviate this concern, I exclude analysts that cover more than 25 firms (proxied by *BUSY_25*), 20 firms (proxied by *BUSY_20*), and 15 firms (proxied by *BUSY_15*), respectively, as alternative proxies for *BUSY_FIRMS*. I also test for the exclusion of analysts covering more than 8 industries (proxied by *BUSY_8*) and 6 industries (proxied by *BUSY_6*), respectively, as alternative proxies for *BUSY_IND*[11]. Table 3.10 examines the relationship between firm-level analyst busyness and crash risk proxies ($NCSKEW_{t+1}$, $DUVOL_{t+1}$, and $COUNT_{t+1}$) when *BUSY_25* is my main variable of interest, replacing *BUSY_FIRMS*. Results remain qualitatively unchanged when I exclude analysts that cover more than 25 firms. As observed in Table 3.10, *BUSY_25* is statistically significant at the 1% level across all specifications.

[11]Using a sample of 356,463 sell-side equity analysts' reports from 2002 to 2009, De Franco et al. (2015) finds that an average analyst in their sample follows 16 to 17 companies across four to five industries. Based on a survey with 365 analysts and 18 follow-up interviews, Brown et al. (2015) find that the median analyst follows 15 firms, and nearly half cover only one industry. However, Brown et al. (2015) is not clear about whether an industry is based on 2-digit/4-digit SIC codes, or Fama-French 48 Industrial Classifications, for example.

Table 3.10. Excluding analysts following more than 25 firms

	Dependent variable:					
	$NCSKEW_{t+1}$		$DUVOL_{t+1}$		$COUNT_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
BUSY_25	0.099^{***}	0.104^{***}	0.032^{***}	0.034^{***}	0.080^{***}	0.091^{***}
	(0.018)	(0.018)	(0.005)	(0.005)	(0.023)	(0.023)
SIGMA		11.424^{***}		2.218^{***}		3.888
		(2.435)		(0.703)		(2.692)
RET		3.882^{***}		1.038^{***}		2.740^{***}
		(0.549)		(0.159)		(0.617)
ROA		0.363^{***}		0.139^{***}		0.741^{***}
		(0.070)		(0.020)		(0.076)
SIZE		0.034^{***}		0.012^{***}		0.062^{***}
		(0.006)		(0.002)		(0.007)
MTB		0.010^{***}		0.005^{***}		0.018^{***}
		(0.002)		(0.001)		(0.002)
LEV		−0.088		-0.033^{**}		-0.148^{***}
		(0.054)		(0.015)		(0.056)
DTURN		0.044^{***}		0.014^{***}		0.057^{***}
		(0.009)		(0.002)		(0.009)
R&D		0.223		0.004		0.384^{***}
		(0.148)		(0.040)		(0.138)
NCSKEW				−0.001		-0.012^{**}
				(0.002)		(0.006)
Constant	-0.200^{***}	-0.564^{***}	-0.116^{***}	-0.203^{***}	-0.752^{***}	-1.116^{***}
	(0.062)	(0.107)	(0.021)	(0.033)	(0.097)	(0.136)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.012	0.020	0.030	0.047	0.018	0.040
F Statistic	7.055^{***}	10.285^{***}	16.320^{***}	22.854^{***}	9.980^{***}	19.636^{***}
Observations	34,955	34,955	34,955	34,955	34,955	34,955

Notes. This table presents the regression results of the effect of firm-level analyst busyness, measured by *BUSY_25*, on stock price crash risk. In columns (1)-(2) crash risk is proxied by negative conditional skewness (*NCSKEW*) in year $t + 1$. In columns (2)-(4) crash risk is proxied by the down-to-up volatility (*DUVOL*) in year $t + 1$. In columns (5)-(6) crash risk is proxied by the number of crashes minus jumps (*COUNT*) in year $t + 1$. In all columns firm-level analyst busyness is measured by *BUSY_25*, the average number of firms covered by analysts of a given firm in a given year, excluding analysts that cover more than 25 firms. I also include industry and year dummies to control for industry and time (year) fixed effects. See Appendix C for other variable definitions. Robust standard errors to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3.11 reports the regression results when *BUSY_20* is my variable of interest. The relationship between firm-level analyst busyness and stock price crash risk holds statistically significant even after excluding analysts following more than 20 firms. *BUSY_20* is statistically significant at the 1% level across all specifications.

Table 3.11. Excluding analysts following more than 20 firms

	Dependent variable:					
	$NCSKEW_{t+1}$		$DUVOL_{t+1}$		$COUNT_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
BUSY_20	0.091***	0.092***	0.032***	0.032***	0.079***	0.085***
	(0.018)	(0.019)	(0.006)	(0.006)	(0.024)	(0.024)
SIGMA		11.754***		2.276***		4.174
		(2.503)		(0.722)		(2.763)
RET		3.874***		1.023***		2.687***
		(0.568)		(0.163)		(0.638)
ROA		0.394***		0.147***		0.766***
		(0.072)		(0.021)		(0.078)
SIZE		0.032***		0.012***		0.061***
		(0.006)		(0.002)		(0.007)
MTB		0.010***		0.004***		0.018***
		(0.002)		(0.001)		(0.002)
LEV		−0.080		−0.033**		−0.147***
		(0.055)		(0.015)		(0.057)
DTURN		0.040***		0.013***		0.056***
		(0.009)		(0.002)		(0.009)
R&D		0.294*		0.021		0.428***
		(0.152)		(0.041)		(0.142)
NCSKEW				−0.001		−0.013**
				(0.002)		(0.006)
Constant	−0.177***	−0.546***	−0.112***	−0.200***	−0.731***	−1.109***
	(0.063)	(0.109)	(0.021)	(0.033)	(0.096)	(0.138)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.012	0.019	0.029	0.045	0.017	0.039
F Statistic	6.698***	9.492***	15.675***	21.355***	9.670***	18.447***
Observations	34,166	34,166	34,166	34,166	34,166	34,166

Notes. This table presents the regression results of the effect of firm-level analyst busyness, measured by *BUSY_20*, on stock price crash risk. In columns (1)-(2) crash risk is proxied by negative conditional skewness (*NCSKEW*) in year $t+1$. In columns (3)-(4) crash risk is proxied by the down-to-up volatility (*DUVOL*) in year $t+1$. In columns (5)-(6) crash risk is proxied by the number of crashes minus jumps (*COUNT*) in year $t+1$. In all columns firm-level analyst busyness is measured by *BUSY_20*, the average number of firms covered by analysts of a given firm in a given year, excluding analysts that cover more than 20 firms. I also include industry and year dummies to control for industry and time (year) fixed effects. See Appendix C for other variable definitions. Robust standard errors to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

In Table 3.12 I regress crash risk proxies ($NCSKEW_{t+1}$, $DUVOL_{t+1}$, and $COUNT_{t+1}$) on *BUSY_15*. *BUSY_15* is statistically significant at the 1% level across all specifications. Collectively, these results partially alleviate concerns that my results are driven by analyst teams when *BUSY_FIRMS* is my variable of interest.

Table 3.12. Excluding analysts following more than 15 firms

	Dependent variable:					
	$NCSKEW_{t+1}$		$DUVOL_{t+1}$		$COUNT_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
BUSY_15	0.058***	0.055***	0.021***	0.020***	0.063***	0.059**
	(0.019)	(0.020)	(0.006)	(0.006)	(0.023)	(0.023)
SIGMA		11.520***		2.391***		6.595**
		(2.681)		(0.774)		(2.947)
RET		3.750***		1.057***		3.298***
		(0.626)		(0.181)		(0.697)
ROA		0.372***		0.144***		0.733***
		(0.078)		(0.022)		(0.083)
SIZE		0.026***		0.010***		0.057***
		(0.006)		(0.002)		(0.007)
MTB		0.009***		0.004***		0.017***
		(0.002)		(0.001)		(0.002)
LEV		−0.065		−0.029*		−0.124**
		(0.058)		(0.016)		(0.059)
DTURN		0.044***		0.014***		0.054***
		(0.009)		(0.003)		(0.010)
R&D		0.265		0.024		0.417***
		(0.161)		(0.044)		(0.150)
NCSKEW				−0.002		−0.015***
				(0.002)		(0.006)
Constant	−0.086	−0.415***	−0.090***	−0.165***	−0.685***	−1.070***
	(0.064)	(0.112)	(0.021)	(0.034)	(0.096)	(0.140)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.011	0.017	0.029	0.042	0.018	0.036
F Statistic	6.013***	7.946***	14.546***	18.803***	9.167***	16.066***
Observations	31,794	31,794	31,794	31,794	31,794	31,794

Notes. This table presents the regression results of the effect of firm-level analyst busyness, measured by *BUSY_15*, on stock price crash risk. In columns (1)-(2) crash risk is proxied by negative conditional skewness (*NCSKEW*) in year $t + 1$. In columns (3)-(4) crash risk is proxied by the down-to-up volatility (*DUVOL*) in year $t + 1$. In columns (5)-(6) crash risk is proxied by the number of crashes minus jumps (*COUNT*) in year $t + 1$. In all columns firm-level analyst busyness is measured by *BUSY_15*, the average number of firms covered by analysts of a given firm in a given year, excluding analysts that cover more than 15 firms. I also include industry and year dummies to control for industry and time (year) fixed effects. See Appendix C for other variable definitions. Robust standard errors to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

In Table 3.13 and 3.14 I investigate the relationship between firm-level analyst busyness and stock price crash risk, respectively replacing *BUSY_IND* with *BUSY_8* and *BUSY_5*. *BUSY_8* (*BUSY_5*) is the average number of industries covered by the analysts of a given firm in a given year, excluding analysts that cover more than 8 (5) industries. As observed in Table 3.13, *BUSY_8* is statistically significant at the 1% in columns (3) and (5) and at the 5% level in columns (1), (2), (4), and (6). These findings suggest that my baseline results when firm-level analyst busyness is proxied by *BUSY_IND* were potentially driven by analyst teams rather than individual analysts since eliminating analysts following more than 8 industries provides contrasting results. As shown in Table 3.13, firms with analysts following more industries (on average) are associated with increased future crash risk.

Table 3.13. Excluding analysts following more than 8 industries

	Dependent variable:					
	$NCSKEW_{t+1}$		$DUVOL_{t+1}$		$COUNT_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
BUSY_8	0.047**	0.044**	0.022***	0.015**	0.074***	0.055**
	(0.021)	(0.021)	(0.006)	(0.006)	(0.025)	(0.026)
SIGMA		12.501***		1.392*		−0.362
		(2.569)		(0.740)		(2.796)
RET		4.118***		0.869***		1.935***
		(0.588)		(0.169)		(0.643)
ROA		0.319***		0.114***		0.609***
		(0.069)		(0.020)		(0.075)
SIZE		0.031***		0.011***		0.055***
		(0.006)		(0.002)		(0.007)
MTB		0.009***		0.004***		0.015***
		(0.002)		(0.001)		(0.002)
LEV		−0.051		−0.022		−0.096*
		(0.056)		(0.016)		(0.057)
DTURN		0.040***		0.014***		0.058***
		(0.009)		(0.002)		(0.009)
R&D		0.167		−0.007		0.313**
		(0.149)		(0.041)		(0.139)
NCSKEW				0.004**		0.005
				(0.002)		(0.006)
Constant	0.091**	−0.244**	0.010	−0.030	−0.175**	−0.312**
	(0.045)	(0.103)	(0.016)	(0.031)	(0.082)	(0.132)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.012	0.019	0.031	0.048	0.019	0.040
F Statistic	6.609***	9.491***	16.258***	22.117***	10.042***	18.551***
Observations	32,909	32,909	32,909	32,909	32,909	32,909

Notes. This table presents the regression results of the effect of firm-level analyst busyness, measured by *BUSY_8*, on stock price crash risk. In columns (1)-(2) crash risk is proxied by negative conditional skewness (*NCSKEW*) in year $t+1$. In columns (3)-(4) crash risk is proxied by the down-to-up volatility (*DUVOL*) in year $t+1$. In columns (5)-(6) crash risk is proxied by the number of crashes minus jumps (*COUNT*) in year $t+1$. In all columns firm-level analyst busyness is measured by *BUSY_8*, the average number of industries covered by the analysts of a given firm in a given year, excluding analysts that cover more than 8 industries. I also include industry and year dummies to control for industry and time (year) fixed effects. See Appendix C for other variable definitions. Robust standard errors to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

In Table 3.14, I present the regression results using *BUSY_5* as the variable of interest. *BUSY_5* is statistically significant at the 5% level in columns (1), (2), (3), and (4), and at the 10% level in columns (5) and (6). Overall, after excluding analysts following more than 8 and 5 industries to take into account the potential influence of analyst teams on the main results, I find strong evidence that the *busyness perspective* plays a dominant role in the relationship between firm-level analyst busyness and stock price crash risk even when analyst busyness is based on the average number of industries covered by the analysts of a given firm in a given year.

Table 3.14. Excluding analysts following more than 5 industries

	Dependent variable:					
	$NCSKEW_{t+1}$		$DUVOL_{t+1}$		$COUNT_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
BUSY_5	0.092***	0.089***	0.028***	0.025***	0.054*	0.052*
	(0.024)	(0.024)	(0.007)	(0.007)	(0.028)	(0.028)
SIGMA		11.402***		1.901**		1.885
		(2.681)		(0.770)		(2.916)
RET		3.954***		0.978***		2.125***
		(0.612)		(0.175)		(0.665)
ROA		0.331***		0.135***		0.719***
		(0.075)		(0.021)		(0.080)
SIZE		0.021***		0.009***		0.052***
		(0.007)		(0.002)		(0.008)
MTB		0.011***		0.004***		0.018***
		(0.002)		(0.001)		(0.002)
LEV		−0.022		−0.014		−0.086
		(0.059)		(0.016)		(0.060)
DTURN		0.037***		0.012***		0.048***
		(0.009)		(0.003)		(0.010)
R&D		0.114		−0.005		0.327**
		(0.157)		(0.042)		(0.143)
NCSKEW				−0.001		−0.013**
				(0.002)		(0.006)
Constant	−0.035	−0.309***	−0.067***	−0.121***	−0.590***	−0.852***
	(0.054)	(0.109)	(0.018)	(0.033)	(0.087)	(0.137)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.012	0.019	0.031	0.047	0.019	0.040
F Statistic	6.334***	8.636***	14.818***	19.773***	9.384***	16.808***
Observations	30,170	30,170	30,170	30,170	30,170	30,170

Notes. This table presents the regression results of the effect of firm-level analyst busyness, measured by *BUSY_5*, on stock price crash risk. In columns (1)-(2) crash risk is proxied by negative conditional skewness (*NCSKEW*) in year $t+1$. In columns (2)-(4) crash risk is proxied by the down-to-up volatility (*DUVOL*) in year $t+1$. In columns (5)-(6) crash risk is proxied by the number of crashes minus jumps (*COUNT*) in year $t+1$. In all columns firm-level analyst busyness is measured by *BUSY_5*, the average number of industries covered by the analysts of a given firm in a given year, excluding analysts that cover more than 5 industries. I also include industry and year dummies to control for industry and time (year) fixed effects. See Appendix C for other variable definitions. Robust standard errors to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

3.4.2 Controlling for analyst coverage

In addition to the control variables specified in Eq. 3.4 (*SIGMA*, *RET*, *ROA*, *SIZE*, *MTB*, *LEV*, *DTURN*, *R&D*, and lagged *NCSKEW*), I include the total number of analysts (as recorded in I/B/E/S) following a firm (*ANALYST*) as a control variable. Table 3.15 reports regression results when I control for analyst following (*ANALYST*). Except for analyst following (*ANALYST*), firm-level controls are ommited for brevity. As shown in Table 3.15, the coefficient on *BUSY_FIRMS* and *BUSY_REP* continues positive and statistically significant. On the other hand, *BUSY_IND* remains not statistically significant at the conventional levels.

Table 3.15. Controlling for analyst following

	Dependent variable:								
	$NCSKEW_{t+1}$	$DUVOL_{t+1}$	$COUNT_{t+1}$	$NCSKEW_{t+1}$	$DUVOL_{t+1}$	$COUNT_{t+1}$	$NCSKEW_{t+1}$	$DUVOL_{t+1}$	$COUNT_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
BUSY_FIRMS	0.043^{**}	0.016^{***}	0.045^{**}						
	(0.017)	(0.005)	(0.022)						
BUSY_IND				−0.007	−0.003	0.006			
				(0.017)	(0.005)	(0.020)			
BUSY_REP							0.027^{*}	0.013^{***}	0.035^{*}
							(0.014)	(0.004)	(0.018)
ANALYST	0.006^{***}	0.002^{***}	0.008^{***}	0.006^{***}	0.002^{***}	0.008^{***}	0.006^{***}	0.002^{***}	0.008^{***}
	(0.001)	(0.0004)	(0.001)	(0.001)	(0.0004)	(0.001)	(0.001)	(0.0004)	(0.001)
Constant	-0.248^{**}	−0.036	-0.255^{*}	−0.115	0.013	−0.142	-0.228^{**}	−0.040	-0.258^{*}
	(0.108)	(0.033)	(0.137)	(0.101)	(0.031)	(0.129)	(0.109)	(0.033)	(0.139)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.022	0.049	0.042	0.022	0.049	0.041	0.022	0.049	0.042
F Statistic	11.060^{***}	24.361^{***}	20.448^{***}	11.005^{***}	24.273^{***}	20.396^{***}	11.037^{***} (	24.364^{***}	20.443^{***}
Observations	35,465	35,465	35,465	35,465	35,465	35,465	35,465	35,465	35,465

Notes. This table presents the regression results of the effect of firm-level analyst busyness on stock price crash risk when I control for analyst following (*ANALYST*). In columns (1), (4), and (7) crash risk is proxied by negative conditional skewness (*NCSKEW*) in year $t + 1$. In columns (2), (5), and (8) crash risk is proxied by the down-to-up volatility (*DUVOL*) in year $t + 1$. In columns (3), (6), and (9) crash risk is proxied by the number of crashes minus jumps (*COUNT*) in year $t + 1$. I also include industry and year dummies to control for industry and time (year) fixed effects. See Appendix C for other variable definitions. Robust standard errors to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

3.4.3 Entropy Balancing

The decision to follow a firm is not random. It is thus important to disentangle selection and treatment effects when trying to examine the relationship between firm-level analyst busyness and stock price crash risk. To address a potential self-selection bias and ensure that my main results are driven by differences in firm-level analyst busyness and not other factors, I employ an entropy balancing approach. First, I classify firms into high (or low) firm-level analyst busyness groups. I define $HIGH\_BUSY\_DUM$ as equal to 1 if a firm-level analyst busyness (based on the average number of firms covered by an analyst) is above the 75$^{\text{th}}$ percentile, and 0 if it is below the 25$^{\text{th}}$ percentile. After the entropy balancing, my matching variables of treatment and controls firms are nearly equal in terms of mean, variance and skewness[12]. Next, I re-estimate my baseline regression using the balanced (re-weighted) sample and reports the results in Table 3.16. The coefficient on $HIGH\_REL\_DUMMY$ is significant in all regressions, suggesting that firms followed by busier analysts are associated with higher stock price crash risk even after taking potential self-selection bias into account.

[12] To save space, I omit the distribution of the control variables before and after entropy balancing. To illustrate, without weighting, the average LEV for treatment firms was 0.225 vs 0.147 for control firms. After weighting, the average LEV is virtually identical.

Table 3.16. Entropy balancing approach

	Dependent variable:		
	NCSKEW$_{t+1}$	DUVOL$_{t+1}$	COUNT$_{t+1}$
	(1)	(2)	(3)
HIGH_BUSY_DUM	0.085**	0.033***	0.061*
	(0.036)	(0.010)	(0.035)
SIGMA	11.186***	1.977*	0.931
	(4.292)	(1.199)	(4.096)
RET	4.740***	1.211***	2.467***
	(0.928)	(0.263)	(0.919)
ROA	0.244*	0.102***	0.474***
	(0.127)	(0.035)	(0.125)
SIZE	0.051***	0.017***	0.062***
	(0.011)	(0.003)	(0.011)
MTB	0.002	0.002	0.016***
	(0.005)	(0.001)	(0.004)
LEV	0.196	0.031	0.037
	(0.140)	(0.036)	(0.109)
DTURN	0.029	0.009*	0.040**
	(0.021)	(0.005)	(0.017)
R&D	1.160***	0.244***	0.575**
	(0.336)	(0.083)	(0.237)
NCSKEW		−0.005*	−0.018*
		0.003	(0.009)
Constant	−0.358*	−0.134**	−0.778***
	(0.186)	(0.056)	(0.217)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
R^2	0.036	0.060	0.048
F Statistic	4.770***	9.690***	7.870***
Observations	17,752	17,752	17,752

Notes. This table presents the regression results of the effect of *HIGH_BUSY_DUM* on stock price crash risk using the entropy balancing approach. In column (1) crash risk is proxied by negative conditional skewness (*NCSKEW*) in year $t+1$. In column (2) crash risk is proxied by negative conditional skewness (*NCSKEW*) in year $t+1$. In column (3) crash risk is proxied by the number of crashes minus jumps over a fiscal year (*COUNT*) in year $t+1$, in which a crash (jump) event occurs when a firm-specific daily return is 3.09 standard deviations below (above) its mean over a fiscal year. See Appendix A for other variable definitions. I also include industry and year dummies to control for industry and time (year) fixed effects. Linearized standard errors are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

3.5 Concluding Remarks

In this paper, I examine the relationship between firm-level analyst busyness and stock price crash risk. I argue that the relationship between firm-level analyst busyness and stock price crash risk reflects the net effect (unknown, *ex ante*) of two opposing perspectives: *busyness* and *networking*. Using a sample of U.S. firms during the period of 2000-2021, I find that firms followed by analysts with larger portfolios (based on the number of firms followed) and by analysts with a high average number of reports issuance are associated with higher stock price crash risk. However, in my baseline results, I fail to find evidence of a statistically significant relationship between the average number of industries covered and stock price crash risk.

My results hold even after controlling for well-known determinants of stock price crash risk, such as leverage, market-to-book ratio, R&D intensity, profitability, size, detrended stock turnover, the standard deviation of firm-specific daily returns, the mean of firm-specific daily returns, analyst coverage, as well as time invariant unobservable industry-specific factors (controlled via industry fixed effects) and year fixed effects. Results remain qualitatively the same after excluding analysts that are likely to be an analyst team when firm-level analyst busyness is proxied by the average number of firms followed by analysts of a given firm or by the average number of reports issuance. On the other hand, I find a positively statistically significant relationship between the average number of industries covered and crash risk after excluding analysts covering more than 8 or 5 industries. My further analysis show that the positive relation between firm-level analyst busyness and crash risk is more pronounced for firms with higher information asymmetry. Collectively, my findings provide support to the notion that firm-level analyst busyness appears to deteriorate firm monitoring, increasing bad news hoarding.

My study adds to the vast literature on stock price crash risk and to the scarce literature on firm-level analyst busyness. I particularly focus on the role of firm-level analyst busyness in exacerbating (or constraining) stock price crash risk, providing new evidence on the economic consequences of analyst busyness. Previous studies mostly focused on forecast accuracy as the quality of the research output. I also contribute to the growing literature on factors predicting stock price crash risk, identifying a new factor that potentially exacerbates crash risk.

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APPENDIX

Appendix A. Variable definitions (Evasive shareholder meetings and stock price crash risk)

A.1. Stock price crash risk

DUVOL - the down-to-up volatility of firm-specific daily returns, as detailed in Section 3.2.2.

NCSKEW - the negative conditional firm-specific daily returns skewness, as detailed in Section 3.2.2.

COUNT - the number of crash days for a firm i in a given year t, as detailed in Section 3.2.2.

A.2. Evasive shareholder meetings

HEADQUARTERS - an indicator variable that equals one if the annual meeting takes place at company headquarters in a given year and zero otherwise.

DISTANCE - the natural logarithm of one plus the distance, in miles, between company headquarters and the annual meeting location.

REMOTE - an indicator variable that equals one if the annual shareholder meeting takes place at a remote location.

TRAVEL - the estimated travel time between firm headquarters and annual shareholders meeting location.

FIRST - an indicator variable that equals one if a firm that never held their annual shareholder meeting on clustering dates in all previous years announced their annual meeting on clustering dates and zero otherwise.

CLUSTER - an indicator variable that equals one for a firm-year when the annual shareholder meeting is held in a clustering date, zero otherwise.

A.3. Firm-level control variables from baseline regression

LEV - the ratio between total debt and total assets.

MTB - the ratio between market value of equity and book value of equity.

R&D - the ratio between research and development R&D expenditure and total assets. This variable is equal to zero if R&D expenditure data is missing.

ROA - the ratio between income before extraordinary items and total assets.

SIZE - the natural logarithm of total assets.

DTURN - The average monthly share turnover over the current year t minus the average monthly share turnover over the previous year.

SIGMA - The standard deviation of firm-specific daily returns over the fiscal year period t.

RET - the mean of firm-specific daily returns over the fiscal year, times 100.

Appendix B. Downloading bulk data from EDGAR.

```python
from sys import argv
from sec_edgar_downloader import Downloader

def download_to(file, tickers_file):
    tf = open(tickers_file, "r+")
    dl = Downloader(file)
    count = 1
    for ticker in tf.readlines():
        try:
            dl.get("DEF 14A", ticker.replace('\n', ''), after="2009-01-01", before="2020-12-31")
            print(str(count)+ ". Download finalizado: " + ticker)
            with open("tickers-baixados.txt", "a") as baixados:
                baixados.write(ticker)
        except KeyboardInterrupt:
            print("Processo interrompido.")
            exit(1)
        except Exception as e:
            print(e)
            print("Deu errado para " + ticker)
            with open("tickers-falhos.txt", "a") as falhas:
                falhas.write(ticker.replace('\n', ''))

        count += 1

    tf.close()

if __name__ == "__main__":
    arg_count = len(argv)
    tickers_file = "tickers.txt"
    if arg_count == 1:
        file = "downloads/"
    elif arg_count == 2:
        file = str(argv[1])
    elif arg_count == 3:
        file = str(argv[1])
        tickers_file = str(argv[2])
    else:
        print("Argumentos inválidos!")
        exit(1)

    print("Inicio do trabalho")
    download_to(file, tickers_file)
    print("Trabalho concluido!")
```

Appendix C. Variable definitions (Are Busy Analysts Detrimental? Evidence from Stock Price Crash Risk)

A.1. Stock price crash risk

NCSKEW - the negative conditional firm-specific daily returns skewness, as detailed in Section 3.2.2.

DUVOL - the down-to-up volatility of firm-specific daily returns, as detailed in Section 3.2.2.

COUNT - the number of crashes minus the number of jumps over the fiscal year, as detailed in Section 3.2.2.

A.2. Analyst busyness

BUSY_FIRMS - the average number of firms covered by analysts of a given firm in a given year.

BUSY_IND - the average number of industries covered by the analysts of a given firm in a given year.

BUSY_REPORTS - the average number of reports issued by the analysts of a given firm in a given year.

BUSY_15 - the average number of firms covered by analysts of a given firm in a given year, excluding analysts that cover more than 15 firms.

BUSY_20 - the average number of reports issued by the analysts of a given firm in a given year, excluding analysts that cover more than 20 firms.

BUSY_25 - the average number of reports issued by the analysts of a given firm in a given year, excluding analysts that cover more than 25 firms.

BUSY_8 - the average number of industries covered by the analysts of a given firm in a given year, excluding analysts that cover more than 8 industries.

BUSY_5 - the average number of industries covered by the analysts of a given firm in a given year, excluding analysts that cover more than 5 industries.

A.3. Firm-level control variables from baseline regression

LEV - the ratio between total debt and total assets.

MTB - the ratio between market value of equity and book value of equity.

R&D - the ratio between research and development R&D expenditure and total assets. This variable is equal to zero if R&D expenditure data is missing.

ROA - the ratio between income before extraordinary items and total assets.

SIZE - the natural logarithm of total assets.

DTURN - The average monthly share turnover over the current year t minus the average monthly share turnover over the previous year.

SIGMA - The standard deviation of firm-specific daily returns over the fiscal year period t.

RET - the mean of firm-specific daily returns over the fiscal year t, times 100.

A.4. Other variables

ANALYST - the total number of analysts (as recorded in I/B/E/S) following a firm.

HIGH_BUSY_DUM - an indicator variable that equals one if a firm-level analyst busyness (based on the average number of firms covered by an analyst) is above the 75^{th} percentile, and zero if it is below the 25^{th} percentile.