Evasive Shareholder Meetings, Meeting Announcement Lag, and Stock Price Crash Risk

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Abstract

We examine the relationship between evasive shareholder meetings practices 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, we find only weak evidence that firms holding annual general meetings in or near headquarters exhibit lower future stock price crash risk, and this weak effect disappears after controlling for firm fixed effects, in specific subsamples or after taking potential self-selection bias into account. On the other hand, we initially find a puzzling strong negative relationship between evasive timing strategies and stock price crash risk. However, after controlling for firm fixed effects, this effect virtually disappears. We also find no evidence that firms are strategically announcing meetings closer to annual meeting dates to withhold bad news from investors. Collectively, we 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

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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 & Markov, 2016; Y. Li & Yermack, 2016; Price, Doran, Peterson, & Bliss, 2012). 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 (Gam, Gupta, Im, & Shin, 2021; Y. Li & Yermack, 2016). Y. 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 Y. 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, we 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 (J. Chen, Hong, & Stein, 2001; Hutton, Marcus, & Tehranian, 2009; Jin & Myers, 2006). 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 & Fang, 2015a; J.-B. Kim & Zhang, 2016; N. Xu, Jiang, Chan, & Yi, 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, i.e., firm-specific stock crashes (Chang, Chen, & Zolotoy, 2017; Y. Chen, Fan, Yang, & Zolotoy, 2021). Empirical evidence supports the view that managers tend to systematically withhold bad news (Kothari, Shu, & Wysocki, 2009). Whether and how 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 (C. Chen, Kim, & Yao, 2017; Francis, Hasan, & Li, 2016; Hutton et al., 2009; Khurana, Pereira, & Zhang, 2018), while accounting conservatism has been shown to mitigate bad news hoarding (J.-B. Kim & Zhang, 2016). Both Ertugrul, Lei, Qiu, and Wan (2017) and C. Kim, Wang, and Zhang (2019) find a greater likelihood of stock price crashes among firms with less readable 10-Ks filings due increased opacity.

Beyond financial reporting' mechanisms, Firth, Wong, and Zhao (2019) show a lower 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, allowing and initiating in-house visits, private meetings or investor days, for example. Empirical evidence on the relationship between corporate site visits and stock price crash risk is somewhat mixed (Gao, Cao, & Liu, 2017; Lu, Fung, & Su, 2018).

We 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, we call *deterrence* and *attention*[1]. 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.

Our contribution is threefold. First, this is the first study to investigate the relationship between evasive shareholder meetings and stock price crash risk. To our knowledge, no empirical studies have addressed this relationship. Second, our paper 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), we were able to investigate whether and how 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, unlike Y. Li and Yermack (2016) emphasis on mean cumulative abnormal stock returns (thus, the central tendency of the return distribution) based on a limited number of subsamples. Third, we 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 reviews prior literature on evasive shareholder

[1]Both hypotheses are based on the bad news hoarding framework developed by Jin and Myers (2006).

meetings and stock price crash risk, and develops our research hypotheses. Section 3 describes data sources, sample, variable measurement and identification strategies. Section 4 reports empirical results. Section 5 addresses endogeneity issues. Section 6 concludes the paper.

2 Literature review and hypothesis development

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 (Dimitrov & Jain, 2011; Y. Li & Yermack, 2016)[2]. 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; Y. Li & Yermack, 2016). Using a sample of annual shareholders meetings held in the Netherlands, De Jong, Mertens, and Roosenboom (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, Karpoff, & McWilliams, 2017).

In contrast, Holland, Lim, and Yi (2021) argues that previous literature fails to find significant market reactions around shareholder meetings because investors constantly up-

[2]Due to COVID-19 pandemic, many firms were forced to hold virtual shareholder meetings in 2020 and 2021 (Brochet, Chychyla, & Ferri, 2020).

date 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 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.

Based on the assumption that firms are more likely to have investors concentrated in their local communities, and that local analysts outperform distant analysts, Y. Li and Yermack (2016) introduce a new approach to evaluate the information content of annual shareholder meetings. Y. 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[3]. Overall, these findings are consistent with the idea that managers strategically schedule evasive shareholder meetings to hide bad

[3]Specifically, Y. 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.

news from investors and stakeholders, as a way to prevent scrutiny by reducing attendance.

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 Y. Li and Yermack (2016), Gam et al. (2021) emphasize timing' particularities of annual shareholder meetings, instead of locations, 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 Stock price crash risk

Stock price crash risk refers to the likelihood of stock price crashes - sudden, abrupt but infrequent large stock price decreases (Hutton et al., 2009; Jin & Myers, 2006). Crash risk is also understood as the conditional skewness, i.e., the third moment, of the return distribution (J. 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' asymmetry – a distribution skewed to left indicates a negative skewness (increasing the frequency of 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 makes financial media headlines[4] 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

[4] 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.

losses (Dang, Lee, Liu, & Zeng, 2018; Y. Li & Zeng, 2019). 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 (J.-B. Kim, Wang, & Zhang, 2016), or from market participants' characteristics (J. Chen et al., 2001; Hong & 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 crash-prone than others. 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. J. 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 & Myers, 2006; Kubick & 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 crash. Hutton et al. (2009) provide empirical evidence consistent with Jin and Myers (2006) 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, stems from a variety of sources, such as compensation (J.-B. Kim, Li, & Zhang, 2011a) and career concerns (Kubick & Lockhart, 2021). For instance, J.-B. 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 why some stocks are more crash-prone than others, 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, Hasan, & Jiang, 2018)[5].

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. J.-B. Kim, Li, and Zhang (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

[5]See Habib et al. (2018) for a detailed review on the determinants of stock price crash risk, up to 2017. They 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.

firms more engaged in accrual-based and real-activities earnings management. C. Chen et al. (2017) show that earnings smoothness is associated with higher crash risk. C. Kim et al. (2019) and Ertugrul et al. (2017) find that less readable 10-Ks fillings are associated with higher crash risk. J.-B. 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, such as CEO and/or CFOs overconfidence (J.-B. Kim et al., 2016; Lee, Lu, & Wang, 2019), power (Al Mamun, Balachandran, & Duong, 2020; Harper, Johnson, & Sun, 2020; Shahab, Ntim, Ullah, Yugang, & Ye, 2020), trustworthiness (Gu, Liu, & Peng, 2020), age (Andreou, Louca, & Petrou, 2017), gender (Y. Li & Zeng, 2019), political orientation (W. Chen, Jin, & Luo, 2020), cultural background (Fu & Zhang, 2019), and early-life experience (Long, Tian, Hu, & Yao, 2020). On the other hand, some studies focus on the relation between board and directors' characteristics and crash risk, such as board diversity (Jebran, Chen, & Zhang, 2020), reforms (Hu, Li, Taboada, & Zhang, 2020), hierarchy (Jebran, Chen, & Zhu, 2019), coalition (L. Xu, Rao, Cheng, & Wang, 2020), director's and officers' liability insurance (Yuan, Sun, & Cao, 2016), and director's foreign experience (F. Cao, Sun, & Yuan, 2019) and external social networks (Fang, Pittman, & Zhao, 2021).

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, such as institutional investor stability (Callen & Fang, 2013), institutional investor attention (Ni, Peng, Yin, & Zhang, 2020; Xiang, Chen, & Wang, 2020), and information interaction among large shareholders (J. Li, Wang, Zhou, & Zhang, 2021). The role of financial analysts has also been a topic of interest among market-level determinants of crash risk, with mixed results. While J.-B. Kim, Lu, and Yu (2019) finds that financial analysts are perceived in the options market as a relevant external monitoring mechanism, considering that a reduction in analyst coverage increase expected crash risk, N. 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 & Fang, 2015b; Deng, Gao, & Kim, 2020; Ni & Zhu, 2016).

A minor fraction of 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, W. Li and Cai (2016) show that Chinese firms registered in areas with higher levels of religiosity exhibit lower crash risk. C. Cao, Xia, and Chan (2016) and X. Li, Wang, and Wang (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, Quan, Yin, and Yuan (2021) provide evidence that firms located in gambling-prone regions are more likely to experience a higher crash risk. Bai, Xu, Yu, and Zurbruegg (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, Faircloth, & Zeng, 2017; Obaydin, Zurbruegg, Hossain, Adhikari, & Elnahas, 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. Both informal and formal institutions affect stock price crash risk to a certain degree.

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 (Han, Kong, & Liu, 2018; Y. Li & Yermack, 2016). Annual shareholders meetings, unlike 10-Ks and other regulatory filings, allows shareholders to ask unscripted questions through an open microphone period (Carrington & Johed, 2007; Y. Li & Yermack, 2016). 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. We call this *deterrence hypothesis*[6].

Hypothesis 1. All else being equal, firms' choice to move 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, Shevlin, & Thornock, 2015; T. Li, Xiang, Liu, & Cai, 2020). For example, T. Li et al. (2020) investigate whether firms conceal bad news by disclosing annual reports during periods of reduced market attention and find that firms strategically timing annual reports disclosure are associated with a greater stock price crash risk. Because attention is a scarce cognitive

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

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). A looser monitoring would increase managerial capabilities to withhold bad news, thus increasing stock price crash risk. We call this *attention hypothesis*[7].

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

It is important to note that we do not discuss an alternative explanation of the relationship between evasiveness of management and stock price crash risk. Based on prior studies (De Jong et al., 2006; Denes et al., 2017), 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, our results may be driven by signalling-only. 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.

[7]We test this hypothesis using meetings timing' decisions as a proxy for the evasiveness of management.

3 Data and methodology

3.1 Data sources and sample

Our initial sample comprise U.S. firms that are listed, headquartered and incorporated in the United States between 2012–2020[8]. 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 our evasiveness' measures, through *zipcodeR* package[9], 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 our initial sample, following the convention. To mitigate the impact of extreme outliers, we winsorize all continuous independent variables at the 1% level in both tails.

We 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 U.S. Securities and Exchange Commission' Electronic Data Gathering, Analysis and Retrieval (*EDGAR*) system[10]. We 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, we retrieve ZIP code data from United States Postal Service (*USPS*) *ZIP Code™ Lookup* platform[11]. We retrieve firm-level annual accounting data and other data on firm characteristics, including headquarters ZIP codes[12], from *COMPUSTAT*. To stock price crash risk measures and some control variables, we use

[8]Our sample begin in 2012, one year after the changes promoted by the Dodd-Frank Wall Street Reform and Consumer Protection Act on shareholder meetings (Y. Li & 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.

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

[10]Unlike Y. Li and Yermack (2016), we will not obtain data on special shareholder meetings.

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

[12]We obtained headquarters addresses from DEF 14-A forms, allowing us to capture potential changes in company headquarters locations over the years.

daily (and monthly) stock data from Center for Research in Security Prices (*CRSP*).

3.2 Crash risk measures

We employ three measures of *ex post*[13] firm-specific stock price crash risk following prior studies: the negative conditional firm-specific daily returns skewness (*NCSKEW*), the down-to-up volatility of firm-specific daily returns (*DUVOL*), and the occurrence of at least one crash day in a given year (*CRDUM*). To ensure that our three stock price crash risk measures represent only firm-specific factors, rather than general market conditions, e.g., economic shocks such as the 2007-2008 Liquidity Crisis or the 2020 Coronavirus Crash, these three measures are based on firm-specific daily returns - log changes in price. To calculate our stock price crash risk measures, we first obtain the firm-specific residual daily returns from the following model, estimated for each firm in each year, based on J.-B. Kim et al. (2011a).

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

$r_{i,t}$ is the return on stock i in day t. $r_{mkt,t}$ is the CRSP value-weighted[14] market index return in day t. We employ $r_{mkt,t}$ leads and lags terms to correct for potential nonsynchronous trading (J.-B. 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 1.

Our 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 (J. Chen et al., 2001; J.-B. Kim et

[13]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) (J.-B. Kim & Zhang, 2014).

[14]I can employ the CRSP equal-weighted market index return as a robustness check.

al., 2011a). Precisely, we calculate *NCSKEW* as:

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

n is the number of daily returns over a year t. As we 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. We 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*" (J. Chen et al., 2001; J.-B. Kim et al., 2011a). Specifically:

$$DUVOL_{i,t} = \log\left\{(n_b - 1)\sum_{Down} W_{i,t}^{2} / (n_a - 1)\sum_{Up} W_{i,t}^{2}\right\} \tag{3}$$

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 J.-B. 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.

3.3 Evasive shareholder meetings

We constructed two classes of evasive shareholder meetings measures based on two dimensions - distance (i.e., annual shareholders meeting and HQ locations) and scheduling (i.e., annual shareholders meeting timing), 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 (Gam et al., 2021; Y. Li & Yermack, 2016). We employ distance-based measures to test our *deterrence hypothesis* and timing-based measures to test our *attention hypothesis*.

3.3.1 Distance-based measures

We construct four distance-based measures of evasive shareholder meetings based upon Y. Li and Yermack (2016) and Gam et al. (2021). Our first proxy, *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 our 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. Our third proxy, *REMOTE*, is an indicator variable that equals one if the annual shareholder meeting takes place at a remote location. Following Y. Li and Yermack (2016), we 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[15]. 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, our fourth evasive shareholder meeting proxy, relies on estimated travel time between firm headquarters and annual shareholders meeting location. We estimate travel time in a way similar to that suggested by Y. Li and Yermack (2016). When a meeting is located on firm headquarters or less than a mile away (about 1,61 kilometer), we 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, we 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), we use driving time

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

calculations from Google Maps to estimate travel time. We collect driving time calculations data from Google Maps through the R package *gmapsdistance*, a function that uses the Google Maps Distance Matrix API to compute time distance between two vectors of points. We convert ZIP codes into latitude-longitude coordinates since *gmapsdistance* only accepts a string or a vector of strings containing the description of the starting point and ending point, which can lead to more errors, or latitude-longitude coordinates, more precisely estimated. Conversion from ZIP codes to latitude-longitude coordinates could be performed through *zipcodeR*.

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, we 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[16]; 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[17]. Finally, *TRAVEL* is the natural logarithm of travel time, in hours, from firm 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 (Y. Li & 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

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

[17] 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 International Airport, while the closest airport to Chevron 2017 Annual Meeting location was the Midland International Airport. We 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.

to a large hub airport.

3.3.2 Timing-based measures

We 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. Our first timing-based proxy, *CLUSTER*, is an indicator variable that equals one if a firm held their annual general meeting on clustering dates, zero otherwise. *CLUSTER* allow me to better explore variations of clustering' decisions by management. Our 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, zero otherwise. Initially, we 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.

3.4 Firm-level control variables

We control for well-known determinants of stock price crash risk documented in prior literature (An, Chen, Naiker, & Wang, 2020; Chang et al., 2017; Chowdhury, Hodgson, & Pathan, 2020; L. Xu, Yu, & Zurbruegg, 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[18], and one-year lagged *NCSKEW*[19].

3.5 Model specification

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

$$CRASH_{i,t+1} = \alpha + \beta EVASIVE_{i,t} + \lambda'\text{Firm}_{i,t} + \text{Year}_t + \text{Industry}_j + \varepsilon_{i,t} \tag{4}$$

CRASH is a placeholder for stock price crash risk measures: *NCSKEW*, *DUVOL*, or *COUNT*, as detailed in Section 3.2. *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 3.3. λ'Firm is the set of one-year-lagged firm-level control variables for stock price crash risk specified in Section 3.4. We 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.

4 Results

4.1 Descriptive statistics

Table 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 our sample is Chemical

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

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

& 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 our 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 presents summary statistics for key variables used in our regression models from 2012 to 2020 for our sample firms. There are 9,086 firm-year observations, and all the continuous independent variables are winsorized at the top and bottom one-percentiles, following Callen and Fang (2015a). The mean (median) values of stock price crash risk measures $NCSKEW_{t+1}$, $DUVOL_{t+1}$, and $COUNT_{t+1}$ are 0.115 (−0.069), 0.0003 (−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 Y. 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[20]. The mean value of *DISTANCE* is 1.076, indicating that the 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 0.593 and 0.382, respectively, while the mean values of *FIRST* at 1% and *FIRST* at 2% are 0.674 and 0.535, respectively. The average firm in our 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 .028.

Table 3 reports Pearson (Spearman) correlations below (above) the diagonal among

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

Table 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.

Table 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	0.115	1.982	−0.761	−0.069	0.735
$DUVOL_{t+1}$	9,086	−0.0003	0.528	−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	0.593	0.491	0	1	1
CLUSTER at 2%	9,086	0.382	0.486	0	0	1
FIRST at 1%	9,086	0.674	0.469	0	1	1
FIRST at 2%	9,086	0.535	0.499	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. Our 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 independent variables are winsorized at the 1st and 99th percentile to mitigate the effect of outliers.

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 $DUVOL_{t+1}$, $NCSKEW_{t+1}$ and $COUNT_{t+1}$, and $DUVOL_{t+1}$ and $COUNT_{t+1}$ are 0.925 (0.936), 0.508 (0.669), and 0.670 (0.724), respectively, indicating that these measures seem to be picking up the same construct, as suggested by Callen and Fang (2013).

Table 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	0.925	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	0.508	0.670	1	0.001	-0.003	0.177	0.116	0.017	0.145	-0.129	0.129	0.012	-0.043
(4) DISTANCE	0.009	0.006	0.002	1	0.350	-0.020	0.002	0.046	-0.020	0.021	-0.021	-0.015	-0.006
(5) TRAVEL	-0.005	-0.004	0.001	0.559	1	0.006	-0.013	0.046	-0.030	-0.004	0.004	-0.014	-0.024
(6) SIZE	0.119	0.168	0.182	0.001	0.005	1	0.436	0.341	0.468	-0.699	0.699	-0.025	-0.128
(7) MTB	0.035	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	0.010	0.018	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	0.101	0.121	-0.022	-0.004	0.397	-0.033	0.062	1	-0.571	0.571	-0.005	-0.307
(10) SIGMA	-0.092	-0.129	-0.145	0.022	0.006	-0.626	-0.049	-0.130	-0.593	1	-1.000	0.161	0.262
(11) RET	0.097	0.127	0.131	-0.033	-0.015	0.499	0.030	0.103	0.560	-0.941	1	-0.160	-0.263
(12) DTURN	0.001	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	-0.018	-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 independent variables are winsorized at the 1st and 99th percentile.

Figure 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 our 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 our 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 our sample of 9,086 meetings, only 25 were held in Delaware. The most distant event in our 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, Massachusetts, and held its 2012 meeting in Sunnyvale, California, 2,681 miles (4,965 kilometers) away.

Figure 2 shows the dates of annual shareholder meetings between 2012 and 2020 for the firms in our sample. Most meetings are concentrated between May and July. The busiest day in our sample was May 22nd, 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 our 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[21].

4.2 Test of Hypothesis 1

Table 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. We control for a set of stock crash risk determinants (discussed in Section 3.5), industry, and year fixed effects. The coefficient estimate on *DISTANCE* ($p = 0.092$, t-value $= 1.683$) is statistically significant at the 10% level, suggesting that firms holding annual general meetings in headquarters or close to headquarters are associated with lower future stock price crash risk (proxied by $NCSKEW_{t+1}$). However, coefficient estimates on *HEADQUARTERS* ($p =$

[21] For this reason, we 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.

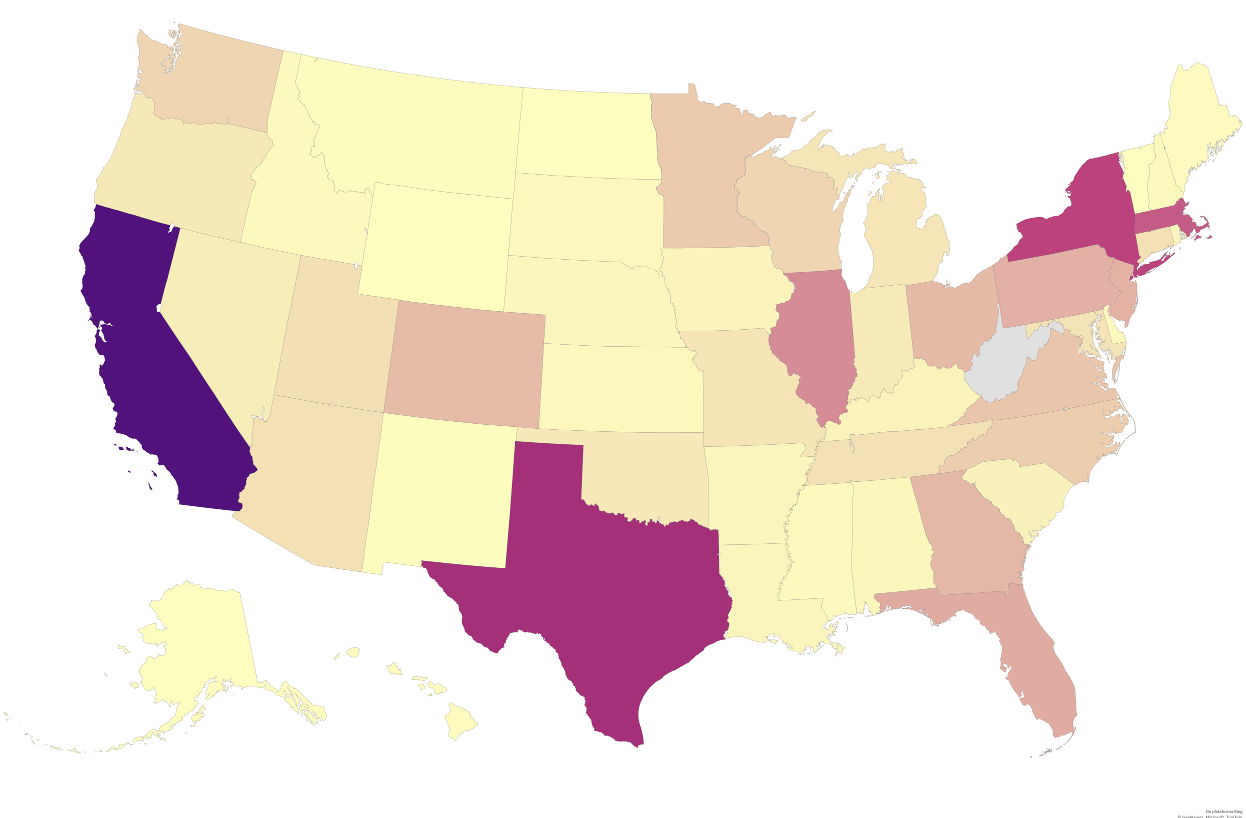

Figure 1: The Geography of Annual Shareholder Meetings

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 our sample held meetings in unincorporated territories of the United States.

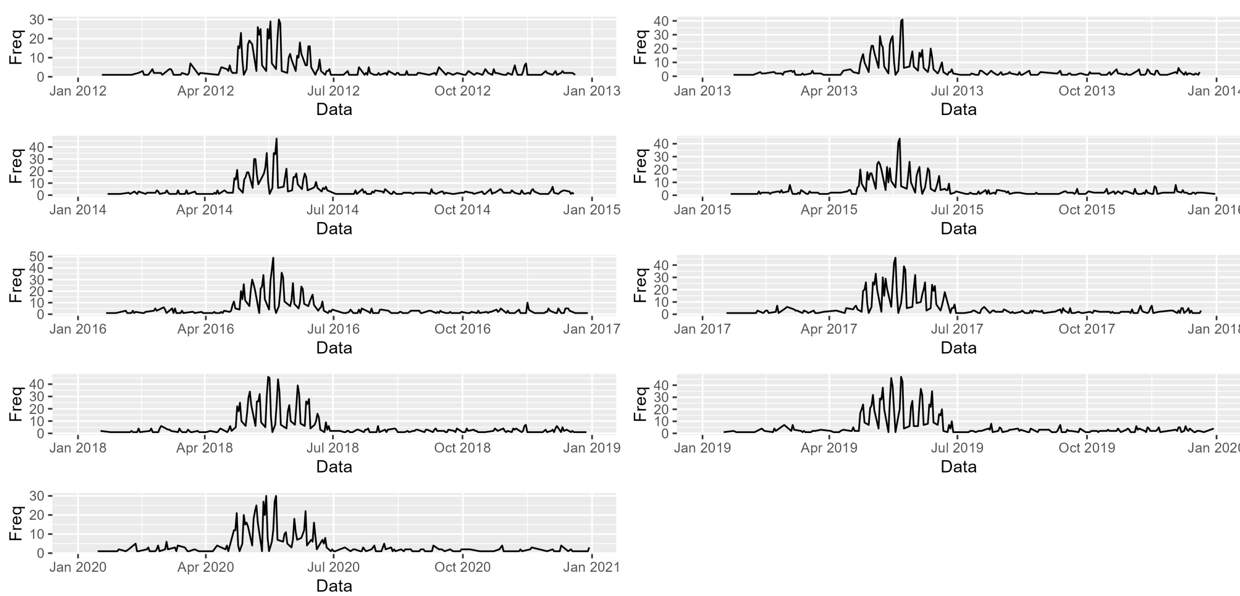

Figure 2: Dates of Annual Shareholder Meetings

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

0.164, t-value = -1.392), *REMOTE* ($p = 0.737$, t-value = 0.336), and *TRAVEL* (p-value = 0.854, t-value = -0.184) are not statistically significant at conventional levels.

Table 4: The effect of distance-based evasiveness on negative conditional skewness

	Dependent variable:			
	NCSKEW_{t+1}			
	(1)	(2)	(3)	(4)
HEADQUARTERS	−0.061			
	(0.044)			
DISTANCE		0.018*		
		(0.011)		
REMOTE			0.063	
			(0.186)	
TRAVEL				−0.450
				(2.444)
SIGMA	19.043***	19.241***	19.167***	19.130***
	(5.992)	(5.993)	(5.994)	(5.997)
RET	6.223***	6.270***	6.226***	6.216***
	(1.404)	(1.405)	(1.405)	(1.406)
ROA	0.055	0.056	0.049	0.047
	(0.143)	(0.143)	(0.143)	(0.143)
SIZE	0.116***	0.116***	0.117***	0.117***
	(0.015)	(0.015)	(0.015)	(0.015)
MTB	0.002	0.002	0.002	0.002
	(0.004)	(0.004)	(0.004)	(0.004)
LEV	−0.175	−0.180	−0.169	−0.169
	(0.126)	(0.126)	(0.126)	(0.126)
DTURN	0.052*	0.053*	0.052*	0.052*
	(0.027)	(0.027)	(0.027)	(0.027)
R&D	0.130	0.138	0.117	0.112
	(0.306)	(0.306)	(0.306)	(0.306)
Constant	−1.644***	−1.724***	−1.692***	−1.663***
	(0.347)	(0.346)	(0.345)	(0.373)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.028	0.028	0.028	0.028
F Statistic	5.043***	5.056***	5.014***	5.013***
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. All models include industry and year fixed effects. Standard errors clustered at the firm-level to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 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. We control for the same set of variables as in the previous model. The coefficient estimate on *HEADQUARTERS* (p = 0.092, t-value = -1.683) is statistically significant at the 10% level, indicating that firms holding annual general meetings in headquarters are associated with lower future stock price crash risk (proxied by $DUVOL_{t+1}$). While coefficient estimates on *DISTANCE* (p = 0.122, t-value = 1.549) and *REMOTE* (p = 0.650, t-value = 0.453) are in the expected directions, they are not statistically significant at conventional levels. The coefficient estimate on *TRAVEL* (p = 0.933, t-value = -0.085) is also not statistically significant.

Table 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	-0.019^{*}			
	(0.012)			
DISTANCE		0.004		
		(0.003)		
REMOTE			0.023	
			(0.051)	
TRAVEL				-0.055
				(0.644)
SIGMA	4.759^{***}	4.819^{***}	4.803^{***}	4.793^{***}
	(1.472)	(1.472)	(1.472)	(1.472)
RET	1.578^{***}	1.590^{***}	1.580^{***}	1.578^{***}
	(0.329)	(0.329)	(0.329)	(0.329)
ROA	0.055	0.054	0.053	0.052
	(0.036)	(0.036)	(0.036)	(0.036)
SIZE	0.039^{***}	0.039^{***}	0.039^{***}	0.039^{***}
	(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	-0.072^{**}	-0.073^{**}	-0.070^{**}	-0.070^{**}
	(0.033)	(0.033)	(0.033)	(0.033)
DTURN	0.019^{***}	0.019^{***}	0.019^{***}	0.019^{***}
	(0.007)	(0.007)	(0.007)	(0.007)
R&D	-0.041	-0.040	-0.044	-0.046
	(0.073)	(0.073)	(0.072)	(0.072)
NCSKEW	-0.004	-0.004	-0.004	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)
Constant	-0.557^{***}	-0.580^{***}	-0.573^{***}	-0.569^{***}
	(0.094)	(0.094)	(0.094)	(0.101)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.054	0.054	0.053	0.053
F Statistic	8.789^{***}	8.782^{***}	8.747^{***}	8.744^{***}
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. All models include industry and year fixed effects. Standard errors clustered at the firm-level to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Finally, Table 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. We 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 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. All models include industry and year fixed effects. Standard errors clustered at the firm-level to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Collectively, we find only weak evidence that firms holding annual general meetings in firms' headquarters or near firms' headquarters exhibit a lower future stock price crash risk. In fact, 10 out of 12 models show no relation between distance-based evasiveness and stock price crash risk, providing limited evidence to support our *deterrence hypothesis*. 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, we 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, Taylor, and Richardson (2022). Additionally, I find that leverage (*LEV*) and lagged *NCSKEW* are negatively associated with crash risk, consistent with prior findings (Callen & Fang, 2015a; Hasan et al., 2022; Wu & Lai, 2020). Finally, I find that return on assets (ROA) is positively associated with crash risk, consistent with the findings of Wen, Xu, Ouyang, and Kou (2019) and Hasan et al. (2022).

4.3 Test of Hypothesis 2

Tables 7 and 8 present results from the regression analysis examining the relationship between timing-based measures of evasiveness and crash risk. In Table 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, we 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 nearly all specifications. The coefficient estimates on *CLUSTER* at 1% (Column 3, $p = 0.002$, t-value = -3.1588) and *CLUSTER* at 2% (Column 6, $p = 0.005$, t-value = -2.8196) are statistically significant at the 1% level. The coefficient estimate on *CLUSTER* at 2% (Column 5, $p = 0.019$, t-value =

-2.341) is statistically significant at the 5%. Finally, the coefficient estimates on *CLUSTER* at 1% (Column 2, $p = 0.088$, t-value = -1.705) and *CLUSTER* at 2% (Column 4, $p = 0.086$, t-value = -1.715) are statistically significant at the 10% level.

In Table 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, firms that never held annual general meetings on clustering dates in previous years, but then held annual general meetings on "busy" dates, exhibit lower stock price crash risk. *FIRST* is statistically significant at conventional levels in nearly all specifications. The coefficient estimate on *CLUSTER* at 1% (Column 3, $p = 0.001$, t-value = -3.364) is statistically significant at the 1% level. The coefficient estimates on *CLUSTER* at 1% (Column 2, $p = 0.011$, t-value = -2.522), *CLUSTER* at 2% (Column 5, $p = 0.039$, t-value = -2.0566) and *CLUSTER* at 2% (Column 6, $p = 0.028$, t-value = -2.192) are statistically significant at the 5% level. Finally, the coefficient estimate on *CLUSTER* at 1% (Column 1, $p = 0.097$, t-value = -1.659) is statistically significant at the 10% level.

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[22]. 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?*

Firms may strategically announce annual shareholder meetings with shorter advance

[22] 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 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%	−0.020	−0.019*	−0.122***			
	(0.043)	(0.011)	(0.039)			
CLUSTER at 2%				−0.075*	−0.027**	−0.108***
				(0.044)	(0.011)	(0.038)
SIGMA	19.329***	4.977***	5.438	19.567***	4.955***	4.929
	(6.001)	(1.473)	(4.946)	(6.003)	(1.474)	(4.933)
RET	6.259***	1.616***	2.470**	6.314***	1.613***	2.374**
	(1.407)	(0.329)	(1.089)	(1.407)	(0.329)	(1.086)
ROA	0.046	0.051	0.358***	0.043	0.051	0.361***
	(0.143)	(0.036)	(0.117)	(0.143)	(0.036)	(0.118)
SIZE	0.117***	0.040***	0.134***	0.118***	0.040***	0.131***
	(0.015)	(0.004)	(0.014)	(0.015)	(0.004)	(0.014)
MTB	0.002	0.002*	0.008***	0.002	0.002**	0.008***
	(0.004)	(0.001)	(0.003)	(0.004)	(0.001)	(0.003)
LEV	−0.167	−0.068**	−0.319***	−0.162	−0.068**	−0.323***
	(0.126)	(0.033)	(0.108)	(0.126)	(0.033)	(0.108)
DTURN	0.052*	0.019***	0.044**	0.052*	0.019***	0.043**
	(0.027)	(0.007)	(0.021)	(0.027)	(0.007)	(0.021)
R&D	0.114	−0.046	0.203	0.115	−0.045	0.204
	(0.306)	(0.072)	(0.222)	(0.306)	(0.072)	(0.223)
NCSKEW		−0.004	−0.013		−0.004	−0.012
		(0.003)	(0.009)		(0.003)	(0.009)
Constant	−1.696***	−0.579***	−2.014***	−1.706***	−0.578***	−1.996***
	(0.345)	(0.093)	(0.348)	(0.345)	(0.094)	(0.349)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.028	0.054	0.049	0.028	0.054	0.049
F Statistic	5.016***	8.790***	8.075***	5.060***	8.832***	8.040***
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. All models include industry and year fixed effects. Standard errors clustered at the firm-level to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 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%	-0.076^{*}	-0.031^{**}	-0.140^{***}			
	(0.046)	(0.012)	(0.042)			
FIRST at 2%				-0.066	-0.023^{**}	-0.085^{**}
				(0.043)	(0.011)	(0.039)
SIGMA	20.103^{***}	5.206^{***}	6.164	19.750^{***}	5.024^{***}	5.120
	(6.026)	(1.479)	(4.962)	(6.015)	(1.477)	(4.943)
RET	6.396^{***}	1.654^{***}	2.578^{**}	6.336^{***}	1.622^{***}	2.392^{**}
	(1.409)	(0.330)	(1.090)	(1.408)	(0.330)	(1.087)
ROA	0.041	0.050	0.356^{***}	0.043	0.051	0.362^{***}
	(0.143)	(0.036)	(0.118)	(0.143)	(0.036)	(0.118)
SIZE	0.120^{***}	0.041^{***}	0.135^{***}	0.119^{***}	0.040^{***}	0.132^{***}
	(0.015)	(0.004)	(0.014)	(0.015)	(0.004)	(0.014)
MTB	0.002	0.002^{*}	0.008^{***}	0.002	0.002^{*}	0.008^{***}
	(0.004)	(0.001)	(0.003)	(0.004)	(0.001)	(0.003)
LEV	-0.159	-0.066^{**}	-0.314^{***}	-0.158	-0.066^{**}	-0.320^{***}
	(0.126)	(0.033)	(0.108)	(0.126)	(0.033)	(0.109)
DTURN	0.052^{*}	0.019^{***}	0.043^{**}	0.052^{*}	0.019^{***}	0.043^{**}
	(0.027)	(0.007)	(0.021)	(0.027)	(0.007)	(0.021)
R&D	0.115	-0.045	0.205	0.118	-0.044	0.208
	(0.306)	(0.073)	(0.222)	(0.306)	(0.072)	(0.222)
NCSKEW		-0.004	-0.013		-0.004	-0.013
		(0.003)	(0.009)		(0.003)	(0.009)
Constant	-1.713^{***}	-0.583^{***}	-2.019^{***}	-1.724^{***}	-0.585^{***}	-2.018^{***}
	(0.345)	(0.093)	(0.349)	(0.347)	(0.094)	(0.349)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.028	0.054	0.049	0.028	0.054	0.048
F Statistic	5.056^{***}	8.845^{***}	8.098^{***}	5.050^{***}	8.811^{***}	7.992^{***}
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. All models include industry and year fixed effects. Standard errors clustered at the firm-level to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

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 our *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 our 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, and thus reducing stock price crash risk.

To test this potential (and unexplored, to our knowledge) evasiveness mechanism, we 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 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). We find no evidence that firms are strategically announcing meetings closer to annual meeting dates to withhold bad news from investors.

Table 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	18.990***	4.786***	4.284
	(5.998)	(1.473)	(4.922)
RET	6.200***	1.577***	2.233**
	(1.407)	(0.329)	(1.084)
ROA	0.048	0.052	0.367***
	(0.143)	(0.036)	(0.118)
SIZE	0.113***	0.039***	0.129***
	(0.015)	(0.004)	(0.014)
MTB	0.002	0.002*	0.008***
	(0.004)	(0.001)	(0.003)
LEV	−0.157	−0.069**	−0.334***
	(0.126)	(0.033)	(0.109)
DTURN	0.052*	0.019***	0.043**
	(0.027)	(0.007)	(0.021)
RD	0.110	−0.046	0.203
	(0.306)	(0.073)	(0.222)
NCSKEW		−0.004	−0.012
		(0.003)	(0.009)
Constant	−1.831***	−0.582***	−1.967***
	(0.357)	(0.096)	(0.360)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Adjusted R^2	0.028	0.053	0.048
F Statistic	5.049***	8.747***	7.915***
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. All models include industry and year fixed effects. Standard errors clustered at the firm-level to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

5 Sensitivity checks

In this section, we conduct numerous tests to check the sensitivity of our main findings. As sensitivity checks, we employ: i) firm fixed effects specifications to control for unobserved heterogeneity; ii) different sub-samples to address potential effects that may arise from different fiscal-year end among firms in our original sample, and; iii) entropy balancing to address a potential self-selection bias.

5.1 Controlling for Firm Fixed Effects

To control for endogeneity that may arise from the existence of time-invariant omitted firm-specific characteristics correlated with both evasive shareholder meetings proxies and stock price crash risk proxies, we re-estimate all main regressions controlling for firm fixed effects. Table 10 reports results from the regression analyses of the relationship between distance-based measures (*HEADQUARTERS*, *DISTANCE*, *REMOTE*, and *TRAVEL*) and stock price crash risk after controlling for firm fixed effects. Crash risk is proxied by *NCSKEW* in Columns (1)-(4), by *DUVOL* in Columns (5)-(8) and by *COUNT* in Columns (9)-(12). The weak effect between distance-based measures of evasiveness and stock price crash risk disappears after the firm-fixed effects are included. Specifically, coefficient estimates on *DISTANCE* (*DISTANCE x NCSKEW*, Column 2, Table 4) and *HEADQUARTERS* (*HEADQUARTERS x DUVOL*, Column 1, Table 5) becomes statistically insignificant after including firm fixed effects.

Table 11 reports results from the regression analyses of the relationship between timing-based measures (*CLUSTER* and *FIRST*) and stock price crash risk after controlling for firm fixed effects. 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), (9), and (12). The statistically significant relationship between timing-based measures and stock price crash risk virtually disappears after controlling for firm fixed effects[23].

[23]In unreported analyses, we employ changes specifications (First-difference) to mitigate the ommited

Table 10: Distance-based measures of evasiveness and stock price crash risk: firm-fixed effects estimations

	Dependent variable:											
	NCSKEW				DUVOL				COUNT			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
HEADQUARTERS	−0.036				−0.001				0.018			
	(0.090)				(0.024)				(0.080)			
DISTANCE		0.015				0.002				0.007		
		(0.018)				(0.005)				(0.017)		
REMOTE			0.087				0.024				0.032	
			(0.193)				(0.054)				(0.190)	
TRAVEL				−0.092				−0.249				1.582
				(3.691)				(0.974)				(3.269)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	No	No	No	No	No	No	No	No	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 within	0.067	0.067	0.067	0.067	0.116	0.116	0.116	0.116	0.065	0.065	0.065	0.065
Observations	9,086	9,086	9,086	9,086	9,086	9,086	9,086	9,086	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 based on Firm Fixed Effects estimations. Controls ommited for brevity. F Statistics 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 the down-to-up volatility (*DUVOL*) in year $t + 1$. In columns (9)-(12) crash risk is proxied by the number of crashes minus jumps over in year $t + 1$. *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. All models include year fixed effects. Standard errors clustered at the firm-level to account for heteroskedasticity are displayed in parentheses.. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 11: Timing-based measures of evasiveness and stock price crash risk: firm-fixed effects estimations

	Dependent variable:											
	NCSKEW				DUVOL				COUNT			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CLUSTER at 1%	0.077	0.010	−0.095									
	(0.083)	(0.021)	(0.071)									
CLUSTER at 2%				−0.071	−0.021	−0.117**						
				(0.062)	(0.016)	(0.057)						
FIRST at 1%							−0.088	−0.020	−0.198			
							(0.162)	(0.042)	(0.126)			
FIRST at 2%										−0.090	−0.025	−0.109
										(0.105)	(0.027)	(0.090)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	No	No	No	No	No	No	No	No	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 within	0.067	0.067	0.067	0.067	0.116	0.116	0.116	0.116	0.065	0.065	0.065	0.065
Observations	9,086	9,086	9,086	9,086	9,086	9,086	9,086	9,086	9,086	9,086	9,086	9,086

Notes. This table presents the regression results of the effect of timing-based measures of evasiveness on stock price crash risk based on Firm Fixed Effects estimations. Controls ommited for brevity. F Statistics 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 the down-to-up volatility (*DUVOL*) in year $t+1$. In columns (9)-(12) crash risk is proxied by the number of crashes minus jumps over 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. 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. All models include year fixed effects. Standard errors clustered at the firm-level to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

5.2 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 we observe a concentration of annual shareholder meetings between April and June in our 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 our 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 our original sample, we re-estimate all main regressions using a subsample of firms whose fiscal year ends on December 31st.

Table 12 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 13 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 12. On the other hand, as shown in Table 13, 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.

variables bias. Results are similar.

Table 12: 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	−0.073				−0.023*				−0.024			
	(0.053)				(0.014)				(0.047)			
DISTANCE		0.023*				0.005				0.005		
		(0.013)				(0.003)				(0.011)		
REMOTE			0.056				0.008				−0.258	
			(0.211)				(0.054)				(0.208)	
TRAVEL				0.885				0.022				−1.053
				(2.910)								(2.611)
Constant	−1.732***	−1.824***	−1.789***	−1.840***	−0.671***	−0.698***	−0.690***	−0.691	−2.576***	−2.603***	−2.591***	−2.533***
	(0.443)	(0.441)	(0.441)	(0.474)	(0.116)	(0.115)	(0.115)	(0.423)	(0.423)	(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	0.024	0.025	0.024	0.024	0.053	0.053	0.053	0.053	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. All models include industry and year fixed effects. Standard errors clustered at the firm-level to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 13: 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%	0.031	−0.015	−0.166***									
	(0.068)	(0.017)	(0.060)									
CLUSTER at 2%				−0.017	−0.014	−0.107**						
				(0.055)	(0.014)	(0.047)						
FIRST at 1%							−0.113	−0.054**	−0.284***			
							(0.101)	(0.025)	(0.084)			
FIRST at 2%										−0.035	−0.018	−0.134**
										(0.074)	(0.019)	(0.062)
Constant	−1.801***	−0.684***	−2.526***	−1.783***	−0.685***	−2.557***	−1.716***	−0.656***	−2.416***	−1.767***	−0.679***	−2.513***
	(0.442)	(0.116)	(0.420)	(0.440)	(0.115)	(0.420)	(0.444)	(0.116)	(0.423)	(0.440)	(0.115)	(0.422)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.024	0.053	0.050	0.024	0.053	0.050	0.024	0.054	0.051	0.024	0.053	0.050
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 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. 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. All models include industry and year fixed effects. Standard errors clustered at the firm-level to account for heteroskedasticity are displayed in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

5.3 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[24]. 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. We first divide our sample into two groups: treatment and control groups. We consider firm-year observations for firms holding annual general meetings outside firms' headquarters as our treatment group ($TREAT$). We denote all other firm-year observations as the control group with TREAT equal to 0. Table 14 reports the summary statistics of the covariates before and after entropy balancing. After the entropy balancing, our matching variables of treatment and control firms are nearly equal in terms of mean, variance, and skewness.

We re-estimate our main distance-based regressions using the balanced (re-weighted) sample and report the results in Table 15. We find no evidence that distance-based evasiveness (proxied by $HEADQUARTERS$) affects future stock price crash risk using a re-weighted sample.

[24]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 14: 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.

Table 15: Entropy balancing approach

	Dependent variable:		
	NCSKEW_{t+1}	DUVOL_{t+1}	COUNT_{t+1}
	(1)	(2)	(3)
HEADQUARTERS	−0.057	−0.020	−0.046
	(0.046)	(0.012)	(0.040)
SIGMA	21.814***	6.053***	10.385**
	(6.607)	1.625	(5.268)
RET	6.869***	1.943***	3.782***
	(1.472)	(0.358)	1.167
ROA	0.115	0.051	0.368***
	(0.147)	0.039	(0.126)
SIZE	0.127***	0.043***	0.137***
	(0.017)	(0.004)	(0.015)
MTB	0.005	0.002	0.008**
	(0.006)	(0.001)	(0.003)
LEV	−0.206	−0.088**	−0.351***
	(0.144)	(0.037)	(0.114)
DTURN	0.059*	0.025***	0.060***
	(0.031)	(0.008)	(0.023)
R&D	0.269	−0.025	0.227
	(0.321)	(0.081)	(0.241)
NCSKEW		−0.003	−0.015
		(0.003)	(0.010)
Constant	−1.921***	−0.652***	−2.182***
	(0.383)	(0.098)	(0.362)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
R^2	0.038	0.047	0.049
F Statistic	9.680***	7.018***	7.450***
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. All models include industry and year fixed effects. The numbers reported in parentheses are t-statistics based on standard errors clustered at the firm-level to account for heteroskedasticity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

6 Concluding Remarks

This study investigates the impact of evasive shareholder meetings practices on future 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, we find only weak evidence that firms holding annual general meetings in or near headquarters exhibit lower future stock price crash risk, and this weak effect totally disappears in sensitivity tests. We initially find a puzzling strong negative relationship between evasive timing strategies and future stock price crash risk. However, this effect virtually disappears after controlling for firm fixed effects or using subsamples. Additionally, we test if firms are strategically announcing meetings closer to annual meeting dates to increase the hoarding of bad news through poorer monitoring. Collectively, we find no evidence that evasiveness affect future stock price crash risk.

These findings challenge the "information hypothesis" proposed by Y. 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, Y. Li and Yermack (2016) focuses on stock performance based on cumulative abnormal stock returns. Our 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)[25]. 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

[25] 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".

field of research.

References

Al Mamun, M., Balachandran, B., & Duong, H. N. (2020). Powerful CEOs and stock price crash risk. *Journal of Corporate Finance*, *62*, 101582.

An, Z., Chen, C., Naiker, V., & Wang, J. (2020). Does media coverage deter firms from withholding bad news? Evidence from stock price crash risk. *Journal of Corporate Finance*, *64*, 101664.

Andreou, P. C., Louca, C., & Petrou, A. P. (2017). CEO age and stock price crash risk. *Review of Finance*, *21*(3), 1287–1325.

Bai, M., Xu, L., Yu, C.-F. J., & Zurbruegg, R. (2020). Superstition and stock price crash risk. *Pacific-Basin Finance Journal*, *60*, 101287.

Bhargava, R., Faircloth, S., & Zeng, H. (2017). Takeover protection and stock price crash risk: Evidence from state antitakeover laws. *Journal of Business Research*, *70*, 177–184.

Brochet, F., Chychyla, R., & Ferri, F. (2020). Virtual shareholder meetings. *Available at SSRN*.

Callen, J. L., & Fang, X. (2013). Institutional investor stability and crash risk: Monitoring versus short-termism? *Journal of Banking & Finance*, *37*(8), 3047–3063.

Callen, J. L., & Fang, X. (2015a). Religion and stock price crash risk. *Journal of Financial and Quantitative Analysis*, *50*(1-2), 169–195.

Callen, J. L., & Fang, X. (2015b). Short interest and stock price crash risk. *Journal of Banking & Finance*, *60*, 181–194.

Cao, C., Xia, C., & Chan, K. C. (2016). Social trust and stock price crash risk: Evidence from China. *International Review of Economics & Finance*, *46*, 148–165.

Cao, F., Sun, J., & Yuan, R. (2019). Board directors with foreign experience and stock price crash risk: Evidence from China. *Journal of Business Finance & Accounting*, *46*(9-10), 1144–1170.

Carrington, T., & Johed, G. (2007). The construction of top management as a good steward: A study of Swedish annual general meetings. *Accounting, Auditing & Accountability Journal*.

Chang, X., Chen, Y., & Zolotoy, L. (2017). Stock liquidity and stock price crash risk. *Journal of Financial and Quantitative Analysis*, *52*(4), 1605–1637.

Chen, C., Kim, J.-B., & Yao, L. (2017). Earnings smoothing: does it exacerbate or constrain stock price crash risk? *Journal of Corporate Finance*, *42*, 36–54.

Chen, J., Hong, H., & Stein, J. C. (2001). Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices. *Journal of Financial Economics*, *61*(3), 345–381.

Chen, W., Jin, H., & Luo, Y. (2020). Managerial Political Orientation and Stock Price Crash Risk. *Journal of Accounting, Auditing & Finance*, 1–19.

Chen, Y., Fan, Q., Yang, X., & Zolotoy, L. (2021). CEO early-life disaster experience and stock price crash risk. *Journal of Corporate Finance*, *68*, 101928.

Chowdhury, H., Hodgson, A., & Pathan, S. (2020). Do external labour market incentives constrain bad news hoarding? The CEO's industry tournament and crash risk reduction. *Journal of Corporate Finance*, *65*, 101774.

Dang, V. A., Lee, E., Liu, Y., & Zeng, C. (2018). Corporate debt maturity and stock price crash risk. *European Financial Management*, *24*(3), 451–484.

DeHaan, E., Shevlin, T., & Thornock, J. (2015). Market (in) attention and the strategic scheduling and timing of earnings announcements. *Journal of Accounting and Economics*, *60*(1), 36–55.

De Jong, A., Mertens, G., & Roosenboom, P. (2006). Shareholders' voting at general meetings: Evidence from the Netherlands. *Journal of Management & Governance*, *10*(4), 353–380.

Denes, M. R., Karpoff, J. M., & McWilliams, V. B. (2017). Thirty years of shareholder activism: A survey of empirical research. *Journal of Corporate Finance*, *44*, 405–424.

Deng, X., Gao, L., & Kim, J.-B. (2020). Short-sale constraints and stock price crash risk: Causal evidence from a natural experiment. *Journal of Corporate Finance*, *60*, 101498.

Dimitrov, V., & Jain, P. C. (2011). It's showtime: Do managers report better news before annual shareholder meetings? *Journal of Accounting Research*, *49*(5), 1193–1221.

Ertugrul, M., Lei, J., Qiu, J., & Wan, C. (2017). Annual report readability, tone ambiguity, and the cost of borrowing. *Journal of Financial and Quantitative Analysis*, *52*(2), 811–836.

Fang, X., Pittman, J., & Zhao, Y. (2021). The Importance of Director External Social Networks to Stock Price Crash Risk. *Contemporary Accounting Research*, *38*(2), 903–941.

Firth, M., Wong, S. M.-L., & Zhao, X. (2019). Corporate Accessibility and Stock Price Crash Risk. *Available at SSRN 2706977*.

Francis, B., Hasan, I., & Li, L. (2016). Abnormal real operations, real earnings management, and subsequent crashes in stock prices. *Review of Quantitative Finance and Accounting*, *46*(2), 217–260.

Fu, X., & Zhang, Z. (2019). CFO cultural background and stock price crash risk. *Journal of International Financial Markets, Institutions and Money*, *62*, 74–93.

Gam, Y. K., Gupta, P., Im, J., & Shin, H. (2021). Evasive shareholder meetings and corporate fraud. *Journal of Corporate Finance*, *66*, 101807.

Gao, S., Cao, F., & Liu, X. (2017). Seeing is not necessarily the truth: Do institutional investors' corporate site visits reduce hosting firms' stock price crash risk? *International Review of Economics & Finance*, *52*, 165–187.

Gu, L., Liu, J., & Peng, Y. (2020). Locality Stereotype, CEO Trustworthiness and Stock Price Crash Risk: Evidence from China. *Journal of Business Ethics*, 1–25.

Habib, A., Hasan, M. M., & Jiang, H. (2018). Stock price crash risk: review of the empirical literature. *Accounting & Finance*, *58*, 211–251.

Hainmueller, J. (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political analysis*, *20*(1), 25–46.

Han, B., Kong, D., & Liu, S. (2018). Do analysts gain an informational advantage by visiting listed companies? *Contemporary Accounting Research*, *35*(4), 1843–1867.

Harper, J., Johnson, G., & Sun, L. (2020). Stock price crash risk and CEO power: Firm-level analysis. *Research in International Business and Finance*, *51*, 101094.

Harvey, C. R., & Siddique, A. (2000). Conditional skewness in asset pricing tests. *The Journal of Finance*, *55*(3), 1263–1295.

Hasan, M. M., Taylor, G., & Richardson, G. (2022). Brand capital and stock price crash risk. *Management Science*, *68*(10), 7221–7247.

Holland, K. V., Lim, C., & Yi, I. (2021). Shareholder Meetings Uncertainty: Evidence from the Options Market. *Available at SSRN*.

Hong, H., & Stein, J. C. (2003). Differences of opinion, short-sales constraints, and market crashes. *The Review of Financial Studies*, *16*(2), 487–525.

Hu, J., Li, S., Taboada, A. G., & Zhang, F. (2020). Corporate board reforms around the world and stock price crash risk. *Journal of Corporate Finance*, *62*, 101557.

Huang, R., & Ritter, J. R. (2009). Testing theories of capital structure and estimating the speed of adjustment. *Journal of Financial and Quantitative analysis*, *44*(2), 237–271.

Hutton, A. P., Marcus, A. J., & Tehranian, H. (2009). Opaque financial reports, R2, and crash risk. *Journal of Financial Economics*, *94*(1), 67–86.

Jebran, K., Chen, S., & Zhang, R. (2020). Board diversity and stock price crash risk. *Research in International Business and Finance*, *51*, 101122.

Jebran, K., Chen, S., & Zhu, D. H. (2019). Board informal hierarchy and stock price crash risk: Theory and evidence from China. *Corporate Governance: An International Review*, *27*(5), 341–357.

Ji, Q., Quan, X., Yin, H., & Yuan, Q. (2021). Gambling preferences and stock price crash risk: Evidence from China. *Journal of Banking & Finance*, *128*, 106158.

Jin, L., & Myers, S. C. (2006). R2 around the world: New theory and new tests. *Journal of Financial Economics*, *79*(2), 257–292.

Kahneman, D. (1973). *Attention and effort* (Vol. 1063). Citeseer.

Keele, L., & Kelly, N. J. (2006). Dynamic models for dynamic theories: The ins and outs of lagged dependent variables. *Political Analysis*, *14*(2), 186–205.

Khurana, I. K., Pereira, R., & Zhang, E. (2018). Is real earnings smoothing harmful? Evidence from firm-specific stock price crash risk. *Contemporary Accounting Research*, *35*(1), 558–587.

Kim, C., Wang, K., & Zhang, L. (2019). Readability of 10-K reports and stock price crash risk. *Contemporary Accounting Research*, *36*(2), 1184–1216.

Kim, J.-B., Li, Y., & Zhang, L. (2011a). CFOs versus CEOs: Equity incentives and crashes. *Journal of Financial Economics*, *101*(3), 713–730.

Kim, J.-B., Li, Y., & Zhang, L. (2011b). Corporate tax avoidance and stock price crash risk: Firm-level analysis. *Journal of Financial Economics*, *100*(3), 639–662.

Kim, J.-B., Lu, L. Y., & Yu, Y. (2019). Analyst coverage and expected crash risk: evidence from exogenous changes in analyst coverage. *The Accounting Review*, *94*(4), 345–364.

Kim, J.-B., Wang, Z., & Zhang, L. (2016). CEO overconfidence and stock price crash risk. *Contemporary Accounting Research*, *33*(4), 1720–1749.

Kim, J.-B., & Zhang, L. (2014). Financial reporting opacity and expected crash risk: Evidence from implied volatility smirks. *Contemporary Accounting Research*, *31*(3), 851–875.

Kim, J.-B., & Zhang, L. (2016). Accounting conservatism and stock price crash risk: Firm-level evidence. *Contemporary Accounting Research*, *33*(1), 412–441.

Kirk, M. P., & Markov, S. (2016). Come on over: Analyst/investor days as a disclosure medium. *The Accounting Review*, *91*(6), 1725–1750.

Kothari, S. P., Shu, S., & Wysocki, P. D. (2009). Do managers withhold bad news? *Journal of Accounting Research*, *47*(1), 241–276.

Kubick, T. R., & Lockhart, G. B. (2021). Industry tournament incentives and stock price crash risk. *Financial Management*, *50*(2), 345–369.

Lee, Y.-C., Lu, Y.-C., & Wang, Y.-C. (2019). Corporate social irresponsibility, CEO overconfidence, and stock price crash risk. *Applied Economics Letters*, *26*(14), 1143–1147.

Lewis, C. M., & Tan, Y. (2016). Debt-equity choices, r&d investment and market timing. *Journal of financial economics*, *119*(3), 599–610.

Li, J., Wang, L., Zhou, Z.-Q., & Zhang, Y. (2021). Monitoring or tunneling? Information interaction among large shareholders and the crash risk of the stock price. *Pacific-Basin Finance Journal*, *65*, 101469.

Li, T., Xiang, C., Liu, Z., & Cai, W. (2020). Annual report disclosure timing and stock price crash risk. *Pacific-Basin Finance Journal*, *62*, 101392.

Li, W., & Cai, G. (2016). Religion and stock price crash risk: Evidence from China. *China Journal of Accounting Research*, *9*(3), 235–250.

Li, X., Wang, S. S., & Wang, X. (2017). Trust and stock price crash risk: Evidence from China. *Journal of Banking & Finance*, *76*, 74–91.

Li, Y., & Yermack, D. (2016). Evasive shareholder meetings. *Journal of Corporate Finance*, *38*, 318–334.

Li, Y., & Zeng, Y. (2019). The impact of top executive gender on asset prices: Evidence from stock price crash risk. *Journal of Corporate Finance*, *58*, 528–550.

Long, W., Tian, G. G., Hu, J., & Yao, D. T. (2020). Bearing an imprint: CEOs' early-life experience of the Great Chinese Famine and stock price crash risk. *International Review of Financial Analysis*, *70*, 101510.

Lu, X.-w., Fung, H.-G., & Su, Z.-q. (2018). Information leakage, site visits, and crash risk: Evidence from China. *International Review of Economics & Finance*, *58*, 487–507.

Nguyen, J. H., & Qiu, B. (2022). Right-to-work laws and corporate innovation. *Journal of*

Corporate Finance, *76*, 102263.

Ni, X., Peng, Q., Yin, S., & Zhang, T. (2020). Attention! Distracted institutional investors and stock price crash. *Journal of Corporate Finance*, *64*, 101701.

Ni, X., & Zhu, W. (2016). Short-sales and stock price crash risk: Evidence from an emerging market. *Economics Letters*, *144*, 22–24.

Obaydin, I., Zurbruegg, R., Hossain, M. N., Adhikari, B. K., & Elnahas, A. (2021). Shareholder litigation rights and stock price crash risk. *Journal of Corporate Finance*, *66*, 101826.

Price, S. M., Doran, J. S., Peterson, D. R., & Bliss, B. A. (2012). Earnings conference calls and stock returns: The incremental informativeness of textual tone. *Journal of Banking & Finance*, *36*(4), 992–1011.

Schwartz-Ziv, M. (2021). How shifting from in-person to virtual-only shareholder meetings affects shareholders' voice. *European Corporate Governance Institute–Finance Working Paper*(748).

SEC. (2020, Apr). *Staff guidance for conducting shareholder meetings in light of covid-19 concerns.* Retrieved from https://www.sec.gov/ocr/staff-guidance-conducting-annual-meetings-light-covid-19-concerns

Shahab, Y., Ntim, C. G., Ullah, F., Yugang, C., & Ye, Z. (2020). CEO power and stock price crash risk in China: Do female directors' critical mass and ownership structure matter? *International Review of Financial Analysis*, *68*, 101457.

Wen, F., Xu, L., Ouyang, G., & Kou, G. (2019). Retail investor attention and stock price crash risk: evidence from china. *International Review of Financial Analysis*, *65*, 101376.

Wu, K., & Lai, S. (2020). Intangible intensity and stock price crash risk. *Journal of Corporate Finance*, *64*, 101682.

Xiang, C., Chen, F., & Wang, Q. (2020). Institutional investor inattention and stock price crash risk. *Finance Research Letters*, *33*, 101184.

Xu, L., Rao, Y., Cheng, Y., & Wang, J. (2020). Internal coalition and stock price crash risk. *Journal of Corporate Finance*, *64*, 101640.

Xu, L., Yu, C.-F. J., & Zurbruegg, R. (2020). The benefit of being a local leader: Evidence from firm-specific stock price crash risk. *Journal of Corporate Finance*, *65*, 101752.

Xu, N., Jiang, X., Chan, K. C., & Yi, Z. (2013). Analyst coverage, optimism, and stock price crash risk: Evidence from China. *Pacific-Basin Finance Journal*, *25*, 217–239.

Yuan, R., Sun, J., & Cao, F. (2016). Directors' and officers' liability insurance and stock price crash risk. *Journal of Corporate Finance*, *37*, 173–192.

Appendix A. Variable definitions

A.1. Stock price crash risk

DUVOL - the down-to-up volatility of firm-specific daily returns, as detailed in Section 3.2.

NCSKEW - the negative conditional firm-specific daily returns skewness, as detailed in Section 3.2.

COUNT - the number of crashes minus the number of jumps in a given year t, as detailed in Section 3.2

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

SIGMA - the standard deviation of firm-specific daily returns.

RET - the average idiosyncratic daily return.

DTURN - the detrended stock trading volume.

SIZE - the natural logarithm of total assets.

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

LEV - the ratio between total debt and total assets.

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

R&D - the ratio between research and development R&D expenditure and total assets.

Appendix B. Downloading bulk data from EDGAR.

```
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!")
```