Stock price crash risk:
A critique of the agency theory viewpoint

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ABSTRACT

This paper explores the *puzzling* trend observed in US-listed firms between 1950 and 2018; specifically, firm-specific stock price crashes rose from 6.5 percent to an astonishing 27 percent. The burgeoning literature attributes stock price crashes to agency-related problems resulting from managerial opportunism that seeks to camouflage bad news through the channels of financial reporting opacity and overinvestment. Our study offers empirical evidence suggesting that these agency-based channels play a limited role in explaining this increasing frequency of stock price crashes. We show, especially in the post-SOX period, that a statistical relationship between the two prominent channels and future stock price crashes is notably absent. This study contributes to the literature by bringing to the fore the stock price crash risk puzzle, for which a prominent explanation in the post-SOX era remains largely undetermined. Further, the study discusses possible explanations wherein future research can look for answers.

Keywords: stock price crashes; bad news hoarding; agency theory; stock price crash channels; corporate governance; managerial incentives

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1. Introduction

The stock price crash risk literature has been undergoing a substantial development over the last decade, while the relationship between crashes and their determinants is a burgeoning research area. Much of this voluminous literature holds the view that management's hoarding of bad news practices is the underlying reason for firm-specific stock price crashes in stock markets. In fact, several important papers theorize, and offer empirical evidence, that the hoarding of bad news hypothesis is propelled by managers' self-interested strategies manifested through two prominent agency-based channels, namely financial reporting *opacity* and *overinvestment* (*e.g.* Hutton, Marcus, and Tehranian, 2009; Kim, Li, and Zhang, 2011a; Callen and Fang, 2013, 2015; Andreou, Antoniou, Horton, and Louca, 2016; Kim and Zhang, 2016; Ni and Zhu, 2016; Andreou, Louca, and Petrou, 2017).

Conversely, this study's empirical findings suggest that these *agency channels play a limited role in explaining* stock price crashes in the US stock market. For instance, the occurrence of stock price crashes for the CRSP-Compustat-Execucomp universe has steadily increased from 15 percent in 1992 to an astonishing 27 percent in 2018; yet, for the same period, we also witness a pronounced attenuation in the levels of opacity and overinvestment. This conundrum becomes more perplexing if one considers that stock price crashes have been rising steadily since 1950, while, in recent decades, there has also been an upsurge of corporate governance regulation, laws and exchange listing standards to combat managerial opportunism and protect shareholder welfare (Bhagat and Bolton, 2013; DeFond and Zhang, 2014; Wintoki, 2007).[1] Altogether, the empirical analyses in this study enable us to criticize the efficacy of the agency paradigm—pertaining to the capacity of opacity and overinvestment—in rationalizing the stock price crash risk phenomenon.

While there are numerous reasons for stock price crashes, extant explanations can be classified under two broad categories: *financial market explanations* and *firm-specific explanations*.

The focus of *financial market explanations*, as portrayed in the dominant study by Hong and Stein, (2003), is on the investor's perspective. In a nutshell, this theory postulates that, in the presence of short-sale constraints faced by at least some investors, different opinions among

[1] Over the past two decades, public company boards have been facing an increasing demand for effective corporate governance. The investment community has also been exerting steady pressure for the development of governance trends. Investors—especially institutional investors, as well as activists—are concerned about board composition and diversity; in their evaluation of firms' boards, they look specifically for value creation and risk mitigation (McKinsey, 2018; O'Kelley, Goodman, Martin, and Reynolds, 2018).

the investment community over a firm's fundamental value leads to more negative skewness in the distribution of stock returns (*i.e.* higher crash risk). This rigorous theory has nevertheless received very limited attention from researchers in the ambit of the crash risk literature.[2]

Unequivocally, studies elaborating on crash risk determinants have lionized *firm-specific explanations*. This literature builds upon agency theory arguments suggesting that information asymmetry between managers and shareholders, offers the potential for self-interested behavior to be manifested by managers (Jensen and Meckling, 1976; Jensen and Smith, 2000). More specifically, the renowned model of Jin and Myers (2006) argues that information asymmetry, compounded by the investors' incompletely secured property rights, enables managers to accumulate bad news. This lack of transparency (*i.e.* opacity) increases in step with the amount of concealed negative information. However, the managers' ability to conceal bad news is not unlimited; when the hoarded bad news crosses a tipping point, negative information comes out all at once, which leads to stock price crashes.

In the same agency context, the theory of Benmelech, Kandel, and Veronesi (2010) draws motivation from the argument that CEOs, aiming to protect and/or increase the component of firm performance that directly affects their financial rewards, exploit information asymmetry to manifest management's self-interested behavior and persistently hide bad news by engaging in overinvestment. Specifically, when the growth rate of investment opportunities starts to decline, concerns about their personal wealth can incentivize CEOs to conceal adverse outcomes from shareholders. As a result, CEOs do not reveal the bad news to the investors in a timely fashion so as to retain both their expectations and the level of stock price. According to this paradigm, CEOs engage in value-destroying investment decisions, at least temporarily, until the real growth rate of the firm's investment opportunities is revealed, which triggers a stock price crash.

Overall, explanations based on agency theory arguments accentuate *opacity* and *overinvestment* as the channels underpinning the relationship between the hoarding of bad news practices and stock price crashes. These two channels enable managers—who hope the tide will turn in their favor—to persistently camouflage bad news around their firm's economic fundamentals.

[2] Chang, Hsiao, Ljungqvist, and Tseng (2020) provide empirical evidence for the link between the role of investor disagreement and stock price crashes, whilst Lobo, Wang, Yu, and Zhao (2020) find a positive association between material weakness in internal controls disclosed under Section 302 of the Sarbanes–Oxley Act and subsequent stock price crashes. We are not aware of any other work that considers the stock price crashes from the financial market perspective.

But why has the crash risk literature been dominated by firm-side explanations? From a historical viewpoint, the increased interest of researchers in stock price crashes can be attributed to the wide coverage of corporate scandals, such as Enron's collapse in 2001 (Kothari, Shu, and Wysocki, 2009; Bhagat and Bolton, 2019). The extensive list of corporations collapsed due to managerial misconduct resulted in policymakers increasing regulation on financial reporting and other business practices at publicly traded companies. Measures have included, *inter alia*, the Regulation Fair Disclosure (Reg FD) in 2000, the Sarbanes-Oxley Act (SOX) of 2002, the Dodd-Frank Act of 2010, and the Corporate Governance Reform and Transparency Act of 2017. It is highly likely that such scandals coming to light triggered the attention of corporate finance research specialists, hence, significantly tilting the focus of the literature toward firm-specific explanations.[3] As Exhibit A.1 in the Online Appendix demonstrates, out of the 61 papers published in top-tier finance and accounting journals, 57 (or 93.4 percent) investigate stock price crash risk determinants pertaining to agency-based issues.[4] Therefore, in this study, we consider the bulk of the empirical research on stock price crashes from a solely agency theory viewpoint, with opacity and overinvestment as the focal channels that facilitate the hoarding of bad news.

Intriguingly, our empirical investigation shows that the occurrence of stock price crashes for the average US-listed firm has grown steadily from 6.5 percent in 1950 to an astounding 27 percent in 2018 in the CRSP-Compustat-Execucomp universe. Similar statistics are observed in the CRSP-Compustat data set, which has been routinely investigated in the crash risk literature, indicating that this phenomenon is not sample-specific. Further analyses demonstrate that the phenomenon is neither industry-specific, because the aforementioned uptrend pattern remains largely unaffected across the 12 Fama-French (1997) industries, nor model/metric-specific, because the same patterns emerge using different stock price crash risk operationalizations as suggested in prior studies (*e.g.* Hutton, Marcus and Tehranian, 2009; Kim, Li and Zhang, 2011a,b; Callen and Fang, 2013, 2015; Kim, Wang and Zhang, 2016; Andreou, Louca, and Petrou, 2017).

[3] Researchers are starting to recognize the importance of information relating to the third moment of stock returns (*i.e.* crash risk) as a determinant of future stock returns, in addition to stock volatility (Andreou, Andreou, and Lambertides, 2021). Interestingly, certain asset pricing studies have concluded that firms' crash risk matters for the tail risk characterizing underdiversified portfolios that are usually held by small investors, and that common variation in the tail risk of individual firms has strong predictive power for aggregate market returns (*e.g.* Bali, Cakici, and Whitelaw, 2014; Kelly and Jiang, 2014). Nevertheless, it remains a paradox that, to date, the literature has not turned its focus to the crash risk phenomenon using financial market-specific explanations.

[4] In fact, 37 out of these 61 studies (or 60.7 percent) exploit opacity, as in the Jin and Myers (2006) agency paradigm, to explain the occurrence of stock price crashes, qualifying this as the most frequently investigated channel.

Assessing this stylized fact from the agency theory viewpoint, the steadily ascending frequency of stock price crashes could *only* have been justified has it been associated with a corresponding pervasiveness in the two dominant channels that managers exploit to hoard bad news. Intriguingly, this has not been the case because as far as opacity is concerned, our results show a noteworthy decrease as of 2011. Especially in the CRSP-Computstat-Execucomp universe, the 2018 mean value of opacity is very similar to its 1992 level, which is at odds with the frequency of stock price crashes that, remarkably, has doubled during this period. Regarding the overinvestment channel, our results show a notably decreasing trend after 2002. Taken together, our investigation supports that the two agency-based channels demonstrate a clear downward trend as of 2000, whereas, in stark contrast, the frequency of stock price crashes has surged in the same time period for the average US public firm. Overall, the evidence provides little credence to an agency-based explanation of the phenomenon.

Next, we investigate if the surge of stock price crashes can be attributed to an overall weakening in firms' corporate governance. In the absence of appropriate monitoring, CEOs might undertake actions that maximize their own wealth to the detriment of shareholder welfare (*e.g.* Callen and Fang, 2013, 2015; Andreou, Antoniou, Horton, and Louca, 2016; Dang, Lee, Liu, and Zeng, 2018). Yet, recent studies suggest that accrual-based earnings management has experienced a significant decline following the passage of SOX (Cohen, Dey, and Lys, 2008; Zhou, 2008) and moreover, the new regulatory regime has resulted in an improved corporate-governance system (Chang and Sun, 2009). For example, Lu and Wang (2015) provide empirical evidence suggesting that higher board independence is associated with less capital investment. It is then natural to assume that the adoption of important regulation and laws over the last two decades (*e.g.* Reg FD and SOX) has significantly contributed to strengthening certain corporate governance functions aiming to mitigate the impact of managerial opportunism and to minimize—if not eliminate—agency problems in the corporate world. Accordingly, due to the sustained efforts of gatekeepers and fiduciary agents to improve corporate governance functions in US-listed firms, one would expect to observe a significant reduction in the frequency of stock price crashes. Therefore, in the spirit of prior studies (*e.g.* Callen and Fang, 2013, 2015; Andreou, Antoniou, Horton, and Louca, 2016; Dang, Lee, Liu, and Zeng, 2018; Mamun, Balachandran and Duong, 2020), we delve deeper to assess the relationship between certain corporate governance functions and future stock price crashes.

In empirical terms, we indeed observe that important corporate governance functions for the average US-listed firm have exhibited noteworthy improvements over the last two decades. For instance, the percentage of independent directors risen to more than 80 percent by 2018, a significant increase from about 60 percent in 1996. Likewise, the percentage of female directors on boards tripled, from about 7 percent in 1997 to about 21 percent in 2018. Similar improvements are observed for other internal governance functions (*e.g.* reduction in CEO duality, fewer busy directors, better director attendance). The same picture emerges for external governance functions known to provide effective monitoring and disciplining processes in public firms. For instance, *inter alia*, we observe a significant increase in non-transient (long-term) institutional ownership from about 15 percent in 1980, to more than 55 percent in 2018 in the CRSP-Compustat universe. Overall, these results provide further empirical support to our claim that the agency paradigm cannot offer material explanation for the crash risk phenomenon, especially over the last two decades. Supplementary, these results enable us to understand some reasons for which the two agency channels (opacity and overinvestment) have been attenuating over time.

Subsequently, we conduct panel regression analyses to justify the above inferences in a multivariate framework using two datasets of US-listed firms. Specifically, the intersections of CRSP-Compustat covering the period 1974-2018 and CRSP-Compustat-Execucomp covering the period 1992-2018. The main analyses are conducted in the spirit of prior studies (Kim, Li, and Zhang, 2011a,b; Kim, and Zhang, 2016; Francis, Hasan, and Li, 2016; Andreou, Louca, and Petrou, 2017; Callen and Fang, 2017; Li, and Zeng, 2019) by using the dichotomous stock price crash measure as the main explanatory variable (similar to the seminal study by Hutton, Marcus, and Tehranian, 2009), after controlling for the determinants known to influence crash risk, as well as industry-, year- or firm-fixed effects. Opacity and overinvestment are also estimated in accordance with prior crash risk studies (*i.e.* Hutton, Marcus, and Tehranian, 2009; Kim, Li, and Zhang, 2011a,b; Callen and Fang, 2013; Kim and Zhang, 2016; Kim, Wang, and Zhang, 2016).

Our multivariate investigation reveals three noteworthy findings. First, irrespective of the model specification or period considered, a statistical relationship between opacity and one-year-ahead stock price crashes cannot be found. This comes as a total surprise given that, to date, the opacity channel, as per Jin and Myers (2006), remains the primary explanation across stock price crash studies. Second, there is a rather weak relationship between overinvestment and one-year-ahead stock price crashes when using the full period of data. Third and intriguingly, when using the post-SOX sample covering the period 2003-2018, there is a remarkable absence of any statistical relationship for either of the agency-based channels, including overinvestment. Overall, the regression evidence empirically supports our argument regarding the limited role of the agency paradigm in explaining stock price crashes in the US market.

Our paper makes two important contributions to the literature. First, it documents the remarkable surge of stock price crashes over the past 60 years—an empirical irregularity that has yet to receive academic attention. The literature theorizes a stock price crash as the occurrence of an extreme idiosyncratic, large negative outlier in the distribution of returns (*e.g.* Chen, Hong, and Stein, 2001; Jin and Myers, 2006). To date, the literature also overwhelmingly relies on a stock price crash risk measure following operationalization, as per the seminal study by Hutton, Marcus, and Tehranian (2009), whereby one would expect the empirical occurrence of firm-specific stock price crashes to be about 5 percent per annum.[5] However, our empirical investigation shows that stock price crashes for US-listed stocks have steadily grown from 6.5 percent in 1950 to 27 percent in 2018. There is a stark contrast between the empirical occurrence of stock price crashes and the 5 percent threshold definition of stock price crash as an extreme event. This huge disparity gives birth to what we call as the *stock price crash risk puzzle*. The puzzle is even more baffling when one considers its theoretical construct in the model by Jin and Myers (2006) that states, "a crash is defined to happen at most once in 100 periods." What surfaces here is an elusive facet of the crash risk phenomenon that future research should consider; more specifically, it should seek to answer (at least) two important questions: (*i*) *why are we observing a steady growth in stock price crash occurrences in the past 60 years?* and (*ii*) *what explains the large gap between the theoretically (i.e. 5 percent) vs. the empirically expected occurrence of stock price crashes?* Overall, the puzzle provides stimulation and food for thought for the research community. At the same time, it indicates the need for additional studies to shed light on the key tenets of stock price crashes.

Second, our paper features an overview of the current state of knowledge in the realm of stock price crash studies and provides a critique regarding the efficacy of the agency paradigm that has been extensively exploited in prior studies. In this vein, our investigation surfaces enthralling evidence suggesting that opacity and overinvestment have significantly attenuated in the past two decades, thus they cannot serve as prominent agency-based channels for explaining stock price crashes. Overall, our findings underscore the limited role of these two

[5] Per Hutton, Marcus, and Tehranian (2009), a stock price crash is when a firm experiences firm-specific weekly returns that fall more than 3.09 standard deviations below the mean firm-specific weekly returns within a fiscal year. The 3.09 is chosen to generate a frequency of 0.1 percent in the normal distribution. Although, Hutton, Marcus, and Tehranian (2009, pg. 74) explain that this threshold is chosen to generate a "reasonable benchmark for extreme events" of approximately 5.07 percent stock price crashes per annum, they instead observed that 17.1 percent of the firm-years in their sample experiencing a crash. Similar empirical irregularities are documented by subsequent studies.

agency channels in driving stock price crashes for the average US-listed firm, especially in the post-SOX period. In this respect, this paper provides an urgent call for future research using alternative motivations and paradigms. The most obvious option is to seek out stock price crash risk explanations within the rather neglected *financial market side* paradigm as delineated in Hong and Stein (2003). Nevertheless, as outlined in our recommendations, future research should also seek explanations elsewhere, for example, looking at market microstructure or investors' irrational exuberance. Expanding the scope of investigation to paradigms beyond those related to agency is imperative to empower policymakers and planners in making more informed decisions, which can, in turn, lead to the reduction of stock price crash risk, as well as a better understanding within the investment community of the phenomenon.

The study unfolds as follows: Section 2 describes the data, measurements and methodology; Section 3 presents the summary statistics, as well as the univariate and multivariate analysis; Section 4 discusses possible explanations, while Section 5 provides a conclusion to the study.

2. Research design

The data for stock price crashes are drawn from the Center for Research in Security Prices (CRSP) for the period 1950 to 2018 covering common stocks (*i.e.* share codes 10 and 11) traded in NYSE, AMEX or NASDAQ. We report results after imposing filtering criteria in the spirit of prior stock price crash literature (*e.g.* Kim, Li, and Li, 2014; Andreou, Antoniou, Louca, Horton, 2016; Kim and Zhang, 2016; Andreou, Louca, Petrou, 2017), specifically, we exclude firm-years: (*i*) with a stock price less than 1 USD at the end of fiscal year, (*ii*) having fewer than 26 weeks of stock returns in a fiscal year, and (*iii*) without available information for computing the baseline control variables. To ensure that our results are not sample specific, we report results using: (*i*) the intersection of CRSP and Compustat for the period 1962 to 2018 featuring 106,740 firm-year observations, and (*ii*) the intersection of CRSP, Compustat and Execucomp for the period 1992 to 2018 featuring 32,203 firm-year observations. Most of the analysis exploits the CRSP-Compustat universe, which comprises the baseline sample.

2.1. Crash risk measure

Jin and Myers (2006) define the firm-specific stock price crash as an idiosyncratic, large negative outlier in the distribution of returns. In the spirit of prior studies that widely adopt this definition (*e.g.* Hutton, Marcus, and Tehranian, 2009; Kim, Li, and Zhang, 2011a; Kim, Wang, and Zhang, 2016; Zhu, 2016; Andreou, Louca, and Petrou, 2017; Chang, Chen, and Zolotoy, 2017; Andreou, Andreou, and Lambertides, 2021), the primary measure used to conduct our analyses—*CRASH*—is an indicator variable set equal to one for fiscal years when a firm experiences an extreme firm-specific left-tail outcome, and zero otherwise. The operationalization of the firm-specific large negative return outlier comes from a two-step procedure.

First, we compute firm-specific weekly returns using the following expanded index model:

$$r_w = a + b_1 r_{MKT,w-2} + b_2 r_{MKT,w-1} + b_3 r_{MKT,w} + b_4 r_{MKT,w+1} + b_5 r_{MKT,w+2} + b_6 r_{IND,w-2} + b_7 r_{IND,w-1} + b_8 r_{IND,w} + b_9 r_{IND,w+1} + b_{10} r_{IND,w+2} + e_w, \quad (1)$$

where r_w is the stock return in week *w*, and $r_{IND,w}$ is the Fama and French (1997) 48-industry value-weighted industry index and $r_{MKT,w}$ is the CRSP value-weighted market index in that week. We include two lead and lag terms of market and industry returns to better control for non-synchronous trading.[6] The inclusion of industry returns contributes to modelling crashes with more precision in cases that that one industry is collapsing (or booming) without necessarily this happening to the market as a whole. *Eq*. (1) separates the firm returns in two components: general systematic weekly returns and *firm-specific weekly returns* captured by the residuals, e_w. The estimation of *Eq.* (1) is conducted on all weekly returns that reside within a fiscal year, whereby we require at least 26 weekly observations.

Second, following the crash risk literature, the firm-specific weekly return for a stock in week *w*, R_w, is defined as the natural logarithm of one plus the residual return:

$$R_w = ln\,(1+e_w). \quad (2)$$

Following Hutton, Marcus, and Tehranian (2009), *CRASH* is defined to be a dichotomous variable set equal to one for fiscal year *t* if within this year the firm experiences firm-specific weekly returns that fall more than 3.09 standard deviations below the mean firm-specific weekly returns over the entire estimation period, with 3.09 chosen to generate a frequency of 0.1 percent in the normal distribution; otherwise, it is set equal to zero. Accordingly, *CRASH* for firm *j* in fiscal year *t* is defined as follows:

$$CRASH_{j,t} = \begin{cases} 1 \text{ if } \exists\, R_w < \mu_R - 3.09 * \sigma_R,\ w = 1, 2, \ldots n \\ 0,\ otherwise \end{cases}, \quad (3)$$

where μ_R and σ_R are, respectively, the mean value and standard deviation of the firm-specific returns as per *Eq*. (2) that fall within the fiscal year *t* for firm *j*.

[6] Hutton, Marcus, and Tehranian (2009) estimate their firm-specific weekly returns using an index model that employs only one lead and lag terms of market and industry returns. For robustness purposes, we have considered this model specification to find out that all our inferences remain quantitatively and qualitatively unchanged.

We also utilize two continuous measures to investigate the evolution of stock price cash risk in time, namely, the negative coefficient of skewness (*NCSKEW*) and the down-to-up volatility (*DUVOL*) as in Chen, Hong and Stein (2001). We calculate *NCSKEW* as the negative value of the third moment of firm-specific weekly returns divided by its standard deviation raised to the third power as follows:

$$NCSKEW_t = -(n\,(n-1)^{\frac{3}{2}}\ \sum \mathrm{R}_t^3\ )\,/\,((n-1)\ (n-2)(\sum \mathrm{R}_t^2\ )^{\frac{3}{2}}), \tag{4}$$

where R_t is estimated as per *Eq.* (2) and represents the sequence of stock weekly returns that fall within fiscal year *t*, whereas *n* is the number of firm-specific weekly returns during the estimation period.

The other continuous crash risk measure, *DUVOL*, is defined as the natural logarithm of the ratio of the volatilities of 'down' weeks to 'up' weeks. We consider a week as "down" ("up") when the firm-specific weekly return as per *Eq.* (2) is below (above) the estimation period's mean weekly return. Specifically, it is calculated as:

$$DUVOL_{j,t} = \log\left(\frac{(\mathrm{n}_u\text{-}1)\sum_{\mathrm{DOWN}} \mathrm{R}_w^2}{(\mathrm{n}_d\text{-}1)\sum_{\mathrm{UP}} \mathrm{R}_w^2}\right), \tag{5}$$

where n_u and n_d are the number of "up" and "down" weeks.

Subsequently, our analysis is primarily conducted by employing the dichotomous *CRASH* measure, whereas *NCSKEW* and *DUVOL* are employed for complementary purposes. Our preference for the dichotomous definition is mainly because: (*i*) it squares nicely with the theoretical underpinnings as in the Jin and Myers (2006) model, ascribing a stock price crash as a large firm-specific negative return outlier, and (*ii*) makes our study more comparable with seminal studies in the ambit of crash risk literature (*e.g.* Hutton, Marcus, and Tehranian, 2009; Kim and Zhang, 2011). On the other hand, *NCSKEW* and *DUVOL* merely capture the negative asymmetry in a firm's stock returns distribution, in essence by capturing stocks that are merely more "crash prone", that is, subject to more left-skewed distribution. As discussed by Andreou, Andreou, and Lambertides (2021), negative asymmetry in returns is possible to arise by the presence of several less extreme negative returns, something that does not necessarily comply with the notion that a stock price crash features an extreme negative firm-specific return outlier triggered by the sudden release of accumulated negative information underpinned by the hoarding of bad news mechanism (see, also, discussions in Chen, Hong, and Stein, 2001; Ak, Rossi, Sloan, and Tracy, 2016; Andreou, Cooper, Louca, and Philip, 2017).

2.2. Channels of stock price crashes

The agency theory viewpoint of firm specific stock price crashes is built upon the theoretical arguments of Jin and Myers (2006) and Benmelech, Kandel, and Veronesi (2010), indicating two channels that enable the manifestation of hoarding of bad news. These two channels, namely *financial reporting opacity* and *overinvestment*, are defined below.

2.2.1. Opacity

Asymmetric information between managers and shareholders, compounded by not fully secured rights of investors, allow top executives to withhold negative information (Jin and Myers, 2006). Subsequently, the accumulated bad news concealed from the investment community causes lack of transparency, *i.e.* opacity. A higher value of opacity indicates that the financial reports are less transparent, merely indicating that less firm-specific information is publicly available. There is evidence suggesting that accruals management obscures at least some firm-specific information and proxies the propensity of executives to conceal news from investors (Sloan, 1996).

Following Hutton, Marcus, and Tehranian (2009), opacity is measured as the three-year moving sum of the absolute value of discretionary accruals (*DACC*):

$$Opacity_t = Abs(\text{DACC}_t) + Abs(\text{DACC}_{t-1}) + Abs(\text{DACC}_{t-2}), \quad (6)$$

where *DACC* is measured as follows:

$$DACC_t = \frac{\text{TA}_t}{\text{ASSETS}_{t-1}} - \left(\text{a}_\text{o} \frac{1}{\text{ASSETS}_{t-1}} + b_1 \frac{\Delta\text{SALES}_t\text{-}\Delta\text{RECEIVABLES}_t}{\text{ASSETS}_{t-1}} + b_2 \frac{\text{PPE}_t}{\text{ASSETS}_{t-1}}\right). \quad (7)$$

In *Eq.* (6) total accruals (*TA*) is estimated cross-sectionally for each fiscal year within each Fama and French (1997) 48 industries:

$$\frac{TA_t}{ASSETS_{t-1}} = \text{a}_\text{o} \frac{1}{\text{ASSETS}_{t-1}} + b_1 \frac{\Delta\text{SALES}_\text{t}\text{-}\Delta\text{RECEIVABLES}_t}{\text{ASSETS}_{t-1}} + b_2 \frac{\text{PPE}_t}{\text{ASSETS}_{t-1}} + e_t, \quad (8)$$

where *ASSETS* denote the firm’s total assets, *ΔSALES* denotes the change in sales, *ΔRECEIVABLES* denotes the change in receivables and *PPE* denotes property, plant, and equipment.

2.2.2. Overinvestment

The theoretical development of Benmelech, Kandel, and Veronesi (2010) is motivated by the argument that information asymmetry enables managers to employ overinvestment, as a mean to conceal bad news. Specifically, this behavior is manifested when the growth in investment opportunities is declining and managers’ increased concerns regarding their personal compensation incentivize them to hide bad news (with the aim to secure their renumeration). Accordingly, pretending that the growth options are still prevalent, they engage in overinvestment so as to retain investors' expectations. In the presence of agency problems, managers are squandering free cash flows, *i.e.* cash flows that exceed the required amount to maintain assets in place and to finance expected new investments, by engaging in wasteful expenditure (Jensen, 1986; Stulz, 1990). A higher amount of overinvestment indicates a greater investment expenditure beyond the necessary amount to maintain assets in place and to finance expected new investments in positive NPV projects.

Overinvestment during the fiscal year is measured following Richardson's (2006) approach. To capture the accumulated effect of overinvestment, which is consistent with the hoarding of bad news theory, we utilized an aggregated measure of overinvestment, similarly to the opacity's measure, estimated as the three-year residuals from the regression model in *Eq.* (10):

$$Overinvestment_t = \text{RESIDUALS}_t + \text{RESIDUALS}_{t-1} + \text{RESIDUALS}_{t-2}, \quad (9)$$

where *RESIDUALS* are derived from the following model:

$$I_{NEW_t} = \text{a}_\text{o} + b_1 \frac{\text{V}_{\text{AIP}}}{\text{MV}}_{t-1} + b_2\text{LEVERAGE}_{t-1} + b_3\text{CASH}_{t-1} + b_4\text{AGE}_{t-1} + b_5\text{SIZE}_{t-1} + b_6\text{STOCK RETURN}_{t-1} + b_7\text{I}_{NEW_{t-1}} + \text{RESIDUALS}_t\,, \quad (10)$$

where V_{AIP} denotes the value of assets in place and is measured as:

$$V_{AIP} = (1 - ar)BV + (1 + \text{r})OI - \text{ar}D, \quad (11)$$

where BV is the book value given by common ordinary equity, OI is the operating income after depreciation, D is annual dividends, r =12% and $a = AEP/(1 + r - AEP)$ where AEP is the abnormal earnings persistence parameter from the Ohlson (1995) framework and equal 0.62, MV is the market value of equity, *LEVERAGE* is the sum of debt in current liabilities and long-term debt divided by book value of equity, *CASH* is the balance of cash and short term investments deflated by total assets at the start of the year, *AGE* is the natural logarithm of the number of years that the firm is covered in Compustat, *SIZE* is the natural logarithm of total assets and *STOCK RETURN* is the stock returns for the year prior to the investment year. Further,

$$I_{NEW} = I_{TOTAL} - I_{MAINTENANCE}, \quad (12)$$

where I_{TOTAL} denotes the total investment expenditure and is measured as the sum of capital expenditure, acquisition expenditure and research and development expenditure less cash receipts from sale of property, plant, and equipment and $I_{MAINTENANCE}$ denotes the investment expenditure necessary to maintain assets in place and is measured as the depreciation and amortization. I_{NEW} is decomposed into the expected investment expenditure in new positive NPV projects, and abnormal/unexpected investment. The abnormal/unexpected investment, which can be positive (negative) denotes the overinvestment (underinvestment).

2.3. Determinants of stock price crashes

Based on an agency viewpoint of the crash risk phenomenon, CEOs tend to exploit information asymmetries to extract rents by hiding bad news through the channels of opacity and overinvestment. However, in the presence of appropriate corporate governance functions that facilitate strong monitoring, managers are more limited to engage in self-interested strategies that maximize their own wealth to the detriment of shareholders' welfare. Accordingly, this section presents the crash risk determinants that we utilize in the empirical analysis, classified under two categories: *internal corporate governance* and *external corporate governance*.[7] This taxonomy abides to the literature that extensively emphasizes the importance of certain corporate governance functions in mitigating the agency-based reasons responsible for fostering future stock price crashes (*e.g.* Callen and Fang, 2013, 2015; Andreou, Antoniou, Horton, and Louca, 2016; Dang, Lee, Liu, and Zeng, 2018). Further, corporate governance functions that fall in these categories are designed to increase or enhance the monitoring of management's actions to promote effective decision-making, limit their opportunistic behavior and reduce the information asymmetry between the firm and its external stakeholders (Andreou, Antoniou, Horton, and Louca, 2016).

2.3.1. Internal corporate governance

Andreou, Antoniou, Horton, and Louca (2016), *inter alia*, emphasize the importance of certain corporate governance functions (*e.g.* board size, insiders' ownership), which help to reduce a firm's stock price crash risk by mitigating managerial opportunism that nurtures the hoarding of bad news mechanism. In the same vein, Li and Zeng (2019) report a negative association between female CFOs and future stock price crash risk, providing credence to the notion that these female executives (or board members) are curbing bad news hoarding activities relating to financial reporting and planning. Also, Mamum, Balachandran, and Duong (2020) explored the influence of powerful CEOs, by observing the dual role of CEO as chairman, which implies that dual-CEOs are more able to coordinate board activities and

[7] The role and importance of another important category, namely, *executive compensation and incentives*, is considered subsequently as an alternative explanation for rationalizing the stock price crash risk puzzle.

impose their self-interested preferences on certain outcomes. Lu and Wang (2015) provide empirical evidence suggesting that higher board independence is associated with less capital investment. In the same vein, Aktas, Andreou, Karasamani, and Philip (2019) show that dual-CEOs have a tendency in making overinvestment in low-growth business segments (relatively to the ones they make to segments with high growth opportunities), with the problem to be more heightened in firms with high agency problems as captured, among other, by the low presence of board independence.

Taking motivation from prior literature, we consider six internal corporate governance functions. Specifically, *Board Size* measured as the total number of directors in the board; the percentage of *Independent Directors* measured as the number of independent directors divided by the board size; the percentage of *Female Directors* measured as the number of female directors divided by the board size; the percentage of *Busy Directors* measured as the number of directors who are also members of other major company boards divided by the board size; the percentage of *Directors not-attend* measured as the number of directors who attended less than 75% of the board meetings divided by the board size; and, *CEO-Duality* measuring the percentage of CEOs who are also Chairpersons of their firms' board. Detailed definitions of these variables appear in the Appendix.

2.3.2. External corporate governance

The mitigating role of various corporate governance functions on the future occurrence of stock price crashes, is not limited only in internal mechanisms, but extends in external corporate governance mechanisms that have intrigued researcher's attention for further investigation. For example, Callen and Fang (2013) present evidence that institutional investor stability as captured by non-transient (long-term) institutional ownership is negatively associated with stock price crash risk, whereas Andreou, Antoniou, Horton, and Louca (2016) find that transient (short-term) institutional ownership increases a firm's stock price crash risk. Callen and Fang (2017) document that auditor tenure is negatively related to crash risk, whilst Li and Zhan (2019) suggest that competitive pressure from the product market aggravates managers' incentive to withhold negative information and find that firms facing more pressure are more prone to stock crashes.

Taking motivation from the prior literature, we consider four internal corporate governance functions. Specifically, *Non-transient institutional investors* (*i.e.* the sum of dedicated and quasi-indexers ownership) and *Transient institutional investors* following the classifications as in Bushee (1998, 2001); the average *Herflndahl-Hirschman index* (*HHI*) as a proxy of product market competition (Giroud and Mueller, 2010), measured as the sum of the square market share of all the firms in an industry (where the market share refers to the sales of the firm over the total sales of all firms in each industry); and, the average *Auditor Tenure* measured as the number of consecutive fiscal years that the auditor has been retained by the client, up to and including the current year. Detailed definitions of these variables appear in the Appendix.

2.4. Control variables

We consider numerous control variables proposed by literature as having a predictive power in explaining stock price crashes (*e.g.* Hutton, Marcus, and Tehranian, 2009; Kim, Li, and Zhang, 2011a; Kim, Wang, and Zhang, 2016; Zhu, 2016; Andreou, Louca, and Petrou, 2017; Callen and Fang, 2017; Li and Zeng, 2019; Andreou, Andreou, and Lambertides, 2021). Specifically, our regression analysis includes the following firm-level variables: *Leverage*, the ratio of total liabilities to total assets; *Market to Book*, the ratio of market value to book value of equity; *Return on Equity*, the ratio of income before extraordinary items to equity; *Size*, the natural logarithm of total assets at fiscal year-end; and *Firm Age*, the number of years that the firm is covered in Compustat. Furthermore, we include the detrended turnover (*Dturn*), estimated as the detrended average weekly stock trading volume during the fiscal year, which captures time-varying impacts on skewness (Chen, Hong, and Stein, 2001). Smaller firms, younger firms with less experience, firms with high growth, firms with less profits and more leverage are expected to be more prone to experience a stock price crash. Furthermore, firms with higher past returns are appeared to have a more negative skewness.

3. Discussion of empirical findings

3.1. Summary Statistics and Correlations

Table 1 displays the summary statistics (Panel A) for the three alternative crash risk measures, namely *CRASH*, *NCSKEW* and *DUVOL*, and the baseline control variables. Specifically, Panel A1 refers to the CRSP-Compustat data set (1962-2018) which consists of 106,740 firm-year observations. The mean value (standard deviation) of *CRASH* is 0.145 (0.352), suggesting that 14.5 percent of these observations experience at least one stock price crash event. The mean value (standard deviation) of *NCSKEW* and *DUVOL* are -0.063 (0.727) and -0.083 (0.343), respectively. Although we utilize a greater sample than the plethora of prior crash risk studies, the occurrence of stock price crashes in our data falls within the range reported in prior studies. For instance, the average frequency for stock price crashes reported in Kim, Li, and Zhang (2011a, b), Kim and Zhang (2016), Kim, Wang, and Zhang (2016), Kubick and Lockhart (2016), Francis, Hasan, and Li (2016), Andreou, Louca, and Petrou (2017), Ertugrul, Lei, Qiu, and Wan (2017), Bao, Fung, and Su (2018), Kim, Wang, and Zhang (2019), Li and Zeng (2019) is 17.2, 16.3, 12.2, 17.2, 19.2, 19.5, 19.2, 20.9, 21.1, 22.5 and 25.4 percent, respectively.

The distribution characteristics of the main control variables are largely consistent with those reported in prior studies utilizing CRSP-Compustat data set (*e.g.* Callen and Fang, 2017; Chen, Kim, and Yao, 2017; Dang, Lee, Liu, and Zeng, 2018). For instance, the average firm in our sample has a size of 5.622 (1.997), sales of 2154.59 (10878.29), market capitalization of 2023.3 (6227.82), firm age of 18.751 (13.69) years, market to book ratio of 2.56 (3.366) and leverage of 0.497 (0.222). The sample firms have a mean (standard deviation) return on equity of 0.034 (0.406). The detrended average weekly stock trading volume is 0.001 (0.016).

Panel A2 refers to the CRSP-Compustat-Execucomp data set for the period 1992-2018 consisting of 32,203 firm-year observations. The mean value (standard deviation) of *CRASH* is 0.199 (0.400), suggesting that 19.9 percent of these observations experience at least one stock price crash event. The mean value (standard deviation) of *NCSKEW* and *DUVOL* are 0.084 (0.745) and -0.001 (0.345), respectively. As expected, firms in the CRSP-Compustat-Execucomp universe are more prone to stock price crashes, given that this analysis is assessing a more recent period. The distribution characteristics of the main control variables are largely consistent with those reported in prior studies utilizing CRSP-Compustat-Execucomp data set (*e.g.* Kim, Li, and Zhang, 2011; Kim, Wang, and Zhang, 2016). For instance, the average firm in our sample has a size of 7.327 (1.586), sales of 5632.45 (18671.68), market capitalization of 5439.92 (10006.09), firm age of 26.446 (16.992) years, market to book ratio of 3.227 (3.627) and leverage of 0.521 (0.221). The sample firms have a mean (standard deviation) return on equity of 0.085 (0.359). The detrended average weekly stock trading volume is 0.001 (0.018).

In general, the distribution characteristics of the main control variables are substantially different in the CRSP-Compustat-Execucomp data set compared to the CRSP-Compustat data set. For instance, the average firm in the intersection of CRSP-Compustat-Execucomp has a greater size, more than twice the amount of sales and market capitalization, on average 8 more years since establishment and greater return on equity. All the differences between the variables in Panel A1 and Panel A2 have been tested for equality and are statistically significant different one another (p-values<0.01), except those of *Leverage* and *Dturn*.

Table 1, Panels B1 and B2 display the Pearson correlations for the crash risk measures, for the two different data sets, whereby one can observe similar results. Particularly, *NCSKEW* and *DUVOL* are highly positively related with the correlation coefficient to exceed 0.95. However, the correlation of the dichotomous *CRASH* variable with *NCSKEW* and *DUVOL* is much lower around 0.60 and 0.55, respectively. All the coefficients are statistically significant (*p*-value<0.01).

3.2. Univariate analysis

3.2.1. Unveiling the stock price crash risk puzzle

Figure 1A depicts the frequencies of stock price crashes as operationalized by *CRASH* for: CRSP universe from 1950 to 2018, CRSP-Compustat universe from 1962 to 2018 and CRSP-Compustat-Execucomp universe from 1992 to 2018. Admittedly, there is a remarkable surge of stock price crash occurrences starting at 5.5 percent in 1950 and growing to about 24 percent in 2018 for the CRSP universe, whereas the 2018 value for the firms in the CRSP-Compustat-Execucomp universe is about 27 percent. Likewise, Figure 1B depicts the time evolution of *NCSKEW* and *DUVOL* for the average US-listed firm from 1962 to 2018 (higher values indicate higher stock price crash risk) and vindicates our inference based on the evidence in Figure 1A. In general, the figures demonstrate slightly higher frequencies of *CRASH* for firms in the Execucomp database than those in Compustat.

[Insert Figures 1A and 1B, here]

Li and Zhan (2019) examine the effect of product market threats on firms' stock price crash risk and finds that firms facing more threats are more prone to stock crashes. Because product market competition is likely to be an industry effect (Giroud and Mueller, 2010), we also investigate whether the phenomenon under scrutiny is not industry specific, meaning not mainly driven by few industries that are by nature more prone to stock price crashes. Figure A1 in the Online Appendix demonstrates the frequencies of stock price crashes per Fama-French 12 industries, using the intersection of CRSP and Compustat for the period 1962 to 2018. Although, one might expect the percentages of crashes to show noticeable differences across industries, interestingly, the upward trend remains largely unchanged across the 12 Fama-French industries, with the frequencies climax to happen in the post-SOX period.

The evidence documented in Figure 1A gives birth to what we call the *stock price crash risk puzzle*. Given Hutton, Marcus, and Tehranian (2009) definition of a stock price crash as per *Eq*. (3) that is widely applied in the burgeoning literature, a firm experiences firm-specific weekly returns that fall more than 3.09 standard deviations below the mean firm-specific weekly returns within a fiscal year, with 3.09 chosen to generate a frequency of 0.1 percent in the normal distribution. Hutton, Marcus, and Tehranian (2009, pg. 74) explain that "if firm-specific returns were normally distributed, one would expect to observe 0.1% of the sample firms crashing in any week", resulting in a crash probability of 5.07 percent over the course of a year. Intriguingly the observed crash frequency reaches 27 percent in 2018, a compelling observation that brings the empirical frequency *at odds* with the hypothetical one in the seminal study of Hutton, Marcus, and Tehranian (2009). Then, one is naturally to wonder *how is possible a percentage of 27 percent to represent a negative outlier in the distribution of firm-specific returns*? However, this is not the only puzzling issue. Figure 1A unveils a persistently upward slopping trend in stock price crashes. Therefore, it is not only that on average there is a high incidence of stock price crashes in the recent years that is out of line, and challenges the expectations as hypothesized by Hutton, Marcus, and Tehranian (2009), but the frequency of stock price crash exhibits an increasing behavior over the time. The latter causes even more contradictions as the mean frequency of stock price crashes opens the wedge from the reference point of 5.07 percent, especially as observed in the past two decades of our sample data.

3.2.2. A firm-side assessment of the crash risk puzzle: Opacity and overinvestment

We assess this stylized fact from the firm side perspective by considering the two prominent agency-based channels, opacity and overinvestment, which facilitate the hoarding of bad news practices. Thus, in Figures 2 and 3 we plot the time evolution of the two channels characterizing the average US-listed firm. The analysis of firms in the CRSP-Compustat universe starts in 1974 which is the first year with sufficient data.

Based on the agency theory's predictions, one would expect to observe a *positive relationship* between: (*i*) opacity and stock price crashes as theorized, *inter alia*, in the studies of Hutton, Marcus, and Tehranian (2009), Kim, Li, and Zhang (2011b), Callen and Fang (2015, 2017), Dang, Lee, Liu, and Zeng (2018), Andreou, Antoniou, Horton, and Louca, 2016; Kim, Wang, and Zhang (2019), and (*ii*) overinvestment and stock price crashes as theorized, *inter alia*, by Benmelech, Kandel, and Veronesi (2010). Accordingly, under the firm side perspective, one would expect the increasing frequencies of (one-year-ahead) stock price crashes as observed in Figure 1A to move in tandem with the levels of opacity and overinvestment.

On the contrary, as far as opacity is concerned, Figure 2 depicts that while it was increasing in the first years of the sample, after 2003 it demonstrates a decreasing trend until 2008, it raises again until 2011 and then decreases and appears rather flat over the last years of the sample, where the crash reaches the highest frequencies. In fact, for the CRSP-Compustat-Execucomp data set, opacity levels appear to decrease after 2009, something that comes at stark contradiction with the fact that stock price crashes appear to peak during these years. As far as overinvestment is concerned, Figure 3 depicts a clear decreasing trend after 2002, with its downward direction to be steeper for the CRSP-Compustat-Execucomp universe.

[Insert Figures 2 and 3, here]

Taken together, the evidence in Figures 2 and 3 suggest an overall decline in the levels of opacity and overinvestment over the last two decades, probably reflecting the efficacy of important regulations (Reg FD and SOX) established in the early 2000's to enhance transparency and curtail managerial opportunism. Unequivocally, especially in the post-SOX period, the plunge in the levels of the two agency-based channels is at odds with the surge in the occurrence of stock price crashes. This makes it very difficult for the firm-side perspective to offer a prominent explanation for the stock price crash risk puzzle, in other words, *opacity and overinvestment appear to play a limited role in explaining* the up-trending occurrence of stock price crashes as observed for the average firm in the US stock market.

3.2.3. A firm-side assessment of the crash risk puzzle: Corporate governance functions

The previous analysis suggests that both opacity and overinvestment have significantly attenuated, especially in the post-SOX period. This evidence leaves little—if no at all—space for the possibility that managers persistently conceal negative information regarding the firms' economic fundamentals, to benefit themselves at the expense of shareholders through these two channels. These findings point to a limited role of an agency-based explanation for the hoarding of bad news hypothesis because the attenuation of the opacity and overinvestment level implies improvements in important corporate governance functions, which have fostered stronger and more effective monitoring and disciplining processes in US-listed firms. Ergo, the subsequent analysis investigates the time evolution of both internal and external corporate governance mechanisms intended to curb management's self-interested strategies and minimise the agency problems in the corporate world.

With reference the average US-listed firm in the CRSP-Compustat-Execucomp universe, Figure 4 demonstrates that the board size remains stable during the years (Figure 4A), the average percentage of duals CEOs has significantly declined from 65% to 40% (Figure 4B), while the average percentage of independent directors in the board significantly increased from 58% to 82% (Figure 4C). Additionally, the average percentage of busy directors and the average percentage of not attended directors, decreased from 23% to 20.5% (Figure 4D) and 2.5% to 0.5% (Figure 4E), respectively. On the other hand, the average percentage of female directors significantly increased from 7% to almost 21% (Figure 4F). Interestingly, all the various internal governance mechanisms have improved markedly in directions indicating lower agency issues for the average US-listed firm as time passes.

[Insert Figures 4A-4F, here]

In the same vein, we examine the time evolution of external corporate governance functions. Regarding the institutional ownership, although the average percentage of transient (short-term) institutional ownership appears to fluctuate around a mean value of 18 percent during the last two decades (Figure 5A), the average percentage of non-transient institutional ownership, which is directly linked with the enhancement of the monitoring, has risen significantly from 15% to approximately 60% in 2018 (Figure 5B). Additionally, we plot the movement of the average product market competition as proxied by the *HHI*, conjecturing that a competitive environment may exert pressure to the firm's management and generally act as a natural discipline function. Despite we observe a declining trend of the average *HHI* from 1990 to 1996 (Figure 5C), in principle this corporate governance function appears stable over the last years. Following the evidence in Li and Zhan (2019) this evidence does not square with the notion that increased product market competition pressures would increase the management's proclivity towards hoarding more bad news that could justify a higher frequency of stock price crashes. Finally, we plot the average auditor tenure (Figure 5D), to investigate the auditor-client relationship across time. Overall, we observe a stable trend, especially for firms in the Execucomp universe, with the average tenure to fluctuate between 15 and 20 years, which is a satisfactory time period for the auditors to acquire the so-called client-specific knowledge that improves their ability to detect and prevent activities related to hoarding of bad news. What is again observed, is a noticeable improvement in the various external corporate governance mechanisms that cannot provide a rationale for the surge in stock price crashes.

[Insert Figures 5A-5D, here]

3.3. Multivariate analysis

To investigate the impact of the two agency-based channels, this section reports results after conducting regression analyses using the two data sets: CRSP-Compustat and CRSP-Compustat-Execucomp. The primary variable of interest is stock price crash as operationalized by *CRASH*, whilst we also report results using *NCSKEW* for vindicating the robustness of our inferences. The dependent variables feature the one-year-ahead stock price crash risk (*i.e.* measured in year $t+1$). In addition to the two variables of interest *Opacity* and *Overinvestment*, all regression specifications include a number of control variables (*i.e. Size*, *Firm Age*, *Market* *to Book*, *Leverage*, *Return on Equity*) identified as important determinants as per prior studies, whereby all are measured in year *t* or at a more distant point in the past (*e.g.* we use one and two lagged values of *NCSKEW* to control for persistency in the stock price crash risk).

Our regression models rely on a *lead-lagged relationship* as implement in prior studies (*e.g.* Kim, Li, and Zhang, 2011a; Callen and Fang, 2013, 2015; Ni and Zhu, 2016; Andreou, Louca, and Petrou, 2017), mainly intending to safeguard our analyses from potential simultaneous causality problems. Further, to control for unobservable and time-invariant characteristics, the estimation of the regression models includes either *industry* and *year* fixed effects or *firm* and *year* fixed effects. For industry effects, we use the 12 industry classifications by Fama and French (1997). Furthermore, standard errors are always clustered at the firm level. All continuous variables included in our analyses are winsorized at the 1st and 99th percentiles to mitigate the effect of outliers. To put the variables on the same scale, all continuous variables are standardized to have a mean value of zero and a standard deviation of one.

Table 2, Panel A reports the results from regressing *CRASH* on *Opacity*, *Overinvestment* and other controls in the CRSP-Compustat universe. The models (1) to (4) include year and industry fixed effects, while the models (5) to (8) include firm and year fixed effects. As far as the stock price crash risk channels are concerned, accounting opacity appears statistically not significant in all model specifications. The overinvestment channel in general is positively associated with the one-year-ahead stock price crash risk (p-values<0.05) in all model specifications. For instance, in the models (2) and (4), the marginal effects of overinvestment are 0.006 and 0.005, respectively, and statistically significant (p-values<0.01). Furthermore, the marginal effects for *Overinvestment* become higher (albeit with lower statistical significance) with the inclusion of firm fixed effects; specifically, 0.009 (p-value<0.05) and 0.007 (p-value<0.05) in models (6) and (8), respectively.

Regarding the control variables, models (3) and (4) show that *Stock Return* and *Dturn* are significant and positively associated with one-year-ahead stock price crashes, consistent with Chen, Hong and Stein (2001). Remarkably, the marginal effects of the market-related variables are higher compared to the marginal effects of either *Opacity* or *Overinvestment*. For instance, the marginal effect of *Stock Return* and *Dturn* is 0.009 for both explanatory variables in model (4), while the marginal effect of overinvestment is only 0.005. This comparison is more pronounced in model (8), where the marginal effects for *Stock Return* and *Dturn* are 0.018 and 0.015, respectively, but the marginal effect of overinvestment is only 0.007.

In general, the results regarding the control variables are consistent with prior studies. Specifically, the coefficients on *Size*, *Market to Book* and *Return on Equity* are positive and statistically significant, implying that an increase in each of the variables is associated with a greater likelihood to experience a future stock price crash, consistent with the findings of prior studies (*e.g.* Chen, Hong, and Stein, 2001; Kim, Li, and Zhang, 2011; Chen, Kim, and Yao, 2017). Conversely, there is a negative and statistically significant relationship between *Leverage* and future stock price crashes, as in prior studies.

In a similar vein, Table 2, Panel B reports results for the CRSP-Compustat-Execucomp universe. In principle, the results are qualitatively similar with the results derived from the intersection of CRSP-Compustat in Panel A. *Opacity* again appears statistically not significant in all model specifications, while overinvestment is statistically positively associated (*p*-value<0.10) with the one-year-ahead stock price crash risk. However, the statistical significance for the marginal effects of *Overinvestment* in Panel B is weaker *vis-à-vis* the one reported in Panel A.

[Insert Table 2, here]

To check the robustness of our findings with regards to the crash risk measurement, Table 3 features regression analysis using the one-year-ahead negative coefficient of skewness (*NCSKEW*) as dependent variable.[8] The structure and model specifications of this table are in the spirit of Table 2.

The results in Table 3, Panel A show that *Opacity* is significantly positive in models (2) and (4) estimated with the inclusion of *year* and *industry* fixed effects, while it is not significant in models (6) and (8) estimated with the inclusion of *firm* and *year* fixed effects. Regarding *Overinvestment*, this is significantly positive in all model specifications.

Table 3, Panel B reports the OLS results using the CRSP-Compustat-Execucomp sample, with most of them to be qualitatively similar with the results derived based on CRSP-Compustat sample in Panel A. The important difference is that *Opacity* appears not significant in all model specifications, in general in line with the evidence observed in Table 2. With regards to *Overinvestment*, we observe again a significant and positive association with one-year-ahead stock price crash risk, while both the magnitude and the significance become weaker after the inclusion of firm (than industry) fixed effects.

[Insert Table 3, here]

Finally, we move forward with subsample analysis focusing on the post-SOX period 2003-2018. We take this step because the evidence in Figures 2 and 3 depict a notable attenuation of

[8] We reach similar conclusions if instead we use *DUVOL* as the dependent variable. These results are included in the Online Appendix.

opacity and overinvestment for the average US-listed firm over the last two decades, whilst, admittedly, stock price crashes have surged during this period. From a helicopter viewpoint it appears that *neither* opacity *nor* overinvestment can rationalize the stock price crash risk puzzle. However, our intent is to vindicate this inference using year-panel regression analysis that accounts for cross-sectional variation in the variables under scrutiny.

Table 4, Panel A reports the results when *CRASH* is the dependent variable and Panel B reports the results when *NCSKEW* is the dependent variable. The models (4) and (8) in both Panels A and B capture the incremental impact of *Opacity* and *Overinvestment*, after controlling for the firm's financial characteristics and after removing both the firm's average crash risk effect (firm fixed effects) over the entire estimation period and any time-series pattern in overall crash risk period (time fixed effects). Overall, there is overwhelming evidence in Table 4, especially for models that employ firm and year fixed effects, suggesting that both *Opacity* and *Overinvestment* are statistical not significant.

Overall, the econometric analysis, particularly the one of Table 4 that focuses on firm-year observations covering the last two decades, strongly supports our claim that the two prominent *agency-based channels* play a limited role in explaining stock price crashes in the US stock market.

[Insert Table 4, here]

4. Potential explanations

The most prevalent explanation proposed by the literature so far, *i.e.* the agency theory explanation of stock price crashes, seems to have a limited power to empirically rationalize the phenomenon. A prominent explanation(s) behind the stock price crash risk puzzle, particularly as this emerges in the post-SOX period, remains undetermined. Below, we elaborate on alternative explanations that can rationalize the phenomenon. Our approach is mostly descriptive aiming to provide "food for thought" to stimulate future research in the area. Seeking for alternative explanations, we focus on financial incentives provided to CEOs through their compensation packages. We also consider some market microstructure characteristics aspiring to push future research towards a financial market viewpoint of interpretation. Apparently, this viewpoint remains largely unexplored. Nevertheless, we provide supplementary results to shed some light on the stock price crash risk puzzle and thus the merit (and plausibility) of the explanations we discuss.

4.1. CEO compensation and incentives

The relationship between executives' financial incentives and stock price crash risk has been under consideration in the burgeoning crash risk literature. For instance, Kim, Li and Zhang (2011) and Andreou, Antoniou, Hutton, and Louca (2016) report positive links between CEOs' compensation and incentives and future stock price crash risk. Additionally, admitting compensation package as a mechanism used to align managers' and shareholders' interests, He (2015) documented that CEO inside debt holdings are associated with a reduction in the likelihood of firm-specific stock price crashes. More recently, Andreou, Louca and Petrou (2017) find that strings of consecutive earnings increases are accompanied by large permanent increases in CEO compensation that do not dissipate with stock price crashes. Therefore, CEOs have financial incentives to hoard bad news earlier in their career to increase their executive remuneration, which subsequently leads to stock-price crashes but without any negative effects on their remuneration packages.

In general, if the optimal executive compensation package is achieved it should be considered as an effective tool to mitigate agency problems in public firms through aligning the interests of managers and shareholders. However, this is not always the case, since an ineffective combination may instead result in "dis-incentives" (Benmelech, Kandel and Veronesi, 2010) and lead managers to make decision to the detriment of shareholders' welfare. Moreover, in the presence of managerial career concerns, there is evidence supporting that it is challenging to determine the optimal incentive contract (Gibbons and Murphy, 1992).

To better understand the relationship between CEO compensation and incentives with future stock price crashes, we investigate for the average US-listed firm the time evolution of the following components of CEO remuneration package: (*i*) *Total Compensation* using the item *TDC1* in Execucomp[9], (*ii*) percentage of *Salary* measured as the dollar value of the base salary (cash and non-cash) earned by the CEO during the fiscal year divided by total compensation, (*iii*) percentage of *Bonus* measured as the dollar value of a bonus (cash and non-cash) earned by the CEO during the fiscal year divided by total compensation, (*iv*) percentage of *Stock Holdings* measured as the total value of restricted stock granted during the fiscal year divided by total compensation, (*v*) percentage of *Option Holdings* measured as the total value of stock options granted (using Black-Scholes) during the fiscal year divided by total compensation, (*vi*) *CEO Pay Slice* measured as the percentage of the total compensation of the top five

[9] Total compensation (TDC1) for the individual year, comprised of the following components: Salary, Bonus, Other Annual, Total Value of Restricted Stock Granted, Total Value of Stock Options Granted (using Black-Scholes), Long-Term Incentive Payouts, and All Other Total.

executives that goes to the CEO, and (*vii*) the *Stock and Option Incentives* ratio following Bergstresser and Philippon (2006).[10]

Accordingly, Figure 6A depicts a significant increase in the total average compensation in time. However, not all total compensation components grow in the same fashion. Specifically, in Figures 6B, 6C and 6D the percentages of the average salary, the average bonus and the average option holdings show a noticeable *decrease* in the period 1992-2018 from 28% to 12%, from 17% to 2% and from 3.5% to 1.5%, respectively. On the other hand, stock holdings (Figure 6E) is the component that explains the upward trending behavior of the total compensation, whereby it has risen from 8% in 1992 to 50% in 2018. Additionally, the increase is not only prevailing in the average total compensation, but also relatively to the rest highly paid top executives. Specifically, the average percentage of the aggregate compensation of the top five executives captured by the CEO has also increased from 35% to 41% (Figure 6F). Finally, while the average CEO option holdings incentives ratio remains stable during the last years of the sample (Figure 6H), CEO stock holdings incentives ratio has raised (Figure 6G). This increase was expected given that the stock holdings have experienced a huge increase, from 8% to 50% during the period 1992-2018.

[Insert Figures 6A-6G, here]

Taken together, in general, the upward trending pattern for the CEOs in US-listed firms shows a resemblance to the surge in stock price crashes, specifically in the post-SOX period. While this evidence may be *coincidental*, it appears that important components of the CEO compensation, such as option holdings, have been steadily decreasing, stock holdings have showed an astonishing increase during this period. From an agency viewpoint, the increase of stock holdings (and stock holding incentives) would suggest lower agency problems for the average US-listed firm, something that does not seem to reconcile with the surge in stock price crashes. Conversely, if stock holdings have reached an unreasonably high level in the recent years, this may result in "dis-incentives" (Benmelech, Kandel, and Veronesi, 2010) and lead managers to make self-interested decisions to the detriment of shareholders' welfare. Therefore, it might be worthwhile to investigate whether the stock price crash risk puzzle can

[10] The stock and option incentives ratios are calculated to capture the part of CEOs' total compensation that would result from a 1% increase in the value of their equity. Specifically, *Stock and Option Incentives* ratios = ONEPCT / (ONEPCT + SALARY + BONUS), where *for stock incentives* ONEPCT = 0.01*PRICE × (SHARES); and *for option incentives* ONEPCT = 0.01*PRICE × (OPTIONS); PRICE is the share price; SHARES is the number of shares held by the CEO; OPTIONS is the number of options held by the CEO; and SALARY and BONUS are the CEO salary and bonus, respectively.

be rationalized by such “dis-incentives” and to identify the channels (other than opacity and overinvestment) through of which they contribute to inflating the firm’s stock price.

Overall, the empirical evidence suggests that while compensation practices are intended to mitigate some types of agency costs, these similar practices may encourage other forms of opportunistic behavior. For instance, there is evidence suggesting that compensation generates opportunistic incentives for managers to manipulate the timing of announcement of both good and bad news to the market (Baker, Collins and Reitenga (2003), Aboody and Kasznik (2000)). A combination of managerial incentives and economics of expectation may consist a potential alternative explanation.

Recent regulatory changes are likely to further increase the importance of shaping investors’ expectations. In addition to addressing the concerns of policymakers, the enacted Dodd-Frank Wall Street Reform and Consumer Protection Act (2010) entails public firms to submit the consent of executive compensation to a shareholder non-binding vote, at least once every three years. By enacting this legislation, shareholders are given the “say-on-pay” right to criticize any “Golden Parachute” compensation to executives. Accordingly, the pressure on management is amplified and the perception of shareholders regarding their reputation and ability is even more important. In this spirit, empirical evidence suggests that managers’ report positive firm news before the annual shareholder meetings, whereby shareholders are expressing their concerns about firms’ performance (Dimitrov and Jain (2011)). This pressure is even higher for highly paid underperforming managers that are expected to justify the “pay without performance” as per Bebchuk and Fried (2009). Therefore, their incentives to report positive news before the annual shareholder meetings are substantially higher.

Likewise, managers aiming to shelter the component of firm performance which directly affects their financial rewards, *i.e.* the stock price level, may seek other ways to exploit information asymmetry to manifest self-interested behaviors. But instead of concealing negative information, they may exploit the desire of investors to acquire more positive firm-specific information to shape their expectations about the firms’ outcomes. As a result, managers might be tempted to provide “fluff” news to obfuscate information regarding future performance prospects. Likewise, managers might be engaging in “cheap talk”, *i.e.* misrepresenting the firms’ prospects with the intention of maximizing the short-term value (Balvers, Gaski and McDonald (2016)) considering the managerial incentives from a value-seeking perspective.

Insights drawn from aforementioned literature are supplemented with those from evidence provided by Bushee, Taylor and Zhu (2020) suggesting that managers may issue voluntary stock-price increasing pre-conference disclosure, which suddenly result in inflated prices, and then benefit from the level of stock price by selling their shares. This accentuates the realization that personal rewards incentivize managers to exploit the heightened visibility, publicity and attention associated with the social setting of conferences (Bushee, Jung and Miller (2011)) and manifest their opportunistic behavior by "hyping" the stock to achieve their personal trading outcomes. At the same time, the easy and usually costless access to global (soft) information, enable firms to utilize all the available communication means to convey such type of positive-promising news via articles, media newswires, and press releases, the content of which mainly consist of qualitative information rather than numerical content. Therefore, even if none of the "expected" stories come true, the manager cannot be legally responsible/exposed to legal consequences for disorientating the investment community.

Altogether, earnings are important to managers since either they directly affect their compensation, or they are indirectly related with the level of stock prices. For instance, Graham, Harvey, and Rajgopal (2005) provide survey field evidence that earnings are "the most important financial metric to external constituents." However, the direct manipulation of earnings is getting harder with the establishment of regulations that make managers accountable for their firms' disclosures, such as SOX. In the same vein, misuse of free cash flows by engaging in overinvestment can also be revealed from accounting information disclosed in financial statements. Accordingly, as time passes, it is more likely that managers no longer hold negative information through opacity or overinvestment, consistent with our empirical findings. Therefore, driven by their compensation incentives it is probable to seek for alternative channels through which they may retain or even inflate investors' expectations and subsequently the unsustainably high level of stock prices.

4.2. Market microstructure

Next, we examine whether market characteristics can explain the crash risk puzzle. In this line, Figure 7A displays the average trading volume which experiences a huge increase during the last years of the sample. Also, Figures 7B shows a percentage decrease of firms listed in NYSE-AMEX stock exchange, both in quantity and market capitalization. After NASADAQ's establishment (in 1971), the percentage of firms listed in NYSE-AMEX declined from about 75% to 40%, with a market capitalization ending down to 55% in 2018 (Figure 7C). Interestingly, the percentage of firms listed in NASDAQ has risen from 25% in 1971 to 60% in 2018 (Figure 7D), with a market capitalization reaching almost 45% in 2018 (Figure 7E). Over the years, it seems that NASDAQ is becoming the focal point of investment activity.

[Insert Figure 7, here]

A closer look at the characteristics of NASDAQ may enable us to shed some light on the stock price crash risk puzzle. NASDAQ established in 1971, was the first electronic stock exchange market. The reason for its establishment was to promote the over-the-counter (OTC) securities, that used to be generally unused by many stock players, up to that point. NASDAQ stock exchange mainly consists of technology stocks and promising companies that vary significantly in terms of their stock prices. It keeps on being US's prevalent market in an era where technology is still considered as a way into the future. However, firms dealing with technological development are associated with many uncertainties, especially in terms of their future technological prospects (Gao, Porter, Wang, Fang, Zhang, Ma, Wang and Huang, 2013), raising challenges in making accurate forecasts regarding their prospects. A framework developed by Gartner Inc, namely "hype cycle model", offers an explanation on the path a technology experiences across time, regarding the expectation of the technological value. The model recommends that technologies progress through consecutive stages, starting with an overestimation of the value, succeeded by the disappointment and the recovery of expectations (Fenn and Raskino, 2008).

The notion relating to the "hype cycle model", accompanied with the easy and costless access to information that penetrated the markets in the past two decades, may have enabled firms to utilize all the means that are in their hands, to convey any arguments that could support the formation of a firm's positive image. At this point, we could borrow the pivotal phrase of Shiller (2000), who questioned the high levels of the stock market before the burst of the dot-com bubble, "*Their behavior is heavily influenced by news media that are interested in attracting viewers or readers, with little incentive to report regularly on quantitative analysis that might give a correct impression of the aggregate stock market level*." Accordingly, the transmission of any positive news that are not (truly) justified by the associated positive changes in the firms' fundamentals, could "hype" investors' expectations leading to overinflated stock prices. Finally, when the expectations could not be met, the investors may become extremely disappointed and reverse the unsustainably high levels of stock prices, by triggering the stock price crashes.

4.3. Irrational Exuberance

Seminal contributions have been made in asset pricing studies, signifying the role for psychological factors such as "irrational exuberance" (Shiller, 2000), "mania" (Ofek and Richardson, 2003), "animal spirits" (Akerlof and Shiller, 2010), and "sentiment" (Baker and

Wurgler, 2006). More specifically, the preceding studies have recognized the deviation of the decisions performed by the market participants from pure rationality. They proposed the linkage of the psychological factors with the level of the market and incorporate them in their research efforts to provide an explanation on bubbles and crashes.

A number of authors in the field of behavioral finance have documented that stock market characteristics resembles the speculative bubble, *i.e.* a condition where the enthusiasm of investment community drive the stock prices at high levels. The irrational exuberance is the psychological basis of speculative bubble. It is a notion closer to a misinterpretation driving by enthusiasm, such as bad judgment which derives from ignoring or partially understanding what we want to understand. In the light of reported conclusions, Shiller (2000) acknowledged irrational exuberance as a representative term to describe the overly high stock market level. In this context, he urges researchers to enhance their investigations by testing them against the "impressive evidence" that proposes that the level of stock prices do not just reflect the total available economic information, as rationality assumes. Furthermore, as Shiller mentioned, individual investors do not completely realize that the level of stock prices is determined by a group of individual investors, whose thinking and information interpretation process may be extremely similar as their own. Therefore, the individual investors overestimate the ability of "sophisticated" institutional investors to set the prices and underestimate their own impact on the level of the market, the impact of "animal spirits".

This potential explanation for the stock price crash risk puzzle highlights, even more, the need to turn attention for possible explanations emerging from the financial market side. Prices are set by the joint behavior of the market participants. Accordingly, if the market participants fail to justify their choices by assessing the firm's true economic fundamental values, and let their enthusiasm to drive them, it is inevitable that bubbles and subsequently crashes will occur, *i.e.* where the prices will primarily grow more than they should, for extended periods and then the revision of the investors' expectations will drive them suddenly down, respectively. Additionally, the electronic era, can notoriously inflate the problem, since available positive news may spur faster and to a greater extent the investor's enthusiasm. As such, the representative investor inflates their own expectations by seeking for information that confirms their positive beliefs and their effort can be achieved easier in the most recent years by having access to different sources of gathering information.

5. Conclusions

This study conducts empirical investigation demonstrating that the occurrence of stock price crashes for US-listed firms steadily rose from 6.5 percent in 1950 to 27 percent in 2018. This result is robust to alternative crash risk measures, sample specifications, industry and time fixed effects. This phenomenon gives birth to the stock price crash risk puzzle.

The most prevalent explanations derived in prior studies based on agency theory arguments, accentuate financial reporting opacity and overinvestment as the channels underpinning the relationship between the hoarding of bad news and stock price crashes. Assessing this stylized fact from the agency theory viewpoint, the increasing occurrence of stock price crashes could have been ascribed to the trend of the two dominant channels that managers could exploit to manifest their self-interested strategies. Conversely, in this study, we provide compelling empirical evidence suggesting that these prominent agency-based channels play a limited role in explaining the up-trending occurrence of stock price crashes of US firms.

In addition, we observe a noteworthy improvement of several important corporate governance mechanisms, indicating an enhancement in the monitoring and discipline process as time passes. Furthermore, the results derived from the multivariate regression analyses provide robust empirical evidence suggesting that especially in the post-SOX period the two agency-based channels cannot explain the surge in stock price crashes. Further analysis demonstrates that after controlling for the firm's financial characteristics and after removing both the firm's average crash risk effect (by using firm fixed effects) over the entire estimation period and any time-series patterns in overall crash risk period (by using time fixed effects), any statistical relationship for either of the two agency-based channels disappears.

Collectively, this evidence provides *little* credence to an agency-based explanation of the phenomenon. While crashes are more prevalent as time passes, US-listed firms are more transparent, overinvest less and seem to have better corporate governance functions. Taken together, not only our empirical evidence shows, but also the upsurge of corporate governance regulation and standards (aiming to combat managerial opportunism) suggest that agency problems have attenuated in the past two decades. Accordingly, the agency viewpoint does not seem to be an explanation; specifically, the agency-based channels, opacity and overinvestment, cannot reconcile the empirical stylized facts pertaining to the surge in stock price crashes. This study offers discussion of various routes that future research can seek answers to rationalize the stock price crash risk puzzle. The study also seeks to expand the stock price crash literature by offering some critical perspective in order to highlight alternative views in explaining the up-trending occurrence of stock price crashes. Accordingly, this study brings to the surface the stock price crash risk puzzle which remains elusive and the mechanisms of its origin need to be further explored.

Appendix

Variable Definitions

Variable	Definition
Panel A: Crash risk measures	
CRASH	An indicator variable set equal to one if a firm experiences at least one crash week during a fiscal year, and zero otherwise. A "crash week" is, when the firm-specific weekly returns fall at least 3.09 standard deviations below the average firm-specific weekly return value during the fiscal year.
NCSKEW	The negative of the third moment of firm-specific weekly returns divided by the standard deviation of firm-specific weekly returns raised to the third power.
DUVOL	The natural logarithm of the difference of the volatilities between the negative and positive firm-specific weekly returns.
Panel B: Channels of stock price crashes	
Opacity	Following Hutton, Marcus, and Tehranian (2009), opacity is measured as the three-year moving sum of the absolute value of discretionary accruals (DACC), where DACC are derived from a modified Jones (1991) model.
Overinvestment	Following Richardson (2006), overinvestment is measured as the three-year residuals of abnormal/unexpected investment, beyond the necessary amount to maintain assets in place and to finance expected new investments in positive NPV projects.
Panel C: Firm characteristics	
Size	The natural logarithm of total assets.
Firm Age	The number of years that the firm is covered in the Compustat universe.
Market to Book	The ratio of market value to book value of equity.
Leverage	The ratio of total liabilities to total assets.
Return on Equity	The ratio of income before extraordinary items to equity.
Market Capitalization	The market capitalization as computed by the multiplication of the market price of the stock by the number of shares outstanding.
Volume	The sum of the trading volumes as reported by CRSP database.
Dturn	The detrended average weekly stock trading volume during the fiscal year.
Panel D: External corporate governance functions	
Non-Transient Inst	The percentage of stock ownership in the firm by dedicated or quasi indexers institutional investors (following the classifications as in Bushee (1998)).
Transient Inst	The percentage of stock ownership in the firm by transient institutional investors (following the classifications as in Bushee (1998)).
HHI	The sum of the square market share of all the firms in an industry, where the market share refers to the sales of the firm over the total sales of all firms in each industry.

Auditor Tenure	Number of consecutive fiscal years that the auditor has been retained by the client, up to and including the current year (following Callen and Fang (2017)).
Panel E: Internal corporate governance functions	
Board Size	Total number of directors on the board.
Independent Directors	Number of independent directors divided by the board size.
Female Directors	Number of female directors divided by the board size.
Busy Directors	Number of directors who are also members of other Major Company Boards divided by the board size.
Not Attended Directors	Number of directors who attended less than 75% of the board meetings divided by the board size.
CEO Duality	An indicator variable set equal to one if the CEO is also the Chairman of the board, and zero otherwise.
Panel F: CEO compensation/incentives	
Total Compensation	Total compensation for the individual year, comprised of the following: Salary, Bonus, Other Annual, Total Value of Restricted Stock Granted, Total Value of Stock Options Granted (using Black-Scholes), Long-Term Incentive Payouts, and All Other Total.
Bonus	The ratio of the dollar value of a bonus (cash and non-cash) earned by the CEO during the fiscal year to total compensation.
Salary	The ratio of the dollar value of the base salary (cash and non-cash) earned by the CEO during the fiscal year to total compensation.
Stock Holdings	The ratio of the Total Value of Restricted Stock Granted during the fiscal year to total compensation.
Option Holdings	The ratio of the Total Value of Stock Options Granted (using Black-Scholes) during the fiscal year to total compensation.
Ceo Pay Slice	The ratio of the total compensation to the top five executives that goes to the CEO.
Stock Incentives	The CEO stock holdings incentives ratio estimated as in Bergstresser and Philippon (2006).
Option Incentives	The CEO option holdings incentives ratio estimated as in Bergstresser and Philippon (2006).

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Figures

Figure 1A: Time evolution of stock price crashes occurrences (dichotomous measure)
This figure depicts the frequencies of stock price crashes (*CRASH*) estimated as per *Eq*. (3) for: CRSP universe from 1950 to 2018, CRSP-Compustat universe from 1962 to 2018 and CRSP-Compustat-Execucomp universe from 1992 to 2018. The sample comprises of common stocks (*i.e*. share codes 10 and 11) traded in NYSE, AMEX or NASDAQ, with stock price greater than 1 USD at the end of fiscal year, and more than 26 weeks of stock returns in a fiscal year. The firm-specific returns are estimated using the market-industry model as per *Eqs.* (1) and (2).

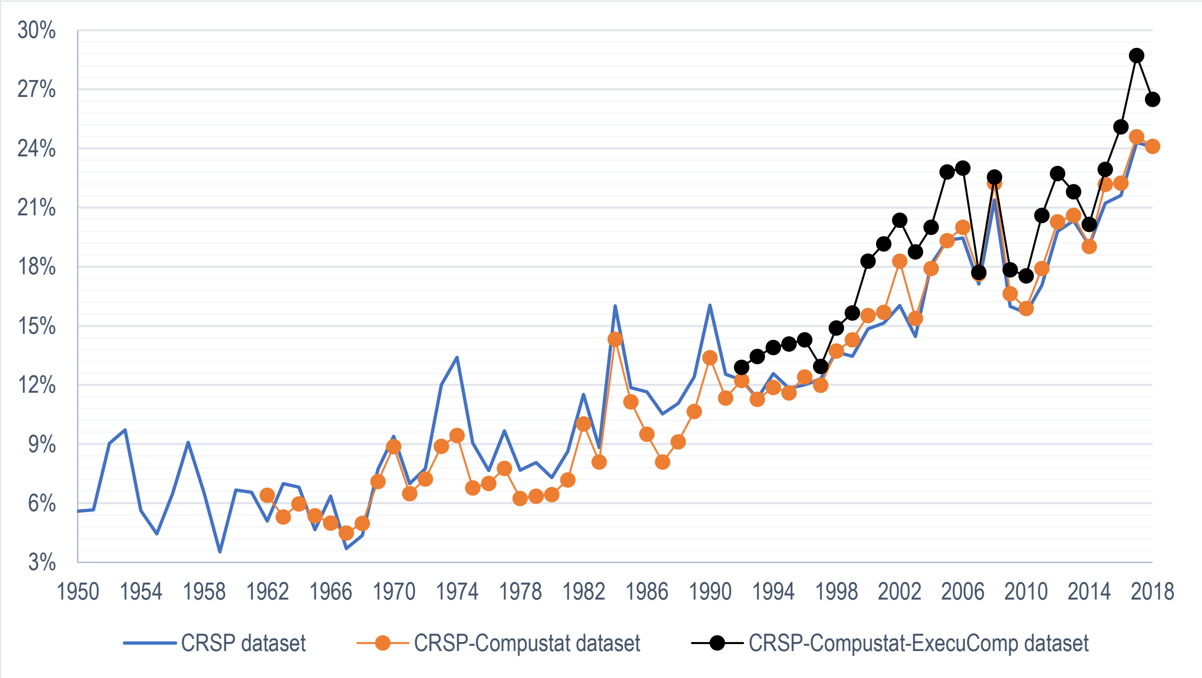


Figure 1B: Time evolution of stock price crashes occurrences (continuous measures)

This figure depicts the two continuous crash risk measures, namely, negative coefficient of skewness (*NCSKEW*) estimated as per *Eq*. (4) and down-to-up volatility (*DUVOL*) estimated as per *Eq*. (5) for: CRSP-Compustat universe from 1962 to 2018 and CRSP-Compustat-Execucomp universe from 1992 to 2018. The sample comprises of common stocks (i.e. share codes 10 and 11) traded in NYSE, AMEX or NASDAQ, with stock price greater than 1 USD at the end of fiscal year, and more than 26 weeks of stock returns in a fiscal year. The firm-specific returns are estimated using the market-industry model as per *Eqs.* (1) and (2).

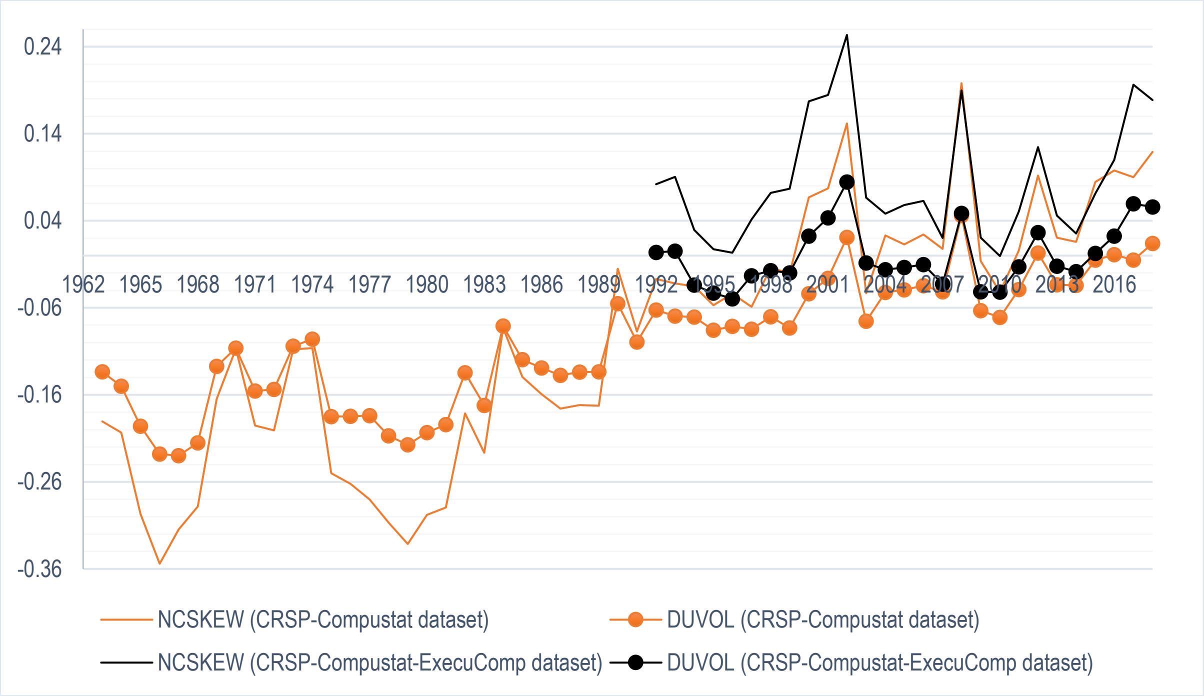


Figure 2: Time evolution of average value of opacity *vs* frequencies of stock price crashes
This figure depicts the average value of opacity estimated as per *Eqs*. (6)-(8) (left axis) and the frequency of stock price crashes estimated as per *Eq*. (3) (right axis) for: CRSP-Compustat universe from 1974 to 2018 and CRSP-Compustat-Execucomp universe from 1992 to 2018.

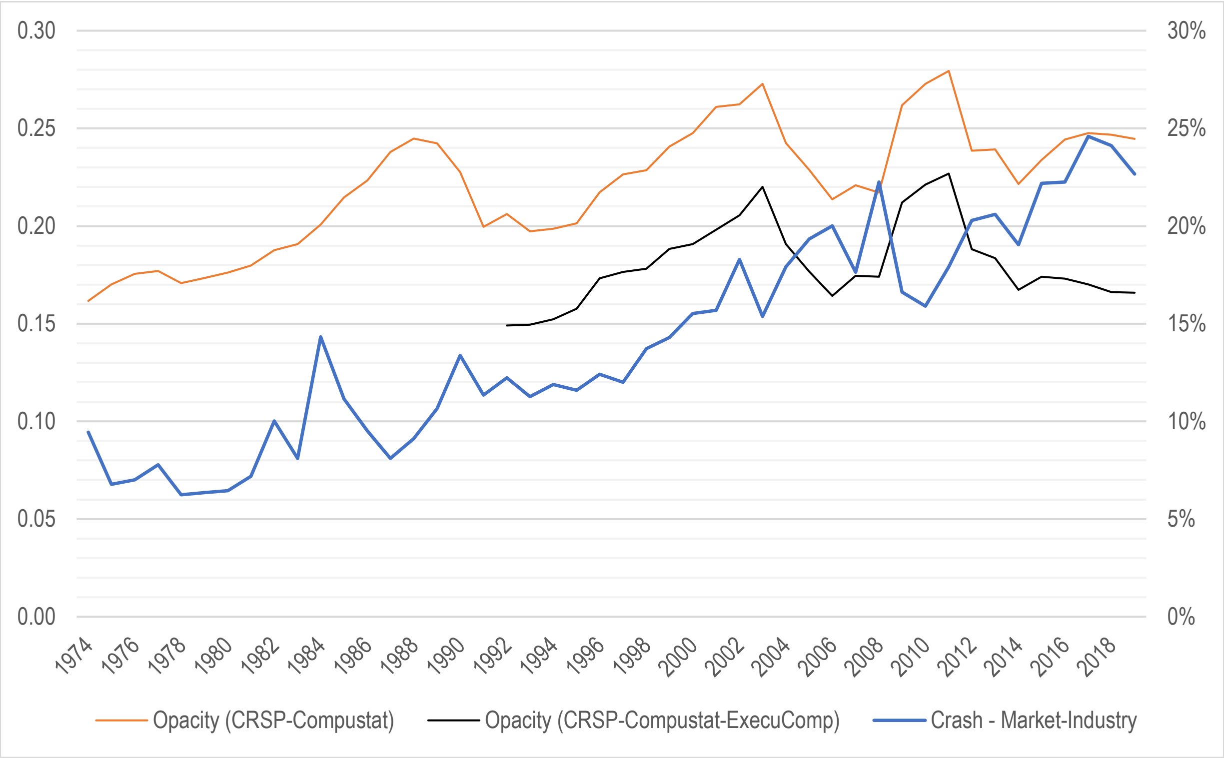


Figure 3: Time evolution of average value of overinvestment *vs* frequencies of stock price crashes
This figure depicts the average value of overinvestment estimated as per *Eqs*. (9)-(12) (left axis) and the frequency of stock price crashes estimated as per *Eq*. (3) (right axis) for: CRSP-Compustat universe from 1974 to 2018 and CRSP-Compustat-Execucomp universe from 1992 to 2018.

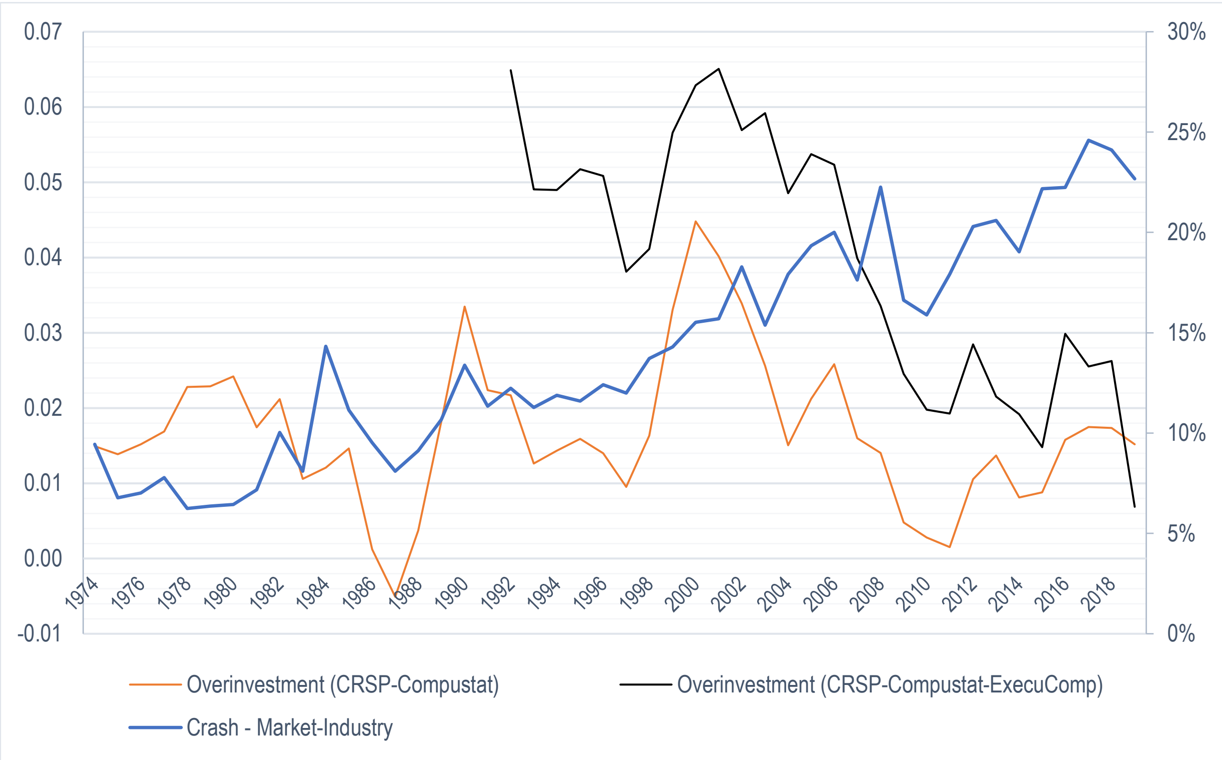


Figure 4: Time evolution of average value of internal corporate governance functions
This figure depicts the average value of internal corporate governance functions (as indicated in each subfigure) for: CRSP-Compustat and CRSP-Compustat-Execucomp universe from 1996 to 2018. Detailed definitions of these variables are presented in each subfigure.

Figure 4A: Average board size
Total number of directors on the board.

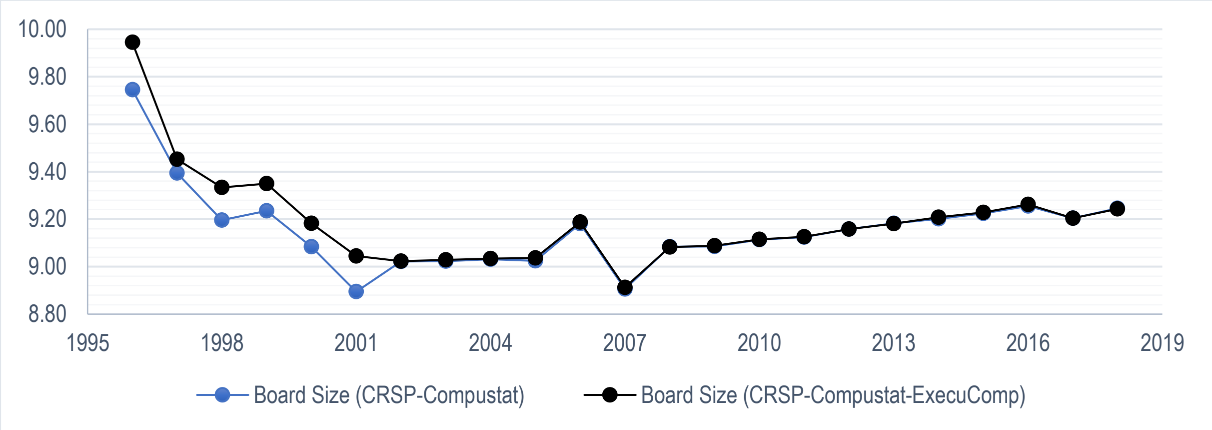


Figure 4B: Average CEO duality
The percentage of CEOs who are also Chairpersons of their firms' board.

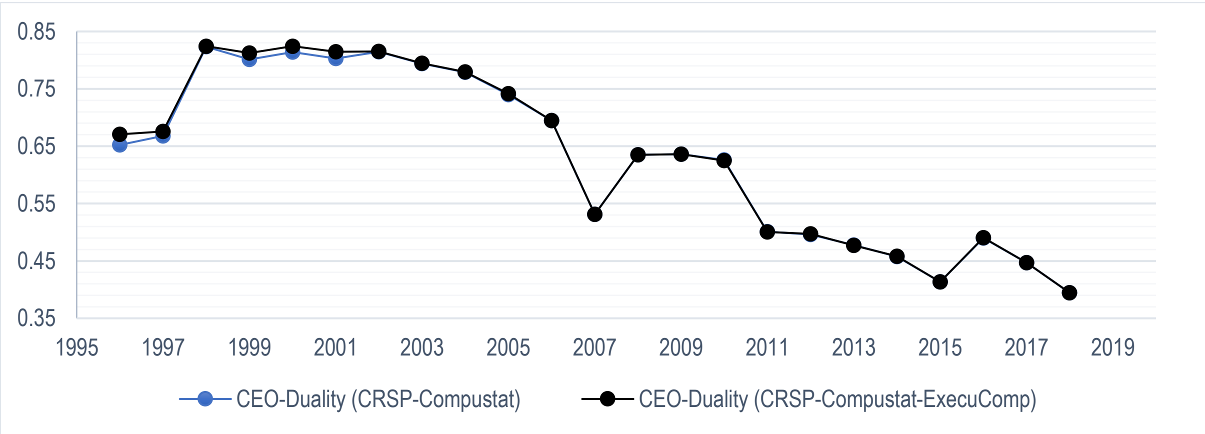


Figure 4C: Average percentage of independent directors
The number of independent directors divided by the board size.

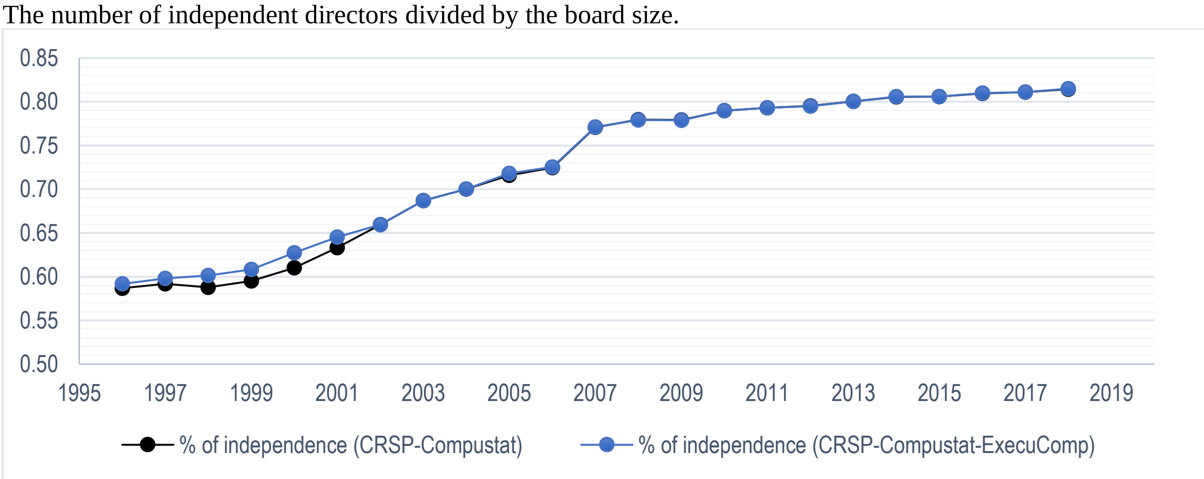


Figure 4D: Average percentage of busy directors
The number of directors who are also members of other major company boards divided by the board size.

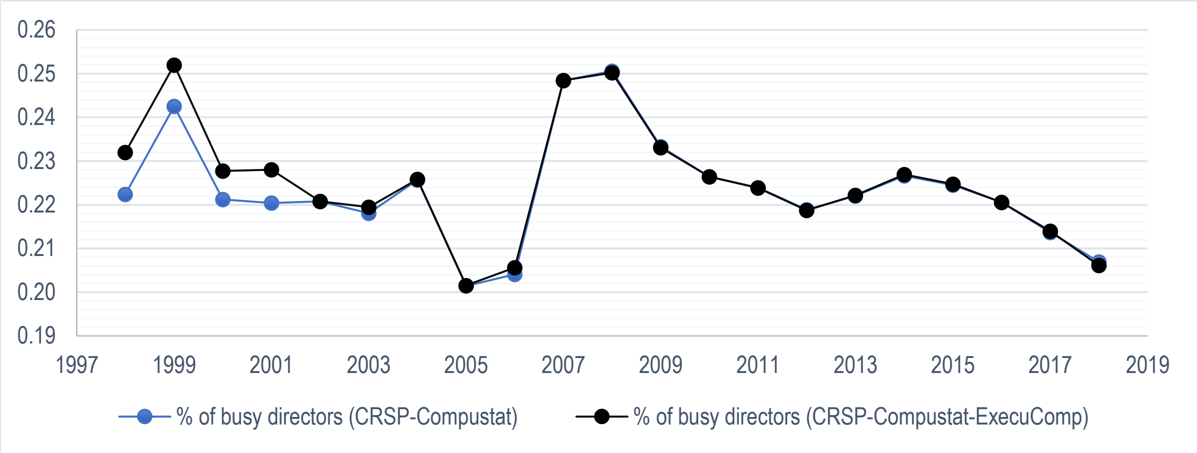


Figure 4E: Average percentage of not attended directors
The number of directors who attended less than 75% of the board meetings divided by the board size.

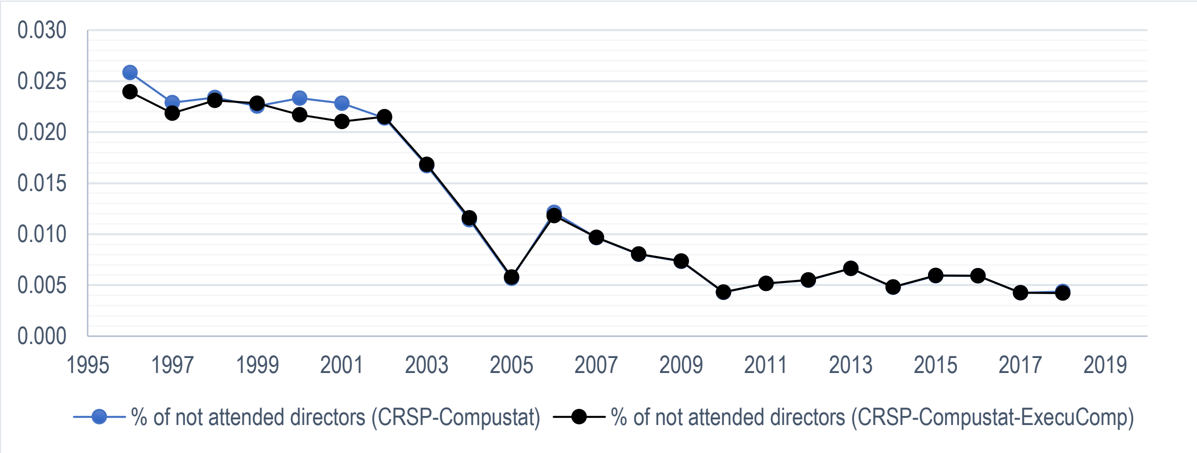


Figure 4F: Average percentage of female directors.
The number of female directors divided by the board size.

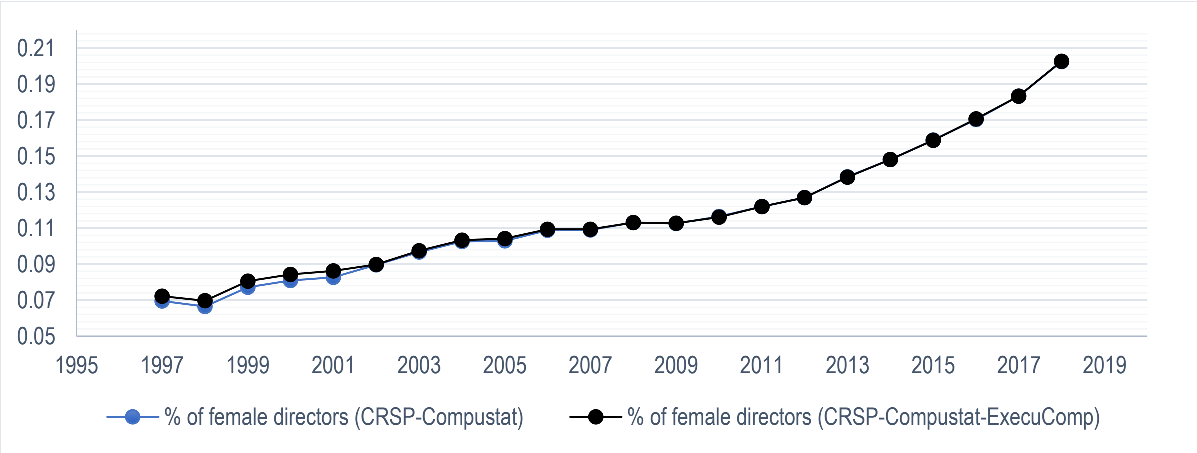


Figure 5: Time evolution of average value of external corporate governance functions

This figure depicts the average value of external corporate governance functions (as indicated in each subfigure) for: CRSP-Compustat and CRSP-Compustat-Execucomp universe. The figure depicts the analysis from the earliest year for which sufficient data are available. Detailed definitions of these variables are presented in each subfigure.

Figure 5A: Average percentage of transient institutional ownership

The percentage of stock ownership in the firm by transient (short-term) institutional investors.

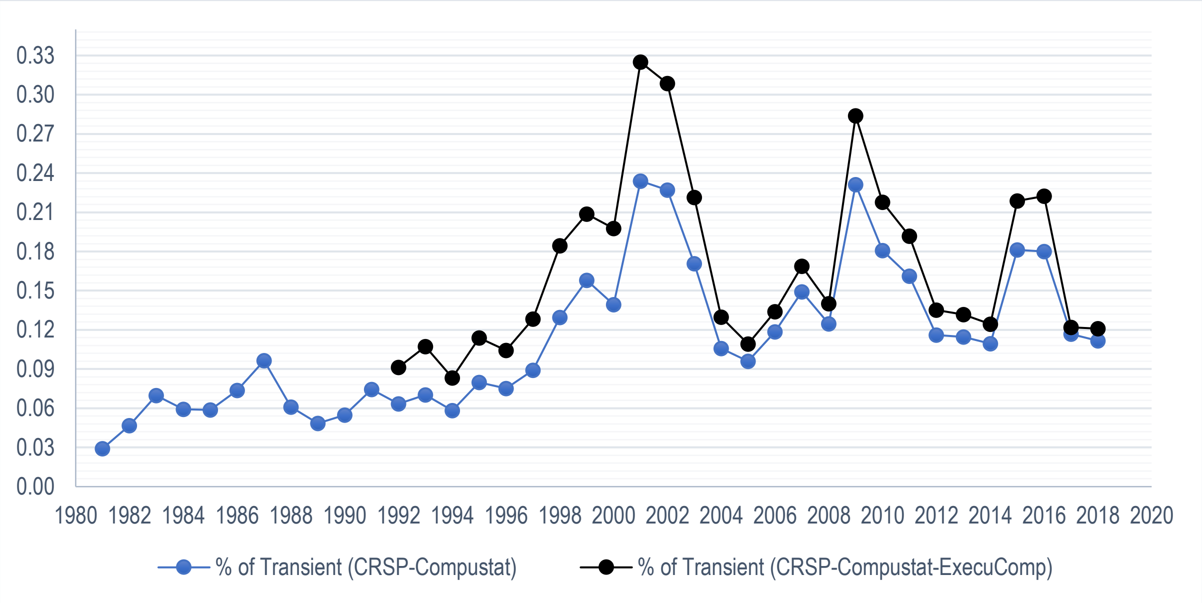


Figure 5B: Average percentage of non-transient institutional ownership

The percentage of stock ownership in the firm by non-transient (dedicated or quasi-indexers) institutional investors.

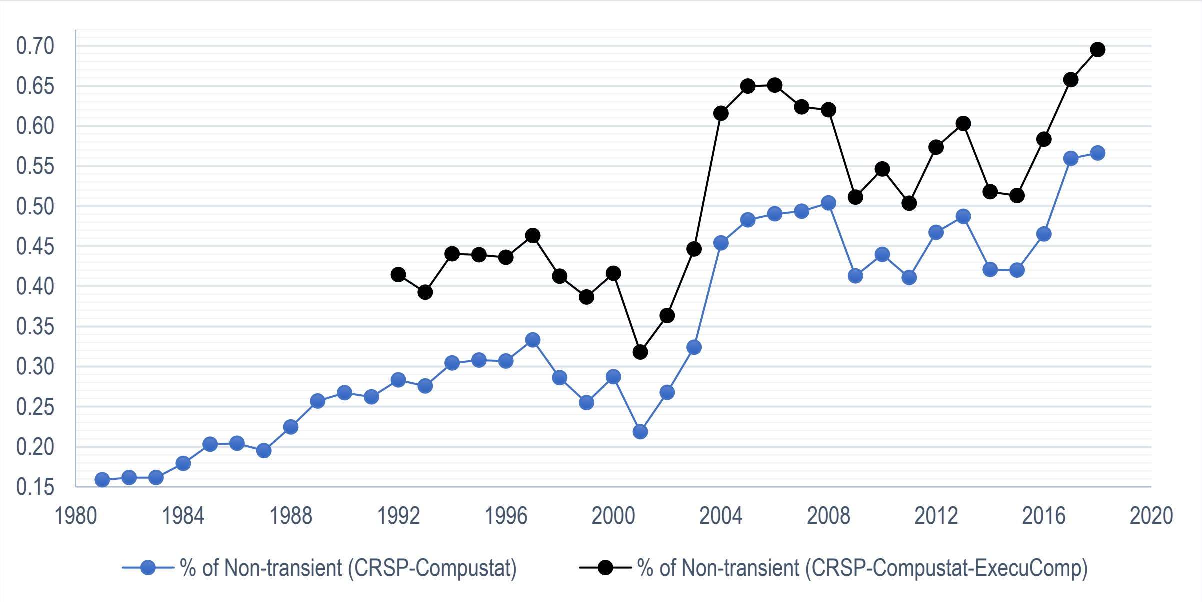


Figure 5C: Average product market competition
The sum of the square market share of all the firms in an industry (where the market share refers to the sales of the firm over the total sales of all firms in each industry).

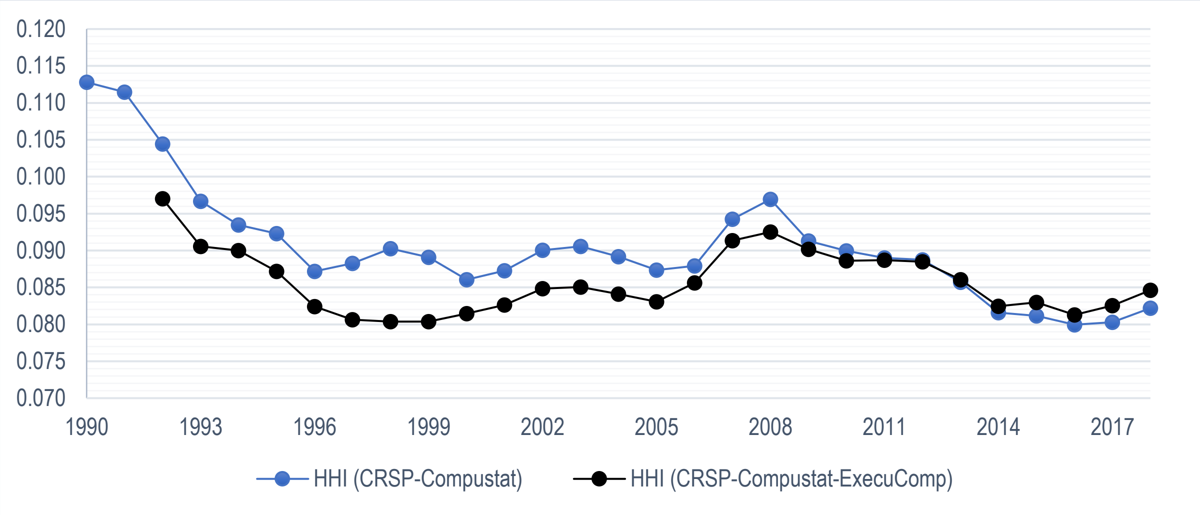


Figure 5D: Average percentage of auditor tenure
The number of consecutive fiscal years that the auditor has been retained by the client.

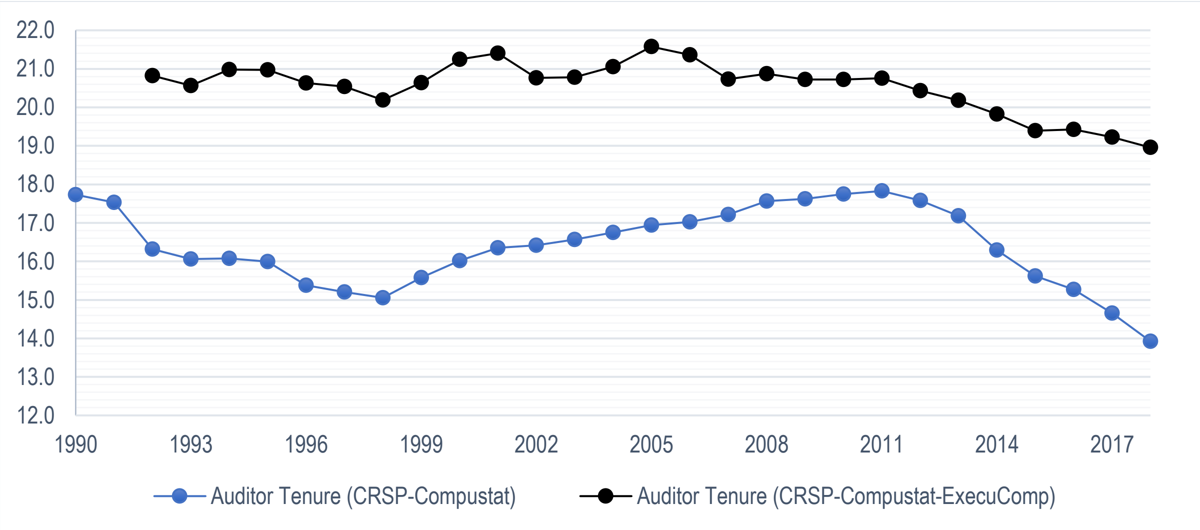


Figure 6: Average value of CEO compensation components and incentives
This figure depicts the average value of CEO compensation components and incentives (as indicated in each subfigure) for CRSP-Compustat-Execucomp universe from 1992 to 2018. Detailed definitions of these variables are presented in each subfigure.

Figure 6A: Average total compensation
Total compensation for the individual year, comprised of the following: Salary, Bonus, Other Annual, Total Value of Restricted Stock Granted, Total Value of Stock Options Granted (using Black-Scholes), Long-Term Incentive Payouts, and All Other Total.

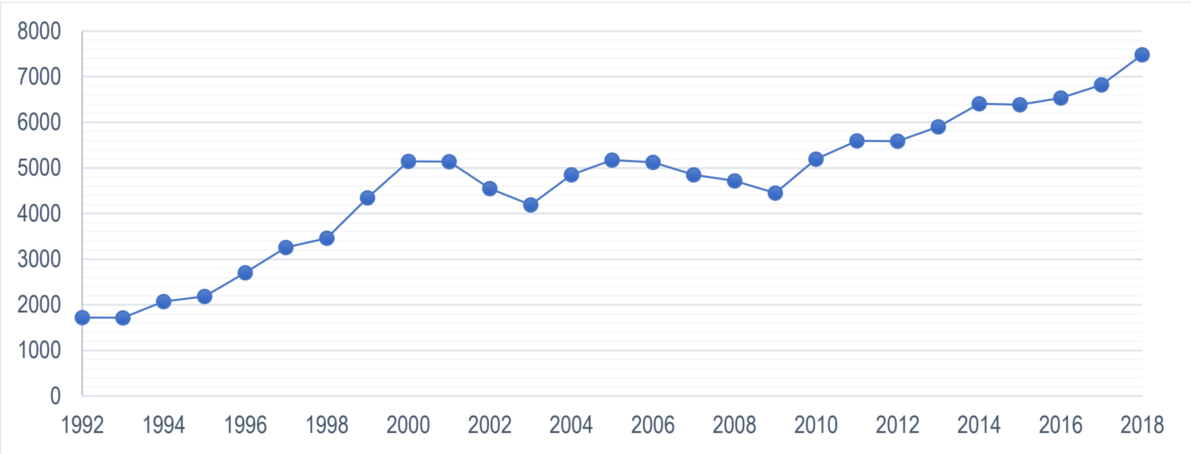


Figure 6B: Average salary
The ratio of the dollar value of the base salary (cash and non-cash) earned by the CEO during the fiscal year to total compensation.

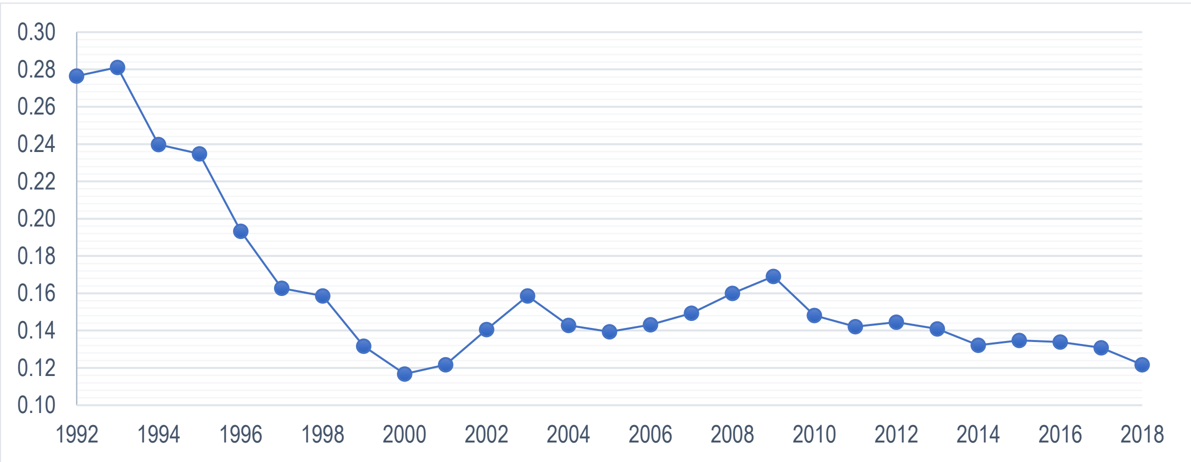


Figure 6C: Average bonus
The ratio of the dollar value of a bonus (cash and non-cash) earned by the CEO during the fiscal year to total compensation.

Figure 6D: Average option holdings
The ratio of the Total Value of Stock Options Granted (using Black-Scholes) during the fiscal year to total compensation.

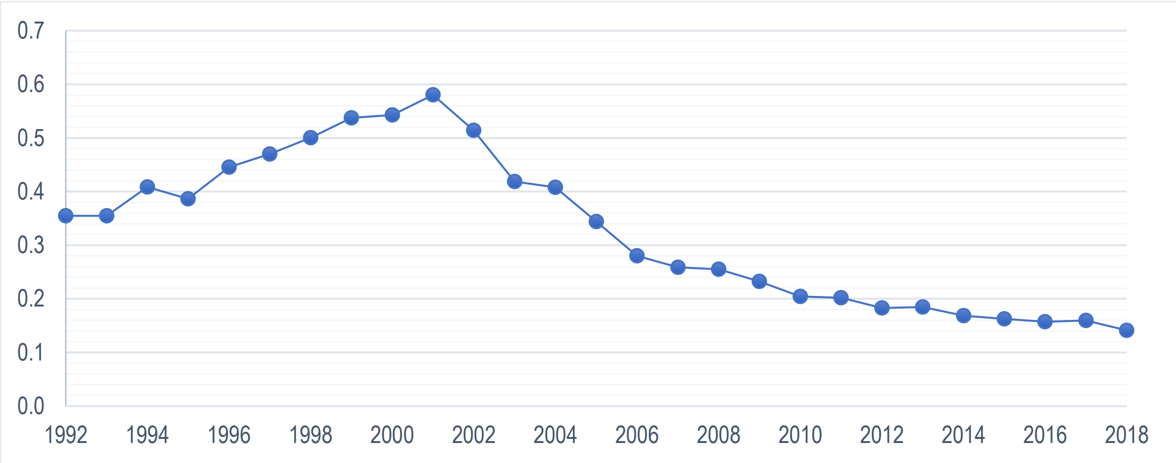


Figure 6E: Average stock holdings
The ratio of the Total Value of Restricted Stock Granted during the fiscal year to total compensation.

Figure 6F: Average CEO pay slice
The ratio of the total compensation to the top five executives that goes to the CEO.

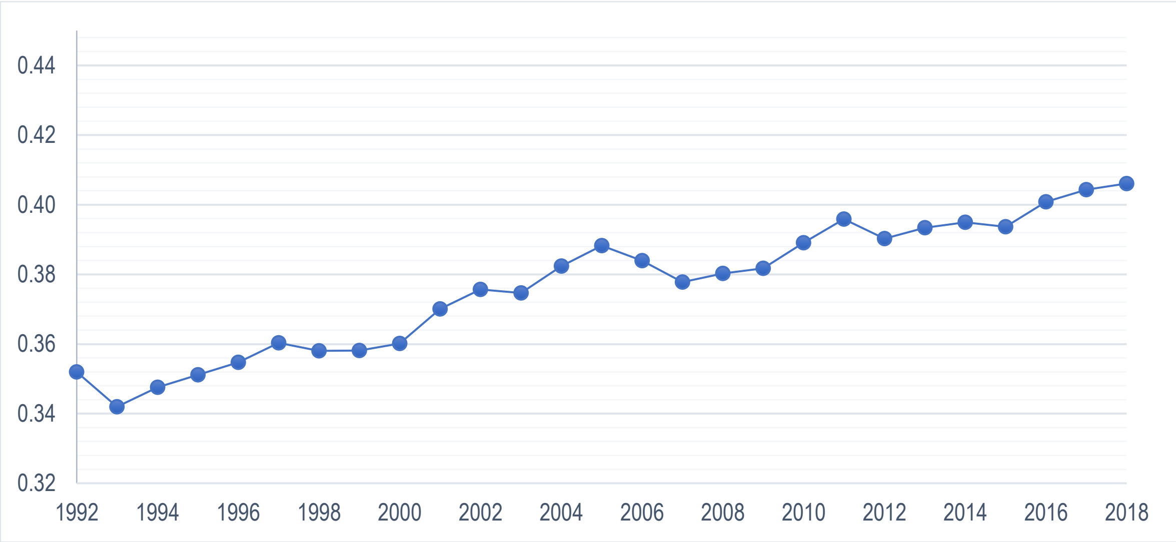


Figure 6G: Average stock incentives
The CEO stock holdings incentives ratio estimated as in Bergstresser and Philippon (2006).

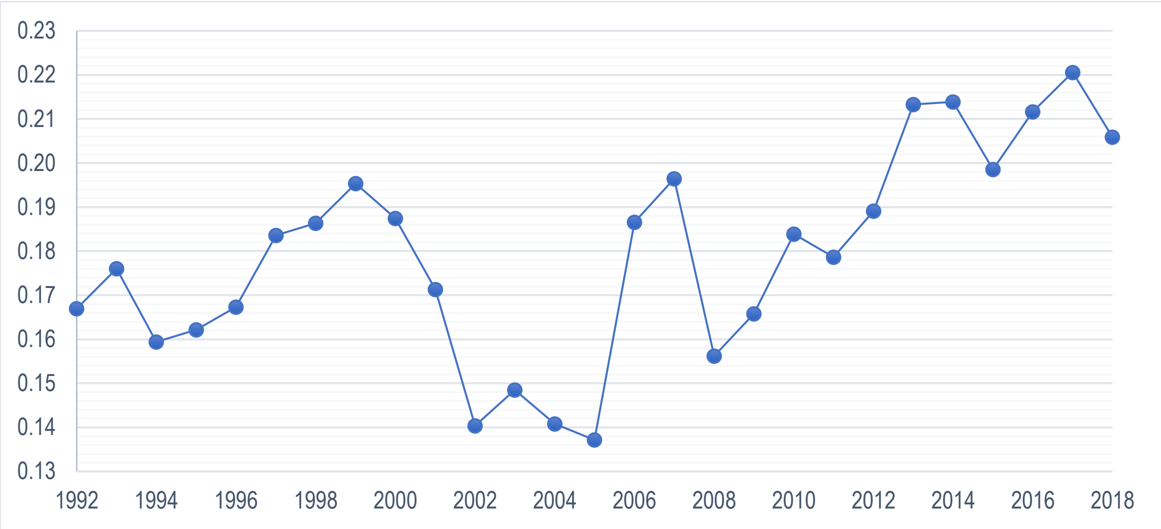


Figure 6H: Average option incentives
The CEO option holdings incentives ratio estimated as in Bergstresser and Philippon (2006).

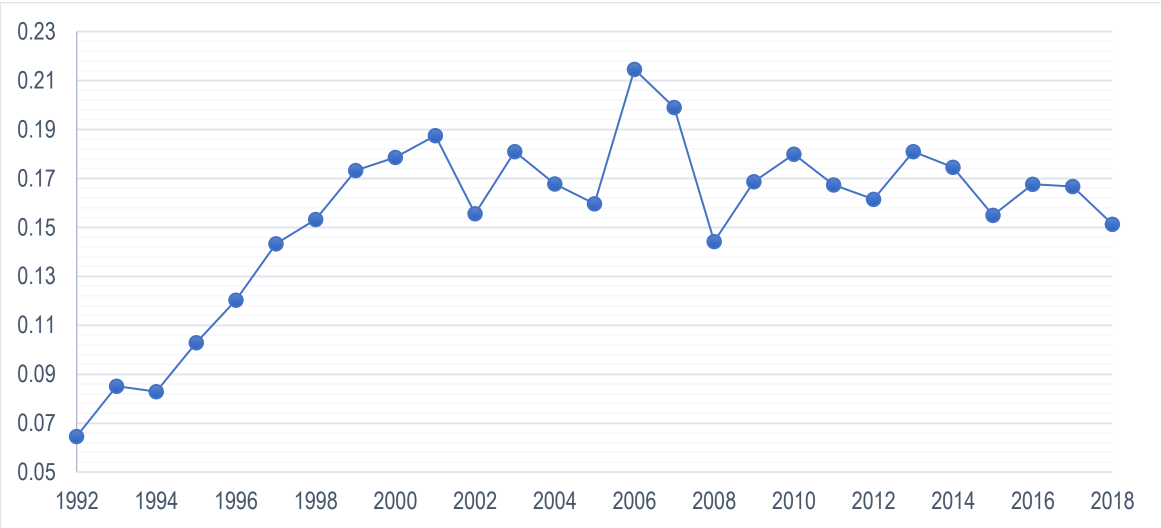


Figure 7: Average value of market microstructure characteristics
This figure depicts the average value of market microstructure characteristics (as indicated in each subfigure) for CRSP-Compustat universe, from the earliest year for which sufficient data are available. Detailed definitions of these variables are presented in each subfigure.

Figure 7A: Average trading volume
The sum of the trading volume.

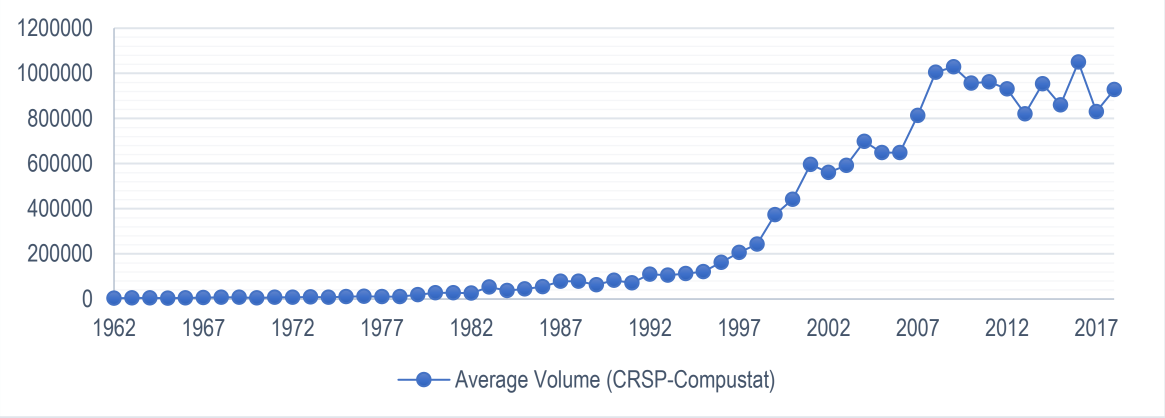


Figure 7B: Proportion of firms listed in NYSE-AMEX
The proportion of firms listed in NYSE (exchange code 1 as reported by CRSP) and AMEX (exchange code 2 as reported by CRSP).

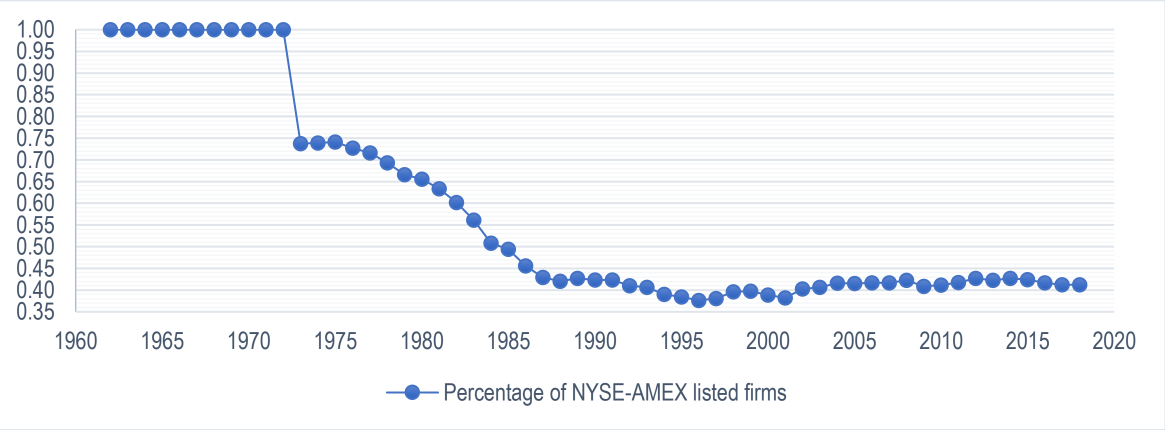


Figure 7C: Proportion of market capitalization of firms listed in NYSE-AMEX
The proportion of market capitalization of firms listed in NYSE (exchange code 1 as reported by CRSP) and AMEX (exchange code 2 as reported by CRSP)

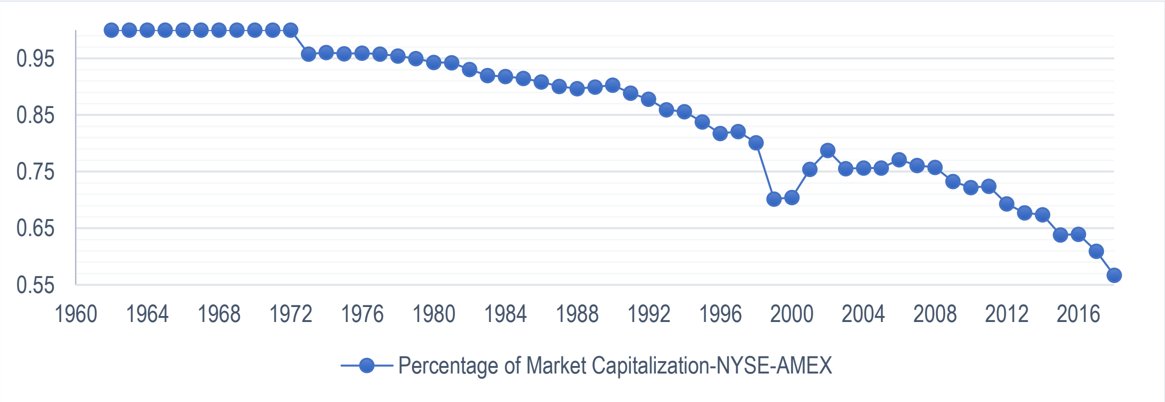


Figure 7D: Proportion of firms listed in NASDAQ
The proportion of firms listed in NASDAQ (exchange code 3 as reported by CRSP).

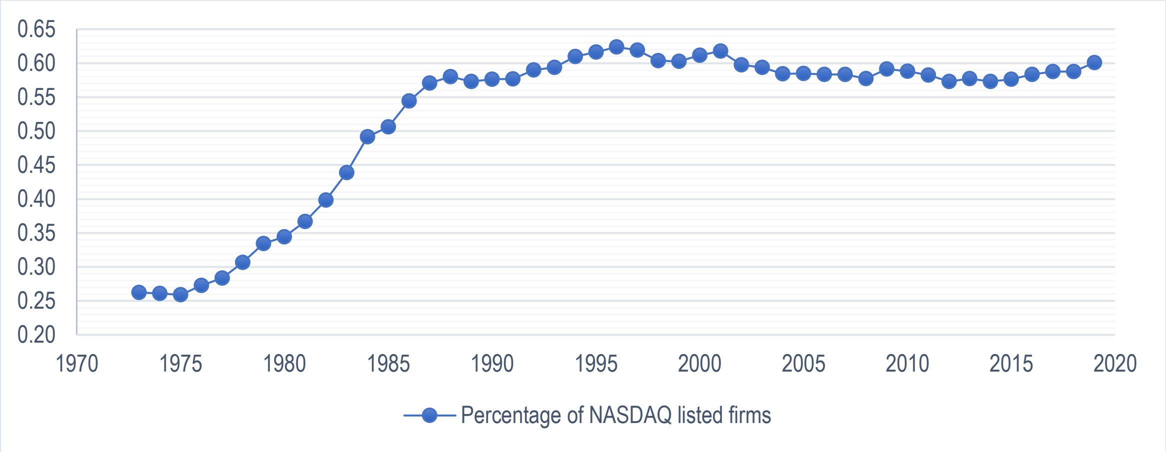
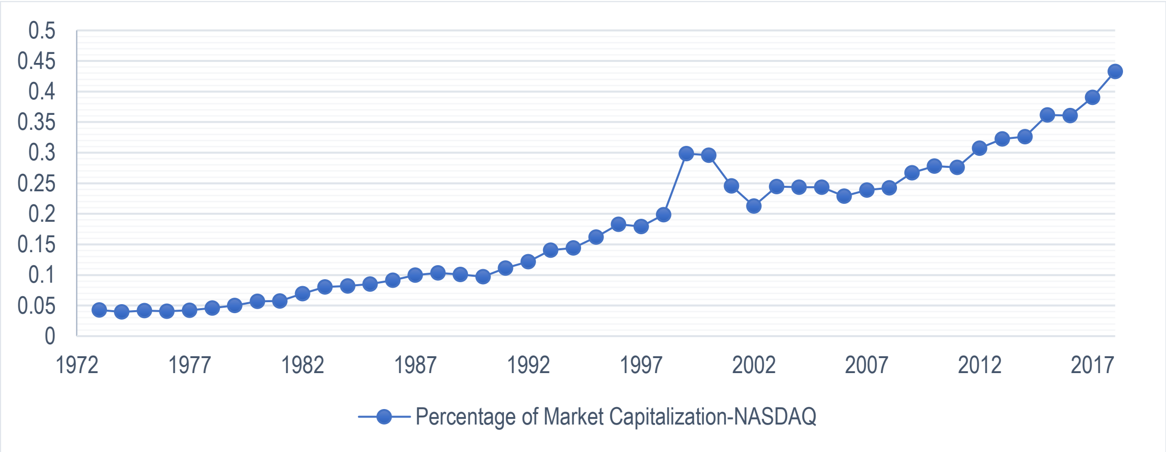


Figure 7D: Proportion of market capitalization of firms listed in NASDAQ
The proportion of market capitalization of firms listed in NASDAQ (exchange code 3 as reported by CRSP).



Tables

Table 1: Summary statistics – Pearson Correlation

This table presents the summary statistics of the stock price crash risk measures, namely *CRASH* estimated as per *Eq.* (3), *NCSKEW* estimated as per *Eq.* (4), and *DUVOL* estimated as per *Eq.* (5), and the main control variables. The CRSP-Compustat data set covering the period 1962-2018 is presented in Panel A1 and consists of 106,740 firm-year observations. The CRSP-Compustat-Execucomp data set covering the period 1992-2018 is presented in Panel A2 and consists of 32,203 firm-year observations. The sample comprises of common stocks (*i.e*. share codes 10 and 11) traded in NYSE, AMEX or NASDAQ, with stock price greater than 1 USD at the end of fiscal year, and more than 26 weeks of stock returns in a fiscal year. All the differences between Panel A1 and Panel A2 have been tested for the equality and are statistically significant (p-values<0.01), except the *Leverage* and *Dturn*. Panel B1 and B2 presents the Pearson's correlation coefficients between the stock price crash risk measures. All the coefficients are statistically significant (p-values<0.01). All variables are defined in the Appendix.

Panel A1: Summary Statistics (CRSP-Compustat data set)

Variable	Mean	Std Dev	Lower Quartile	Median	Upper Quartile
CRASH	0.145	0.352	0	0	0
NCSKEW	-0.063	0.727	-0.449	-0.08	0.289
DUVOL	-0.083	0.343	-0.307	-0.093	0.128
Size	5.622	1.997	4.142	5.468	6.989
Sales	2154.59	10878.29	62.488	237.005	1012.6
Market Capitalization	2023.3	6227.82	47.625	211.395	1005.3
Firm Age	18.751	13.69	8	15	26
Market to Book	2.56	3.366	1.032	1.719	2.982
Leverage	0.497	0.222	0.335	0.501	0.64
Return on Equity	0.034	0.406	0.023	0.104	0.162
Return on Assets	0.014	0.153	0.008	0.044	0.079
Dturn	0.001	0.016	-0.003	0	0.004

Panel A2: Summary Statistics (CRSP-Compustat-Execucomp Dataset)

Variable	Mean	Std Dev	Lower Quartile	Median	Upper Quartile
CRASH	0.199	0.4	0	0	0
NCSKEW	0.084	0.745	-0.327	0.04	0.425
DUVOL	-0.001	0.345	-0.228	-0.011	0.209
Size	7.327	1.586	6.163	7.238	8.407
Sales	5634.45	18671.68	456.327	1279.25	3917.2
Market Capitalization	5439.92	10006.09	553.638	1482.98	4614.87
Firm Age	26.446	16.992	12	22	41
Market to Book	3.227	3.627	1.531	2.345	3.823
Leverage	0.521	0.221	0.365	0.528	0.665
Return on Equity	0.085	0.359	0.048	0.115	0.182
Return on Assets	0.042	0.106	0.02	0.051	0.088
Dturn	0.001	0.018	-0.006	0	0.007

Panel B1: Pearson Correlation (CRSP-Compustat Dataset)

	CRASH	NCSKEW	DUVOL
CRASH	1		
NCSKEW	0.584***	1	
DUVOL	0.531***	0.951***	1

Panel B2: Pearson Correlation (CRSP-Compustat-Execucomp Dataset)

	CRASH	NCSKEW	DUVOL
CRASH	1		
NCSKEW	0.628***	1	
DUVOL	0.572***	0.953***	1

Table 2: The impact of the agency-based channels (opacity and overinvestment) on future stock price crashes (*CRASH*)
This table presents the marginal effects of logit regression estimates between the one-year-ahead value of *CRASH* (estimated as per *Eq.* (3)) and the agency-based channels of *Opacity* (estimated as per *Eqs.* (6)-(8)) and *Overinvestment* (estimated as per *Eqs.* (9)-(12)) measured in year *t*. The estimates presented in **Panel A** are derived from the CRSP-Compustat data set from 1962 to 2018, while the estimates presented in **Panel B** are derived from CRSP-Compustat-Execucomp data set from 1992 to 2018. The estimates presented in models (1)-(4) in both Panels include dummy variables to control for time-invariant year and industry-specific fixed effects, while the estimates presented in models (5)-(8) in both Panels include dummy variables to control for time-invariant year and firm-fixed effects. The sample comprises of common stocks (*i.e*. share codes 10 and 11) traded in NYSE, AMEX or NASDAQ, with stock price greater than 1 USD at the end of fiscal year, and more than 26 weeks of stock returns in a fiscal year. All variables are defined in the Appendix. Standard errors are reported in parentheses. All continuous variables are winsorized at the 1st and 99th percentiles and are standardized to have a mean value of zero and variance of one. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent, respectively.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Opacity		-0.000		0.001		-0.000		0.001
		(0.00)		(0.00)		(0.003)		(0.003)
Overinvestment		0.006***		0.005***		0.009**		0.007**
		(0.00)		(0.00)		(0.003)		(0.003)
Stock Return			0.008**	0.009*			0.021***	0.018***
			(0.00)	(0.00)			(0.004)	(0.005)
Dturn			0.009***	0.009***			0.015***	0.015***
			(0.00)	(0.00)			(0.002)	(0.002)
NCSKEW			0.005***	0.004***			-0.020***	-0.023***
			(0.00)	(0.00)			(0.002)	(0.002)
NCSKEW (*lag* 1)			0.004***	0.004***			-0.018***	-0.018***
			(0.00)	(0.00)			(0.002)	(0.002)
NCSKEW (*lag* 2)			0.005***	0.006***			-0.023***	-0.021***
			(0.00)	(0.00)			(0.003)	(0.003)
Size	0.016***	0.015***	0.013***	0.012***	0.112***	0.116***	0.118***	0.120***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.007)	(0.009)	(0.007)	(0.009)
Firm Age	-0.011***	-0.010***	-0.010***	-0.010***	0.044***	0.053***	0.050***	0.057***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.005)	(0.007)	(0.006)	(0.006)
Market to Book	0.005***	0.004***	0.004***	0.003**	0.021***	0.018***	0.015***	0.013***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.002)	(0.003)	(0.003)	(0.003)
Leverage	-0.005***	-0.005***	-0.004***	-0.004**	-0.013***	-0.013**	-0.011**	-0.012**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.003)	(0.004)	(0.004)	(0.004)
Return on Equity	0.005***	0.005***	0.005***	0.005***	0.013***	0.012***	0.010***	0.007*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.002)	(0.003)	(0.003)	(0.003)
Year FE			YES				YES	
FF12 Industry FE			YES				NO	
Firm FE			NO				YES	
Observations	106740	70360	92872	70311	106740	70360	92872	70311
Pseudo Likelihood	-49091.27	-33914.1	-42576.98	-33847.52	-35801.18	-24488	-31102.49	-24340.57
Pseudo R2	0.041	0.038	0.042	0.040	0.020	0.020	0.025	0.025

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Opacity		-0.003		-0.002		-0.007		-0.006
		(0.00)		(0.00)		(0.005)		(0.005)
Overinvestment		0.006**		0.006**		0.009*		0.008*
		(0.00)		(0.00)		(0.004)		(0.004)
Stock Return			0.009**	0.013**			0.027***	0.032***
			(0.00)	(0.01)			(0.008)	(0.009)
Dturn			0.009***	0.009***			0.014***	0.014***
			(0.00)	(0.00)			(0.003)	(0.003)
NCSKEW			0.008***	0.007***			-0.018***	-0.018***
			(0.00)	(0.00)			(0.003)	(0.003)
NCSKEW (*lag* 1)			0.004	0.003			-0.020***	-0.020***
			(0.00)	(0.00)			(0.003)	(0.003)
NCSKEW (*lag* 2)			0.010***	0.013***			-0.019***	-0.016***
			(0.00)	(0.00)			(0.004)	(0.004)
Size	-0.009**	-0.009*	-0.010**	-0.011**	0.126***	0.130***	0.130***	0.131***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.012)	(0.013)	(0.012)	(0.013)
Firm Age	-0.006**	-0.009***	-0.007***	-0.009***	0.036***	0.036***	0.032**	0.033**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.010)	(0.011)	(0.010)	(0.011)
Market to Book	0.002	0.001	0.002	0.001	0.017***	0.018***	0.013***	0.014***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.004)	(0.004)	(0.004)	(0.004)
Leverage	-0.002	-0.000	-0.001	0.000	-0.019***	-0.022***	-0.018**	-0.019**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.006)	(0.006)	(0.006)	(0.006)
Return on Equity	0.001	0.000	0.000	-0.000	-0.003	-0.005	-0.007	-0.009*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.004)	(0.004)	(0.004)	(0.004)
Year FE	YES				YES			
FF12 Industry FE	YES				NO			
Firm FE	NO				YES			
Observations	32203	28099	30844	28091	32203	28099	30844	28091
Pseudo Likelihood	-17323.7	-15265	-16594.4	-15235.5	-12763.3	-11124.2	-12147.1	-11055.8
Pseudo R2	0.017	0.019	0.019	0.021	0.011	0.012	0.017	0.018

Table 3: The impact of the agency-based channels (opacity and overinvestment) on future stock price crashes (*NCSKEW*)
This table presents regression estimates between the one-year-ahead of *NCSKEW* (estimated as per *Eq.* (4)) and the agency-based channels of *Opacity* (estimated as per *Eqs.* (6)-(8)) and *Overinvestment* (estimated as per *Eqs.* (9)-(12)) measured in year *t*. The estimates presented in **Panel A** are derived from the CRSP-Compustat data set from 1962 to 2018, while the estimates presented in **Panel B** are derived from CRSP-Compustat-Execucomp data set from 1992 to 2018. The estimates presented in models (1)-(4) in both Panels include dummy variables to control for time-invariant year and industry-specific fixed effects, while the estimates presented in models (5)-(8) in both Panels include dummy variables to control for time-invariant year and firm-fixed effects. The sample comprises of common stocks (*i.e*. share codes 10 and 11) traded in NYSE, AMEX or NASDAQ, with stock price greater than 1 USD at the end of fiscal year, and more than 26 weeks of stock returns in a fiscal year. All variables are defined in the Appendix. Standard errors are reported in parentheses. All continuous variables are winsorized at the 1st and 99th percentiles and are standardized to have a mean value of zero and variance of one. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent, respectively.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Opacity		0.009***		0.009***		0.001		0.001
		(0.00)		(0.00)		(0.004)		(0.004)
Overinvestment		0.029***		0.028***		0.023***		0.022***
		(0.00)		(0.00)		(0.003)		(0.003)
Stock Return			0.004	0.005			0.004	0.000
			(0.00)	(0.00)			(0.003)	(0.003)
Dturn			0.027***	0.024***			0.021***	0.020***
			(0.00)	(0.00)			(0.002)	(0.003)
Ncskew	0.024***	0.018***	0.023***	0.018***	-0.036***	-0.042***	-0.036***	-0.043***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.002)	(0.003)	(0.002)	(0.003)
Ncskew (*lag* 1)	0.016***	0.013***	0.018***	0.015***	-0.035***	-0.039***	-0.034***	-0.037***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.002)	(0.003)	(0.002)	(0.003)
Ncskew (*lag* 2)	0.020***	0.020***	0.020***	0.020***	-0.047***	-0.048***	-0.047***	-0.048***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.003)	(0.004)	(0.003)	(0.004)
Size	0.114***	0.105***	0.113***	0.104***	0.211***	0.212***	0.210***	0.212***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.008)	(0.010)	(0.008)	(0.010)
Firm Age	-0.036***	-0.031***	-0.037***	-0.031***	-0.026***	-0.012	-0.026***	-0.012
	(0.00)	(0.00)	(0.00)	(0.00)	(0.006)	(0.007)	(0.006)	(0.007)
Market to Book	0.043***	0.039***	0.041***	0.037***	0.050***	0.046***	0.048***	0.044***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.003)	(0.003)	(0.003)	(0.003)
Leverage	-0.037***	-0.040***	-0.036***	-0.039***	-0.041***	-0.046***	-0.040***	-0.047***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.004)	(0.004)	(0.004)	(0.004)
Return on Equity	0.020***	0.019***	0.018***	0.018***	0.023***	0.020***	0.021***	0.019***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.003)	(0.003)	(0.003)	(0.003)
Year FE			YES			YES		
FF12 Industry FE			YES			NO		
Firm FE			NO			YES		
Observations	108572	82859	108572	82859	108572	82859	108572	82859
Pseudo Likelihood	-115942	-90017	-115874	-89973	-110217	-85455	-110172	-85422
R2	0.053	0.051	0.054	0.052	0.022	0.023	0.022	0.024

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Opacity		0.001		0.002		-0.007		-0.006
		(0.01)		(0.01)		(0.007)		(0.007)
Overinvestment		0.022***		0.021***		0.015**		0.014*
		(0.00)		(0.00)		(0.006)		(0.006)
Stock Return			0.008	0.011**			0.006	0.008
			(0.01)	(0.01)			(0.007)	(0.007)
Dturn			0.019***	0.018***			0.018***	0.017***
			(0.00)	(0.00)			(0.004)	(0.004)
Ncskew	0.012***	0.012***	0.011***	0.011**	-0.047***	-0.048***	-0.048***	-0.049***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.004)	(0.004)	(0.004)	(0.004)
Ncskew (*lag* 1)	0.002	0.002	0.004	0.004	-0.051***	-0.052***	-0.049***	-0.050***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.004)	(0.004)	(0.004)	(0.004)
Ncskew (*lag* 2)	0.012*	0.016**	0.012*	0.017**	-0.059***	-0.057***	-0.059***	-0.056***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.006)	(0.006)	(0.006)	(0.006)
Size	0.029***	0.028***	0.028***	0.026***	0.241***	0.247***	0.239***	0.247***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.018)	(0.020)	(0.018)	(0.020)
Firm Age	-0.018***	-0.017***	-0.018***	-0.017***	-0.114***	-0.110***	-0.113***	-0.110***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.014)	(0.015)	(0.014)	(0.015)
Market to Book	0.025***	0.025***	0.025***	0.025***	0.041***	0.045***	0.040***	0.044***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.005)	(0.006)	(0.005)	(0.006)
Leverage	-0.029***	-0.030***	-0.029***	-0.030***	-0.042***	-0.049***	-0.042***	-0.049***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.008)	(0.009)	(0.008)	(0.009)
Return on Equity	0.004	0.004	0.003	0.002	-0.004	-0.007	-0.005	-0.007
	(0.01)	(0.01)	(0.01)	(0.01)	(0.006)	(0.006)	(0.006)	(0.006)
Year FE	YES				YES			
FF12 Industry FE	YES				NO			
Firm FE	NO				YES			
Observations	33575	30877	33575	30877	33575	30877	33575	30877
Pseudo Likelihood	-38238	-35314	-38225	-35304	-36601	-33721	-36587	-33711
R2	0.014	0.014	0.014	0.015	0.018	0.019	0.019	0.020

Table 4: The impact of the agency-based channels (opacity and overinvestment) on future stock price crashes (*CRASH*) during the post SOX period

Panel A of this table presents the marginal effects of logit regression estimates between the one-year-ahead value of *CRASH* (estimated as per *Eq.* (3)) and the agency-based channels of *Opacity* (estimated as per *Eqs.* (6)-(8)) and *Overinvestment* (estimated as per *Eqs.* (9)-(12)) measured in year *t*. **Panel B** of this table presents regression estimates between the one-year-ahead of *NCSKEW* (estimated as per *Eq.* (4)) and the agency-based channels of *Opacity* and *Overinvestment* measured in year *t*. Estimates in both panels are derived from the post-SOX CRSP-Compustat-Execucomp data set from 2003 to 2018. The estimates presented in models (1)-(4) in both Panels include dummy variables to control for time-invariant year and industry-specific fixed effects, while the estimates presented in models (5)-(8) in both Panels include dummy variables to control for time-invariant year and firm-fixed effects. The sample comprises of common stocks (*i.e*. share codes 10 and 11) traded in NYSE, AMEX or NASDAQ, with stock price greater than 1 USD at the end of fiscal year, and more than 26 weeks of stock returns in a fiscal year. All variables are defined in the Appendix. Standard errors are reported in parentheses. All continuous variables are winsorized at the 1st and 99th percentiles and are standardized to have a mean value of zero and variance of one. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent, respectively.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Opacity		-0.002		-0.000		-0.002		-0.000
		(0.00)		(0.00)		(0.006)		(0.006)
Overinvestment		0.004		0.004		0.001		-0.001
		(0.00)		(0.00)		(0.005)		(0.005)
Stock Return			0.013*	0.017**			-0.025***	-0.026***
			(0.01)	(0.01)			(0.003)	(0.003)
Dturn			0.011***	0.011***			-0.015***	-0.013***
			(0.00)	(0.00)			(0.003)	(0.003)
Ncskew			0.006**	0.006**			0.044***	0.050***
			(0.00)	(0.00)			(0.009)	(0.009)
Ncskew (*lag* 1)			0.003	0.002			0.015***	0.014***
			(0.00)	(0.00)			(0.003)	(0.003)
Ncskew (*lag* 2)			0.009***	0.011***			-0.023***	-0.024***
			(0.00)	(0.00)			(0.003)	(0.003)
Size	-0.013**	-0.011**	-0.014***	-0.015**	0.137***	0.151***	0.133***	0.142***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.016)	(0.018)	(0.017)	(0.018)
Firm Age	-0.006**	-0.010***	-0.008**	-0.010***	0.038*	0.023	0.036*	0.023
	(0.00)	(0.00)	(0.00)	(0.00)	(0.015)	(0.016)	(0.015)	(0.016)
Market to Book	0.002	0.003	0.003	0.003	0.016***	0.018***	0.011*	0.012**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.004)	(0.005)	(0.004)	(0.005)
Leverage	-0.003	-0.000	-0.000	0.001	-0.023**	-0.022**	-0.016*	-0.014
	(0.00)	(0.00)	(0.00)	(0.00)	(0.007)	(0.008)	(0.007)	(0.008)
Return on Equity	-0.000	-0.002	-0.001	-0.003	-0.007	-0.011*	-0.012**	-0.016***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.005)	(0.005)	(0.005)	(0.005)
Year FE			YES				YES	
FF12 Industry FE			YES				NO	
Firm FE			NO				YES	
Observations	21253	19432	20661	19430	21253	19432	20661	19430
Pseudo Likelihood	-11291.95	-10344.27	-10950.67	-10321.25	-7871.41	-7147.05	-7548.46	-7056.82
Pseudo R2	0.012	0.013	0.014	0.015	0.008	0.008	0.020	0.020

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Opacity		0.006		0.007		-0.004		-0.001
		(0.01)		(0.01)		(0.010)		(0.010)
Overinvestment		0.017**		0.016**		-0.002		-0.002
		(0.01)		(0.01)		(0.008)		(0.008)
Stock Return			0.011	0.018			0.041***	0.045***
			(0.01)	(0.01)			(0.012)	(0.013)
Dturn			0.016***	0.016***			0.018***	0.018***
			(0.00)	(0.00)			(0.005)	(0.005)
Ncskew	0.009	0.009	0.008	0.009	-0.069***	-0.070***	-0.069***	-0.071***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.005)	(0.006)	(0.005)	(0.006)
Ncskew (*lag* 1)	0.002	0.000	0.003	0.002	-0.066***	-0.069***	-0.063***	-0.066***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.005)	(0.006)	(0.005)	(0.006)
Ncskew (*lag* 2)	0.014**	0.017***	0.015**	0.017***	-0.046***	-0.045***	-0.045***	-0.044***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.005)	(0.006)	(0.005)	(0.006)
Size	0.017*	0.019*	0.015	0.015	0.397***	0.407***	0.380***	0.391***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.031)	(0.035)	(0.032)	(0.035)
Firm Age	-0.010*	-0.011*	-0.010*	-0.011*	-0.097***	-0.104***	-0.094***	-0.102***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.025)	(0.026)	(0.025)	(0.026)
Market to Book	0.019***	0.021***	0.019***	0.020***	0.035***	0.040***	0.033***	0.039***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.007)	(0.007)	(0.007)	(0.007)
Leverage	-0.029***	-0.030***	-0.028***	-0.029***	-0.048***	-0.052***	-0.043***	-0.048***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.012)	(0.013)	(0.012)	(0.013)
Return on Equity	0.003	-0.000	0.002	-0.002	-0.009	-0.014	-0.011	-0.017*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.007)	(0.008)	(0.007)	(0.008)
Year FE			YES				YES	
FF12 Industry FE			YES				NO	
Firm FE			NO				YES	
Observations	20855	19616	20855	19616	20855	19616	20855	19616
Pseudo Likelihood	-25108.39	-23708.40	-25102.92	-23703.22	-23707.11	-22326.98	-23695.06	-22315.39
Pseudo R2	0.009	0.010	0.010	0.010	0.028	0.029	0.029	0.030