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A Critique of the Agency Theory Viewpoint of Stock Price Crash Risk: The Opacity and Overinvestment Channels

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This study documents a puzzling historical trend in crash risk for US-listed firms: between 1950 and 2019, the firm-year occurrences of idiosyncratic stock price crashes rose from 5.5% to an astonishing 27%. The vastness of the literature notoriously attributes crashes to agency reasons, i.e. self-interested executives who strategically camouflage bad news via the financial reporting *opacity* and *overinvestment* channels. Nonetheless, we document that the opacity– and overinvestment–crash relations are non-significant, especially in the period following the enforcement of the Sarbanes–Oxley Act. The statistically non-significant relations are also witnessed in tests that account for the effect of equity-based compensation incentives and corporate governance functions. Overall, this study criticizes the efficacy of opacity and overinvestment as channels in explaining crash risk. Our conclusions offer avenues for future research to pursue in rationalizing the puzzling surge in stock price crashes.

Introduction

A stock price crash features a low-probability event that produces a large, negative outlier in the distribution of idiosyncratic returns. The relation between crash risk and its determinants – more importantly, the underpinning channels that mediate this relation – has attracted a lot of attention over the last decade and remains a burgeoning research area. A voluminous literature postulates an agency-driven hoarding of bad news mechanism, whereby self-interested managers opportunistically exploit information asymmetries to conceal adverse information and engage in short-sighted price maximization at the expense of shareholders. This literature theorizes that the hoarding of bad news is manifested through two prominent channels, namely financial reporting *opacity* and *overinvestment* (e.g. Hutton, Marcus and Tehranian, 2009; Kim, Li and Zhang, 2011a; Callen and Fang, 2013, 2015b; Andreou *et al.*, 2016; Kim and Zhang, 2016; Andreou *et al.*, 2017).

Our study provides evidence to suggest that these two channels play a limited role in explaining stock price crashes. For instance, the incidence of stock price crashes for the CRSP–Compustat–Execucomp universe presents an astonishing increase from 17% in 2009 to 27% firm-year occurrences in 2019. Yet, for the same period, we witness an attenuation of about −19% in the levels of opacity and −24% in the levels of overinvestment. This puzzling surge in stock price crashes becomes more perplexing if one considers that in the last two decades, there has also been an upsurge of corporate governance regulations to combat managerial opportunism and protect shareholder welfare

(Bhagat and Bolton, 2013; DeFond and Zhang, 2014; Gayle, Li and Miller, 2022; Wintoki, 2007).[1]

To date, explanations for idiosyncratic crashes generally fall in two broad categories: *financial market explanations* and *firm-specific explanations*. The focus of financial market explanations, as portrayed in Hong and Stein (2003), is on the investor's perspective. In a nutshell, they theorize that in the presence of short-sale constraints faced by at least some investors, disagreements among investors over a firm's fundamental value lead to higher crash risk. This rigorous theory has nevertheless received limited attention in the literature (e.g. Chang *et al.*, 2022; Lobo *et al.*, 2020).

The strand of the literature using firm-specific explanations primarily builds upon the agency models of Jin and Myers (2006) and Benmelech, Kandel and Veronesi (2010), which, respectively, theorize *opacity* and *overinvestment* as the channels that managers strategically exploit to camouflage bad news.[2]

In terms of the opacity channel, Jin and Myers (2006) argue that information asymmetries, compounded by investors' incompletely secured property rights, enable managers to accumulate bad news. Financial reporting opacity offers managers opportunities to disguise bad news through earnings management manipulations. The more opaque the firm, the greater the amount of hidden, firm-specific bad news that may arrive at a given time. While managers have incentives to stockpile adverse economic fundamental information about the firm, their capacity to conceal bad news is not unlimited; when the accumulated negative information crosses a tipping point, adverse information comes out all at once, which leads to a stock price crash.

In terms of the overinvestment channel, Benmelech, Kandel and Veronesi (2010) argue that CEOs exploit information asymmetries to manifest self-interested behaviour by persistently hiding bad news through 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. Likewise, Bleck and Liu (2007) argue that managers in more opaque financial markets are able to keep unprofitable projects by hiding their poor performance with the aim of realizing greater compensation. Ergo, CEOs do not reveal adverse fundamental information in a timely fashion to retain investor expectations and, by extension, the level of stock price. The overinvestment-related bad news hoarding continues until the firm's managers lose the ability or incentive to conceal it any more. The accumulated bad news is then released all at once, resulting in a stock price crash.

The studies focusing on firm-specific explanations have clearly lionized the crash risk literature. To demonstrate this, we have conducted a qualitative meta-analysis of 94 papers published since 2009 in prestigious journals (for details, see the Internet Appendix), which merely demonstrates the over-reliance of the extant literature on agency theory. Figure 1 illustrates the cloud of keywords that these papers quote on their first page. The most frequently used keywords are 'corporate governance', 'information asymmetry', 'earnings management', 'managerial opportunism', 'information environment', and so on, all of which underlie important aspects of agency theory pertaining to opacity. Further, Figure 2 illustrates that about 90% of these papers explore agency theory in their investigations. Specifically, 66% of them motivate their investigation through opacity, 3% through overinvestment and 11% simultaneously rely on both opacity and overinvestment.[3] Also, another 11% justify their findings through a general agency-related context, without specifying the channel. Interestingly, about 85% of these 94 papers have been published since 2016 using data that

[1]These include the Regulation Fair Disclosure of 2000, the Sarbanes–Oxley Act of 2002, the Dodd–Frank Act of 2010 and the Corporate Governance Reform and Transparency Act of 2017.

[2]He and Ren (2022) suggest that default risk is related to bad news hoarding and propose it as a separate channel that explains crash risk. In the same spirit, Andreou, Andreou and Lambertides (2021) provide evidence supporting a positive distress–crash risk relation, which is consistent with an agency explanation for the impact of the probability of default on crashes. While our focus is on the relation between opacity, overinvestment and future crashes, our regression analysis explicitly controls for potential confounding effects associated with a firm's default risk.

[3]The increased interest of researchers in stock price crashes in the last two decades might be attributed to the wide coverage of corporate scandals, such as Enron's collapse in 2001. It is highly likely that such scandals coming to light steered the attention of the literature towards firm-specific explanations, particularly the opacity channel, which involves earnings management practices.

Figure 1. Keywords used in selected stock price crash risk papers. This figure depicts the cloud of keywords from a corpus of 94 stock price crash risk papers published since 2009 in prestigious journals. Term sizes are proportional to their frequency in the corpus. [Colour figure can be viewed at wileyonlinelibrary.com]

mostly cover the post Sarbanes–Oxley (SOX) Act period, which, as we discuss later, both opacity and overinvestment have attenuated.

This study constitutes a critique of the extant literature, arguing about the inefficacy of opacity and overinvestment to rationalize the stock price crash risk phenomenon. Our empirical investigation shows that the firm-year crash occurrences have grown steadily from 5.5% in 1950 to 23% in 2019 in the CRSP universe, and to 27% in the CRSP–Compustat–Execucomp universe. Assessing this from the agency theory viewpoint, the steadily increasing frequency of stock price crashes could only have been justified if it had been associated with a corresponding persistent elevation in the levels of opacity and/or overinvestment. Intriguingly, this has not been the case because, as far as opacity is concerned, the results show a noteworthy decrease as of 2011. Regarding overinvestment, the results show a notably decreasing trend after 2002. Overall, our investigation supports that both channels have attenuated in the post-SOX period for the average US-listed firm, whereas, in stark contrast, the frequency of stock price crashes has notably surged.

We investigate the above inferences in a multivariate regression framework. Our analysis reveals three important findings. First, irrespective of the period considered, there is an absence of a statistically significant relation between opacity and one-year-ahead stock price crashes. This comes as a surprise given that, to date, the vast literature relies on opacity as the predominant channel to explain crashes. Second, there is a weak statistically significant relation between overinvestment and one-year-ahead crashes when using the full period of data (1974–2019). Third, and most intriguingly, when using the post-SOX sample covering the period 2003–2019, there is no statistical significance neither for the opacity−crash nor the overinvestment−crash relation. The inferences remain unaltered when we conduct regression analysis with the inclusion of equity-based compensation incentives, as well as

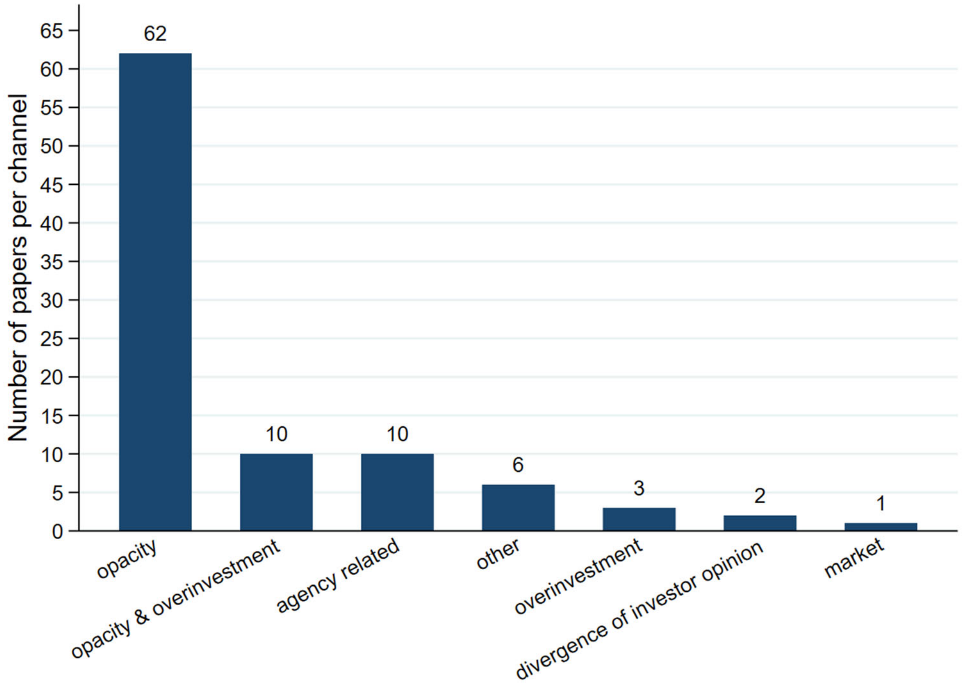

Figure 2. Number of papers per crash risk channel. This figure depicts the number of papers across different crash risk channels. The analysis utilizes a corpus of 94 stock price crash risk papers published since 2009 in prestigious journals. [Colour figure can be viewed at wileyonlinelibrary.com]

corporate governance functions that might influence these channels. Lastly, cross-sectional tests show that the opacity– and overinvestment–crash relations remain statistically non-significant even in situations where managers have more leeway to hoard bad news under weak corporate governance. Overall, the regression evidence supports the limited role of opacity and overinvestment in explaining crashes, especially in the post-SOX period.

Our study makes two important contributions. First, it documents an astounding surge of stock price crashes over the past 70 years, an empirical irregularity that has yet to receive attention. To date, the vast majority of the literature, as in this paper, defines stock price crashes following the seminal study by Hutton, Marcus and Tehranian (2009), whereby one would theoretically expect the empirical occurrence of idiosyncratic crashes to be about 5% per annum.[4] However, our empirical investigation shows that stock price crashes have grown steadily from 5.5% in 1950 to 27% in 2019. The huge disparity between the empirical versus theoretical thresholds, and more importantly the persistent upward trend in the firm-year crash occurrences, is what we call the *stock price crash risk puzzle*. Our study surfaces an elusive facet of the crash risk phenomenon that the extant literature has missed, and that future research should strive to explain by pondering, *inter alia*, on two important questions: (i) what explains the large gap between the theoretical versus empirical frequencies of stock price crashes and (ii) what drives the observed steady increase in stock price crashes over the past 70 years?

Second, this paper features a critique regarding the efficacy of the opacity and overinvestment channels to explain stock price crashes. Our investigations surface evidence suggesting that opacity and overinvestment have attenuated significantly and underscore their limited role in explaining crashes for US-listed firms, especially in the post-SOX period. In this respect, our paper provides

[4]A stock price crash is when a firm experiences idiosyncratic weekly returns that fall more than 3.09 standard deviations below their corresponding mean value within a year, with 3.09 chosen to generate a frequency of 0.1% in the normal distribution. Then, theoretically, the frequency of extreme events is approximately 5.07% per annum ($1 - (1 - 0.001)^{52} = 0.0507$).

an urgent call for future research to expand the scope of investigations beyond these two agency channels.

The study unfolds as follows: the next section describes the data, measurements and methodology; the third section presents the summary statistics, as well as the univariate and multivariate analysis; the fourth section discusses possible avenues for future research; while the fifth provides a conclusion to the study.

Research design

The data for stock price crashes are drawn from CRSP for the period 1950–2019, covering common stocks traded on the NYSE, AMEX and NASDAQ. We exclude firm-years with a stock price less than \$1 at the end of any fiscal year and having fewer than 26 weekly returns in a fiscal year. To ensure that our results are not sample-specific, the regression models are estimated using: (i) the CRSP–Compustat universe for 1974–2019, featuring 109,311 firm-year observations and (ii) the CRSP–Compustat–Execucomp universe for 1992–2019, featuring 34,723 firm-year observations.

Measuring stock price crashes

We define a stock price crash as the incidence of an *extreme left-tail event* in the distribution of idiosyncratic returns. Let $\mathrm{w} = 1, 2, \ldots, \mathrm{n}$ be the weeks within a fiscal year t. The *idiosyncratic return*, $\mathrm{R}_{\mathrm{j,w}}$, for firm j in week w is defined as:

$$\mathrm{R}_{\mathrm{j,w}} = \ln(1 + \epsilon_{\mathrm{j,w}}), \tag{1}$$

where $\epsilon_{\mathrm{j,w}}$ is a residual return from an index model regression. Residual returns are log-transformed to treat for potential positive skewness in (raw) returns and enable us to symmetrically identify extreme left- versus right-tail events. In this study, $\epsilon_{\mathrm{j,w}}$ is estimated as the residual from an expanded market and industry index model regression, as follows:

$$r_{\mathrm{j,w}} = \alpha + \sum_{i=-2}^{i=+2} \beta_{i,j} \mathrm{r}_{\mathrm{MKT,w+i}} + \sum_{i=-2}^{i=+2} \gamma_{i,j} \mathrm{r}_{\mathrm{IND,w+i}} + \epsilon_{\mathrm{j,w}}, \tag{2}$$

where $r_{\mathrm{j,w}}$ is firm j's stock return, $\mathrm{r}_{\mathrm{MKT,w}}$ is the CRSP value-weighted market index return and $\mathrm{r}_{\mathrm{IND,w}}$ is the Fama and French (1997) value-weighted 48-industry index return in week w. We include up to two lead and lag weekly return terms for the market and industry indices, to control for booms and busts that might happen around the week of interest, allowing us to measure the firm's idiosyncratic return with higher precision. To preclude look-ahead bias that accounts for the effect of earnings release when the subsequent crash risk measures are matched with financial statements data, Equation (2) is estimated over the 52-week window ending 13 weeks after the fiscal year-end.

We define $\mathrm{CRASH}_{\mathrm{j,t}}$ as the likelihood of an idiosyncratic, extreme left-tail event measured with a binary variable set equal to one if within fiscal year t the firm j experiences at least one 'crash week' (i.e. a large negative idiosyncratic return that falls more than λ standard deviations below its mean return), and zero otherwise. Specifically:

$$\mathrm{CRASH}_{\mathrm{j,t}} = \begin{cases} 1 & \text{if } \exists w \in \{1, 2, \ldots, n\} : \\ & \quad \mathrm{R}_{\mathrm{w}} < \mu_R - \lambda * \sigma_R \\ 0, & \text{otherwise} \end{cases}, \tag{3}$$

where μ_{R} and σ_{R} are, respectively, the mean and standard deviation of the idiosyncratic returns over the weeks that fall within fiscal year t. Following Hutton, Marcus and Tehranian (2009), we set λ equal to 3.09 to generate a frequency of 0.1% extreme left-tail events as per the normal distribution.

Our analyses are conducted using CRASH as the primary dependent variable for two reasons. First, its operationalization is consistent with the seminal papers of Jin and Myers (2006) and Hutton, Marcus and Tehranian (2009), who delineate a stock price crash as the likelihood of observing an idiosyncratic, large negative outlier in the distribution of returns. Second, this measure has been widely adopted by researchers in the ambit of empirical crash risk studies, *inter alia*, Kim, Li and Zhang (2011a), Robin and Zhang (2015), Zhu (2016), Andreou, Louca and Petrou (2017), Cheng, Li and Zhang (2020), Chang *et al.* (2022) and He and Ren (2022). Yet, for completeness, we also use six alternative operationalizations of crash risk.

We define PCRASH as a restricted version of CRASH to identify firm-years that *purely* include low-probability, left-tail events, as follows:

$$\mathrm{PCRASH}_{j,t} = \begin{cases} 1 & \text{if } \forall w : \mathrm{R_w} \leq \mu_{\mathrm{R}} + \lambda * \sigma_{\mathrm{R}} \ \& \ \exists w : \\ & \quad \mathrm{R_w} < \mu_{\mathrm{R}} - \lambda * \sigma_{\mathrm{R}},\ w \in \{1, 2, \ldots, n\} \\ 0, & \text{otherwise} \end{cases}, \quad (4)$$

with λ set equal to 3.09. This measure addresses the cases, for example, whereby a 'crash week' ($\mathrm{R_w} < \mu_{\mathrm{R}} - \lambda * \sigma_{\mathrm{R}}$) occurs as a market correction to a preceding 'jump week' ($\mathrm{R_w} > \mu_{\mathrm{R}} + \lambda * \sigma_{\mathrm{R}}$), or vice versa. PCRASH is also resilient to the possibility that a crash event is merely the outcome of the market becoming more volatile, thus making stock returns more susceptible to both idiosyncratic crash and jump events.

We employ the two continuous measures suggested by Chen, Hong and Stein (2001), namely, the negative coefficient of skewness defined as:

$$\mathrm{NCSKEW}_{j,t} = -\left(n(n-1)^{3/2} \sum_{w=1}^{n} \mathrm{R}_{j,w}^{3}\right) / \left((n-1)(n-2)\left(\sum_{w=1}^{n} \mathrm{R}_{j,w}^{2}\right)^{3/2}\right), \quad (5)$$

and the down-to-up volatility defined as:

$$\mathrm{DUVOL}_{j,t} = \log\left\{\left((n_u - 1) \sum_{\mathrm{DOWN}} \mathrm{R}_{j,w}^{2}\right) / \left((n_d - 1) \sum_{UP} \mathrm{R}_{j,w}^{2}\right)\right\}, \quad (6)$$

where $\mathrm{n_d}$ and $\mathrm{n_u}$ are, respectively, the number of DOWN and UP weeks in fiscal year t. A week is considered as DOWN when $\mathrm{R_w} < \mu_{\mathrm{R}}$ and UP when $\mathrm{R_w} \geq \mu_{\mathrm{R}}$.

We use the COUNT measure of Callen and Fang (2013, 2015a,b) calculated as the difference between the number of weeks with negative extreme idiosyncratic returns and the number of weeks with positive extreme idiosyncratic weekly returns, specifically:

$$\mathrm{COUNT}_{j,t} = \sum_{w=1}^{n} 1_{(\mathrm{R_w} < \mu_{\mathrm{R}} - \lambda * \sigma_{\mathrm{R}})} - \sum_{w=1}^{n} 1_{(\mathrm{R_w} > \mu_{\mathrm{R}} + \lambda * \sigma_{\mathrm{R}})}, \quad (7)$$

with λ set equal to 3.09.

Following Andreou, Andreou and Lambertides (2021) and He and Ren (2022), we employ the negative coefficient of the standardized minimum return:

$$\mathrm{NCMRET}_{j,t} = -\left(\frac{R_{min} - \mu_{\mathrm{R}}}{\sigma_{\mathrm{R}}}\right), \quad (8)$$

where $\mathrm{R_{min}}$ is the minimum idiosyncratic weekly return in fiscal year t.

In general, higher values of NCSKEW, DUVOL, COUNT and NCMRET signify greater stock price crash risk.

Lastly, we employ a dichotomous measure to capture the left–tail asymmetry in idiosyncratic returns. Thus, we define a binary variable set equal to one if the probability of negative extreme idiosyncratic returns is greater than the probability of positive extreme idiosyncratic returns within a fiscal year. Specifically:

$$\mathrm{LEFTA}_{j,t} = \begin{cases} 1 & \text{if } \sum_{w=1}^{n} 1_{(\mathrm{R_w} < \mu_{\mathrm{R}} - \lambda * \sigma_{\mathrm{R}})} \\ & \quad > \sum_{w=1}^{n} 1_{(\mathrm{R_w} > \mu_{\mathrm{R}} + \lambda * \sigma_{\mathrm{R}})} \\ 0, & otherwise \end{cases}, \quad (9)$$

where λ takes the value of 2.58, which corresponds to frequencies of 1% in the normal distribution. Defining LEFTA at 1% threshold helps to differentiate this measure from the configurations of PCRASH and COUNT.

Measuring opacity of financial reports and overinvestment

We follow the seminal work of Hutton, Marcus and Tehranian (2009) and measure opacity for firm j in fiscal year t as the three-year moving sum of the absolute value of annual discretionary accruals (DiscAcc):

$$\mathrm{Opacity}_{j,t} = |\mathrm{DiscAcc}_{j,t}| + |\mathrm{DiscAcc}_{j,t-1}| + |\mathrm{DiscAcc}_{j,t-2}|, \quad (10)$$

whereby discretionary accruals are estimated based on the modified Jones model (Dechow, Sloan and Sweeney, 1995). The appealing aspect of Opacity is that firms with consistently large absolute values of discretionary accruals are more likely to be managing reported earnings to camouflage bad news.

Overinvestment involves money spent on negative net present value (NPV) projects (i.e. investment expenditure beyond that required to maintain assets in place and to finance expected new investments in positive NPV projects). We follow Richardson's (2006) approach to measure overinvestment. Let $I_{\mathrm{NEW}_{\mathrm{j,t}}}$ be the investment expenditure on new projects for firm j in fiscal year t (scaled by total assets measured at the beginning of the year). This can be decomposed into expected investment expenditure in new positive NPV projects ($\mathrm{I}^{*}_{\mathrm{NEW}_{\mathrm{j,t}}}$) and abnormal investment ($\mathrm{I}^{\epsilon}_{\mathrm{NEW}_{\mathrm{j,t}}}$). The abnormal component of investment can be negative, signifying underinvestment, or positive, signifying overinvestment. We define overinvestment in accordance with the hoarding of bad news mechanism, whereby incentivized managers tend to withhold adverse information for prolonged periods (e.g. Bleck and Liu, 2007; Benmelech, Kandel and Veronesi, 2010), thus

$$\mathrm{Overinvestment}_{\mathrm{j,t}} = \mathrm{I}^{\epsilon}_{\mathrm{NEW}_{\mathrm{j,t}}} + \mathrm{I}^{\epsilon}_{\mathrm{NEW}_{j,t-1}} + \mathrm{I}^{\epsilon}_{\mathrm{NEW}_{j,t-2}}. \tag{11}$$

The use of a three-year moving sum, which is in line with the measurement of Opacity in Equation (10), is more likely to capture the managers' multi-year effects of hoarding of bad news through investments in negative NPV projects. The estimation details of Equations (10) and (11) are discussed in the Appendix.

Control variables

We use the following baseline control variables: Size, Firm Age, Leverage, Market to Book, Zscore and Return on Equity (e.g. Hutton, Marcus and Tehranian, 2009; Kim and Zhang, 2016; Callen and Fang, 2013; He and Ren, 2022). More elaborated regression models also include Stock Return and Detrended Turnover as in Chen, Hong and Stein (2001), as well as up to two period lagged values of Ncskew to take into account the time persistency of crash risk as in Andreou, Louca and Petrou (2017). All control variables are defined in the Appendix.

Baseline regression model specification

We employ the following logistic model that estimates the probability of firm j experiencing a crash event within fiscal year $t + 1$:

$$\mathrm{CRASH}_{j,t+1} = \alpha + \beta_1 \mathrm{Opacity}_{\mathrm{j,t}} + \beta_2 \mathrm{Overinvestment}_{\mathrm{j,t}} + \gamma \mathbf{X}_{\mathrm{j}} + \mathrm{Y}_{\mathrm{fe}} + I_{\mathrm{fe}}[\mathrm{or} F_{\mathrm{fe}}] + e_{j,t+1}, \tag{12}$$

where $\mathrm{CRASH}_{j,t+1}$ is defined as in Equation (3); $\mathrm{Opacity}_{\mathrm{j,t}}$ and $\mathrm{Overinvestment}_{i,t}$ are measured in year t and defined as in Equations (10) and (11), respectively; $\mathbf{X}_j$ includes the control variables described in the previous subsection, whereby all are measured in year t or earlier. Further, Y_{fe} features year fixed effects, I_{fe} industry fixed effects and F_{fe} firm fixed effects, respectively. For industry effects, we use the 48 industry classifications by Fama and French (1997).

We estimate two versions of Equation (12). One that captures the (pooled cross-sectional variation and includes year and industry fixed effects, and another that captures the within-firm variation and includes year- and firm-fixed effects. In all estimations, standard errors are clustered at the firm level and all continuous variables are winsorized at the 1st and 99th percentiles to mitigate the effect of outliers. Also, all continuous variables are standardized to have a mean value of zero and a standard deviation of one.

Discussion of empirical findings

Summary statistics

Table 1, Panel A shows summary statistics for the CRSP–Compustat universe (1974–2019). The mean value of CRASH is 0.147, suggesting that almost 15% of these firm-year observations experience at least one crash event. Although we utilize a greater sample and a longer period than most prior crash risk studies, the occurrence of stock price crashes in our data falls within the observed range of previous papers (e.g. Hutton, Marcus and Tehranian, 2009; Kim, Li and Zhang, 2011b; Kim and Zhang, 2016; Kim, Li and Zhang, 2011a). With respect to the two channels, the mean value (standard deviation) of Opacity is 0.213 (0.202), similar to those reported in Hutton, Marcus and Tehranian (2009). The mean value (standard deviation) of Overinvestment is 0.019 (0.222).[5]

In terms of the control variables, the mean Stock Return is −0.164, the mean Detrended Turnover is 0.001 and the mean Ncskew is −0.051. Additionally, the average firm in our sample has a Size of

[5]The mean value (standard deviation) of our annual estimates for abnormal investment is 0.006 (0.289), which is close to the 0.000 (0.110) reported by Richardson (2006). The discrepancy in standard deviation can be attributed to the significant difference between sample sizes and periods.

Table 1. Summary statistics

Variable	Observations	Mean	SD	Lower quartile	Median	Upper quartile
Panel A: CRSP–Compustat						
CRASH	109,311	0.147	0.354	0.000	0.000	0.000
Opacity	80,270	0.213	0.202	0.092	0.153	0.259
Overinvestment	80,270	0.019	0.222	−0.099	−0.013	0.085
Stock Return	93,549	−0.144	0.169	−0.176	−0.088	−0.043
Detrended Turnover	93,549	0.001	0.015	−0.003	0.000	0.004
Ncskew	93,549	−0.050	0.672	−0.432	−0.065	0.303
Size	109,311	5.644	2.018	4.149	5.482	7.028
Firm Age	109,311	18.400	14.286	7.000	15.000	26.000
Market to Book	109,311	2.703	3.589	1.080	1.811	3.151
Leverage	109,311	0.489	0.226	0.321	0.493	0.639
Zscore	109,311	5.462	2.156	4.467	4.714	5.397
Return on Equity	109,311	0.036	0.406	0.019	0.103	0.165
Panel B: CRSP–Compustat–Execucomp						
Variable	Observations	Mean	SD	Lower quartile	Median	Upper quartile
CRASH	34,723	0.196	0.397	0.000	0.000	0.000
Opacity	30,496	0.179	0.171	0.078	0.130	0.219
Overinvestment	30,496	0.042	0.212	−0.069	0.012	0.104
Stock Return	32,729	−0.102	0.131	−0.121	−0.060	−0.030
Detrended Turnover	32,729	0.001	0.018	−0.006	0.000	0.007
Ncskew	32,729	0.084	0.687	−0.317	0.044	0.430
Size	34,723	7.297	1.605	6.124	7.203	8.378
Firm Age	34,723	25.902	17.198	11.000	22.000	40.000
Market to Book	34,723	3.315	3.883	1.545	2.379	3.897
Leverage	34,723	0.519	0.222	0.362	0.525	0.663
Zscore	34,723	5.438	1.932	4.525	4.789	5.435
Return on Equity	34,723	0.085	0.370	0.048	0.116	0.183

This table presents summary statistics of the stock price crash risk measure (CRASH) estimated as per Equation (3), opacity, overinvestment, and control variables. The CRSP-Compustat data set covering the period 1974–2019 is presented in Panel A. The CRSP–Compustat–Execucomp dataset covering the period 1992–2019 is presented in Panel B. The number of observations for each variable corresponds to the number of non-missing observations for the variables included in the estimations of models (1)–(3) as per Table 2. For variable definitions and details of their computation, see the Appendix.

5.644, Firm Age of 18.4 years, Market to Book ratio of 2.703 and Leverage of 0.489. The sample firms have a mean Zscore of 5.462 and a mean Return on Equity of 0.036. In general, the distribution characteristics of control variables are consistent with prior studies utilizing the CRSP–Compustat universe (e.g. Callen and Fang, 2017; Chen, Kim and Yao, 2017; Dang *et al.*, 2018).

Table 1, Panel B refers to the CRSP–Compustat–Execucomp universe for the period 1992–2019. The mean value of CRASH is 0.196, suggesting that almost 20% of these firm-year observations experience at least one crash event. As expected, firms in this sample are more prone to stock price crashes, given that this analysis is covering a more recent period. The mean value (standard deviation) of Opacity is 0.179 (0.171) and Overinvestment is 0.042 (0.212), close to those reported for the CRSP–Compustat universe. Further, the distribution characteristics of the main control variables are largely consistent with those reported in prior studies utilizing the CRSP–Compustat–Execucomp universe (e.g. Kim, Li and Zhang, 2011a; Kim, Wang and Zhang, 2016; Andreou, Louca and Petrou, 2017).

Time trends of stock price crashes for the average US-listed firm

Figure 3 depicts the time evolution of CRASH for: (i) the CRSP universe in 1950–2019; (ii) the CRSP–Compustat universe in 1974–2019; and (iii) the CRSP–Compustat–Execucomp universe in 1992–2019. Admittedly, there is a remarkable surge of

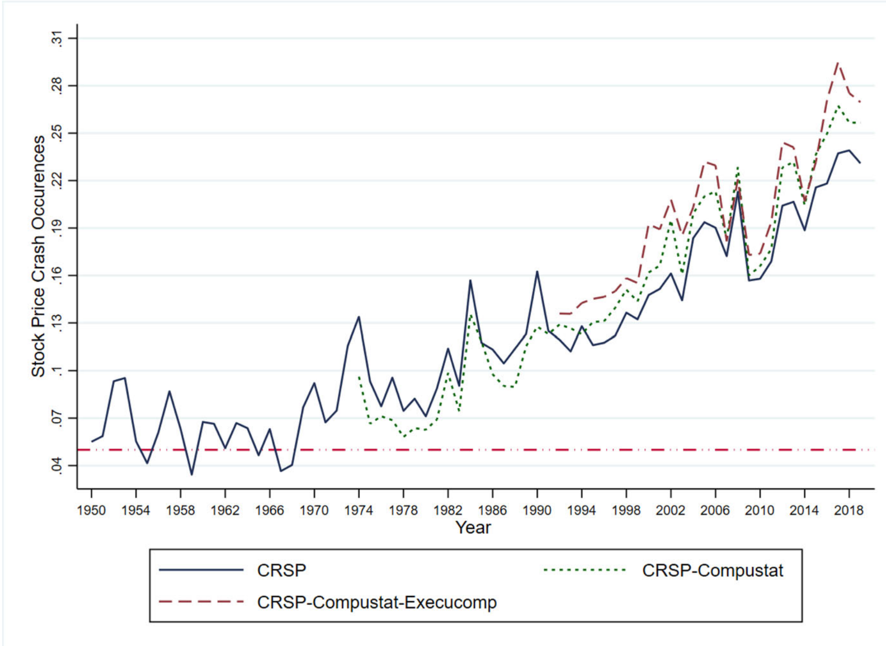

Figure 3. Time evolution of stock price crash occurrences for the average US-listed firm. This figure depicts the firm-year frequencies of stock price crashes (CRASH) estimated as per Equation (3) for the CRSP universe from 1950 to 2019; the CRSP–Compustat universe from 1974 to 2019; and the CRSP–Compustat–Execucomp universe from 1992 to 2019. The horizontal dotted line is showing a crash probability of 5.07%, which one would theoretically expect to observe over the course of a year under the assumption that firm-specific returns are normally distributed and λ in Equation (3) is set equal to 3.09 to generate a frequency of 0.1% of extreme left-tail events. The sample comprises common stocks (share codes 10 and 11) traded on the NYSE, AMEX or NASDAQ, with stock price greater than 1 USD at the end of the fiscal year and more than 26 weeks of stock returns in a fiscal year [Colour figure can be viewed at wileyonlinelibrary.com]

crashes, starting at 5.5% in 1950 and growing to 23% for CRSP, and to 27% for CRSP–Compustat–Execucomp in 2019.

Li and Zeng (2019) examine the effect of product market threats on firm stock price crash risk and find that firms facing more threats are more prone to crashes. Because product market competition is likely to be an industry effect (Giroud and Mueller, 2010), we also investigate whether the phenomenon is driven by certain industries. Results across the 12 Fama–French industries reported in the Internet Appendix demonstrate that the upward trend remains largely consistent across the industries.

The evidence that emerges in Figure 3 gives birth to a phenomenon that we call the *stock price crash risk puzzle*. The seminal study of Hutton, Marcus and Tehranian (2009) defines a stock price crash consistent with Equation (3), with λ equal to 3.09 to generate a frequency of 0.1% extreme left-tail events as per the normal distribution. The authors explain that 'if firm-specific returns were normally distributed, one would expect to observe 0.1% of the sample firms crashing in any week' (p. 74), resulting in a crash probability of 5.07% over the course of a year. Intriguingly, the observed crash frequency reaches 27% by 2019, a compelling observation that brings the empirical frequency at odds with the hypothetical one. Figure 3 depicts a persistently upward-sloping trend in stock price crashes. Therefore, we are not only dealing with, on average, a higher incidence of crashes, but also a persistently increasing frequency of crashes over time. This causes a puzzle that calls for more research to rationalize it.

The effect of the opacity and overinvestment channels

In this subsection, we consider the role of opacity and overinvestment in explaining stock price crashes. We begin with graphical evidence, whereby Figures 4 and 5 depict the time evolution of these channels for the average US-listed firm. Based on agency theory predictions, one would expect to observe *a positive relation between*:

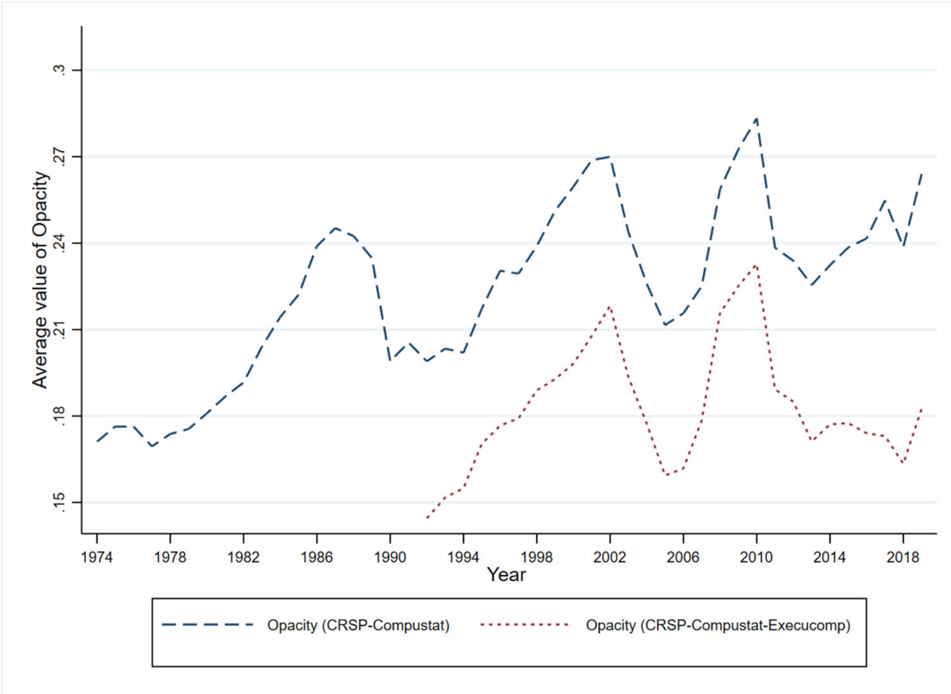

Figure 4. Time evolution of opacity for the average US-listed firm. This figure depicts the average value of opacity for the CRSP–Compustat universe from 1974 to 2019 and the CRSP–Compustat–Execucomp universe from 1992 to 2019 [Colour figure can be viewed at wileyonlinelibrary.com]

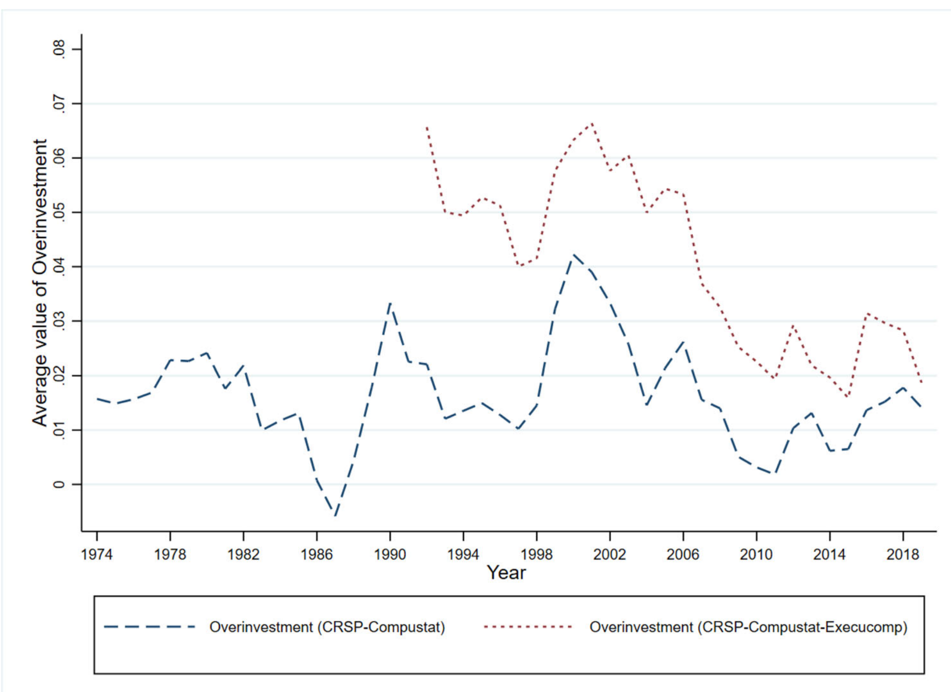

Figure 5. Time evolution of overinvestment for the average US-listed firm. This figure depicts the average value of overinvestment for the CRSP–Compustat universe from 1974 to 2019 and CRSP–Compustat–Execucomp universe from 1992 to 2019 [Colour figure can be viewed at wileyonlinelibrary.com]

(i) *Opacity* and *crashes* as theorized, for example, in Hutton, Marcus and Tehranian (2009), Kim, Li and Zhang (2011b), Callen and Fang (2015b, 2017), Andreou *et al.* (2016), Dang *et al.* (2018) and Kim and Zhang (2019) and (ii) *Overinvestment* and *crashes* as theorized, for example, in Bleck and Liu (2007), Benmelech, Kandel and Veronesi (2010), Kim and Zhang (2016) and Habib and Hasan (2017). Accordingly, one would expect the increasing frequency of stock price crashes to move in tandem with the levels of opacity and overinvestment.

On the contrary, Figure 4 depicts that, while opacity increases in the first years of the sample, after 2003 it demonstrates a decreasing trend until 2008, when it starts to rise again and continues to do so over the next three years until 2011. Opacity then decreases and remains rather flat towards the final years of the sample, which is the period when the crash rate reaches its highest frequency. In fact, for the CRSP–Compustat–Execucomp universe, opacity levels deepen after 2009. This finding aligns with studies suggesting that accrual-based earnings management has experienced a significant decline following the passage of SOX (Cohen, Dey and Lys, 2008; Zhou, 2008; Hutton, Marcus and Tehranian, 2009; Andreou *et al.*, 2016). As far as overinvestment is concerned, Figure 5 depicts a clear decreasing trend after 2002, with a steeper downward direction for the CRSP–Compustat–Execucomp universe.

Altogether, the evidence in Figures 4 and 5 suggests an overall attenuation in the levels of opacity and overinvestment in the post-SOX period, most likely reflecting the impact of key regulations established in the early 2000s aiming to enhance transparency and curtail managerial opportunism. At the same time, the attenuation in the levels of opacity and overinvestment is at odds with the surge in stock price crashes in the last two decades.

Going forward, we conduct multivariate regression analyses. Table 2, Panel A reports the results from estimating Equation (12) to investigate the relation between Opacity, Overinvestment and CRASH using the CRSP–Compustat universe (1974–2019). Models (1)–(4) report pooled cross-sectional variation results, while models (5)–(8) report within-firm variation results.[6] Apparently, Opacity appears statistically non-significant in all model specifications.[7] The overinvestment channel is positively associated with the one-year-ahead stock price crash risk in all model specifications. For instance, in models (2) and (4), the coefficients of Overinvestment are, respectively, 0.049 and 0.051, and both statistically significant (p-values < 0.01). Nonetheless, in the within-firm regression models (6) and (8), the coefficients for Overinvestment show weaker statistical significance; coefficient values of 0.036 (p-value < 0.05) and 0.032 (p-value < 0.1), respectively.

Table 2, Panel B reports results for the CRSP–Compustat–Execucomp universe (1992–2019). In general, the results are qualitatively similar to the results derived from the CRSP–Compustat universe. Again, Opacity appears statistically non-significant in all model specifications, while Overinvestment is positively associated with the one-year-ahead stock price crash. The statistical significance for the coefficients of Overinvestment in Panel B is notably weaker compared to the one reported in Panel A, especially in models (6) and (8) (p-values < 0.10).

Table 3 reports results focusing on the post-SOX period (2003–2019) by using the CRSP–Compustat–Execucomp universe. We take this step because the evidence in Figures 4 and 5 depicts a pronounced attenuation of opacity and overinvestment for the average US-listed firm over the last two decades, whilst stock price crashes surge in this same period. Overall, there is notable evidence in Table 3 that both Opacity and Overinvestment are statistically non-significant across all models, supporting that both channels possibly play a limited role in explaining stock price crashes in the post-SOX period.[8]

[6]Inclusion of firm fixed effects over random effects is supported by a Hausman test (p-value < 0.01).

[7]For comparability purposes, we use our sample data to replicate the baseline results as in Hutton, Marcus and Tehranian (2009) for the period 1991–2005. Our logistic regression results show that the coefficient of Opacity is positive and statistically significant (p-value < 0.01), which replicates their findings. Therefore, the absence of a statistically significant relation between opacity and stock price crashes reported in Table 2 of our study is driven by the post-SOX period. This is also discussed in Hutton, Marcus and Tehranian (2009), who note that earnings management had dissipated in the post-SOX environment.

[8]In the Internet Appendix, following Hutton, Marcus and Tehranian (2009), we assess whether our findings are affected by the square term of opacity (Opacity^2). Overall, Opacity^2 is statistically non-significant and its inclusion

Table 2. The effect of opacity and overinvestment on future stock price crashes

Panel A: CRSP–Compustat (1974–2019)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Opacity		−0.001		0.018		0.000		0.009
		(0.01)		(0.01)		(0.014)		(0.015)
Overinvestment		0.049***		0.051***		0.036**		0.032*
		(0.01)		(0.01)		(0.012)		(0.013)
Stock Return			0.082***	0.095***			0.138***	0.148***
			(0.01)	(0.02)			(0.017)	(0.020)
Detrended Turnover			0.069***	0.064***			0.063***	0.065***
			(0.01)	(0.01)			(0.009)	(0.010)
Ncskew			0.037***	0.028***			−0.096***	−0.105***
			(0.01)	(0.01)			(0.010)	(0.010)
Ncskew (lag 1)			0.029***	0.026**			−0.081***	−0.086***
			(0.01)	(0.01)			(0.010)	(0.010)
Ncskew (lag 2)			0.031***	0.033***			−0.066***	−0.066***
			(0.01)	(0.01)			(0.010)	(0.010)
Size	0.135***	0.123***	0.090***	0.073***	0.559***	0.535***	0.569***	0.549***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.033)	(0.043)	(0.039)	(0.045)
Firm Age	−0.088***	−0.077***	−0.088***	−0.080***	−0.396	−0.336	−0.330	−0.375
	(0.01)	(0.01)	(0.01)	(0.01)	(0.341)	(0.362)	(0.352)	(0.365)
Market to Book	0.031***	0.021*	0.021**	0.016	0.060***	0.057***	0.047***	0.040**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.011)	(0.014)	(0.013)	(0.014)
Leverage	−0.030**	−0.034**	−0.012	−0.014	−0.004	−0.016	0.000	−0.008
	(0.01)	(0.01)	(0.01)	(0.01)	(0.017)	(0.020)	(0.019)	(0.021)
Zscore	0.035***	0.040***	0.047***	0.047***	0.107***	0.127***	0.107***	0.119***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.015)	(0.020)	(0.018)	(0.021)
Return on Equity	0.046***	0.042***	0.036***	0.035***	0.050***	0.048***	0.033**	0.026*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.010)	(0.013)	(0.012)	(0.013)
Fixed effects	Year, Industry	Year, Industry	Year, Industry	Year, Industry	Year, Firm	Year, Firm	Year, Firm	Year, Firm
Observations	109,311	80,270	93,549	78,404	94,017	68,984	80,726	67,397
Pseudo log-likelihood	−45,122.97	−33,334.56	−38,414.01	−32,558.33	−32,432.90	−23,978.41	−27,647.54	−23,295.68
Pseudo R-squared	0.039	0.040	0.041	0.042	0.025	0.025	0.031	0.031

Panel B: CRSP–Compustat–Execucomp (1992–2019)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Opacity		−0.002		0.010		−0.015		−0.009
		(0.02)		(0.02)		(0.03)		(0.03)
Overinvestment		0.042***		0.046***		0.035*		0.035*
		(0.02)		(0.02)		(0.02)		(0.02)
Stock Return			0.045*	0.083***			0.132***	0.177***
			(0.03)	(0.03)			(0.04)	(0.04)
Detrended Turnover			0.044***	0.047***			0.055***	0.060***
			(0.01)	(0.01)			(0.01)	(0.02)
Ncskew			0.030**	0.029**			−0.109***	−0.108***
			(0.01)	(0.01)			(0.02)	(0.02)
Ncskew (lag 1)			0.016	0.012			−0.105***	−0.109***
			(0.01)	(0.01)			(0.01)	(0.02)
Ncskew (lag 2)			0.028*	0.036**			−0.078***	−0.073***
			(0.01)	(0.01)			(0.02)	(0.02)
Size	−0.045*	−0.053*	−0.066**	−0.086***	0.634***	0.651***	0.647***	0.646***
	(0.02)	(0.03)	(0.03)	(0.03)	(0.07)	(0.08)	(0.08)	(0.09)
Firm Age	−0.031*	−0.038**	−0.037**	−0.040**	−0.258	−0.315	−0.300	−0.408
	(0.02)	(0.02)	(0.02)	(0.02)	(0.40)	(0.42)	(0.43)	(0.45)
Market to Book	0.002	0.009	0.007	0.008	0.043**	0.063***	0.037*	0.048**
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Leverage	−0.013	−0.014	−0.006	−0.004	−0.020	−0.042	−0.022	−0.035
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)

Table 2. (Continued)

Panel B: CRSP–Compustat–Execucomp (1992–2019)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Zscore	0.001	−0.013	−0.008	−0.011	0.119***	0.129***	0.093***	0.104***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)
Return on Equity	0.032**	0.031*	0.020	0.022	0.022	0.010	−0.006	−0.009
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Fixed effects	Year, Industry	Year, Industry	Year, Industry	Year, Industry	Year, Firm	Year, Firm	Year, Firm	Year, Firm
Observations	34,723	30,496	32,729	30,212	32,127	27,995	30,209	27,713
Pseudo log-likelihood	−17,212.27	−15,145.03	−16,244.23	−14,993.14	−15,423.66	−13,463.26	−14,453.79	−13,260.93
Pseudo R-*squared*	0.020	0.022	0.022	0.023	0.088	0.091	0.093	0.096

This table reports logistic regression estimates for the relation between opacity, overinvestment and stock price crashes. Estimates in Panel A are derived using the CRSP-Compustat universe from 1974 to 2019, while estimates in Panel B are derived from the CRSP–Compustat–Execucomp universe from 1992 to 2019. The dependent variable is CRASH estimated as per Equation (3) and measured in fiscal year t+1. The explanatory variables are measured in fiscal year t or earlier. Models (1)–(4) present estimation results from the pooled cross-sectional regression analyses, whilst models (5)–(8) presents estimation results from the time-series (within-firm) regression analyses. For variable definitions and details of their computation, see the Appendix. The estimates include a constant and different conditional fixed effects (as indicated at the bottom of each panel) whose coefficients are suppressed. Industry fixed effects are defined based on the Fama-French 48-industry classification. All continuous variables are winsorized at the 1^{st} and 99^{th} percentiles and are standardized to have a mean value of zero and a variance of one. Robust standard errors clustered at the firm level are shown in parentheses. Due to computational issues, models (5) to (8) are (exceptionally) estimated without clustered standard errors. The symbols ***, ** and * denote two-tailed statistical significance at the 1%, 5% and 10% level, respectively.

Table 4 reports results to investigate the effect of opacity and overinvestment on alternative stock price crash risk measures in the post-SOX period. Model (1) reports the linear probability estimate of Equation (12). The rest of the models estimate Equation (12) using alternative crash risk measures as the dependent variable. Overall, the results corroborate our main findings that Opacity and Overinvestment do not qualify as prominent channels for explaining stock price crashes.

We also check whether our inferences remain unchanged with: (i) opacity operationalized using the probability of misstatement (Dechow *et al.*, 2011), accruals quality (Dechow and Dichev, 2002), earnings smoothing (Tucker and Zarowin, 2006), accounting conservatism (Khan and Watts, 2009), real earnings management (Roychowdhury, 2006; Cohen and Zarowin, 2010)[9] and (ii) overinvestment operationalized using the inefficient investment proxy of Hubbard (1998), four alternative industry-adjusted capital expenditure measures and the overinvestment measure proposed by He and Ren (2022). The regression results are reported in the Internet Appendix and attest that irrespective of the alternative measure considered, our conclusions remain unaltered.

Next, we investigate whether the effect of opacity and overinvestment on future crashes is confounded by omitted variables that relate to short-termism practices through which managers might reveal an opportunistic behaviour. In this vein, Table 5 presents pooled cross-sectional logistic estimates from regressing Opacity and Overinvestment on CRASH, after controlling for equity-based incentives in models (1)–(4), and in addition controlling for important corporate governance functions in model (5).

Altogether, the evidence in Table 5 continues to suggest an absence of any statistically significant relation between opacity, overinvestment and future crashes. Importantly, the results also show that the CEO's/CFO's option incentives are negatively related to future crash risk in the post-SOX period (p-values < 0.05), supporting the notion that equity-based compensation contributes towards confining the hoarding of bad news. Actually, these results are not supportive of the agency model of Benmelech, Kandel and Veronesi

in various models does not alter our conclusions in any way.

[9]We also explored whether our main findings are driven by income-increasing or income-decreasing earnings management, following the Kim, Kim and Zhou (2017) approach. The results continue to show that Opacity and Overinvestment are statistically non-significant in both the subsample featuring income-increasing earnings management observations and the subsample featuring income-decreasing earnings management observations.

Table 3. The effect of opacity and overinvestment on future stock price crashes in the post-SOX period

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Opacity		0.012		0.026		0.023		0.025
		(0.02)		(0.03)		(0.03)		(0.03)
Overinvestment		0.019		0.025		−0.012		−0.015
		(0.02)		(0.02)		(0.03)		(0.03)
Stock Return			0.083**	0.132***			0.229***	0.281***
			(0.04)	(0.04)			(0.06)	(0.06)
Detrended Turnover			0.049***	0.047***			0.066***	0.066***
			(0.02)	(0.02)			(0.02)	(0.02)
Ncskew			0.018	0.021			−0.146***	−0.147***
			(0.02)	(0.02)			(0.02)	(0.02)
Ncskew (lag 1)			0.015	0.010			−0.134***	−0.143***
			(0.02)	(0.02)			(0.02)	(0.02)
Ncskew (lag 2)			0.033**	0.040**			−0.092***	−0.087***
			(0.02)	(0.02)			(0.02)	(0.02)
Size	−0.055*	−0.052	−0.079**	−0.091***	0.695***	0.786***	0.726***	0.781***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.11)	(0.12)	(0.12)	(0.13)
Firm Age	−0.027	−0.034	−0.033*	−0.036*	−0.224	−0.319	−0.277	−0.377
	(0.02)	(0.02)	(0.02)	(0.02)	(0.45)	(0.46)	(0.49)	(0.51)
Market to Book	0.002	0.016	0.005	0.014	0.044**	0.067***	0.028	0.043*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Leverage	−0.009	−0.009	0.004	0.004	−0.006	−0.015	0.008	0.009
	(0.02)	(0.03)	(0.02)	(0.03)	(0.04)	(0.05)	(0.05)	(0.05)
Zscore	0.015	0.003	0.010	0.004	0.007	−0.021	−0.031	−0.047*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)
Return on Equity	0.027	0.015	0.008	0.001	0.176***	0.180***	0.124**	0.133**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.05)	(0.05)	(0.05)
Fixed effects	Year, Industry	Year, Industry	Year, Industry	Year, Industry	Year, Firm	Year, Firm	Year, Firm	Year, Firm
Observations	21,452	19,509	20,443	19,322	19,571	17,711	18,647	17,530
Pseudo log-likelihood	−11,298.49	−10,286.63	−10,756.47	−10,168.37	−9,903.50	−8,957.98	−9,338.14	−8,773.79
Pseudo R-squared	0.017	0.018	0.019	0.020	0.095	0.097	0.104	0.106

This table reports logistic regression estimates for the relation between opacity, overinvestment, and stock price crashes. Estimates are derived using the CRSP–Compustat–Execucomp universe in the post-SOX period from 2003 to 2019. The dependent variable is CRASH estimated as per Equation (3) and measured in fiscal year t+1. The explanatory variables are measured in fiscal year t or earlier. Models (1)–(4) present estimation results from the pooled cross-sectional regression analyses, while models (5)–(8) present estimation results from the time-series (within-firm) regression analyses. For variable definitions and details of their computation, see the Appendix. The estimates include a constant and different conditional fixed effects (as indicated at the bottom of the table) whose coefficients are suppressed. Industry fixed effects are defined based on the Fama–French 48-industry classification. All continuous variables are winsorized at the 1st and 99th percentiles and are standardized to have a mean value of zero and a variance of one. Robust standard errors clustered at the firm level are shown in parentheses. The symbols ***, ** and * denote two-tailed statistical significance at the 1%, 5% and 10% level, respectively.

(2010), which predicts that equity-based compensation incentivizes managers to act opportunistically by concealing bad news that increases future crash risk. Neither are they supportive of the empirical study by Kim, Li and Zhang (2011a), reporting that CFO option incentives are significantly and positively related to future crash risk.

The option incentives-crash evidence in Table 5 suggests that SOX possibly has worked as a catalyst in strengthening important internal corporate governance functions to limit the hoarding of bad news. To provide some support for this assertion, with reference to the CRSP–Compustat–Execucomp universe in the period 1996–2019, Figure 6 demonstrates that the average percentage of dual CEOs has declined significantly from 65% to 40%, while the average percentage of independent directors on the board increased significantly from 58% to 82%. Additionally, the average percentage of firms with more than one female director increased significantly from 15% to almost 70%. On the other hand, the average percentage of not attended directors decreased from 2.5%

Table 4. The effect of opacity and overinvestment on future stock price crashes in the post-SOX period: Alternative stock price crash risk measures

Panel A: Pooled cross-sectional variation models

	(1) LCRASH	(2) PCRASH	(3) NCSKEW	(4) DUVOL	(5) COUNT	(6) NCMRET	(7) LEFTA
Opacity	0.004	−0.004	0.010	0.012	0.002	0.014	−0.010
	(0.00)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Overinvestment	0.005	0.032	0.022**	0.014*	0.013	0.014	0.018
	(0.00)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Year, Industry	Year, Industry	Year, Industry	Year, Industry	Year, Industry	Year, Industry	Year, Industry
Observations	19,322	19,322	19,322	19,322	19,322	19,322	19,322
Pseudo log-likelihood	−10,431.74	−9695.83	−28,980.63	−28,194.46	−28,721.43	−29,193.62	−11,645.25
Pseudo R-squared/R-squared	0.021	0.017	0.015	0.017	0.010	0.026	0.010

Panel B: Time-series (within-firm) variation models

	(1) LCRASH	(2) PCRASH	(3) NCSKEW	(4) DUVOL	(5) COUNT	(6) NCMRET	(7) LEFTA
Opacity	0.004	−0.003	0.003	0.007	0.005	0.006	−0.018
	(0.01)	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)
Overinvestment	−0.002	−0.017	−0.002	−0.004	−0.008	−0.003	−0.021
	(0.00)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm
Observations	19,186	17,248	19,186	19,186	19,186	19,186	18,459
Pseudo log-likelihood	−9072.75	−8369.19	−27,429.72	−26,700.24	−27,323.68	−27,605.96	−10,437.63
Pseudo R-squared/R-squared	0.142	0.099	0.139	0.139	0.124	0.154	0.083

This table reports regression estimates for the relation between opacity, overinvestment and alternative measures of stock price crash risk. Estimates are derived using the CRSP–Compustat–Execucomp universe in the post-SOX period from 2003 to 2019. The dependent variables are measured in fiscal year t+1, while the explanatory variables are measured in fiscal year t or earlier. Panel A presents estimation results from the pooled cross-sectional regression analyses, whilst Panel B presents estimation results from the time-series (within-firm) regression analyses. All models report OLS regression estimates, except models (2) and (7), which report logistic regression estimates. For variable definitions and details of their computation, see the Appendix. The estimates include a constant and different fixed effects (as indicated at the bottom of each panel) and control variables, whose coefficients are suppressed. The detailed coefficients of the control variables are presented in the Internet Appendix. In models (2) and (7), conditional fixed effects are used. Industry fixed effects are defined based on the Fama–French 48-industry classification. All continuous variables are winsorized at the 1st and 99th percentiles and are standardized to have a mean value of zero and a variance of one. Robust standard errors clustered at the firm level are shown in parentheses. The symbols ***, ** and * denote two-tailed statistical significance at the 1%, 5% and 10% level, respectively.

to 0.5%. Interestingly, internal governance mechanisms have markedly improved in directions indicating progressively stronger monitoring and disciplining governance functions that should have contributed to mitigating agency issues in the corporate world. The latter also aligns with Gayle, Li and Miller (2022), who report that SOX reduced the conflict of interest between shareholders and their CEOs, mainly by reducing shareholder loss from CEOs deviating from their goal of expected value maximization.

Finally, we conduct subsample analysis to investigate whether the effect of opacity and overinvestment becomes prevalent in firms that are potentially exposed to (more severe) agency problems. We use four proxies for the severity of agency issues. In the spirit of Chen and Ngo (2022) who report recent evidence that the severity of agency problems is reduced in firms obligated to distribute free cash flow to investors, we use a firm's free cash flow as the first proxy. Following Andreou *et al.* (2016), we employ exploratory principal component analysis to derive a factor out of the various

Table 5. The effect of managerial equity-based incentives and corporate governance on future stock price crashes

Panel A: CEOs

	(1)	(2)	(3)	(4)	(5)
Stock Incentives	0.009		0.006		−0.018
	(0.02)		(0.02)		(0.03)
Option Incentives		−0.033*		−0.040**	−0.049**
		(0.02)		(0.02)	(0.02)
CEO Duality					0.025
					(0.05)
Independent Directors					−0.161
					(0.21)
Female Directors					0.066
					(0.05)
Not Attended Directors					0.439
					(0.72)
Transient Inst					0.597**
					(0.28)
HHI					−1.095**
					(0.45)
Auditor Tenure					0.002
					(0.00)
Opacity			0.026	0.029	0.027
			(0.03)	(0.03)	(0.04)
Overinvestment			0.026	0.027	0.013
			(0.02)	(0.02)	(0.03)
Control variables	Yes	Yes	Yes	Yes	Yes
Fixed effects	Year, Industry	Year, Industry	Year, Industry	Year, Industry	Year, Industry
Observations	19,958	20,365	18,881	19,248	13,110
Pseudo log-likelihood	−10,507.15	−10,712.34	−9939.44	−10,124.59	−6963.11
Pseudo R-squared	0.020	0.019	0.020	0.020	0.027

Panel B: CFOs

	(1)	(2)	(3)	(4)	(5)
Stock Incentives	0.020		0.017		0.004
	(0.02)		(0.02)		(0.03)
Option Incentives		−0.441**		−0.497**	−0.653***
		(0.20)		(0.21)	(0.24)
CEO Duality					0.015
					(0.05)
Independent Directors					−0.099
					(0.22)
Female Directors					0.070
					(0.06)
Not Attended Directors					0.540
					(0.74)
Transient Inst					0.437
					(0.29)
HHI					−1.083**
					(0.47)
Auditor Tenure					0.002
					(0.00)
Opacity			0.037	0.038	0.026
			(0.03)	(0.03)	(0.04)
Overinvestment			0.010	0.019	0.000
			(0.02)	(0.02)	(0.03)
Control variables	Yes	Yes	Yes	Yes	Yes
Fixed effects	Year, Industry	Year, Industry	Year, Industry	Year, Industry	Year, Industry

Table 5. (Continued)

Panel B: CFOs					
	(1)	(2)	(3)	(4)	(5)
Observations	17,884	18,986	16,991	18,016	12,254
Pseudo log-likelihood	−9420.56	−9996.06	−8959.93	−9493.60	−6519.35
Pseudo R-squared	0.021	0.020	0.022	0.021	0.028

This table reports pooled cross-sectional logistic regression estimates for the relation between opacity, overinvestment and stock price crash risk controlling for managerial equity-based incentives and corporate governance. Estimates are derived using the CRSP–Compustat–Execucomp universe in the post-SOX period from 2003 to 2019. The dependent variable is CRASH estimated as per *Eq.* (3) and measured in fiscal year t+1. The explanatory variables are measured in fiscal year t or earlier. Panel A presents estimation results for stock and option incentives referring to CEOs, whilst Panel B presents estimation results for stock and option incentives referring to CFOs. For variable definitions and details of their computation, see the Appendix. The estimates include a constant, conditional year and industry fixed effects and control variables, whose coefficients are suppressed. The detailed coefficients of the control variables are presented in the Internet Appendix. Industry fixed effects are defined based on the Fama–French 48-industry classification. All continuous variables are winsorized at the 1st and 99th percentiles and are standardized to have a mean value of zero and a variance of one. Robust standard errors clustered at the firm level are shown in parentheses. The symbols ***, ** and * denote two-tailed statistical significance at the 1%, 5% and 10% level, respectively.

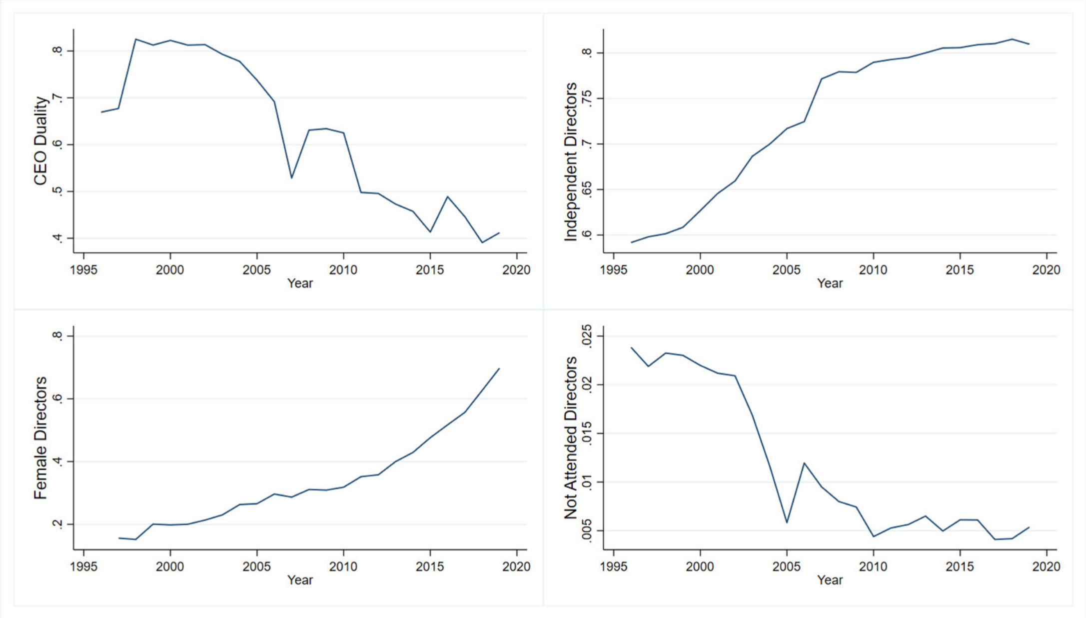

Figure 6. Time evolution of internal corporate governance functions for the average US-listed firm. This figure depicts the average value of internal corporate governance functions for the CRSP–Compustat–Execucomp universe from 1996 to 2019. CEO Duality (top-left subfigure) is proxied by an indicator variable set equal to one if the CEO is also the chairman of the board, and zero otherwise. Independent Directors (top-right subfigure) is estimated as the number of independent directors divided by board size. Female Directors (bottom-left subfigure) is proxied by an indicator variable set equal to one if the firm has more than one female director on the board, and zero otherwise. Not Attended Directors (bottom-right subfigure) is estimated as the number of directors who attended less than 75% of board meetings divided by board size [Colour figure can be viewed at wileyonlinelibrary.com]

corporate governance functions employed in Table 5 as our second proxy. We further use the G-Index (Gompers, Ishii and Metrick, 2003) and E-Index (Bebchuk, Cohen and Ferrell, 2009) as proxies for firms having more entrenched managers. Table 6 presents the results for subsamples based on whether an observation belongs in a below-median (LOW) versus above-median (HIGH) value for each proxy. It is noteworthy that, irrespective of the subsample considered, the evidence shows statistically non-significant relations between the two agency channels and future crashes.

Table 6. The effect of opacity and overinvestment on future stock price crashes in the post-SOX period: Subsample analysis

	(1) FREE CASH FLOW	(2)	(3) PCA	(4)	(5) G-INDEX	(6)	(7) E-INDEX	(8)
	HIGH	LOW	HIGH	LOW	HIGH	LOW	HIGH	LOW
Opacity	0.009	0.039	0.061	0.015	0.023	0.020	0.068	0.002
	(0.03)	(0.04)	(0.06)	(0.05)	(0.06)	(0.04)	(0.05)	(0.05)
Overinvestment	0.012	0.039	−0.018	0.019	−0.052	0.042	−0.002	0.021
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Year, Industry	Year, Industry	Year, Industry	Year, Industry	Year, Industry	Year, Industry	Year, Industry	Year, Industry
Observations	9662	9660	6796	6527	4032	9876	6004	6605
Pseudo log-likelihood	−5190.55	−4926.21	−3605.89	−3440.51	−2195.86	−5168.18	−3188.37	−3474.27
Pseudo R-squared	0.023	0.025	0.034	0.030	0.036	0.026	0.036	0.032

This table reports pooled cross-sectional regression estimates for the relation between opacity, overinvestment and alternative measures of stock price crash risk, in various subsamples based on free cash flow and corporate governance. Estimates are derived using the CRSP–Compustat–Execucomp universe in the post-SOX period from 2003 to 2019. The dependent variable is CRASH estimated as per Equation (3) and measured in fiscal year t+1. The explanatory variables are measured in fiscal year t or earlier. For variable definitions and details of their computation, see the Appendix. The estimates include a constant, conditional year and industry fixed effects and control variables, whose coefficients are suppressed. The detailed coefficients of the control variables are presented in the Internet Appendix. Industry fixed effects are defined based on the Fama–French 48-industry classification. All continuous variables are winsorized at the 1st and 99th percentiles and are standardized to have a mean value of zero and a variance of one. Robust standard errors clustered at the firm level are shown in parentheses. The symbols ***, ** and * denote two-tailed statistical significance at the 1%, 5% and 10% level, respectively.

Collectively, the graphical and regression results leave little space for the possibility that managers exploit the opacity and overinvestment channels to strategically conceal negative information to benefit themselves at the expense of shareholders, especially in the post-SOX period.

Potential avenues for future research

In this section, we endeavour to encourage researchers to seek possible alternative explanations for the stock price crash risk phenomenon. Our approach is mostly descriptive, aiming to stimulate future research in the area, and it is non-exhaustive since possibly there are other explanations that elude our attention.

We believe that our study offers conclusive evidence to unveil the inefficacy of opacity and overinvestment as agency channels in rationalizing the stock price crash risk puzzle in the post-SOX period. Yet, we note that there might be other agency channels that managers could commit to opportunistic behaviour and indulge in excessive benefits for themselves. Accordingly, the economics of expectations might provide a potential alternative channel (e.g. Walentin, 2014; Shiller, 2020). Under this paradigm, incentivized managers might be tempted to obfuscate information regarding their firms' prospects by engaging in 'cheap talk', misrepresenting their firms' prospects pertaining to 'uncertain and hard to verify information' with the intention of maximizing short-term value (e.g. Balvers, Gaski and McDonald, 2016; Adams, Murphy and Clarke, 2009; Andreou *et al.*, 2021; Ni, Wang and Yin, 2021).

Along the line of the economics of expectations, there is recent evidence suggesting that expectations become more relevant as we move from an industrial economy to a 'new economy' relying heavily on services and information technology (Barth, Li and McClure, 2022). In a world where stock prices are primarily determined by intangible assets and growth opportunities that are hard to measure and value, an accurate forecast of their valuation prospects is a challenging task (Roper and Love, 2002; Artz *et al.*, 2010; Gao *et al.*, 2013). Thus, in more recent years, managers might have more leeway in exploiting soft information to manipulate investors' expectations. For example, Wu and Lai (2020) provide stimulating evidence suggesting that intangible-intensive firms are more prone to experience future stock price crashes, by

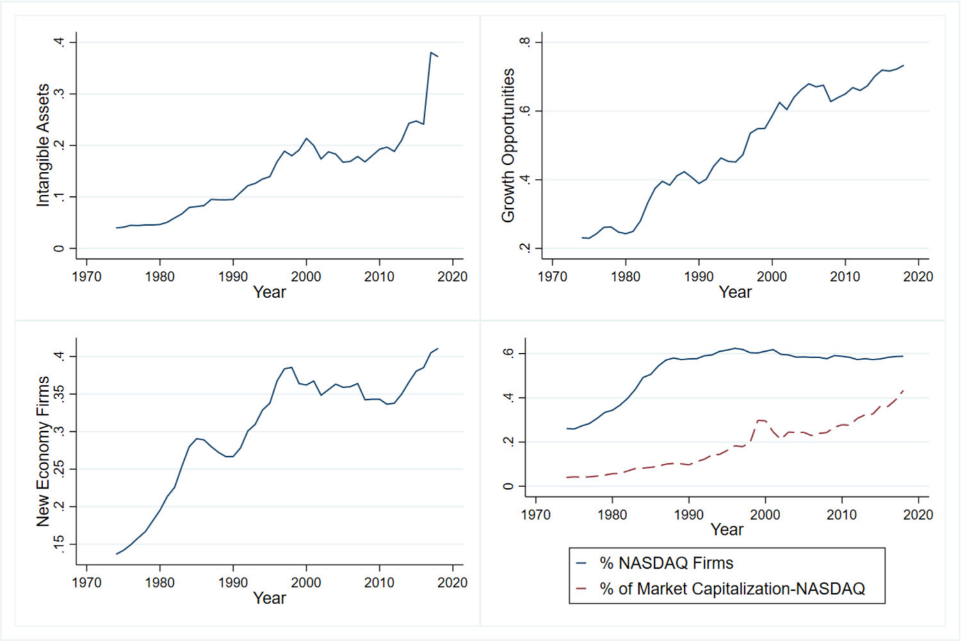

Figure 7. Time evolution of intangible assets, growth opportunities, new economy firms and NASDAQ firms. This figure depicts the average value of intangible assets and growth opportunities, as well as the proportion of new economy and NASDAQ firms for the CRSP–Compustat universe from 1974 to 2019. Intangible Assets *are defined as intangible assets per total assets.* Growth Opportunities *are defined as cash and short-term investments per total assets. As per Barth, Li and McClure (2022), a firm is classified as a 'new economy' firm if it is in a technology industry (three-digit SIC industries, i.e. 283, 357, 360–368, 481, 737 and 873) or had its IPO in 1971 or latter and reported a loss in its IPO year; accordingly, the subfigure in the bottom-left corner reports the proportion of CRSP–Compustat firms that can be considered as belonging in the new economy.* % NASDAQ Firms *is the proportion of CRSP–Compustat firms that are listed on the NASDAQ and* % of Market-Capitalization-NASDAQ *is the market capitalization of firms listed on the NASDAQ divided by the market capitalization for all firms in the CRSP–Compustat universe [Colour figure can be viewed at wileyonlinelibrary.com]*

highlighting the fragility of intangible assets that increases information asymmetry and the uncertainty of firm valuations.

Other recent evidence suggests that managers opportunistically exploit heightened attention around investor conferences to hype expectations (Bushee, Taylor and Zhu, 2022). Also, there is evidence suggesting that the conveying of positive signals pertaining to technology and innovation capabilities may retain or enhance investor interest (Merkley, 2014; Yekini, Wisniewski and Millo, 2016; Giannetti and Yu, 2021; Andreou *et al.*, 2021). Such behaviours can hype investors' expectations and drive stock values well beyond those justified by economic fundamentals, which makes a firm more susceptible to future crashes.

To provide some conceptual evidence for the link between the economics of expectations and crashes, in Figure 7 we present the time evolution of: (i) intangibles, defined as intangible assets per total assets; (ii) growth opportunities, defined as cash and short-term investments per total assets; (iii) the proportion of firms that belong to the new economy, whereby a firm is classified as a 'new economy firm' according to Barth, Li and McClure (2022) if it is in a technology industry (three-digit SIC industries, i.e. 283, 357, 360–368, 481, 737 and 873) or had its initial public offering (IPO) in 1971 or latter and reported a loss in its IPO year; and (iv) the proportion of US-listed firms traded on the NASDAQ, which includes leading companies in technology as well as companies in other cutting-edge industries like biotechnology. The graphical evidence unveils a persistently upward-sloping trend not only in the levels of intangible assets and growth opportunities, but also the proportion of firms that belong to the new economy or trade on the NASDAQ. To the degree that these upward trends associate with increasing opportunities for managers to hype investors' expectations, exploring the economics of the expectations channel might offer a promising avenue in rationalizing the stock price crash risk puzzle.

Future research could also seek possible explanations within the behavioural economics arena. For example, Shiller (2020) argues that if market participants fail to justify their choices by assessing the firm's true economic fundamental values, and are instead driven by irrational exuberance, then speculative bubbles and crashes become inevitable (see also Shiller, 2003; Barberis and Thaler, 2005; Singh, 2012; De Bondt, 2018; Bayer, Mangum and Roberts, 2021).[10] Shiller urges researchers to enhance their investigations by testing them against the evidence that the level of stock prices does not merely reflect the total available economic information, as rationality assumes.

In the fourth industrial revolution era in which we live, modern information technologies facilitate the dissemination of information to a significantly greater and broader extent (Gao and Huang, 2020; Ni, Wang and Yin, 2021). For example, Blankespoor, deHaan and Zhu (2018) discuss how algorithms give rise to robo-journalism articles that synthesize information from firms' press releases, analyst reports and stock performance and are widely disseminated by major news outlets a few hours after the earnings release. In this regard, the problem of speculative bubbles is possibly heightened because positive news is spun more quickly and to greater audiences. The paper by Barber *et al.* (2022) also discusses how apps like Robinhood indulge new and inexperienced investors through 'added features to make investing more like a game', something that overemphasizes the fun of trading. The authors suggest that with turnover rates many times higher than those of other brokerage firms, Robinhood users are more likely to trade speculatively and have the potential to move stock prices in mostly uninformative ways. Ergo, one could consider whether trading activity has intensified over the years, as information technologies and especially user-friendly and low-cost fintech brokerage have boosted the market participation of a greater number of inexperienced and uninformed traders, who do not possess the sophistication to correctly infer the content of the information (Ozik, Sadka and Shen, 2021).

Motivated by the above arguments, we provide some stimulating evidence regarding the time evolution of: (i) average trading volume to total market capitalization, calculated as the average daily trading volume accumulated across all firms within a fiscal year, divided by the total market capitalization at the fiscal year-end and (ii) the proportion of firms that are traded above their historical average trading volume, calculated as the number of firms with their average trading volume in fiscal year t higher compared to their historical average trading volume, divided by the number of firms in that year.

The evidence depicted in Figure 8 illustrates a steadily increasing trend in both measures. Interestingly, trading activity gets heightened during the COVID-19 pandemic lockdown. This evidence is consistent with Ozik, Sadka and Shen (2021), who report that because of ample free time and access to financial markets facilitated by fintech innovations, the stock market participation of inexperienced retail investors exhibited a sharp increase during this period. Inexperienced investors, however, are unlikely to have developed their own clear criteria for buying stock, and are more heavily influenced by biases that lead to returns-chasing and overly trading activity at the cost of sound investment practices (e.g. Seasholes and Wu, 2007; Greenwood and Nagel, 2009; Barber *et al.*, 2022). To the extent that the surge in trading volume is driven by the increased participation of unsophisticated investors who are susceptible to biases and engage in speculative trades, the evidence in Figure 8 may encourage future research endeavouring to investigate the effects of the trading behaviour of retail investors on crash risk.[11]

Finally, we suggest that researchers also turn their attention to the methodologies employed to operationalize stock price crashes. Hitherto, some researchers estimate the idiosyncratic weekly

[10]Shiller (2000) postulates that irrational exuberance is akin to a misinterpretation driven by enthusiasm, or bad judgement, which derives from ignoring or partially understanding what we want to understand, and it is the psychological basis of a speculative bubble. Some other similar psychological factors that have intrigued the interest of researchers include 'mania' (Ofek and Richardson, 2003), 'animal spirits' (Akerlof and Shiller, 2010) and 'sentiment' (Baker and Wurgler, 2006).

[11]Trading volume investigations could potentially be linked to financial market explanations for crash risk, elaborating on the role of investor disagreement in asset pricing as in the Hong and Stein (2003) model. This is because trading volume proxies for the intensity of disagreement and – based on the Hong–Stein model – negative skewness (i.e. higher crash risk) in stock returns will be most pronounced around periods of heavy trading volume (see further discussions and empirical evidence in Chen, Hong and Stein, 2001).

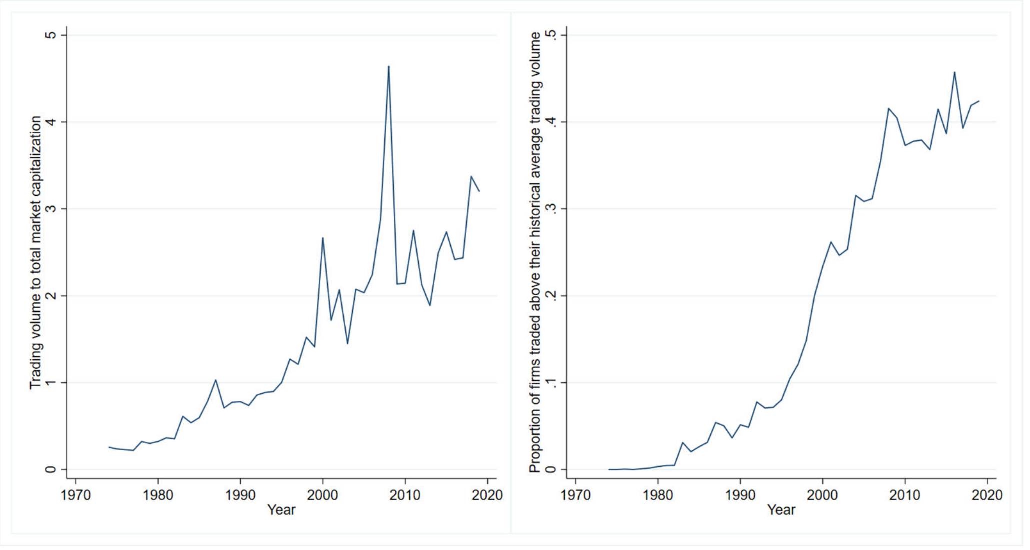

Figure 8. Time evolution of the trading volume to total market capitalization and proportion of firms traded above their historical average trading volume. This figure depicts the average value of trading volume to total market capitalization and the proportion of firms that trade above their historical average trading volume for the CRSP–Compustat universe from 1974 to 2019. The average trading volume to total market capitalization is estimated as the average of the daily trading volume within a fiscal year for all CRSP–Compustat firms, divided by their market capitalization at year-end. The proportion of firms that trade above their historical average trading volume is estimated as the number of firms in the CRSP–Compustat universe with their daily average trading volume within year t *higher then their historical daily average trading volume, divided by the total number of firms in the CRSP–Compustat universe within year* t*. The historical daily average trading volume for a firm is computed with all available data in the CRSP–Compustat universe up to year* t − 1 *[Colour figure can be viewed at wileyonlinelibrary.com]*

returns as the residuals coming from an index model – in the spirit of Equation (2) – that sometimes considers only information from the CRSP value-weighted market index return (e.g. Kim, Li and Zhang, 2011a, 2011b; Andreou *et al.*, 2016; Kubick and Lockhart, 2016), while in some other cases it considers information from both the CRSP value-weighted market index return and a value-weighted industry index return (e.g. Callen and Fang, 2013; An and Zhang, 2013; Kim and Zhang, 2016; Francis, Iftekhar and Lingxiag, 2016). Also, the crash literature primarily utilizes two different cut-off points in accordance with Equation (3). In one stream of studies, a 'crash week' is defined in the spirit of Hutton, Marcus and Tehranian (2009) and CRASH is set equal to one when the idiosyncratic weekly returns fall at least 3.09 standard deviations below the mean idiosyncratic weekly return; in another stream, CRASH is defined in the spirit of Kim, Li and Zhang (2011a, 2011b) and set equal to one when the idiosyncratic weekly returns fall at least 3.20 standard deviations below the mean idiosyncratic weekly return.

Contemplating the above and to spark interest, we investigate whether the persistent upward trend in crash occurrences is merely the outcome of methodological configurations. In this vein, Figure 9 considers 12 alternative configurations for the estimation of CRASH as per Equation (3) and PCRASH as per Equation (4) using: (i) three different cut-off points of $\lambda = (3.09, 3.20, 3.50)$ and (ii) two different versions of idiosyncratic returns, one that follows in step with Equation (2) and another (reduced version) that only includes the CRSP value-weighted market index return terms.

The evidence depicted in Figure 9 shows a steadily upward trend in crash incidents, irrespective of the configuration used. Albeit the stock price crash risk puzzle continues to persist with alternative configurations of the traditional method, it may fade away if the incidence of low-probability events that produce large, negative outliers in the distribution of idiosyncratic returns were to be estimated using the extreme value theory approach. In this direction, Andreou *et al.* (2022) employ a method in which crashes are directly estimable from conditional extremal quantiles of idiosyncratic returns. While such methods seem to conform to the extremeness that characterizes the nature of crashes, more work is

Figure 9. Time evolution of stock price crash occurrences for the average US-listed firm. This figure depicts the frequencies of stock price crashes using various alternative configurations for the CRSP–Compustat universe from 1974 to 2019. The sample comprises common stocks (share codes 10 and 11) traded on the NYSE, AMEX or NASDAQ, with stock price greater than 1 USD at the end of the fiscal year, and more than 26 weeks of stock returns in a fiscal year. CRASH *is defined in Equation (3) as a binary variable set equal to one for fiscal years when a firm experiences at least one 'crash week', and zero otherwise.* PCRASH *is defined in Equation (4) as a binary variable set equal to one if, within a fiscal year, the firm experiences at least one 'crash week' and no 'jump week'. A 'crash week' is when an idiosyncratic weekly return falls by at least λ standard deviations below its mean value during the fiscal year. Symmetrically, a 'jump week' is when an idiosyncratic weekly return exceeds at least λ standard deviations above its mean value during the fiscal year. The different permutations consider three values λ = 3.09, 3.20, 3.50. In the spirit of Equation (2), the idiosyncratic weekly returns are estimated as the residuals from an index model regression that either includes only the CRSP value-weighted market index return (M) or both the CRSP value-weighted market index return and the Fama and French (1997) value-weighted 48-industry index return (M&I). The cut-off value for λ and the configuration for the index regression model are shown in parentheses next to the type of crash operationalization (*CRASH *or* PCRASH*) [Colour figure can be viewed at wileyonlinelibrary.com]*

necessary to understand their time-series dynamics and whether they can resolve the stock price crash risk puzzle.

Conclusion

This study surfaces a puzzling phenomenon whereby the occurrence of stock price crashes for US-listed firms rose steadily from 5.5% in 1950 to 27% in 2019. Assessing this puzzling phenomenon from the agency theory viewpoint, it should be possible to attribute the increasing occurrence of crashes to opacity and overinvestment. This is because prior literature has relied extensively on these two agency channels to theorize that managers exploit them to manifest their self-interested strategies at the expense of shareholders. Yet, we provide compelling empirical evidence suggesting that in the post-SOX period, both opacity and overinvestment could only play a limited role in explaining the uptrend occurrence of stock price crashes.

The results derived from the multivariate regression analyses in the post-SOX period provide robust evidence suggesting that after controlling for financial characteristics, managerial equity-based incentives and corporate governance, there is still a notable absence of any statistically significant relation either for opacity or overinvestment with future crash risk.

All things considered, our findings show that while crashes have become increasingly prevalent in the post-SOX period, US-listed firms have also become more transparent and less likely to overinvest, and at the same time, they seem to have stronger corporate governance functions that enhance board purview and oversight of management's actions. In addition to the empirical evidence that we provide in this study, the enactment of several corporate governance regulations and standards aiming to combat managerial opportunism in the real world also suggest that agency problems should have attenuated in the past two decades. As such, the agency viewpoint of opacity and overinvestment seems less capable of offering an adequate explanation of the surge in stock price crashes for the average US-listed firm.

Finally, this study offers a discussion of various routes for future research to pursue in rationalizing the stock price crash risk puzzle. As such, it seeks to expand the stock price crash literature by highlighting alternative channels that have the potential to explain the upsurge occurrence of stock price crashes.

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Appendix: Variable definitions

Panel A: Crash risk

CRASH	A binary 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. Firm-specific weekly returns are estimated using Equations (1) and (2). [Source: CRSP]
PCRASH	A binary variable set equal to one if a firm experiences at least one 'crash week' and not a 'jump week' within the 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. A 'jump week' is when the firm-specific weekly returns exceed at least 3.09 standard deviations above the average firm-specific weekly return value during the fiscal year. Firm-specific weekly returns are estimated using Equations (1) and (2). [Source: CRSP]
NCSKEW	The negative of the third moment of firm-specific weekly returns within the fiscal year, divided by the associated standard deviation of firm-specific weekly returns raised to the third power. Firm-specific weekly returns are estimated using Equations (1) and (2). [Source: CRSP]
DUVOL	The log difference of volatilities, derived from the positive and negative firm-specific weekly returns. Firm-specific weekly returns are estimated using Equations (1) and (2). [Source: CRSP]
COUNT	The number of 'crash weeks' minus the number of 'jump weeks' occurring within a fiscal year. Firm-specific weekly returns are estimated using Equations (1) and (2). [Source: CRSP]
NCMRET	The distance − in terms of standard deviations − between the minimum idiosyncratic weekly return from the mean of the idiosyncratic returns over the weeks that fall within a fiscal year. Firm-specific weekly returns are estimated using Equations (1) and (2). [Source: CRSP]
LEFTA	A binary variable set equal to one if the probability of negative extreme idiosyncratic returns is greater than the probability of positive extreme idiosyncratic returns within a fiscal year. We compute this measure where the probabilities are evaluated at the 1st and 99th percentiles (i.e. 2.58 standard deviation away from the mean). [Source: CRSP]

Panel B: Channels of stock price crashes

Opacity	Following Hutton, Marcus and Tehranian (2009), discretionary accruals (DiscAcc) are measures based on the modified Jones model (Dechow, Sloan and Sweeney, 1995). The following equation is estimated cross-sectionally per fiscal year for each of the Fama and French (1997) 48 industries: $\frac{TA_t}{ASSETS_{t-1}} = a_o \frac{1}{\mathrm{ASSETS}_{t-1}} + b_1 \frac{\Delta\mathrm{SALES}_t}{\mathrm{ASSETS}_{t-1}} + b_2 \frac{\mathrm{PPE}_t}{\mathrm{ASSETS}_{t-1}} + e_t$, where TA denotes total accruals (income before extraordinary items minus cash flow from operating activities adjusted for extraordinary items and discontinued operations), $ASSETS$ denotes the firm's total assets, $\Delta SALES$ denotes the change in sales and PPE denotes property, plant and equipment. Then, the estimated coefficients from the previous are used to calculate DiscAcc as follows: $\mathrm{DiscAcc}_t = \frac{\mathrm{TA}_t}{\mathrm{ASSETS}_{t-1}} - (\hat{a}_o \frac{1}{\mathrm{ASSETS}_{t-1}} + \hat{b}_1 \frac{\Delta\mathrm{SALES}_t - \Delta\mathrm{RECEIVABLES}_t}{\mathrm{ASSETS}_{t-1}} + \hat{b}_2 \frac{PPE_t}{\mathrm{ASSETS}_{t-1}})$, where $\Delta RECEIVABLES$ is the change in accounts receivable. Finally, opacity is measured as the 3-year moving sum of the absolute value of discretionary accruals (DiscAcc): $\mathrm{Opacity}_t = \lvert\mathrm{DiscAcc}_t\rvert + \lvert\mathrm{DiscAcc}_{t-1}\rvert + \lvert\mathrm{DiscAcc}_{t-2}\rvert$, whereby a higher value of opacity indicates that a firm's financial reporting becomes less transparent, resulting in a dearth in publicly available firm-specific information. [Source: Com-pustat]
Over-investment	Following Richardson (2006), overinvestment is measured as the 3-year abnormal investment, beyond the necessary amount to maintain assets in place and to finance expected new investments as follows: $\mathrm{Overinvestment}_t = \mathrm{I}^{\epsilon}_{\mathrm{NEW}_t} + \mathrm{I}^{\epsilon}_{\mathrm{NEW}_{t-1}} + \mathrm{I}^{\epsilon}_{\mathrm{NEW}_{t-2}}$ where $\mathrm{I}^{\epsilon}_{\mathrm{NEW}_t}$ is derived from the following model: $\mathrm{I}_{\mathrm{NEW}_t} = a_o + b_1 \frac{\mathrm{V}_{\mathrm{AIP}}}{\mathrm{MV}_{t-1}} + b_2\mathrm{LEVERAGE}_{t-1} + b_3\mathrm{CASH}_{t-1} + b_4\mathrm{AGE}_{t-1} + b_5\mathrm{SIZE}_{t-1} + b_6\mathrm{STOCK\ RETURN}_{t-1} + b_7\mathrm{I}_{\mathrm{NEW}_{t-1}} + \mathrm{I}^{\epsilon}_{\mathrm{NEW}_t}$,

Panel B: Channels of stock price crashes	
	with: $\mathrm{I}_{\mathrm{NEW}} = \mathrm{I}_{TOTAL} - \mathrm{I}_{MAINTENANCE}$, where I_{TOTAL} denotes the total investment expenditure and $\mathrm{I}_{MAINTENANCE}$ denotes the investment expenditure necessary to maintain assets in place, both scaled with total assets measured at the beginning of the fiscal year. I_{NEW} is decomposed into the expected investment expenditure in new projects, and unexpected (or abnormal) investment as captured by the residual term $\mathrm{I}^{\epsilon}_{NEW}$. The abnormal investment, which can be positive (negative), denotes the overinvestment (underinvestment) in a fiscal year. V_{AIP} denotes the value of assets in place and is measured as: $V_{AIP} = (1 - ar)BV + (1 + r)OI - arD$, 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 is equal to 0.62. Further, 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. [Source: Compustat and CRSP]
Panel C: Firm characteristics	
Stock Return	Average firm-specific weekly return during the fiscal year. [Source: CRSP]
Detrended Turnover	The detrended average weekly stock trading volume during the fiscal year. [Source: CRSP]
Size	The natural logarithm of total assets (AT). [Source: Compustat]
Firm Age	The number of years that the firm is covered in the Compustat universe. [Source: Compustat]
Market to Book	Market to book value of equity (CSHO × PRCC_F)/CEQ. [Source: Compustat]
Leverage	Total liabilities (LT) divided by total assets (AT). [Source: Compustat]
Zscore	The fitted value using the updated coefficients of the model proposed by Altman, following Hillegeist *et al.* (2004). [Source: Compustat]
Return on Equity	The ratio of income before extraordinary items (IB) to book value of equity (CEQ). [Source: Compustat]
Panel D: Corporate governance functions	
CEO Duality	An indicator variable set equal to one if the CEO is also the chairman of the board, and zero otherwise. [Source: Execucomp]
Independent Directors	The percentage of independent directors estimated as the number of independent directors divided by board size. [Source: ISS]
Female Directors	An indicator variable set equal to one if the firm has more than one female director on the board, and zero otherwise. [Source: ISS]
Not Attended Directors	The percentage of not attended directors estimated as the number of directors who attended less than 75% of board meetings divided by board size. [Source: ISS]
Transient Institutional	The percentage of stock ownership in the firm owned by transient institutional investors, where, following Bushee and Noe (2000) and Bushee (2001), transient investors are denoted as those with high portfolio turnover and diversified portfolios. [Source: Thomson Reuters Institutional (13F) Holdings and Professor Brian Bushee's personal website]
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. [Source: Compustat]
Auditor Tenure	Number of consecutive fiscal years that the auditor (AU) has been retained by the client, up to and including the current year, following Callen and Fang (2017). [Source: Compustat]
Panel E: CEO incentives	
Stock Incentives	The CEO/CFO stock holdings incentives ratio estimated as in Bergstresser and Philippon (2006) as ONEPCT_S / (ONEPCT_S + SALARY + BONUS), where ONEPCT_S = 0.01 × PRICE × SHARES; PRICE is the share price at the fiscal year end, SHARES is the number of shares held by the CEO and SALARY and BONUS are the CEO's/CFO's salary and bonus, respectively. [Source: Execucomp]
Option Incentives	The CEO/CFO option holdings incentives ratio estimated as in Bergstresser and Philippon (2006) as ONEPCT_O / (ONEPCT_O + SALARY + BONUS), where ONEPCT_O = 0.01 × PRICE × OPTIONS; PRICE is the share price at the fiscal year end, OPTIONS is the number of options held by the CEO and SALARY and BONUS are the CEO's/CFO's salary and bonus, respectively. [Source: Execucomp]

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Supporting Information

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