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PRODUCTIVITY UNCERTAINTY AND STOCK PRICE CRASH RISK

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Abstract

This study examines the impact of productivity uncertainty on stock price crash risk. Empirical results show that higher productivity uncertainty contributes to higher stock price crash risk. This effect holds firmly after addressing potential endogeneity and the performing of robustness tests. Moreover, the positive impact of productivity uncertainty on stock price crash risk is more pronounced for firms with weak market competition and less independent boards. The findings of this study are meaningful as they offer a risk-based explanation for stock price crash risk which is based on the presumption of investors' behaviours, and the examination of channel effect further supports this view.

JEL Codes: G30, G32

Keywords: **Productivity Uncertainty, Stock Price Crash Risk, Monitoring**

1. Introduction

The distribution of stock returns is often non-symmetric and displays negative skewness. It means that sizable negative stock returns are more frequently observed than large positive stock returns, a phenomenon referred to the concept of stock price crash risk (Harvey and Siddique, 2000; Chen et al., 2001; Conrad et al., 2013; Kim et al., 2014). The mainstream argument for the cause of stock price crash risk, as evidenced by Jin and Myers (2006), Hutton et al. (2009), and Kothari et al. (2009), is based on the notion that management has motivations to hoard negative news for prolonged periods of time. After the cumulation of negative news reaches the tipping point, the sudden release to the market leads the stock price to plummet. Guided by this argument, from different perspectives, various groups of subsequent studies have made efforts to explore factors that would potentially affect the stock price crash risk: financial reporting (e.g., Hutton et al., 2009; De Fond et al., 2015; Kim et al., 2016; Chen et al., 2017a); managerial incentives (e.g., Kim et al., 2011a; He, 2015; Park, 2017); capital market characteristics (e.g., Chen et al., 2001; Callen and Fang, 2015b; Chang et al., 2016); corporate governance (e.g., Xu et al., 2014; Andreou et al., 2016; Chen et al., 2017b); informal institutions (e.g., Callen and Fang, 2015a; Cao et al., 2016; Lee and Wang, 2017).

However, could companies' stock price crash risk be due to the nature of their fundamental business risk? This is an aspect that has received little attention by previous studies. For example, energy companies may have very risky field operations and are subject to the fluctuations of global energy price movements; technology companies may have niche markets and face fierce competition. If positive news and negative news are not symmetrically released or priced by the market, then stock returns of those firms may exhibit negative skewness, i.e., stock price crash risk. Cao et al. (2002) lay the groundwork for this risk-based explanation. Their study introduces the "information blockage effect". The effect indicates that an upward stock price trend is forged and maintained by informed investors through active trading. But less informed investors normally are wary and delay their market participation until the stock price plummets. In other words, bullish stock price movements are mainly pushed up by informed investors. However, bearish stock price movements are compounded by the selloffs of both informed and less informed investors. Hong & Stein (2003) laterally support the "information blockage effect" by proposing a model based on investors' opinions. Their model suggests that bearish investors normally don't participate in the market in time because of short-sales constraints so their negative sentiment is not revealed initially. However, when bullish investors exit the market, those originally bearish investors tend to become marginal buyers. Hence, the prior hidden negative information shows up and leads to the stock price crash. Moreover, the "information blockage effect" also echoes the so-called "volatility feedback effect". Proposed by prior studies such as French et al. (1987), Campbell and Hentschel (1992), Bekaert and Wu (2000), Wu (2001), and Carr and Wu (2017), the "volatility feedback effect" suggests that investors would re-adjust their assessment of stock volatility and increase required risk premiums when they observe stock price movements in large magnitudes. This investing behaviour tends to reinforce the impact of negative information but offset the effect of positive information, thus leading to the formation of negative skewness. Therefore, based on the two effects proposed by prior studies, it is plausible to envision that firms' business risk might be related to stock price crash risk.

A firm's business risk is largely captured by its productivity uncertainty, measured by the riskiness of cash flow per unit of asset (Zhao and Sing, 2016). Previous literature indicates that firms with higher productivity uncertainty, though proxied by different factors, exhibit greater financial constraints in various channels. Moshirian et al. (2017) and Harris and Roark (2019) document that firms with high productivity uncertainty exhibit low levels of capital investment. The values of prospective investment projects are determined by firms' discount rates. However, firms with high productivity uncertainty are considered risky so their discount rates are high because investors would demand high rates of return to compensate for bearing the risk. High discount rates effectively make many potential investment projects unprofitable and force those firms to forgo a large percentage of them. Sometimes those companies may have to invest in projects with negative NPVs and subsequently, firm values are decreased. Hirth and Uhrig-Homburg (2010) and Hirth and Viswanatha (2011) suggest that firms with high productivity uncertainty are associated with high financing costs and possible liquidity issues. When markets experience friction and shocks, this effect is largely magnified. Keefe and Yaghoubi (2016) echo these studies by showing that productivity uncertainty has a significant impact on capital structure, as firms with higher cash flow risk tend to use higher financial leverage and are subject to greater distress risk. In summary, although these prior studies are from different perspectives and yield different results of productivity uncertainty, they all support the argument that higher productivity uncertainty implies higher financial risk. Since financial risk is observed and priced by investors who are subject to the aforementioned "information blockage effect" and "volatility feedback effect", productivity uncertainty is hypothesized to be positively associated with stock price crash risk.

Using a comprehensive dataset from 2001 to 2021, this study finds that productivity uncertainty is significantly positively associated with stock price crash risk. This positive relationship holds firmly after addressing potential endogeneity and the performing of robustness tests. Also, the influence of monitoring quality is tested for firms with different levels of market competition and board independence. The findings of this study are meaningful because many prior studies of stock price crash risk build on the argument that management has motivations to hoard negative information. However, under the presumption of investors' behaviours, this study demonstrates that firms' business risk, proxied by productivity uncertainty, is a significant source of stock price crash risk.

The paper is organized as follows: Section 2 details the research design. Section 3 exhibits the empirical results and robustness tests. Section 4 concludes this study.

2. Research Design

2.1 Sample Description

This study uses multiple data sources to construct a comprehensive sample of publicly traded firms from 2001 to 2021. Firm fundamental data are obtained from the COMPUSTAT database. The measures of stock price crash risk are calculated by using stock performance data retrieved from the Center of Research in Security Prices (CRSP). Board information is garnered from the BoardEx database. Auxiliary data are obtained from Bloomberg and I/B/E/S database. Due to high regulation, financial firms, and utility firms (4-digit SIC 6000-6999 and 4900-4999) are excluded. For the concern of the potential impact of low liquidity, following prior studies (e.g., Hutton et al., 2009; Kim et al., 2011a, 2011b; Kim et al., 2014; Kim et al., 2016), observations are dropped for those with year-end closing stock price below $1, fewer than 26 weeks of return data, negative book value of total assets, or insufficient data entries. The finalized sample contains a number of 39,126 firm-year observations.

2.2 Measures of Productivity Uncertainty

According to Zhao and Sing (2016), a company's productivity refers to the notion of output per unit of capital. It is estimated by the cash flow from operations divided by the book value of total assets, denoted as *CFOA*. Two measures of productivity uncertainty are constructed as follows: as shown in Eq. (1) and denoted as *PUCA*, the first measure is the rolling standard deviation of a firm's *CFOA* over the last five years. Hence, companies with high productivity uncertainty would exhibit high values of *PUCA*. In order to capture the effect of potential business cycle shocks, as shown in Eq. (2) and denoted as *PUCI*, the second measure is the rolling standard deviation of a firm's time-variant productivity deviations from the industry average over the last five years, where $CFOI_{i,t} = CFOA_{i,t} - \frac{1}{N}\sum_{i=1}^{N} CFOA_{i,t}$ and *N* is the number of firms in the same industry of firm i.

$$PUCA = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(CFOA_{i,t} - \frac{1}{T}\sum_{t=1}^{T} CFOA_{i,t})^2} \qquad (1)$$

$$PUCI = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(CFOI_{i,t} - \frac{1}{T}\sum_{t=1}^{T} CFOI_{i,t})^2} \qquad (2)$$

2.3 Measures of Stock Price Crash Risk

Following Chen et al. (2001), Kim et al. (2011a, 2011b), and Kim et al. (2014), this study employs two well-acknowledged measures of stock price crash risk, i.e., negative conditional skewness denoted as *NCSKEW* and down-to-up volatility denoted as *DUVOL*. These two measures are both derived from firm-specific weekly returns that are calculated by using the residuals of a market model shown in Eq. (3). Specifically, a firm-specific weekly return $W_{i,\tau}$ is the natural logarithm of one plus the residual return, i.e., $W_{i,\tau} = \text{Ln}(1+\hat{\varepsilon}_{i,\tau})$. The advantage of this approach is that it controls the influence of broad market movements and delivers the unique information of an individual firm's stock price crash risk.

$$r_{i,\tau} = \alpha_i + \beta_{1,i} r_{m,\tau-2} + \beta_{2,i} r_{m,\tau-1} + \beta_{3,i} r_{m,\tau} + \beta_{4,i} r_{m,\tau+1} + \beta_{5,i} r_{m,\tau+2} + \varepsilon_{i,\tau} \qquad (3)$$

The first measure of stock price crash risk called negative conditional skewness (*NCSKEW*), as shown in Eq. (4), is calculated by using the third moment of $W_{i,\tau}$ which is normalized by the standard deviation of $W_{i,\tau}$ to the power of three, where n is the number of observations of a firm's $W_{i,\tau}$ in a given year. The negative sign is put before the mathematical expression so that a higher value of *NCSKEW* indicates higher stock price crash risk. The second measure of stock price crash risk is the down-to-up volatility (*DUVOL*) which is specified in Eq. (5). For an individual firm in a given year, its weekly returns, i.e., $W_{i,\tau}$, are classified into two groups: "down weeks" group and "up weeks" group. The "down weeks" group contains all weekly returns below the annual average and the "up weeks" group contains all weekly returns above the annual average. *DUVOL* is constructed by taking the natural logarithm of the standard deviation of $W_{i,\tau}$ of the "down weeks" group divided by the standard deviation of $W_{i,\tau}$ of the "up weeks" group. In a given year, n_d is the number of $W_{i,\tau}$ belonging to the "down weeks" group and n_u is the number of $W_{i,\tau}$ belonging to the "up weeks" group. Similar to the direction interpretation of *NCSKEW*, a higher value of *DUVOL* indicates higher stock price crash risk. Table 1 presents the summary statistics for all variables. An average firm has a stock price crash risk measure of 0.126 and -0.013 in *NCSKEW* and *DUVOL* respectively. Meanwhile, it has a productivity uncertainty measure of 0.865 and 0.824 in *PUCA* and *PUCI* respectively. The estimates are generally comparable and consistent with prior literature such as Kim et al. (2014), Kubick and Lockhart (2016), Beladi et al. (2021) with variations due to different sample selections.

Table 1: Summary Statistics

	Mean	P25	Median	P75	St. Dev.
Main variables					
NCSKEW	0.126	-0.512	0.108	0.529	1.166
DUVOL	-0.013	-0.297	-0.037	0.288	0.461
PUCA	0.865	0.026	0.079	0.136	0.125
PUCI	0.824	0.017	0.072	0.128	0.098
Control variables					
DTURN	0.019	-0.246	0.012	0.255	0.391
RET	-0.229	-0.330	-0.217	-0.115	0.766
MB	2.186	1.365	1.752	3.359	1.763
SIZE	7.628	6.643	7.531	8.672	1.689
SIG	0.059	0.037	0.056	0.725	0.030
LEV	0.179	0.006	0.141	0.275	0.181
ROA	0.077	0.011	0.095	0.163	0.156
ACCU	0.361	0.061	0.264	0.508	0.322

$$NCSKEW = -\left[n(n-1)^{3/2}\sum W_{i,\tau}^{3}\right] / \left[(n-1)(n-2)\left(\sum W_{i,\tau}^{2}\right)^{3/2}\right] \quad (4)$$

$$DUVOL = Ln\left\{(n_u-1)\sum_{down} W_{i,\tau}^{2} / (n_d-1)\sum_{up} W_{i,\tau}^{2}\right\} \quad (5)$$

2.4 Methodology

To empirically test the effect of productivity uncertainty on stock price crash risk, this study specifies a multivariate regression model as the follows:

$$CRASH\_RISK_{i,t} = \beta_0 + \beta_1 PROD\_UNCTY_{i,t-1} + \beta_2 CRASH\_RISK_{i,t-1} + \beta_3 DTURN_{i,t-1} + \beta_4 RET_{i,t-1} + \beta_5 MB_{i,t-1} + \beta_6 SIZE_{i,t-1} + \beta_7 SIG_{i,t-1} + \beta_8 LEV_{i,t-1} + \beta_9 ROA_{i,t-1} + \beta_{10} ACCU_{i,t-1} + \gamma_{year} + \mu_{ind} + \varepsilon_{i,t} \quad (6)$$

The dependent variable *CRASH_RISK* takes two measures: the negative conditional skewness (*NCSKEW*) and the down-to-up volatility (*DUVOL*). The independent variable *PROD_UNCTY* is proxied by *PUCA* and *PUCI*. Following prior studies represented by Chen et al. (2001), Kim et al. (2011a, 2011b), Kim et al. (2014), and Dang et al. (2022), a set of control variables are defined: the one-year time-lagged *CRASH_RISK* is controlled for potential time-series correlation of the crash risk. *DTURN* measures the average difference of monthly share turnover over the last fiscal year and the year before. *RET* is the average of firm-specific weekly returns. *MB* is the market-to-book ratio, calculated by taking the ratio of market value of equity to the book value of equity. Firm size, i.e., *SIZE*, is measured by the natural logarithm of market value of equity. *SIG* is the standard deviation of firm-specific weekly returns. *LEV* represents a firm's financial leverage, calculated as the ratio of long-term debts to total assets. Return of assets, i.e., *ROA*, is computed as the income before extraordinary items divided by total assets. *ACCU* measures earnings management. It is the absolute value of abnormal accruals derived based on the modified Jones model (Dechow et al., 1995). Year fixed effects and industry fixed effects are controlled in all models.

3. Empirical Results

3.1 The Effect of Productivity Uncertainty on Stock Price Crash Risk

Table 2 presents the regression results of the relationship between productivity uncertainty and stock price crash risk. Columns 1 and 3 employ *PUCA* as the proxy for productivity uncertainty while columns 2 and 4 employ *PUCI*. Stock price crash risk takes two measures, i.e., *NCSKEW* and *DUVOL*, with each of them being regressed on *PUCA* and *PUCI* respectively. Continuous variables are winsorized at the 1st and 99th percentiles and robust standard errors are clustered at the firm-level.

As exhibited in Table 2, the results strongly suggest that a firm's productivity uncertainty is positively associated with stock price crash risk. The estimated coefficients of *PUCA* and *PUCI* are statistically significant at the 5% level or better across all models. In terms of economic significance, column 1 indicates that a one percent increase of *PUCA* leads to 0.026 increase of *NCSKEW* and column 3 shows that a one percent increase of *PUCA* leads to 0.012 increase of *DUVOL*, ceteris paribus. Additionally, columns 2 and 4 also provide very consistent and comparable results for the impact of *PUCI* on *NCSKEW* and *DUVOL* respectively. Under the presumption of the influence of investors' "information blockage effect" and "volatility feedback effect", the evidence is very supportive for the argument that firms with higher productivity uncertainty tend to exhibit greater stock price crash risk. The estimated coefficients of control variables are consistent with prior studies, e.g., Kim et al. (2014), Jebran et al. (2020), and Dang et al. (2022), suggesting that firms with higher past stock return, higher market-to-book ratio, larger size, greater stock volatility, higher ROA, and higher earnings management are associated with greater stock price crash risk.

Table 2: Effect of Productivity Uncertainty on Stock Price Crash Risk

	(1) $NCSKEW_t$	(2) $NCSKEW_t$	(3) $DUVOL_t$	(4) $DUVOL_t$
$PUCA_{t-1}$	0.026**		0.012**	
	(2.12)		(2.31)	
$PUCI_{t-1}$		0.033**		0.015***
		(1.98)		(3.01)
$NCSKEW_{t-1}$	0.008*	0.005		
	(1.76)	(1.61)		
$DUVOL_{t-1}$			0.002	0.002
			(1.12)	(1.35)
$DTURN_{t-1}$	0.012	0.015	0.005	0.003
	(0.52)	(0.31)	(0.66)	(0.79)
RET_{t-1}	0.046***	0.039***	0.012***	0.018***
	(3.82)	(5.26)	(2.98)	(3.31)
MB_{t-1}	0.008***	0.007***	0.003***	0.003***
	(6.82)	(7.19)	(5.56)	(5.82)
$SIZE_{t-1}$	0.018***	0.016***	0.009***	0.009***
	(8.12)	(8.96)	(9.51)	(9.26)
SIG_{t-1}	1.326**	1.256**	0.721***	0.695**
	(2.06)	(1.88)	(2.58)	(2.29)
LEV_{t-1}	-0.079	-0.083	-0.036	-0.032
	(0.26)	(0.31)	(0.61)	(0.55)
ROA_{t-1}	0.296***	0.281**	0.156**	0.161**
	(2.88)	(2.15)	(1.97)	(2.08)
$ACCU_{t-1}$	0.005*	0.006*	0.002*	0.002**
	(1.75)	(1.69)	(1.88)	(1.96)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	39,126	39,126	39,126	39,126
Adj. R-squared	0.056	0.052	0.068	0.065

*Note: This table shows the regressions results of stock price crash risk on productivity uncertainty. As defined in section 2.2 and 2.3, independent variable is measured by PUCA and PUCI and dependent variable is measured by NCSKEW and DUVOL. Control variables are defined in section 2.4 and continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the firm-level. The t-statistics are reported in the parentheses. ***, **, and * represent significance at the 1%, 5% and 10% levels respectively.*

3.2 Addressing Endogeneity

The positive relationship between productivity uncertainty and stock price crash risk may be affected by potential endogeneity. Hence, it is imperative to use econometric methods to address this concern. This study employs two approaches, i.e., two-stage least square regressions and first-difference regressions, to retest the relationship between productivity uncertainty and stock price crash risk. Following prior studies, e.g., El Ghoul et al. (2011), Lin et al. (2013), Kim et al. (2014), two instrumental variables (IV) are individually constructed as follows for productivity uncertainty measures: *IND_PUCA* = $\sum_{j=1}^{M} \frac{PUCA_j}{M}$ and *IND_PUCI* = $\sum_{j=1}^{M} \frac{PUCI_j}{M}$ where *M* is the number of firms in the same Fama-French 48 industry. The meaning of these two instrumental variables is straightforward as they represent the average productivity uncertainty in the same industry. They are ideal IVs because a firm's productivity uncertainty is considered to be vastly correlated with the industry average. Nevertheless, a firm's stock price crash risk is largely influenced by its own productivity uncertainty. Hence, *IND_PUCA* are *IND_PUCI* should be strictly exogenous.

Table 3: Two-stage Least Square Regressions to Address Endogeneity

Panel A. First stage: instrumenting productivity uncertainty		
	(1) PUCA	(2) PUCI
IND_PUCA	0.926*** (6.29)	
IND_PUCI		0.895*** (8.61)
Control variables	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
F-statistic	36.65	42.92

Panel B. Second stage: coefficients of 2SLS regressions				
	(1) $NCSKEW_t$	(2) $NCSKEW_t$	(3) $DUVOL_t$	(4) $DUVOL_t$
$PUCA_{t-1}$	0.046** (2.06)		0.021* (1.89)	
$PUCI_{t-1}$		0.051** (2.28)		0.027** (2.51)
$NCSKEW_{t-1}$	0.006 (1.51)	0.003* (1.69)		
$DUVOL_{t-1}$			0.001 (0.98)	0.001 (0.91)
$DTURN_{t-1}$	0.010 (0.86)	0.012 (0.42)	0.003 (0.76)	0.002 (0.85)
RET_{t-1}	0.068*** (3.12)	0.053*** (4.96)	0.019*** (2.82)	0.018*** (2.99)
MB_{t-1}	0.015*** (7.32)	0.012*** (7.72)	0.005*** (6.82)	0.006*** (7.01)
$SIZE_{t-1}$	0.018*** (8.12)	0.016*** (8.96)	0.009*** (9.51)	0.009*** (9.26)
SIG_{t-1}	1.891*** (2.67)	1.685** (2.27)	1.126** (2.21)	1.092** (2.21)
LEV_{t-1}	-0.112 (0.32)	-0.126 (0.45)	-0.051 (0.89)	-0.045 (0.72)
ROA_{t-1}	0.198** (2.39)	0.212* (1.92)	0.109* (1.79)	0.132** (1.97)
$ACCU_{t-1}$	0.072** (2.06)	0.085** (2.39)	0.019* (1.91)	0.015** (1.82)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	39,126	39,126	39,126	39,126
Adj. R-squared	0.028	0.025	0.039	0.032

*Note: This table displays the results of 2SLS regressions to address endogeneity. IND_PUCA and IND_PUCI are the two instrumental variables defined as the averages of PUCA and PUCI in the same Fama–French 48 industry respectively. Control variables are defined in section 2.4 and continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the firm-level. The t-statistics are reported in the parentheses. ***, **, and * represent significance at the 1%, 5% and 10% levels respectively.*

Table 3 displays the results of the two-stage least square regressions. As shown in Panel A, the first stage instruments the measures of productivity uncertainty by regressing them on instrumental variables along with other control variables. The estimated coefficients of *IND_PUCA* and *IND_PUCI* are both statistically significant at the 1% level. Also, the associated F-statistics are well above 10, suggesting that both instrumental variables are statistically strong. The second stage regresses *NCSKEW* and *DUVOL* on the fitted values of *PUCA* and *PUCI* obtained from the first stage while controlling all control variables. The corresponding estimated coefficients are significant at the 5% level in columns 1, 2, and 4 with a significance of 10% level in column 3. In summary, the results of Table 3 indicate that the positive relationship between productivity uncertainty and stock price crash risk holds firmly after implementing the instrumental variable approach.

Table 4: First-difference Regressions to Address Endogeneity

	(1) $\Delta NCSKEW_t$	(2) $\Delta NCSKEW_t$	(3) $\Delta DUVOL_t$	(4) $\Delta DUVOL_t$
$\Delta PUCA_{t-1}$	0.038** (2.06)		0.018** (2.20)	
$\Delta PUCI_{t-1}$		0.029* (1.88)		0.020** (2.12)
$\Delta NCSKEW_{t-1}$	0.003 (1.51)	0.007 (1.33)		
$\Delta DUVOL_{t-1}$			0.001 (0.99)	0.002 (1.05)
$\Delta DTURN_{t-1}$	0.009 (0.38)	0.011 (0.42)	0.008 (0.41)	0.008 (0.60)
ΔRET_{t-1}	0.021*** (2.86)	0.018** (1.99)	0.010* (1.83)	0.013** (2.39)
ΔMB_{t-1}	0.002 (1.52)	0.003* (1.66)	0.001* (1.70)	0.001 (1.17)
$\Delta SIZE_{t-1}$	0.015* (1.91)	0.014** (2.07)	0.011* (1.85)	0.010* (1.77)
ΔSIG_{t-1}	0.882*** (2.72)	0.797** (2.49)	0.593** (1.98)	0.608*** (3.12)
ΔLEV_{t-1}	0.069 (0.33)	0.059 (0.57)	0.021 (0.29)	0.046 (0.38)
ΔROA_{t-1}	0.127* (1.69)	0.136* (1.75)	0.097** (2.28)	0.102 (1.53)
$\Delta ACCU_{t-1}$	0.008 (1.39)	0.010* (1.80)	0.001 (1.26)	0.002 (0.93)
Year FE	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No
Observations	39,126	39,126	39,126	39,126
Adj. R-squared	0.039	0.042	0.059	0.061

*Note: This table presents the results of first-difference regressions to address endogeneity. All variables are first-differenced to capture the year-over-year temporal changes (Δ denotes the first-difference operator). Continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the firm-level. The t-statistics are reported in the parentheses. ***, **, and * represent significance at the 1%, 5% and 10% levels respectively.*

Moreover, to perform the first-difference regressions, all variables are first-differenced so that the year-over-year temporal changes are captured. Table 4 presents the regression results in which Δ denotes the first-difference operator. The estimated coefficients of *ΔPUCA* and *ΔPUCI* are positively significant at 10% level or better across all columns. The results confirm that the positive relationship between productivity uncertainty and stock price crash risk is evident.

3.3 The Channel Effect of Implied Cost of Equity Capital

As discussed previously, the positive relationship between firms' productivity uncertainty and stock price crash risk is based on the presumption of "information blockage effect" and "volatility feedback effect" (e.g., Cao et al., 2002; Hong & Stein, 2003; Wu, 2001; Carr and Wu, 2017). Although these two theories are from different perspectives to model investors' behaviors, they all support the notion that investors are risk-averse and constantly adjust their risk assessment when information is presented. Since productivity uncertainty reflects a firm's business risk, the information should be captured by the implied cost of equity capital which serves as a channel for investors to exhibit their risk premium sentiment (e.g., Gay et al., 2011; Huber and Huber, 2019; Balakrishnan et al., 2021).

To test this channel effect, following Gebhardt et al. (2001), Claus and Thomas (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005), this study constructs four measures of implied cost of equity capital (denote R_{GLS}, R_{CT}, R_{OJ}, and R_{MPEG} respectively. See Appendix for details). These measures are derived based on analysts' earnings forecasts which serve as the main venues for investors' assessment on firms' riskiness. In general, risky firms tend to have higher implied cost of equity capital and vice versa. The average of the four measures (denote R_{ICEC}) minus the risk-free rate is used for regression analysis to avoid potential deviation caused by a single estimate (e.g., Ghoul et al., 2011; Chen et al., 2011). Two multivariate regression models are specified below. Eq. (7) is used to test the statistical significance of productivity uncertainty on the mediator. Subsequently, Eq. (8) is designed to reveal the channel effect by examining the mediation role of implied cost of equity capital on stock price crash risk. All control variables follow the same definitions as described in section 2.4.

$$R_{ICECi,t} - R_{f,t} = \beta_0 + \beta_1 PROD\_UNCTY_{i,t-1} + \sum CONTROLS + \gamma_{year} + \mu_{ind} + \varepsilon_{i,t} \quad (7)$$

$$CRASH\_RISK_{i,t} = \beta_0 + \beta_1 PROD\_UNCTY_{i,t-1} + \beta_2 (R_{ICEC} - R_f)_{i,t-1} + \sum CONTROLS + \gamma_{year} + \mu_{ind} + \varepsilon_{i,t} \quad (8)$$

Table 5 presents the empirical results for the channel effect of implied cost of equity capital. Panel A. shows that both *PUCA* and *PUCI* are positively and significantly associated with $R_{ICEC} - R_f$. This is the prerequisite for the mediation role and it demonstrates that firms with high productivity uncertainty tend to have high implied cost of equity capital. Panel B. confirms the channel effect as the estimated coefficient of the mediator, i.e., $R_{ICEC} - R_f$, is significant across all models. It is important to note that the coefficient magnitude and statistical significance of *PUCA* and *PUCI* are diminished as compared with those in Table 2, which validates the channel effect.

Table 5: Channel Effect of Implied Cost of Equity Capital

Panel A. Association between productivity uncertainty and mediator		
	(1) $R_{ICEC} - R_f$	(2) $R_{ICEC} - R_f$
PUCA	0.239*** (3.08)	
PUCI		0.305** (2.36)
Control variables	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes

Panel B. Mediation of implied cost of equity capital on stock price crash risk				
	(1)	**(2)**	**(3)**	**(4)**
	$NCSKEW_t$	**$NCSKEW_t$**	**$DUVOL_t$**	**$DUVOL_t$**
$PUCA_{t-1}$	0.018**		0.009*	
	(2.01)		(1.89)	
$PUCI_{t-1}$		0.027*		0.013**
		(1.79)		(2.52)
$(R_{ICEC} – R_f)_{t-1}$	0.012**	0.010**	0.007***	0.005*
	(2.25)	(1.99)	(2.67)	(1.68)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	39,126	39,126	39,126	39,126
Adj. R-squared	0.060	0.055	0.071	0.067

*Note: This table presents the regression analysis for the channel effect of implied cost of equity capital. RICEC is the average of RGLS, RCT, ROJ, and RMPEG. See Appendix for detailed definitions. Rf is the risk-free rate. PUCA, PUCI, NCSKEW, and DUVOL are defined in section 2.2 and 2.3. Control variables are defined in section 2.4 and continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the firm-level. The t-statistics are reported in parentheses. ***, **, and * represent significance at the 1%, 5% and 10% levels respectively.*

3.4 The role of market competition and board independence

From the perspective of agency cost, previous literature argues that management has incentives to hoard negative information for extended periods of time. This type of behaviour causes the buildup of negative information, which leads to the subsequent stock price crash (e.g., Hutton et al., 2009; Kothari et al., 2009). Therefore, if this argument holds, then monitoring quality should make a difference in stock price crash risk, because managers of firms with good monitoring aren't able to withhold bad news easily or for a long period of time, and vice versa. Prior studies indicate that monitoring quality is affected by two important factors, i.e., market competition and board independence. Baggs and De Bettignies (2007) and Giroud and Mueller (2010, 2011) suggest that market competition mitigates agency cost by serving as a form of monitoring. Firms in non-competitive markets or industries have weaker corporate governance and less information transparency. On the other hand, Setia-Atmaja et al. (2011), Bradley and Chen (2015), and Fuzi et al. (2016) collectively suggest that a higher degree of board independence is associated with better monitoring, which can improve firm performance and better align the interests of management and shareholders. Therefore, the effect of productivity uncertainty on stock price crash risk should be stronger for firms with weak market competition or a low degree of board independence, since those firms are subject to weak monitoring and low efficiency in flow of information. To empirically test this argument, two dummy variables are defined as follows: for the measure of market competition, *HHI_Hi* equals one if a firm's Herfindahl-Hirschman Index (HHI) is above the sample median in a given year, and zero otherwise. Since a high Herfindahl-Hirschman Index means a high market concentration, *HHI_Hi* with a value of one indicates a low degree of market competition; for the measure of board independence, *BRDIN_Hi* equals one if a firm's board independence ratio, i.e., the number of independent directors divided by the total number of directors, is above the sample median in a given year, and zero otherwise. *BRDIN_Hi* with a value of one indicates a high degree of board independence. As shown in Table 6, regression results show that the effect of productivity uncertainty on stock price crash risk is more pronounced for firms with weak market competition in terms of both statistical and economic significance. The estimated coefficients of the measures of productivity uncertainty interacted with *HHI_Hi* are significant at the 5% level or better. However, those that interacted with *1-HHI_Hi* display lower levels of significance. Regarding the magnitude of the effect, e.g., column 1, on average one percent increase of *PUCA* leads to 0.031 increase of *NCSKEW* for firms with weak market competition, ceteris paribus. In comparison, this effect diminishes to 0.02 for firms with strong market competition. On the other hand, as shown in Table 7, the effect of productivity uncertainty on stock price crash risk is more pronounced for firms with less independent boards. In general, the estimated coefficients of those interacted with

1-BRDIN_Hi exhibit higher levels of significance. Regarding the magnitude of the effect, e.g., column 1, on average one percent increase of *PUCA* leads to 0.029 increase of *NCSKEW* for firms with less independent boards, ceteris paribus. In contrast, this effect lowers to 0.023 for firms with more independent boards.

Table 6: Regression Analysis of the Influence of Market Competition

	(1) NCSKEW$_t$	(2) NCSKEW$_t$	(3) DUVOL$_t$	(4) DUVOL$_t$
PUCA*(1-HHI_Hi)$_{t-1}$	0.020*		0.009**	
	(1.79)		(2.03)	
PUCA*HHI_Hi$_{t-1}$	0.031***		0.016***	
	(3.29)		(3.65)	
PUCI*(1-HHI_Hi)$_{t-1}$		0.028*		0.013*
		(1.71)		(1.86)
PUCI*HHI_Hi$_{t-1}$		0.039**		0.018***
		(2.39)		(4.05)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	39,126	39,126	39,126	39,126
Adj. R-squared	0.056	0.052	0.068	0.065

*Note: This table presents the results of regression analysis for the influence of market competition on the effect of productivity uncertainty on stock price crash risk. HHI_Hi is a dummy variable that equals one if a firm's Herfindahl-Hirschman Index (HHI) is above the sample median in a given year, and zero otherwise. As defined in section 2.2 and 2.3, independent variable is measured by PUCA and PUCI and dependent variable is measured by NCSKEW and DUVOL. Control variables are defined in section 2.4 and continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the firm-level. The t-statistics are reported in the parentheses. ***, **, and * represent significance at the 1%, 5% and 10% levels respectively.*

Table 7: Regression Analysis of the Influence of Board Independence

	(1) NCSKEW$_t$	(2) NCSKEW$_t$	(3) DUVOL$_t$	(4) DUVOL$_t$
PUCA*(1-BRDIN_Hi)$_{t-1}$	0.029**		0.015***	
	(2.31)		(2.69)	
PUCA*BRDIN_Hi$_{t-1}$	0.023*		0.010*	
	(1.88)		(1.75)	
PUCI*(1-BRDIN_Hi)$_{t-1}$		0.037**		0.017***
		(2.16)		(3.55)
PUCI*BRDIN_Hi$_{t-1}$		0.030*		0.011**
		(1.68)		(2.36)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	39,126	39,126	39,126	39,126
Adj. R-squared	0.056	0.052	0.068	0.065

*Note: This table presents the results of regression analysis for the influence of board independence on the effect of productivity uncertainty on stock price crash risk. BRDIN_Hi is a dummy variable that equals one if a firm's board independence ratio is above the sample median in a given year, and zero otherwise. As defined in section 2.2 and 2.3, independent variable is measured by PUCA and PUCI and dependent variable is measured by NCSKEW and DUVOL. Control variables are defined in section 2.4 and continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the firm-level. The t-statistics are reported in the parentheses. ***, **, and * represent significance at the 1%, 5% and 10% levels respectively.*

3.5 Robustness check

For the examination of robustness, two alternative measures of productivity uncertainty are employed based on prior studies. Following Daniel et al. (2008) and Deng et al. (2013), *PUCS* is defined as the cash flow short fall divided by total assets, where cash flow short fall equals to the expected investment plus expected dividend then minus available cash flow. Following Jayaraman (2008) and Chaya and Suh (2009), *PUCV* is defined as the operating profit volatility, which is estimated by calculating the standard deviation of operating rate of return. These two measures assess productivity uncertainty from different cash flow perspectives, but both of them gauge the riskiness of output on a per unit of asset basis. Table 8 shows the regression results of robustness tests. The estimated coefficients of *PUCS* and *PUCV* are significant at the 5% level or better across all models. The results are very consistent with the outcome of the main regression, confirming that productivity uncertainty is positively associated with stock price crash risk.

Table 8: Robustness Tests Using Alternative Measures of Productivity Uncertainty

	(1) $NCSKEW_t$	(2) $NCSKEW_t$	(3) $DUVOL_t$	(4) $DUVOL_t$
$PUCS_{t-1}$	0.021** (2.29)		0.007*** (2.61)	
$PUCV_{t-1}$		0.029** (2.36)		0.008** (2.39)
$NCSKEW_{t-1}$	0.011 (1.59)	0.015* (1.82)		
$DUVOL_{t-1}$			0.005 (1.52)	0.006* (1.69)
$DTURN_{t-1}$	0.016 (0.31)	0.018 (0.12)	0.001 (0.81)	0.002 (0.92)
RET_{t-1}	0.031*** (4.11)	0.036*** (4.75)	0.021*** (3.16)	0.026*** (3.51)
MB_{t-1}	0.010*** (5.85)	0.012*** (6.09)	0.002*** (5.12)	0.001*** (4.96)
$SIZE_{t-1}$	0.015*** (8.53)	0.012*** (8.66)	0.006*** (9.75)	0.005*** (9.31)
SIG_{t-1}	1.105* (1.92)	1.182** (2.00)	0.787*** (2.72)	0.751*** (2.63)
LEV_{t-1}	-0.068 (0.35)	-0.077 (0.46)	-0.029 (0.55)	-0.030 (0.551)
ROA_{t-1}	0.316** (2.41)	0.302** (2.28)	0.168** (2.02)	0.179** (2.16)
$ACCU_{t-1}$	0.005* (1.69)	0.006 (1.58)	0.001* (1.81)	0.002* (1.90)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	39,126	39,126	39,126	39,126
Adj. R-squared	0.057	0.055	0.062	0.061

*Note: This table presents the results of robustness tests using two alternative measures of productivity uncertainty, i.e., PUCS and PUCV. Dependent variable is measured by NCSKEW and DUVOL. Control variables are defined in section 2.4 and continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the firm-level. The t-statistics are reported in the parentheses. ***, **, and * represent significance at the 1%, 5% and 10% levels respectively.*

4. Conclusion

This study examines the impact of productivity uncertainty on stock price crash risk. A firm's business risk is captured by its productivity uncertainty. Under the presumption of investors' information blockage effect and volatility feedback effect, stock returns of firms with higher productivity uncertainty should exhibit greater negative skewness, i.e., higher stock price crash risk. The empirical results of this study support this argument by showing that there is a significantly positive association between productivity uncertainty and stock price crash risk. This result holds firmly after addressing for potential endogeneity and the performing of robustness tests. The examination of channel effect further suggests that firms' implied cost of equity capital serves as a mediator that facilitates the information transmission of productivity uncertainty to the stock market. Moreover, this study also examines the influence of monitoring quality in terms of market competition and board independence. Consistent with the explanation based on agency cost, the positive impact of productivity uncertainty on stock price crash risk is more pronounced for firms with weak market competition and less independent boards.

Appendix

Measures of implied cost of equity capital

Notation	Formula	Reference
R_{GLS}	$P_t = B_t + \sum_{k=1}^{11} \frac{E_t[(ROE_{t+k} - R_{GLS}) \times B_{t+k-1}]}{(1 + R_{GLS})^k} + \frac{E_t[(ROE_{t+12} - R_{GLS}) \times B_{t+11}]}{R_{GLS} \times (1 + R_{GLS})^{11}}$	Gebhardt et al. (2001)
R_{CT}	$P_t = B_t + \sum_{k=1}^{5} \frac{E_t[(ROE_{t+k} - R_{CT}) \times B_{t+k-1}]}{(1 + R_{CT})^k} + \frac{E_t\{[(ROE_{t+5} - R_{CT}) \times B_{t+4}] \times (1 + g_l)\}}{(R_{CT} - g_l) \times (1 + R_{CT})^5}$	Claus and Thomas (2001)
R_{OJ}	$R_{OJ} = A + \sqrt{A^2 + \frac{E_t(EPS_{t+1})}{P_t} \times (g_s - g_l)}$ where $A = 0.5 \times [g_l + \frac{E_t(DPS_{t+1})}{P_t}]$	Ohlson and Juettner-Nauroth (2005)
R_{MPEG}	$P_t = \frac{E_t(EPS_{t+2}) + R_{MPEG} \times E_t(DPS_{t+1}) - E_t(EPS_{t+1})}{R_{MPEG}^2}$	Easton (2004)

Note: P_t is the market share price; B_t is the book value of equity; E_t is the expectation operator; ROE is the return on equity forecast; EPS and DPS are earnings per share and dividends per share forecasts; g_s is the short-term EPS growth rate forecast; g_l equals the contemporary 10-year T-bond yield minus 3%.

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