Surviving the economic downturn:

Operating flexibility, productivity, and stock crash

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Abstract

Operating flexibility enables firms to promptly curtail further losses during challenging times, thereby reducing their risk of stock price crashes. We for this insight by studying a real-options asset-pricing model. Consistent with the loss-curtailment mechanism, the results from our empirically grounding analytics reveal that operating flexibility mitigates crash risk, especially during periods of recession. Moreover, the effect is more pronounced for firms with lower productivity, lower profitability, or higher operating leverage. Using U.S. data between 1961 and 2020, we document a relationship between firms' ability to downsize operations and firm performance that varies in economically sensible ways: a negative correlation exists between the operation downscale flexibility and firm stock price crash risk, and this relation is more significant during the longer and severer recessions.

Keywords: operating flexibility, productivity, economic recessions, crash risk, firm resilience, real options

1. Introduction

Can firms' flexibility in downsizing their operations help them survive during the economic downturns? In periods of low profitability during economic recessions, firms' ability to cut operations costs help protect firm value by curtailing further losses, thus reducing the likelihood of a plummet in stock prices. Despite many studies (see, e.g., Datta et al. 2010; Samson and Swink 2023) arguing that layoffs or factory closures do not always benefit firm productivity, profitability, or stock prices, scaling down operations emerges as an obvious strategic choice for firms to cope with the economic downturn. For instance, leading technology firms including Google, Microsoft, and Amazon exhibit no hesitation in announcing mass redundancy plans when facing uncertain economic outlooks and falling stock prices.

Researchers often employ the concept of resilience, which denotes a firm's capacity to anticipate, adjust, and adapt in an ever-changing and unpredictable environment (Ambulkar et al., 2015; Ortiz-de-Mandojana and Bansal, 2016; Cohen et al., 2022), to interpret these management practices with an attempt to understand how organizations and systems respond to exogenous disturbances. Resilience helps firms survive and eventually thrive by improving their capacity to endure and adapt to environmental changes (Markman and Venzin, 2014; Ortiz-de-Mandojana and Bansal, 2016; DesJardine et al., 2019). Other management theories also support the idea that resilient firms are more capable of developing operating flexibility and therefore enable them to prepare for and navigate through challenging economic conditions. For instance, contingency theory argues that firms with high operating flexibility are better positioned to handle uncertain and evolving environments (Dong et al., 2022). The resource-based view theory considers operating flexibility a critical resource that enables firms to adapt to changing market conditions and stay ahead of competitors (Bromiley and Rau, 2016; Hitt et al., 2016).

Both industry practices and management theories indicate that firms with larger flexibility in downsizing operations are more resilient compared to others during economic recessions. Since firms' resilience often involves minimizing losses during disruptive events, a common method of assessing firm resilience involves evaluating their performance in the face of major disruptions or black swan events, such as the 2008 financial crisis and the COVID-19 Pandemic (Ambulkar et al., 2015;

DesJardine et al., 2019; Jiang et al., 2023). For publicly listed firms, an essential criterion for surviving and navigating economic recessions is to manage the risk of stock crashes. Noteworthily, the existing and rather extensive finance literature on stock crash risk primarily focuses on information asymmetry, arguing that business managers' bad news hoarding behaviors tend to trigger stock crashes (see, e.g., Jin and Myers, 2006; Hutton et al., 2009; Kim et al., 2011). However, this literature overlooks firms' underlying operations capability and performance, leaving this apparent benchmark narrative of firm operations largely unexplored. In contrast to the behavioral channel where managers withhold bad news and release it all at once, thus resulting in abrupt stock price crashes, firms' operational flexibility is arguably a *more fundamental factor*. In other words, it is plausible that firms' ability to adjust their real operations plays an important role in explaining stock price crash risk and cultivating resilient firms.

This paper addresses this facet by providing both theoretical link and empirical evidence. Real options theory suggests that companies can create value by investing in capabilities that provide real options to adjust based on changing circumstances (Pandza et al., 2003). We adopt the real-options asset-pricing framework developed by Hackbarth and Johnson (2015, henceforth referred to as HJ) to investigate the implications of operating flexibility on stock price crash risk. The HJ model considers how a firm, equipped with the ability to adjust its scale of operations, optimally chooses its investment policy in response to productivity shocks, while accounting for the presence of adjustment frictions. The lump-sum nature of these adjustment frictions leads to a discrete scale adjustment policy, characterized by firms' productivity levels in relation to endogenously determined scale adjustment thresholds.

Through exploring the association between firm values and the optimal downsizing adjustment policy, we uncover the implications of the HJ model on stock price crash risk (defined as the negative skewness of log returns). Our analytical work starts with a straightforward interpretation. During periods of low productivity, the fixed operation costs associated with assets in place amplify crash risk due to the operating leverage effect. The contraction option, on the other hand, counters the operating-leverage effect, especially when productivity approaches the option-exercise threshold. Furthermore, firms with higher operating flexibility, as characterized by lower downscale adjustment frictions, exhibit a more pronounced real-option effect. Therefore, we propose three testable hypotheses: (i) firms' operating flexibility, i.e. their ability to scale down operations timely, reduces the risk of stock price crashes; (ii) the attenuating effect of firm operating flexibility on crash risk is more prominent during recession periods (iii) the impact of operating flexibility is stronger for firms with lower productivity. These hypotheses link firms' operating flexibility with stock price crash risk without appealing to the bad news withholding argument.

To test the hypotheses, we utilize a large sample of U.S. public firms between 1961 and 2020. In our empirically grounding analytical investigation, we adopt several widely recognized crash risk measures from the literature (e.g., Chen et al., 2001; Jin and Myers, 2006; Hutton et al., 2009). Drawing upon the firm-level inflexibility measure of Gu et al. (2018) and motivated by the HJ model, we construct a proxy for operating flexibility, denoted as FLEX, by calculating the reciprocal of the standardized firm-specific maximum level of costs over sales. The model counterpart of FLEX is negatively associated with downscale adjustment frictions. Our empirical analysis indicates a statistically significant negative association between FLEX and crash risk. Moreover, the economic impact of FLEX is comparable to other important determinants of crash risk, e.g. investor heterogeneity (Chen et al., 2001) and accrual manipulation (Hutton et al., 2009).

We carry out several cross-sectional tests to investigate the mechanism underlying the negative association between operating flexibility and stock crash risk. Our analytical results assert that the operating-flexibility effect is more pronounced near the option-exercise threshold, i.e., when firm productivity and profitability are low and when operating leverage is high. Therefore, we partition the sample based on firms' productivity, profitability, and operating leverage and estimate the FLEX effect for each respective subset. Consistent with our predictions, we find that the negative association primarily manifests in firm-year that exhibit low productivity, low profitability, or high operating leverage. These results, taken together, support the real-options mechanism as the driving force behind the negative association between FLEX and stock price crashes.

Our study addresses the gap in the existing literature by investigating the effects of firms' downscale operation flexibility on mitigating the negative impact of economic recessions through empirically grounding analytics. Our research asserts that US firms with greater flexibility in curtailing operational expenditure, such as inventory (Udenio et al., 2018; Wu et al., 2019) and R&D capital (Kim and Zhu, 2018; You et al., 2020), are better positioned to withstand and navigate through economic downturns. These discoveries provide a comprehensive outlook on how firms' operations fundamentals – ranging from productivity and profitability to operating flexibility – affect firms' resilience and the crucial role played by operational resources and strategies in reducing the adverse impact of challenging external economic environments. Our approach within the operations management framework diverges from previous research that has predominantly focused on other factors such as corporate governance (Graham et al., 2011), diversification (Kuppuswamy and Villalonga, 2016), and brand capital (Hasan et al., 2022). It is important to note that our study acknowledges the significance of those non-OM factors but instead seeks to strike a balance in the ongoing academic debates by presenting an OM perspective.

Second, our paper contributes to a growing literature on the role of real options in shaping corporate behaviors. Early research on investment under uncertainty demonstrates that firms' (dis)investment frictions govern their investment policies (e.g., Abel and Eberly, 1996). Operation flexibility also affects firms' hedging activities in the futures market (Ho, 1984; Kamara, 1993). Recent theoretical and empirical works tease out the asset pricing implications of real flexibility, showing that real options play a pivotal role in explaining firms' risk and return patterns (Cooper, 2006; Hackbarth and Johnson, 2015). Furthermore, several papers highlight that various forms of flexibility – whether at the firm, supply chain, or industry level – affect capital structure (MacKay, 2003; Reinartz and Schmid, 2016; Serfling, 2016; D'Acunto et al., 2018; Jiang et al. 2023). Our research enriches this expanding literature by shedding light on the role of real flexibility in managing risk of stock price crash.

Third, our work contributes to the literature on the mechanisms underlying stock price crash risk. The majority of crash risk research resides within the agency theory framework, which posits that heightened levels of information asymmetry between corporate managers and shareholders exacerbate stock price crash risk. Examples include the reporting environment's impact on crash risk through the channels of, e.g., accounting standards change and accounting conservatism (Jin and Myers, 2006), tax avoidance practices (Kim et al., 2011), earnings management (Kim et al., 2014), and accounting information transparency (Hutton et al., 2009). Additionally, the capital market structure may either encourage or discourage managers' bad news hoarding behavior through, e.g., constraints or frictions on short selling (Chen et al., 2001; Hong and Stein, 2003). Our findings that firms' flexibility in their operations can influence their stocks' crash risk represent a substantial deviation from this conventional notion of bad news withholding argument. This novel mechanism has been largely overlooked in the extant literature. By introducing a real-operations-based explanation, our findings complement the prevailing behavioral explanations rooted in the bad news hoarding literature.

The rest of this paper is organized as follows. Section 2 develops our hypotheses as motivated from our model. Section 3 introduces the sample and measures used in the empirical tests. Section 4 reports our empirical results. Section 5 concludes our findings.

2. Hypothesis Development

2.1. Model framework

We employ the production-based asset-pricing model developed by Hackbarth and Johnson (2015) to examine the association between operating flexibility and stock price crash risk. The HJ model allows businesses to expand in good times and contract in bad times through real options. Since our research centers on understanding firms' resilience during economic downturns, we focus on the contraction option and its implications on crash risk. Essentially, we consider a simplified version of the HJ model, by "turning off" the expansion option. The firm receives profit flow per unit time $\Pi_t = \theta_t^{1-\gamma} K_t^{\gamma} - mK_t$, where K denotes the capital assets, and θ is the productivity level. $\gamma \in (0,1)$ captures the decreasing return to scale, and $m > 0$ measures operating cost per unit capital asset. The productivity θ evolves exogenously according to a diffusion process with drift μ and volatility σ, and in response, the firm chooses its optimal scale of operations K_t to maximize the firm value J, the discounted value of the above profit stream, subject to downscale adjustment costs. These are the fixed adjustment costs $f_U \theta^{1-\gamma} K^{\gamma}$ and the variable deadweight loss $(1 - p_U)\Delta K$ corresponding to a resale amount of ΔK, where $f_U \geq 0$ and $p_U \leq 1$ are the parameters characterizing the adjustment frictions.

As these adjustment frictions are lumpy in nature, occurring only upon scale adjustments, the firm strategically pursues a discrete capital adjustment policy. In the absence of adjustment frictions, the firm would always set K_t to its target value $K_t^* = (m/\gamma)^{1/(\gamma-1)}\theta_t$ to maximize its profit flow. However, with the presence of lumpy frictions, the firm would have to wait for K_t to deviate from K_t^* by a sufficiently large amount before the benefit of scale adjustment outweighs the cost. Because both the profit flow and adjustment costs are linearly homogenous in θ and K, the firm's optimal policy can be captured by a single state variable $Z_t = K_t/\theta_t$, the inverse scaled productivity. See FIGURE 1 for an illustration of the optimal policy. The state variable $Z_t = K_t/\theta_t$ (the inverse scaled productivity) evolves within the interval $(0, U)$. Upon contacting the boundary at U, downward adjustment on K_t occurs and Z_t jumps to the target level at H. The parameters, U and H, are determined by a set of optimality conditions for the firm's value-maximization problem. See Appendix A for detailed characterization.

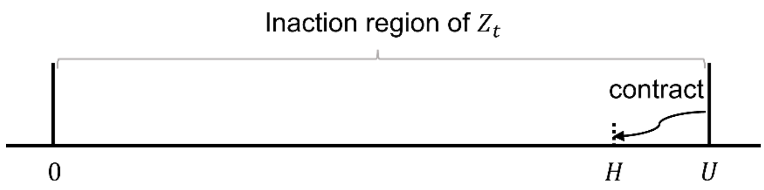

FIGURE 1. The firm's optimal investment policy

2.2. Negative return skewness

Conditional on the optimal policy, the firm's value J evolves stochastically in response to productivity changes. Let $R = (\Delta J + \Pi\Delta t)/J$ denote the total return of the firm's equity over a horizon of Δt. The closed-form expression of J as a function of θ, facilitated by the tractability of the HJ model, enables us to explicitly derive the moments of R. We define negative return skewness ($NegSkew$) as the negative of the coefficient of skewness of the log returns $lR = \log(1 + R)$, i.e.,

$$NegSkew = -E\left[\left(\frac{lR - \mu_{lR}}{\sigma_{lR}}\right)^3\right].$$

Here μ_{lR} and σ_{lR} are the mean and standard deviation of lR, respectively. The use of log returns, instead of raw returns, is consistent with the stock crash risk measures used in the empirical literature (see, e.g., Chen et al., 2001). When returns follow the benchmark of a lognormal distribution, $NegSkew$ is equal to 0.

For the convenience of discussion, we establish the following proposition in terms of the scaled productivity $P_t = \theta_t/K_t$, instead of its reciprocal Z_t.

Proposition 1. *The leading order, in Δt, of the negative return skewness, conditional on the scaled productivity P, is $NegSkew(P) = NSKEW(P)\sqrt{\Delta t} + o(\sqrt{\Delta t})$, where*

$$NSKEW(P) = 3\sigma\left(\frac{Q'}{Q} - \frac{Q''}{Q'}\right).$$

Here $Q = J/K$ is firm value scaled by capital assets, and the derivatives are taken with respect to $\log P$, *i.e., $Q' = \frac{d\,Q}{d\log \mathrm{P}}$, and $Q'' = \frac{d\,Q'}{d\log P}$.*

Unsurprisingly, the negative skewness is related to the convexity of the firm value in productivity (Q''/Q'), which captures the asymmetric response of the firm value to productivity shocks. Furthermore, it is also positively related to operating leverage, as manifested in the term Q'/Q representing the elasticity of firm value to productivity fluctuations.

In the absence of contraction options, the firm's value is simply the discounted value of the profit stream. Given that θ evolves according to a diffusion process, it is straightforward to see that the firm's value follows the same functional form as the profit flow, i.e., $J(\theta, K) = A\theta^{1-\gamma}K^{\gamma} - SK$, where A and S are some positive constants. The two terms in the above expression correspond to the contributions to the firm value from the revenues and operational costs, respectively. Consequently, $Q = J/K = AP^{1-\gamma} - S$, and thus $Q''/Q' = (1-\gamma)$; and $Q'/Q = A(1-\gamma)P^{1-\gamma}/(AP^{1-\gamma} - S)$, which is positive and increases as productivity drops, as the firm's operational costs (the SK term in J) become more important compared to its revenues (the $A\theta^{1-\gamma}K^{\gamma}$ term in J). Therefore, in the absence of contraction options, the non-trivial dependence of $NegSkew$ on P derives contribution solely from the operating-leverage effect.[1] We denote this contribution as the *assets-in-place* component.

On the other hand, exercising the option curtails the firm from further losses following unfavorable productivity movements, adding value to the firm. The added value is more sizeable near the option-exercise threshold. Superimposing on the otherwise diminishing firm value, the contraction option makes the firm value more convex in productivity. Therefore, we expect the contraction option to reduce $NegSkew$, especially so when productivity is near the contraction-option exercise threshold. We denote this contribution as the *contraction-option* component, which is negative and more sizable as productivity drops. We summarize the above discussions in the proposition below and leave the formal proofs in Appendix B.

Proposition 2. *The instantaneous negative return skewness, $NSKEW(P)$, can be decomposed as $NSKEW(P) = NSKEW_{AIP}(P) + NSKEW_{CO}(P)$, where the components denote contributions from the assets-in-place (AIP) and the contraction option (CO), respectively. Moreover, the signs and monotonicity of the components are*

$$NSKEW_{AIP}(P) > 0, \qquad NSKEW_{CO}(P) < 0,$$

$$NSKEW'_{AIP}(P) < 0, \qquad NSKEW'_{CO}(P) > 0,$$

where $NSKEW'_{AIP}(P) = \frac{d\, NSKEW_{AIP}(P)}{d\, \log P}$, etc.

The interplay of the assets-in-place and contraction-option effects leads to a non-linear relationship between $NSKEW$ and P, see FIGURE 2 for illustration. When P is large, both the operating-leverage effect and the contraction-option effect are weak, therefore, $NSKEW$ approaches 0. As P drops, operating leverage comes into play and $NSKEW$ increases. As P

[1] Formally, the operating leverage may be defined as the elasticity of profits with respect to productivity shocks, i.e., $(\theta/\Pi)(d\Pi/d\theta) = (1-\gamma)P^{1-\gamma}/(P^{1-\gamma} - m)$. Note the resemblance of this expression with Q'/Q.

drops further, the contraction option kicks in, opposing the operating-leverage effect. This can reverse the operating-leverage effect when P becomes very low.

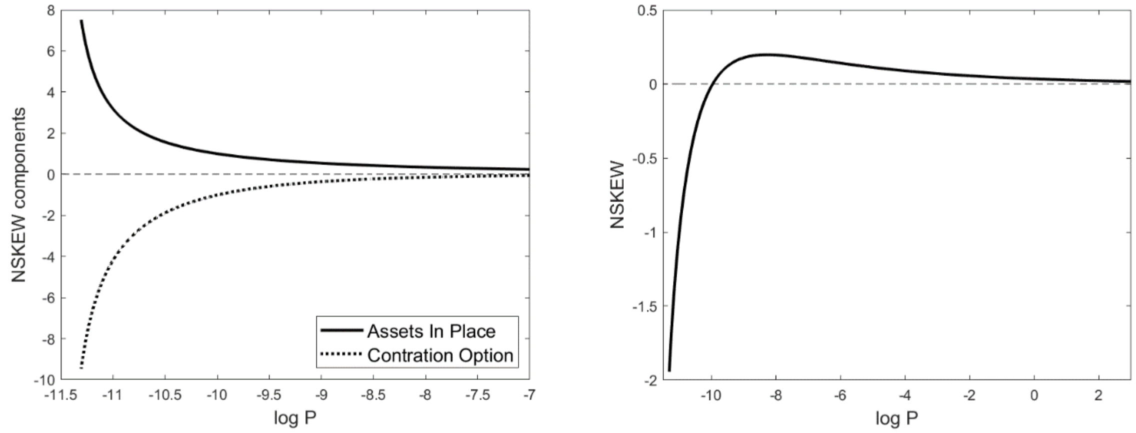

FIGURE 2. The components of negative skewness ($NSKEW$) according to the Proposition 2 (left) and the total negative skewness resulting from their sum (right)

2.3. Testable hypotheses

According to Proposition 2, the contraction option induces a negative contribution to negative skewness ($NSKEW_{CO} < 0$). Therefore, firms that are more flexible in exercising their contraction options, manifested in fewer adjustment frictions, should display lower stock price crash risk. To illustrate, Figure 3shows how the variable adjustment-cost parameter for disinvestment (p_U) affects $NSKEW$, with other parameters fixed at the baseline calibration values provided by Hackbarth and Johnson (2015).[2] p_U denotes the resale price per one unit of capital assets when exercising the contraction option. Or, put in other words, $(1 - p_U)\Delta K$ reprsents the deadweight loss corresponding to a resale amount of ΔK. Lower values of p_U corresponds to higher adjustment frictions and hence lower levels of operating flexibility. The figure shows clearly that more flexible firms (with higher p_U) are associated lower levels of stock price crash risk (represented by $NSKEW$).

[2] Specifically, the model parameters mentioned in Section 2.1 take their baseline values as: $\gamma = 0.78$, $m = 0.0669$, $\mu = 0.146$, $\sigma = 0.61$, $p_U = 0.1345$, $f_U = 0.0077$.

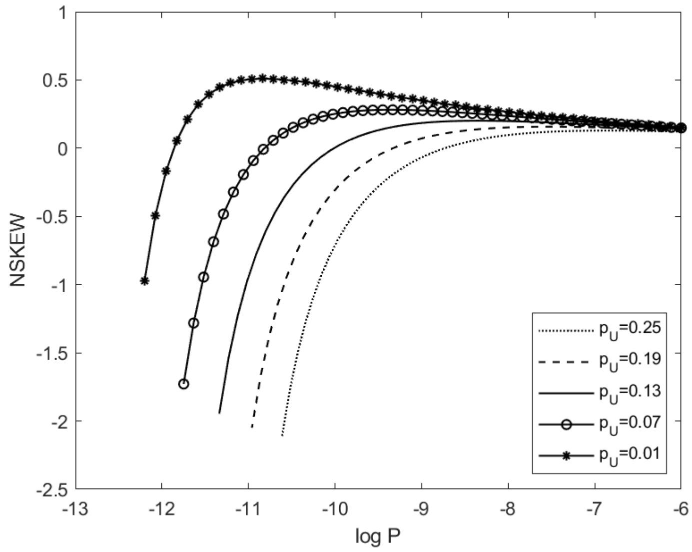

FIGURE 3. The impact of operating flexibility, in terms of contraction frictions, on negative skewness ($NSKEW$)

Hypothesis 1. *Firms with greater flexibility in downscaling operation experience lower stock price crash risk.*

Moreover, as our model indicates, the loss-curtail mechanism of operating flexibility manifests itself most prominently when it is most beneficial to cut down unproductive operations and capital. While the empirical literature has focused extensively on the determinants of stock price crash risk, it has paid less attention to its dependence on market characteristics. In this regard, an economic downturn is the ideal setting for testing our model's predictions, leading to our second hypothesis.

Hypothesis 2. *The protection of downscale operation flexibility from stock price crash risk is stronger during economic downturns.*

Furthermore, Proposition 2 gives additional insights on the conditional pattern of the impact of operating flexibility. Specifically, $NSKEW'_{CO}(P) > 0$ indicates that the negative contribution of the contraction option to the crash risk is more sizeable for lower levels of productivity, i.e., when the firm is closer to its option-exercise threshold. Therefore, the crash-risk-reduction effect of operating flexibility is stronger for these firms. This phenomenon is also demonstrated in Figure 3, where the $NSKEW$ spread, across firms with different levels of operating flexibility, is broader when $\log P$ is lower. Since, in our model, productivity and profitability are synonymous, both of which are negatively associated with operating leverage, the conditional pattern may be expressed in all these three variables.

Hypothesis 3. *The protection from downscale operation flexibility is stronger for firms with lower productivity, lower profitability, or higher operating leverage.*

3. Data and Measures

3.1. Data and sample

Our sample comprises U.S. non-financial and non-utility firms publicly traded on the NYSE, AMEX, and NASDAQ stock exchanges from 1961 to 2020. We obtain firms' financial accounting data from the Compustat Fundamentals annual dataset. To compute crash risk measures, we obtain daily stock returns from the Center for Research in Security Prices (CRSP). We keep common stocks and exclude firm-years that contain fewer than 26 weeks of returns. Additionally, we exclude stocks with share prices below $1 at the fiscal year-end.

3.2. Measuring operating flexibility

Within our model, a firm's operating flexibility is determined by its scale adjustment frictions. Empirically, these frictions can be hard to measure. The model implies a monotonous relationship between the contraction threshold U and the friction parameters. Intuitively, a firm with higher adjustment frictions tends to wait for productivity θ to drop to a lower level before opting for downscale adjustments. This results in an elevated threshold U for the inverse scaled productivity $Z = K/\theta$. Figure 4 presents an illustration of the positive relationship between U and the deadweight loss per unit resale amount $1 - p_U$.

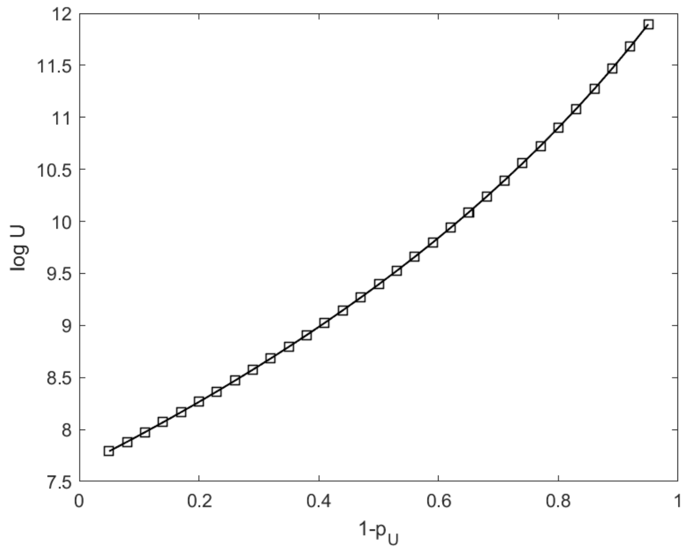

FIGURE 4. The relationship between contraction boundary (U) and adjustment friction ($1-p_U$)

This motivates us to measure U empirically using the maximum level of the firm's historical operational costs over sales $OPCS = mK/(\theta^{1-\gamma}K^{\gamma})$, which is positively related to Z. We further scale U by the volatility of productivity σ, because U increases in σ given the same level of adjustment frictions. In other words, we define contraction inflexibility for firm j in year t as

$$INFLEX_{j,t} = \frac{\max_{\tau\in I_j} \frac{Operational\ Costs_{j,\tau}}{Sales_{j,\tau}}}{\operatorname{std}_{\tau\in I_j}\left(\Delta \log \frac{Sales_{j,\tau}}{Assets_{j,\tau}}\right)},$$

where I_j is the time window used to construct the proxy. The above expression closely mimics the inflexibility measure of Gu et al. (2018), who uses the range of $OPCS$ in the numerator instead of the maximum.

We further define operating flexibility as $FLEX = 1/INFLEX$. Depending on the choice of the time window I_j, we construct three versions of operating flexibility: FLEX, with I_j being the 20-year rolling window $(t-20, t)$; FLEX2, with I_j being the period from the beginning of the firm to year t; and FLEX3, with I_j being firm j's full period in our sample. We require 10 non-missing observations in each window for the computation of FLEX, FLEX2, and FLEX3.

3.3. *Measuring stock crash risk*

The stock price crash risk literature primarily follows Chen et al. (2001) in computing crash risk measures based on firm-specific weekly returns, estimated as the regression residuals derived from an expanded market model. Let $W_{j,\tau}$ denotes stock j's specific return in week τ of year t, Chen et al. (2001) define the negative coefficient of skewness NSKEW and down-to-up volatility DUVOL as follows:

$$NSKEW_{j,t} = -\frac{n(n-1)^{\frac{3}{2}}\sum_{\tau} W_{j,\tau}^{3}}{(n-1)(n-2)\left(\sum_{\tau} W_{j,\tau}^{2}\right)^{\frac{3}{2}}}, \text{and } DUVOL_{j,t} = \log\frac{(n_u-1)\sum_{\tau,Down} W_{j,\tau}^{2}}{(n_d-1)\sum_{\tau,Up} W_{j,\tau}^{2}},$$

where n is the number of stock j's weekly returns during year t, and n_u and n_d are the number of up and down weeks. A weekly return $W_{j,\tau}$ is classified as a up (down) return if it is above (below) the firm-specific annual mean. In addition, Hutton et al. (2009) construct a binary measure $CRASH_{j,t}$ to indicate the presence of a crash event during year t. $CRASH_{j,t}$ is set to 1 if stock j, in year t, has at least one weekly return $W_{j,\tau}$ that lies 3.09 standard deviations below its annual mean, and is set to 0 otherwise. The choice of the 3.09 cut-off point is based on a 0.1% frequency of weekly crash events, assuming a normal distribution for the weekly firm-specific returns.

We obtain the firm-specific weekly returns $W_{j,\tau}$ as follows. Following Kim et al. (2011), for each firm-year, we assign weekly returns to the 12-month period ending three months after the fiscal year-end. For our baseline crash risk measures, we follow Jin and Myers's (2006) expanded market models to estimate $W_{j,\tau}$,

$$r_{j,\tau} = \alpha_j + \beta_{1,j} r_{m,\tau-2} + \beta_{2,j} r_{m,\tau-1} + \beta_{3,j} r_{m,\tau} + \beta_{4,j} r_{m,\tau+1} + \beta_{5,j} r_{m,\tau+2} + \epsilon_{j,\tau},$$

where $r_{j,\tau}$ is stock j's return in week τ, and $r_{m,\tau}$ is the return on the CRSP value-weighted market index. The inclusion of the lead and lag terms are adopted to correct for nonsynchronous trading (Dimson, 1979). The firm-specific weekly return is then defined as $W_{j,\tau} = \log(1 + \epsilon_{j,\tau})$.

To provide a more independent measure, we also construct the above crash risk measures using another widely used market model. Specifically, we follow Hutton et al. (2009) and introduce the industry index into the expanded market model,

$$r_{j,\tau} = \alpha_j + \beta_{1,j} r_{m,\tau-1} + \beta_{2,j} r_{i,\tau-1} + \beta_{3,j} r_{m,\tau} + \beta_{4,j} r_{i,\tau} + \beta_{5,j} r_{m,\tau+1} + \beta_{6,j} r_{i,\tau+1} + \epsilon_{j,\tau} ,$$

where $r_{i,\tau}$ is the return on the Fama and French value-weighted 49-industry index in week τ. We label the corresponding crash risk measures as NSKEW2, DUVOL2 and CRASH2, respectively.

Before using these empirical measures of crash risk to test our hypotheses, one might rightly question whether they can truly represent their counterpart analytical version set out in Proposition 1, which gives the leading order negative skewness in an infinitesimal horizon $\Delta t \to 0$. To address this concern, we simulate the firm's returns over various lengths of the horizon Δt conditional on productivity and compute their negative skewness, see Figure 5.[3] The negatives skewness of simulated returns is scaled by $\sqrt{\Delta t}$ to be comparable with $NSKEW(P)$ of our analytical result. It is evident that our analytical result is a very good approximation for horizons up to quarterly returns but deviates slightly from the annual returns, although the conditional pattern of $NSKEW$ vs. P remains accurate. This indicates that the above empirical measures of crash risk, computed from returns over the weekly horizon, are suitable for testing the hypotheses derived from our analytical results.

[3] The model parameters used in this exercise are the baseline calibration values taken from Hackbarth and Johnson (2015).

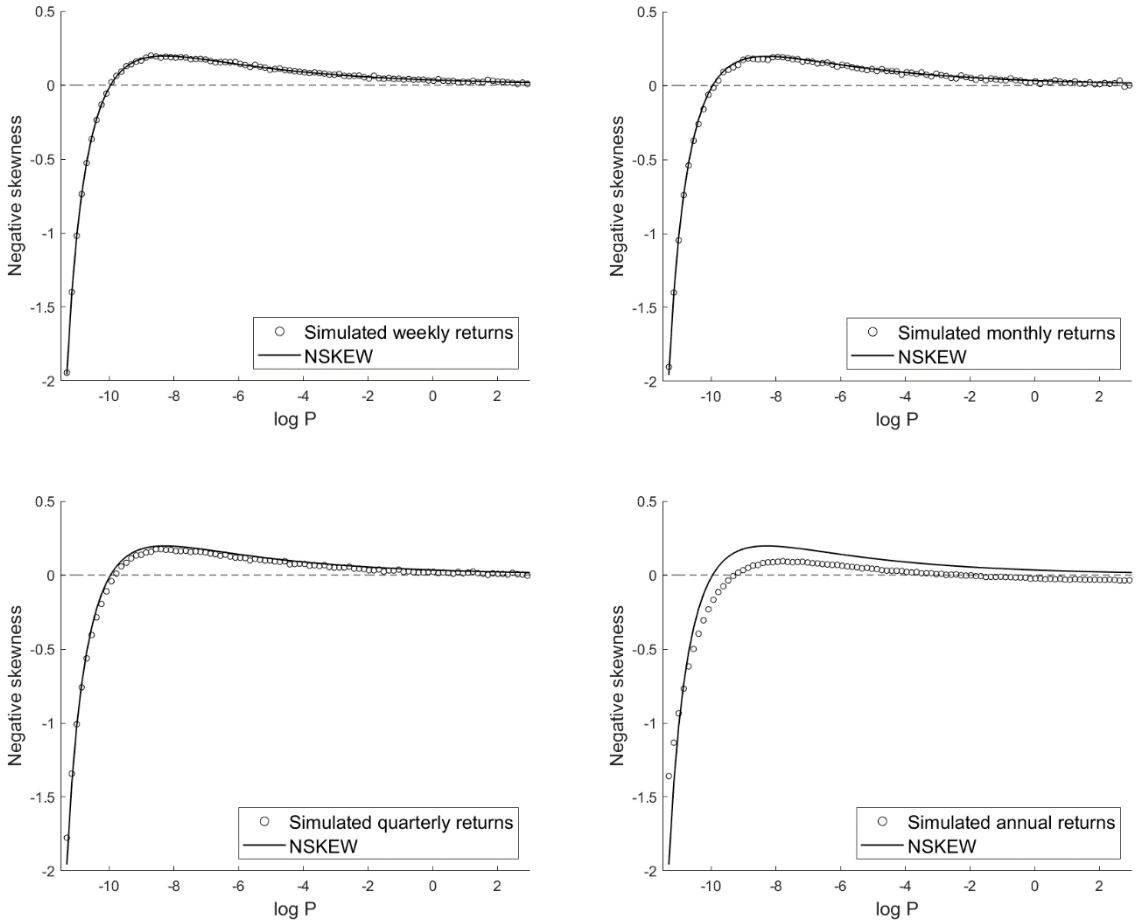

FIGURE 5. Comparison of the analytical negative skewness ($NSKEW$) with the negative skewness of simulated returns

3.4. Control variables

We adopt a set of control variables that prior studies have identified as important in explaining stock price crash risk. Following Kim et al. (2011; 2014), we control for stock return volatility SIGMA and, to account for serial correlation of crash risk, the lagged crash risk measure l.NSKEW. Chen et al. (2001) document that past returns (RET) and market-to-book (MB) can forecast crash risk through the mechanism of bubble buildup and subsequent price reversion to the financial fundamentals. Chen et al. (2001) also show that investor heterogeneity affects crash risk. We, therefore, include RET, MB, and stock turnover (DTURN) as control variables, where RET is computed as the annual mean of $W_{j,\tau}$.[4] Harvey and Siddique (2000) document that firm size (SIZE) has predictive power for crash risk. Following prior studies (e.g., Chen et al., 2001; Hutton et al., 2009), we also control for financial leverage (LEV), return on assets (ROA), and discretionary accruals (ACCM). The distributions of these control variables within our sample are comparable to those observed in existing studies in the crash risk literature.[5] This indicates that our sample is representative of the broader mainstream empirical works.

To test Hypothesis 3, we employ conditioning variables to split the sample into high and low productivity, profitability, and operating leveraging groups. Concerning productivity, we employ Tobin's Q (TobinQ) as an alternative proxy alongside MB. We use return on assets (ROA) and gross profits over sales (GPOA) to measure profitability. Finally, for assessing operating leverage, we use operational costs over sales (OPCS) and Gu et al.'s (2018) quasi-fixed costs (QFC). We discuss these in more detail in Section 4.5.

3.5. Summary statistics

We report the descriptive statistics of all the variables used in our tests in Table 1. To minimize the impact of outliers, we winsorize all continuous variables at the 1% and 99% levels. See Table C.1 for detailed variable definitions.

TABLE 1. Descriptive statistics

	Count	Mean	SD	P25	P50	P75
Operating flexibility measures						
FLEX	78,915	0.174	0.104	0.101	0.149	0.219
FLEX2	78,960	0.171	0.101	0.103	0.148	0.212
FLEX3	114,736	0.176	0.096	0.114	0.157	0.215
Stock price crash risk measures						
NSKEW	130,981	-0.189	0.812	-0.615	-0.193	0.220
DUVOL	130,981	-0.219	0.738	-0.699	-0.234	0.243
CRASH	130,981	0.159	0.365	0.000	0.000	0.000
NSKEW2	130,957	-0.176	0.790	-0.595	-0.181	0.223
DUVOL2	130,957	-0.203	0.724	-0.677	-0.218	0.252
CRASH2	130,957	0.168	0.374	0.000	0.000	0.000
Control variables						
SIGMA	128,052	0.056	0.029	0.035	0.050	0.070

[4] SIGMA2, RET2, and l.NSKEW2 are variables similar to SIMGA, RET, and NSKEW but are estimated under the second extended market model described in Section 3.3.
[5] For example, the means and standard deviation values of SIGMA, RET, SIZE, MB, and ROA are similar to the corresponding values reported by Kim et al. (2011; 2014) and Dang et al. (2018).

RET	128,052	-0.199	0.225	-0.242	-0.121	-0.062
l.NSKEW	128,052	-0.160	0.763	-0.588	-0.181	0.226
DTURN	118,140	0.013	0.750	-0.169	0.001	0.175
SIZE	128,849	5.361	2.111	3.785	5.238	6.794
MB	124,144	2.978	3.558	1.129	1.894	3.327
LEV	130,614	0.178	0.176	0.015	0.142	0.278
ROA	129,803	0.012	0.217	0.006	0.052	0.097
ACCM	124,532	0.136	0.169	0.037	0.084	0.165
SIGMA2	128,005	0.055	0.029	0.034	0.048	0.068
RET2	128,005	-0.188	0.218	-0.229	-0.113	-0.056
l.NSKEW2	128,005	-0.148	0.743	-0.568	-0.171	0.225
Conditioning variables						
TobinQ	127,157	1.955	1.553	1.064	1.430	2.186
GPOA	130,725	0.381	0.268	0.216	0.354	0.521
QFC	108,817	0.268	0.598	0.015	0.131	0.334
OPCS	119,027	0.913	0.298	0.822	0.888	0.941

Note: Continuous variables are winsorized at the 1% and 99% levels, and all variables are defined in Table C.1.

The distributions of the crash risk measures, NSKEW, DUVOL, and CRASH, are similar to those reported in prior literature (see, e.g., Kim et al., 2011). For example, CRASH has a mean value of 0.159, suggesting that, on average, about 16% of stocks experience a crash event each year. NSKEW and DUVOL exhibit a high correlation, with a coefficient of 0.96, as seen in Panel B of Table C.2. In view of this, one might question whether DUVOL is sufficiently different from NSKEW to be used as an alternative measure for the empirical tests. However, as indicated in Panel B of Table C.2, the correlations of the three measures of crash risk between the two market models are lower (0.92, 0.89, and 0.85, respectively) compared to that between NSKEW and DUVOL (0.96). Therefore, using the alternative market model provides a more meaningful robustness check.

A comparison of mean and standard deviation values reveals substantial variation among the different flexibility measures. In untabulated results, we find that about 10% of variation can be attributed to industry factors. This implies that a significant proportion of the variation remains within industries.[6] Therefore, the flexibility measure based on the HJ model is superior to other industry-level measures of various aspects of firms' operating flexibility, e.g.,

[6] More precisely, through ANOVA analysis across Fama-French 49-industry groups, we find that industry explains 11.0%, 11.5%, and 9.6% of the overall variation in FLEX, FLEX2 and FLEX3, respectively.

inflexible employment (Syverson, 2004), the capital resalability index (Balasubramanian and Sivadasan, 2009), and wage premium (Kim, 2016).[7] Such a firm-level measure enables us to examine operating flexibility's association with crash risk beyond mere industry characteristics.

Our flexibility measures are persistent over time, with autocorrelations of 0.98, 0.99, and 1 for FLEX, FLEX2, and FLEX3, respectively. These findings accord with the model's assumption that the adjustment frictions represent a stable firm attribute. Arguably, FLEX reflects the firm's most recent operational information and, therefore, should be the most appropriate measure in capturing contemporaneous operating flexibility. FLEX3, on the other hand, weighs the firm's entire history equally. However, given FLEX's high persistence and the greater number of observations in our sample for FLEX3, the empirical suitability of each depends on the trade-off between measurement precision and statistical power. Consequently, besides the baseline version of FLEX, we compute FLEX2 and FLEX3 to facilitate additional robustness checks.

4. Empirical results

4.1. Baseline

We examine the role of operating flexibility on future stock price risk using the following linear regression model and report the regression estimates in Table 2.

$$NSKEW_{j,t} = \beta_0 + \beta_1 FLEX_{j,t-1} + controls_{j,t-1} + \text{Year \& Industry } FE + \epsilon_{j,t}.$$

The whole-sample result in column (3) shows that downscale operation flexibility is significantly and negatively associated with stock price crash risk, supporting our Hypothesis 1. Moreover, the economic significance of operating flexibility is comparable to other determinants of crash risk. For example, one inter-quartile-range change in FLEX is associated with a 1.37% inter-quartile-range change in NSKEW, compared with, for example, 0.87% for

[7] Gu et al. (2018) provide tests to demonstrate that the inflexibility measure INFLEX is significantly correlated to these industry-level inflexibility measures. These results support the role of INFLEX in capturing various forms of frictions associated with adjusting physical and labour capital assets.

DTURN and 1.47% for ACCM.[8] Our results for the effects of the control variables are also in line with previous findings. Firms that have higher past returns, higher return volatility, higher past crash risk, a higher investor heterogeneity, a higher market-to-book ratio, a larger size and more evidence of accrual manipulation are associated with higher stock price crash risk (see, e.g., Harvey and Siddique, 2000; Chen et al., 2001; Hutton et al., 2009; Kim et al., 2011; Kim et al., 2014).

To test Hypothesis 2, which suggests that the operating flexibility's protection effect is stronger during economic downturns, we first classify firm-year observations into recession and non-recession groups using the US Business Cycle dates provided by the National Bureau of Economic Research (NBER, see also Radin, 2023).[9] A firm-year observation is categorized as a recession observation if any month of the firm's 12-month crash-risk estimation window lies within a recession period. We then re-estimate our baseline regression model using the recession subsample. As evident in column (2) of Table 2, the coefficient of FLEX remains negative and statistically significant. Importantly, its magnitude is significantly larger in comparison to the whole sample (-0.153 vs. -0.097). This increase in statistical significance is especially noticeable when compared with other crash risk determinants. For example, one inter-quartile-range change in FLEX is associated with a 2.17% inter-quartile-range change in NSKEW, compared with, for example, 0.83% for DTURN and 0.51% for ACCM. Overall, these results strongly support Hypothesis 2, and thus corroborate our model's insight that operating flexibility helps firms navigate episodes of declined economic activities.

TABLE 2. Operating flexibility and stock price crash risk

	(1) Recession Periods	(2) Non-recession Periods	(3) Whole Sample
FLEX	-0.153***	-0.079**	-0.097***
	(-2.76)	(-2.17)	(-3.19)
SIGMA	3.456***	5.731***	5.077***

[8] To illustrate the calculations, $1.37\% = 0.097 \times (0.219 - 0.101)/(0.220 + 0.615)$.
[9] The NBER business cycle data is publicly available at https://www.nber.org/research/business-cycle-dating.

	(4.06)	(10.23)	(10.86)
RET	0.503***	0.651***	0.608***
	(4.68)	(9.04)	(10.17)
l.NSKEW	0.007	0.023***	0.019***
	(0.96)	(4.37)	(4.37)
DTURN	0.020**	0.022***	0.021***
	(2.27)	(3.55)	(4.18)
SIZE	0.070***	0.082***	0.079***
	(19.40)	(34.29)	(39.51)
MB	0.005**	0.002	0.003***
	(2.51)	(1.57)	(2.64)
LEV	-0.107***	-0.106***	-0.107***
	(-2.96)	(-4.57)	(-5.44)
ROA	0.214***	0.279***	0.260***
	(3.85)	(8.21)	(8.99)
ACCM	0.033	0.120***	0.096***
	(0.82)	(4.30)	(4.15)
Constant	-0.649***	-0.833***	-0.783***
	(-15.55)	(-30.07)	(-33.94)
Observations	20,971	56,623	77,594
R-squared	0.088	0.062	0.067
Year FE	YES	YES	YES
Industry FE	YES	YES	YES

Note: t-statistics are given in the parentheses *** p<0.01, ** p<0.05, * p<0.1. Recession periods are determined using the US Business Cycle dates provided by National Bureau of Economic Research (NBER).

4.2. Robustness

4.2.1. Alternative crash risk measures

We perform a number of robustness checks using alternative crash risk measures and report the results in Panels A and B of Table 3 for the recession periods and the whole sample, respectively. To facilitate comparison, column (1) shows the baseline estimates. In column (2), following prior studies (e.g., Chen et al., 2001), we use DUVOL as the dependent variable. In column (3), as a more independent scrutiny, we assess the impact of FLEX on the likelihood of a crash event using a logistic regression of CRASH. Furthermore, we follow Hutton et al. (2009) and estimate the crash risk measures using the expanded market model, explained in Section 3.3, which adjusts stock returns by industry-level index returns in addition to the market index returns. We repeat the regression analyses of NSKEW, DUVOL and CRASH and report the estimates for NSKEW2, DUVOL2, and CRASH2 in columns (4)-(6), respectively. The results across all columns and both panels demonstrate that our baseline findings, in regard to Hypotheses 1 and 2, are robust to using alternative methods of measuring the stock price crash risk.

TABLE 3 Robustness

Panel A. Alternative crash risk measures – Recession periods

	(1) NSKEW	(2) DUVOL	(3) CRASH	(4) NSKEW2	(5) DUVOL2	(6) CRASH2
FLEX	-0.153***	-0.151***	-0.465**	-0.160***	-0.143***	-0.471**
	(-2.76)	(-2.99)	(-2.08)	(-2.91)	(-2.81)	(-2.24)
Observations	20,971	20,971	20,967	20,970	20,970	20,966
(Pseudo) R^2	0.088	0.103	0.043	0.078	0.090	0.044
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES

Panel B. Alternative crash risk measures – Whole sample

	(1) NSKEW	(2) DUVOL	(3) CRASH	(4) NSKEW2	(5) DUVOL2	(6) CRASH2
FLEX	-0.097***	-0.104***	-0.242**	-0.106***	-0.098***	-0.233**
	(-3.19)	(-3.79)	(-2.22)	(-3.55)	(-3.61)	(-2.26)
Observations	77,594	77,594	77,594	77,581	77,581	77,581
(Pseudo) R^2	0.067	0.080	0.046	0.060	0.071	0.048
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES

Panel C. Alternative operating-flexibility measures

	(1)	(2)	(3)	(4)
	Recession Periods		Whole Sample	
FLEX2	-0.157***		-0.074**	
	(-2.82)		(-2.40)	
FLEX3		-0.132***		-0.094***
		(-2.79)		(-3.60)
Observations	20,981	30,013	77,639	110,279
R-squared	0.087	0.099	0.067	0.076
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES

Note: t-statistics are given in the parentheses *** p<0.01, ** p<0.05, * p<0.1.

4.2.2. Alternative operating flexibility measures

Our main measure for operating flexibility $FLEX_{j,t}$ is constructed using a 20-year rolling window $(t-20, t)$ of firm j's fundamentals. To explore the robustness of our findings in relation to this choice, we repeat the baseline analyses by replacing FLEX with two alternative measures: $FLEX2_{j,t}$ uses firm j's fundamentals from its beginning to year t; $FLEX3_j$ uses firm j's fundamentals for the entire period in our sample. We report the results in Table 3 Panel C.

FLEX2 shows the expected signs of impact on NSKEW, albeit with a lower level of statistical significance compared to FLEX. We interpret this as an indication of greater measurement error associated with FLEX2, likely due to its reliance on older information compared to FLEX. However, for the recession periods, the coefficient on FLEX2 aligns closely with the estimate of FLEX. The coefficient estimates of FLEX3 are slightly lower in magnitude but higher in statistical significance compared to FLEX. This consistency supports the notion that FLEX3 contains a greater degree of measurement error, offset by its higher number of observations, thereby enhancing its statistical power. Despite these differences, the overall pattern is clear — our baseline results, in regard to Hypotheses 1 and 2, hold when estimated with alternative versions of the operating flexibility measure.

4.3. Length of recession exposure

As argued in our hypothesis development section (Section 2.3), an economic downturn provides an ideal setting for testing our model's predictions. To further utilize the Business Cycle data, we examine how the value of operating flexibility varies with the duration of a firm's exposure to recessions. Similar to analyses in Section 4.1, we partition our sample according to the number of months during which a firm-year's crash-risk estimation window falls within a recession period. Accordingly, we re-estimate the baseline model and report the results in Table 4.

Column (1) duplicates Table 2 column (1) for ease of comparison. The coefficient of FLEX increases steadily and drastically as the time exposure to recession grows. To illustrate this, for a firm exposed to a recession for an entire year, the benefit of operating flexibility exceeds those of the entire sample by over threefold (i.e., contrast -0.334 with -0.097). Therefore, as the economy becomes more deeply entrenched in an economic downturn, a typical firm will find downsizing operation flexibility more beneficial in mitigating stock price crash risk.

TABLE 4. Length of recession exposure

	(1)	(2)	(3)	(4)	(5)
	Recession exposure for at least				
	1 month	3 months	6 months	9 months	12 months
FLEX	-0.153***	-0.191***	-0.207***	-0.289***	-0.334**
	(-2.76)	(-3.00)	(-2.60)	(-2.81)	(-2.40)
Observations	20,971	16,658	9,711	5,704	2,861
R-squared	0.088	0.093	0.103	0.084	0.086
Controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES

Note: t-statistics are given in the parentheses *** p<0.01, ** p<0.05, * p<0.1.

4.4. Nature of recession

Is the value of operating flexibility uniform across all recessionary periods? Guided by our model, the FLEX proxy captures a firm's ability to reduce operational expenditures during adverse circumstances. Consequently, to the extent that different recessions originate from different causes, the benefit of downscale operation flexibility might vary. To explore this closely, we split our sample into groups of firm-years that are exposed to different recession events. We then rerun our baseline model separately for these subsamples and report the results in Table 5. The FLEX coefficients exhibit considerable variation across different recession periods. We find that downscale operation flexibility is most valuable in mitigating stock price crash risk during the recession in 1973-1975, 1980, and 1990-1991. This result is understandable since each of these periods was marked by substantial spikes in oil prices. Consequently, higher costs are directly transmitted to firms' operations, and it was the firms with greater downscale operation flexibility that were able to brace themselves against such real-side shocks.

The effect of downscale operation flexibility on crash risk, however, appears to be less significant during other recession periods, which arise from causes that are not directly related to escalated production costs. For example, the 1969-1970 recession was brought about by excessive Federal spending to fund the US's military efforts during the Vietnam War, among other forms of increased public expenditure. The 1981-1982 recession, known as the "double-dip recession", followed the Fed's aggressive monetary policy to tackle high inflation, resulting in an economic slowdown. The 2001 recession was triggered by the collapse of the Dotcom Bubble, characterized by unrealistically overvalued technology stocks. The 2007-2009 recession was initiated by a plunge in housing prices that precipitated a global financial crisis, encompassing a complex sequence of events, including the spikes and crashes of oil prices in mid-2008. The short and abrupt 2020 recession followed the swift spread of the COVID-19 pandemic that led to sudden travel restrictions and a surge in unemployment.

Overall, our findings here demonstrate that downscale operation flexibility offers protection to firms by augmenting their operational responsiveness in the presence of negative *real-side* shocks.

TABLE 5**. Nature of recession**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Recession period							
	69m12 -70m11	73m11 -75m3	80m1 -80m7	81m7 -82m11	90m7 -91m3	01m3 -01m11	07m12 -09m6	20m2 -20m4
FLEX	-0.210	-0.320**	-0.340*	0.162	-0.661***	-0.012	-0.064	-0.007
	(-0.67)	(-2.13)	(-1.94)	(1.02)	(-2.88)	(-0.08)	(-0.59)	(-0.04)
Observations	1,033	2,435	2,431	3,021	1,595	2,695	5,115	2,641
R-squared	0.111	0.130	0.098	0.124	0.100	0.100	0.049	0.058
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: t-statistics are given in the parentheses *** p<0.01, ** p<0.05, * p<0.1.

4.5. Firm characteristics

To further examine whether the crash-risk reduction effect of FLEX is manifested through the mechanism of contraction options as set out by our model, we look into relevant firm characteristics. We expect the impact of FLEX to be stronger for firms that are closer to their option-exercise boundaries. In terms of our model notation, this corresponds to firms with lower levels of scaled productivity P.

Empirically, P may be proxied by various measures of productivity, profitability, and operating leverage, because these are all monotonously related in the model and therefore *equivalently* describe the model's state variable P. For example, Hackbarth and Johnson (2015) verify the HJ model's implied risk premium conditional on productivity (as proxied by the market-to-book ratio) and profitability (as proxied by the return on assets). Gu et al. (2018) use operating leverage to measure the closeness to real-option-exercising thresholds and find that operating-leverage risk-premium is moderated by operational flexibility. Gu et al. (2019) study the impact of operating flexibility on financial leverage and argue that unproductive firms (defined as firms with a high book-to-market ratio) find contraction options more valuable in maintaining a high level of financial leverage. We follow these studies closely in conducting cross-sectional analysis based on productivity, profitability and operating leverage. Specifically, to test Hypothesis 3, we categorize firms into subsets with high or low productivity, profitability, or operating leverage, and assess the magnitude of the FLEX effect in each subsample.

4.5.1. Productivity

Our model implies a monotonous relationship between productivity θ and market value of equity J. Therefore, a natural proxy for the scaled productivity P is the ratio of market equity to book equity (MB), as also adopted by Hackbarth and Johnson (2015). From another point of view, firms with a low MB ratio are typically equipped with high levels of unproductive capital and may be regarded as having low levels of productivity. Modelling an all-equity financed firm, our analytical framework does not differentiate the value of total assets from equity. In view of this, we also employ Tobin's Q (TobinQ) as an alternative proxy, defined as the market value of total assets scaled by the book value of total assets.

We run the baseline regression for each productivity subsample constructed using the median of MB and TobinQ. Estimation results are reported in Table 6. The table shows that FLEX is negatively and statistically significantly associated with stock price crash risk for firms with low levels of productivity. In contrast, the association is weak for firms with high productivity. This pattern is consistent across the two measures of productivity, and for both the whole sample and the recession sample. These findings support Hypothesis 3 that the crash-risk-reduction effect of operating flexibility is more pronounced for firms with lower productivity. This also accords with the validity of FLEX in capturing contraction option flexibility, which manifests its impact primarily when firms are in episodes of low productivity, so that their contraction options become more valuable.

TABLE 6. Firm characteristics: High/low productivity subsamples

Panel A. Market-to-book (MB)

	(1)	(2)	(1)	(2)
	Recession Periods		Whole Sample	
NSKEW	Low MB	High MB	Low MB	High MB
FLEX	-0.321***	0.006	-0.173***	-0.010
	(-4.38)	(0.07)	(-4.33)	(-0.21)
Observations	11,682	9,289	42,727	34,867
R-squared	0.084	0.059	0.067	0.043
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES

Panel B. Tobin's Q (TobinQ)

	(1)	(2)	(3)	(4)
	Recession Periods		Whole Sample	
NSKEW	Low TobinQ	High TobinQ	Low TobinQ	High TobinQ
FLEX	-0.243***	-0.056	-0.171***	-0.004
	(-3.33)	(-0.65)	(-4.36)	(-0.08)
Observations	11,733	9,163	42,985	33,890
R-squared	0.084	0.054	0.066	0.040
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES

Note: t-statistics are given in the parentheses *** p<0.01, ** p<0.05, * p<0.1.

4.5.2. Profitability

In our model, the profit flow rate scaled by capital assets, $\Pi/K = P^{1-\gamma} - m$, is monotonously increasing in the scaled productivity P. Therefore, we may use profitability to test the conditional effect of FLEX on stock price crash risk. We adopt two proxies of profitability for this exercise — the return on assets (ROA) (Hendricks et al., 2009; Swift et al. 2019) and the gross profits over assets (GPOA). Similar to the last section, we split the firms into high and low profitability subsamples according to the median level of ROA and GPOA, respectively, and run the baseline regressions for each subsample, and report the estimates in Table 7. The results show that FLEX has a significant negative impact on NSKEW in the low ROA and GPOA subsamples, whilst the association is weak in the high ROA and GPOA subsamples. These findings support our Hypothesis 3 that the crash-risk-reduction effect of operating flexibility is more pronounced for firms with lower profitability, which are closer to their contraction-option exercise thresholds.

TABLE 7. Firm characteristics: High/low profitability subsamples

Panel A. Return on assets (ROA)

	(1)	(2)	(3)	(4)
	Recession Periods		Whole Sample	
NSKEW	Low ROA	High ROA	Low ROA	High ROA
FLEX	-0.172**	-0.099	-0.114***	-0.041
	(-2.26)	(-1.20)	(-2.73)	(-0.91)
Observations	9,826	11,144	37,037	40,557
R-squared	0.089	0.087	0.063	0.066
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES

Panel B. Gross profits over assets (GPOA)

	(1)	(2)	(3)	(4)
	Recession Periods		Whole Sample	
NSKEW	Low GPOA	High GPOA	Low GPOA	High GPOA
FLEX	-0.215***	-0.049	-0.162***	0.036
	(-3.04)	(-0.53)	(-4.15)	(0.72)
Observations	10,191	10,779	38,078	39,516

R-squared	0.088	0.096	0.065	0.073
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES

Note: t-statistics are given in the parentheses *** p<0.01, ** p<0.05, * p<0.1.

4.5.3. Operating leverage

From our model's perspective, we may naturally frame the real-options effect on crash risk in terms of operating leverage. Exercising contraction options cuts down operational costs associated with unproductive capital. This becomes particularly valuable when the firm's operational costs gain significance relative to its revenue, indicating high operating leverage. We employ two proxies of operating leverage to test this conditional effect of FLEX on stock price crash risk. Motivated by the HJ model itself, Gu et al. (2018) measure operating leverage with quasi-fixed costs (QFC). The authors use the firm's past data on sales and operational costs to predict the next period's expected costs even if the current sales were zero, and then define QFC as the predicted costs scaled by actual sales. To complement this proxy, we also measure operating leverage as the simple ratio of operational costs to sales (OPCS).

Similar to previous cross-sectional tests, we split the firms into high and low operating leverage subsamples according to the median level of QFC and OPCS each year, respectively, and run the baseline regressions for each subsample, and report the estimates in Table 8. Our results show that FLEX has a significant negative impact on NSKEW in the high QFC and OPCS subsamples, whilst the association is weaker in the low QFC and OPCS subsamples. These findings support our Hypothesis 3 that the crash risk-reduction effect of operating flexibility is more pronounced for firms with high operating leverage, for which cutting down operational costs associated with unproductive capital becomes more important.

TABLE 8. Firm characteristics: High/low operating leverage subsamples

Panel A. Quasi-fixed costs (QFC)

	(1)	(2)	(3)	(4)
	Recession Periods		Whole Sample	
NSKEW	High	Low	High	Low

FLEX	-0.193**	-0.110	-0.136***	-0.069
	(-2.27)	(-1.41)	(-2.88)	(-1.61)
Observations	9,331	10,364	35,522	37,850
R-squared	0.095	0.080	0.073	0.059
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES

Panel B. Operational costs over sales (OPCS)

NSKEW	(1)	(2)	(3)	(4)
	Recession Periods		Whole Sample	
	High	Low	High	Low
FLEX	-0.236***	-0.056	-0.098**	-0.044
	(-2.73)	(-0.73)	(-2.11)	(-1.01)
Observations	9,506	10,175	35,331	37,362
R-squared	0.094	0.077	0.070	0.058
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES

Note: t-statistics are given in the parentheses *** p<0.01, ** p<0.05, * p<0.1.

5. Conclusion

This paper examines how firms' operating flexibility affects the crash risk of their stock prices. Particularly, during periods of low productivity, a firm's ability to cut down operational costs associated with unproductive capital can curtail firm losses and thereby reduce its downside risk. We formally study this mechanism using Hackbarth and Johnson's (2015) real-options asset-pricing model. Our analytical insights show that firms' operating flexibility, facilitated by their real options, can reduce the stock price crash risk. Importantly, the operating-flexibility effect is most pronounced during phases of low productivity and profitability, consistent with the loss-curtailment mechanism that we propose.

Utilizing U.S. data spanning from 1961 to 2020, we present empirical evidence that supports our theoretical predictions. Motivated by our model, we construct a firm-level operating flexibility measure FLEX to proxy for firms' ease of exercising their contraction options. Our analyses reveals a significant and robust negative association between FLEX and crash risk. This association is particularly stronger during recession periods, and becomes even more prominent as a firm becomes more entrenched in a recession. Furthermore, the crash-risk reduction effect of FLEX is more pronounced when firms have lower profitability, lower productivity, or higher operating leverage. Lastly, using FLEX as a conditioning variable, we find evidence that operating flexibility attenuates or reverses the operating-leverage effect on crash risk. Taken together, these results confirm the real-options mechanism for stock price crash risk.

When the corporate sector was shocked by economic downturns, we document a relationship between firms' ability of downsizing operations and firm performance that varies in economically sensible ways. Specifically, we observe a negative association between the flexibility of downscaling operations and the risk of stock price crashes, with this link becoming more pronounced during longer and more severe recessions. Our research provides empirical evidence that highlights the role of downscale operation flexibility as an important insurance mechanism for both firms and investors, safeguarding them against bad economic states of the world. This new perspective adds the operations management dimension to other management factors such as corporate governance, diversification, and brand capital (Graham et al., 2011; Kuppuswamy and Villalonga, 2016; Hasan et al., 2022).

Our study emphasizes a somewhat largely overlooked mechanism that may affect stock price crash risk – firms' real operations decisions. While the extant literature primarily studies stock price crash risk through the perspective of bad news withholding in an information-asymmetric environment (see, e.g., Jin and Myers, 2006; Hutton et al., 2009; Kim et al., 2011), our work suggests that firms' operational decisions may play an important role in explaining stock price crashes. Our findings also complement a growing body of real-options and operations management research which reveals that real flexibility can affect, for example, corporate investment strategies, risk and return profiles, and financial policies (see, e.g., Hackbarth and Johnson, 2015; Reinartz and Schmid, 2016; Serfling, 2016; D'Acunto et al., 2018; Jiang et al., 2023). This provides a fruitful avenue for future studies to explore these dynamics. Understanding how managers' real-operations decisions and their disclosure decisions, taken together, affect the firms' future stock price crash risk may have interesting and useful implications.

Besides the academic audience, our findings have practical implications for the decision-making of both corporate managers and investors. Stock price crashes lead to large declines in firm valuation and represent a severe downside risk for both firms and their investors. As a result, corporate managers should take decisive actions to develop greater operating flexibility and improve their ability to succeed in a dynamic and unpredictable business environment. While our results suggest that, in general, firms should manage their operations in a flexible manner to navigate through economic downturns, it is critical to recognize the unique characteristics of each firm and the specific type of economic crisis they are confronting. For investors, their aversion to crash risk directly influences their portfolio selection and the valuation of stocks and derivatives (Harvey and Siddique, 2000; Conrad et al., 2013). The concern over elevated levels of crash risk is especially heightened for small investors who typically hold a limited number of stocks in their portfolios (Barber and Odean, 2013). Our results suggest that both corporate managers and investors would be wise to factor in firms' operation flexibility into their decision-making processes.

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Appendix A Model Solution

In this appendix, we provide the set of optimality conditions for the solution of the model introduced in Section 2.1. Hackbarth and Johnson (2015) show that the firm's value, in the inaction region, can be written as $J(\theta, K) = \theta\, V(Z)$, where $Z = K/\theta$. $V(Z)$ satisfies an ordinary differential equation with general solution $V(Z) = AZ^{\gamma} - SZ + D_N Z^{\lambda_N} + D_P Z^{\lambda_P}$, where the coefficients $A > 0$, $S > 0$, $\lambda_P > 1$ and $\lambda_N < 0$ are constants independent of scale adjustment frictions, and D_N and D_P are coefficients of the complementary solutions to the ordinary differential equation and are determined by boundary conditions that we elaborate below.

In the absence of the expansion option, when firm productivity $\theta \to \infty$, i.e., when $Z \to 0$, the firm's value approaches the scenario without real options, i.e., $V(Z) \to AZ^{\gamma} - SZ$. This implies $D_N = 0$. Therefore, we may now assume $V(Z) = AZ^{\gamma} - SZ + D_P Z^{\lambda_P}$.

Upon reaching the contraction boundary U, Z adjusts downwards to H. Pre- and post-adjustment firm values differ by the adjustment frictions; therefore, we obtain the following value matching conditions (VMC):

$$V(H) = V(U) + f_U U^{\gamma} + p_U (H - U). \quad \text{(A.1)}$$

The optimality for the choice of H and U yields their corresponding first order conditions, which can be obtained as smooth pasting conditions (SPC) below by functionally differentiating (A.1) with respect to H and U, respectively:

$$V'(H) = p_U, \quad \text{(A.2)}$$

$$V'(U) = -\gamma f_U U^{\gamma-1} + p_U\,. \quad \text{(A.3)}$$

The three equations (A.1-3) determine the values of the unknown parameters D_N, U and H. As these are non-linear equations (especially in terms of U and H), we employ a numerical algorithm to solve them.

Appendix B Proofs

We first prove a lemma below.

Lemma 1. Let P be a diffusion process with drift μ and volatility σ, and let $\Phi(P)$ be a function of P. The skewness of Φ conditional on P, in the interval Δt, is then given by

$$Skewness_{\Phi}(P) = 3\sigma \frac{\Phi''}{\Phi'} \sqrt{\Delta t} + o\left(\sqrt{\Delta t}\right),$$

where $\Phi' = \frac{d\,\Phi}{d \log \mathrm{P}}, and\ \Phi'' = \frac{d\,\Phi'}{d \log P}$.

Proof of Lemma 1.

The next-period increment of Φ can be expressed in terms of ΔP as $\Delta\Phi = a\,\Delta\log P + b(\Delta\log P)^2 + \cdots$, where $a = \Phi' = \frac{d\,\Phi}{d\log P}$, and $b = \frac{1}{2}\Phi'' = \frac{1}{2}\frac{d\,\Phi'}{d\log P}$. The skewness of $\Delta\Phi$, as a quadradic function of the normally distributed $\Delta\log P \sim N(\mu\Delta t, \sigma^2\Delta\mathrm{t})$, can be easily obtained using the moments of normal distribution well known up to any order. Specifically, the skewness of $\Delta\Phi$ is $Skewness_\Phi = E\left[\left(\frac{\Delta\Phi-\mu_{\Delta\Phi}}{\sigma_{\Delta\Phi}}\right)^3\right]$, where $\mu_{\Delta\Phi} = E[\Delta\Phi]$, and $\sigma_{\Delta\Phi} = \sqrt{E[\Delta\Phi^2] - E[\Delta\Phi]^2}$. Let $X = \Delta\log P$, then skewness is a function of moments of X. The first four moments are required in this exercise, and they are $E[X] = \mu\Delta t, E[X^2] = \sigma^2\Delta\mathrm{t} + \mu^2\Delta t^2, E[X^3] = 3\mu\sigma^2\Delta t^2 + \mu^3\Delta t^3, E[X^4] = 3\sigma^4\Delta t^2 + 6\mu^2\sigma^2\Delta t^3 + \mu^4\Delta t^4$. Therefore, the return skewness is eventually a function of Δt. Extracting the leading order of skewness in Δt, using a Taylor expansion in Δt, yields $Skewness_\Phi(P) = 6\sigma b/a\sqrt{\Delta t} + o\left(\sqrt{\Delta t}\right)$. Substituting $a = Q'$ and $b = Q''/2$ into this equation completes the proof. ■

Proof of Proposition 1.

For the ease of notation, we label the quantities at the beginning of the interval Δt with a subscript '0', whereas the quantities without subscript represent values at the end of the period. The log return can then be written as $lR = \log[(J + \Pi_0\Delta t)/J_0] = \log J + \log(1 + \Pi_0\Delta t/J) - \log J_0$, the leading order skewness of which comes from the $\log J$ term. Using $Q = J/K$, we can write $\log J = \log Q + \log K$, and only the $\log Q$ term contributes to the skewness because K evolves deterministically, i.e., $\Delta\log K_t = -\delta\Delta t$. Therefore, the skewness of lR is equal to that of $\log Q$ in the leading order.

By an application of Ito's lemma, it can be seen that $P = \theta/K$ follows a diffusion process $d\log P_t = \mu_P dt + \sigma_P dW_t$, where $\mu_P = \mu_\theta - \sigma_\theta^2/2 + \delta$, and $\sigma_P = \sigma_\theta$. Therefore, we may apply Lemma 1 to $\Phi = \log Q$ to obtain the skewness of lR. Differentiating with respect to $\log P$, we find $\Phi' = Q'/Q$, and $\Phi'' = Q''/Q - (Q'/Q)^2$. Therefore, according to Lemma 1,

$$Skewness_{lR}(P) = 3\sigma(Q''/Q' - Q'/Q)\sqrt{\Delta t} + o\left(\sqrt{\Delta t}\right).$$

The negative skewness of the log return lR is obtained by reversing the sign of the above formula. This completes the proof of Proposition 1. ■

Proof of Proposition 2.

According to Appendix A, the value function is $V(Z) = AZ^\gamma - SZ + D_P Z^{\lambda_P}$, where $A, S, D_P > 0$, $0 < \gamma < 1$ and $\lambda_P > 1$. Hence the scaled firm value is $Q(Z) = J/K = V/Z = AZ^{\gamma-1} - S + D_P Z^{\lambda_P - 1}$. In terms of the scaled productivity $P = 1/Z$, we can write $Q(P) = AP^{1-\gamma} - S + D_P P^{1-\lambda_P}$. Applying Proposition 1 to this expression, we obtain

$$NSKEW = 3\sigma\left[\frac{A(1-\gamma)P^{1-\gamma} + D_P(1-\lambda_P)P^{1-\lambda_P}}{AP^{1-\gamma} - S + D_P P^{1-\lambda_P}} - \frac{A(1-\gamma)^2 P^{1-\gamma} + D_P(1-\lambda_P)^2 P^{1-\lambda_P}}{A(1-\gamma)P^{1-\gamma} + D_P(1-\lambda_P)P^{1-\lambda_P}}\right].$$

Denote the D_P dependence of the above expression as $3\sigma \cdot NS(D_P)$, then we may decompose the above as $NSKEW = NKSEW_{AIP} + NSKEW_{CO}$, where $NKSEW_{AIP} = 3\sigma \cdot NS(0)$ and $NKSEW_{CO} = 3\sigma[NS(D_P) - NS(0)]$. We now prove the signs and monotonicity of these components with respect to P as follows.

Setting $D_P = 0$, we obtain

$$NS(0) = \frac{A(1-\gamma)P^{1-\gamma}}{AP^{1-\gamma} - S} - (1-\gamma) = \frac{(1-\gamma)S}{AP^{1-\gamma} - S},$$

which is clearly positive and decreasing in P. The positivity of the denominator $AP^{1-\gamma} - S$ is required by the firm's value being positive. This demonstrates that $NSKEW_{AIP}(P) > 0$ and $NSKEW'_{AIP}(P) < 0$.

The case for $NS(D_P) - NS(0)$ is a bit more algebraically involving. We split it into three terms $NS(D_P) - NS(0) = a + b + c$, where

$$a = \frac{A(1-\gamma)P^{1-\gamma}}{AP^{1-\gamma} - S + D_P P^{1-\lambda_P}} - \frac{A(1-\gamma)P^{1-\gamma}}{AP^{1-\gamma} - S},$$

$$b = \frac{D_P(1-\lambda_P)P^{1-\lambda_P}}{AP^{1-\gamma} - S + D_P P^{1-\lambda_P}}, \qquad \text{and}$$

$$c = (1-\gamma) - \frac{A(1-\gamma)^2 P^{1-\gamma} + D_P(1-\lambda_P)^2 P^{1-\lambda_P}}{A(1-\gamma)P^{1-\gamma} + D_P(1-\lambda_P)P^{1-\lambda_P}}.$$

a can be rewritten as

$$a = \frac{A(1-\gamma)P^{1-\gamma}}{AP^{1-\gamma} - S + D_P P^{1-\lambda_P}} - \frac{A(1-\gamma)P^{1-\gamma}}{AP^{1-\gamma} - S} = -\left[\frac{A(1-\gamma)P^{1-\gamma}}{AP^{1-\gamma} - S}\right]\left[\frac{D_P \frac{P^{1-\lambda_P}}{AP^{1-\gamma} - S}}{1 + D_P \frac{P^{1-\lambda_P}}{AP^{1-\gamma} - S}}\right].$$

The terms $\frac{P^{1-\gamma}}{AP^{1-\gamma}-S}$ and $\frac{P^{1-\lambda_P}}{AP^{1-\gamma}-S}$ are both positive and decreasing in P. Therefore, both terms in the square brackets are positive and decreasing in P, hence is their product. Thus a is negative and increasing in P, i.e., $a < 0$ and $a' > 0$.

b can be rewritten as

$$b = (1-\lambda_P)\left[\frac{D_P \frac{P^{1-\lambda_P}}{AP^{1-\gamma} - S}}{1 + D_P \frac{P^{1-\lambda_P}}{AP^{1-\gamma} - S}}\right].$$

The term in the square bracket is exactly the same as the second square bracket of a, and hence is positive and decreasing in P. $\lambda_P > 1$ implies b is negative and increasing in P, i.e., $b < 0$ and $b' > 0$.

Finally, c can be rewritten as

$$c = (1 - \lambda_P)\left[\frac{D_P(\lambda_P - \gamma)}{A(1-\gamma)P^{\lambda_P - \gamma} + D_P(1 - \lambda_P)}\right].$$

$\gamma < 1 < \lambda_P$ implies that the term in the square bracket is positive and decreasing, and that $1 - \lambda_P < 0$. To guarantee the positivity of the denominator in the square bracket, we have used the fact that $Q' > 0$, which in turn derives from the assumption $\partial J/\partial\theta > 0$, as proposed by Hackbarth and Johnson (2015). Therefore, c is negative and increasing in P, i.e., $c < 0$ and $c' > 0$.

Adding the above three summands a, b and c together yields $NSKEW_{CO}(P) < 0$ and $NSKEW'_{CO}(P) > 0$. ■

Appendix C Additional Tables

Table C.1 gives the definition of variables used in our empirical tests.

Table C.1 Variable Definitions

Stock price crash risk measures

For each firm-year, we assign weekly returns to the 12-month period ending three months after the fiscal year-end, and obtain firm-specific weekly returns ($W_{j.\tau}$) as log(1+residual), where the residuals are estimated from either of the two following expanded market models:

$$r_{j,\tau} = \alpha_j + \beta_{1,j} r_{m,\tau-2} + \beta_{2,j} r_{m,\tau-1} + \beta_{3,j} r_{m,\tau} + \beta_{4,j} r_{m,\tau+1} + \beta_{5,j} r_{m,\tau+2} + \epsilon_{j,\tau} \quad \text{(M1)}$$

$$r_{j,\tau} = \alpha_j + \beta_{1,j} r_{m,\tau-1} + \beta_{2,j} r_{i,\tau-1} + \beta_{3,j} r_{m,\tau} + \beta_{4,j} r_{i,\tau} + \beta_{5,j} r_{m,\tau+1} + \beta_{6,j} r_{i,\tau+1} + \epsilon_{j,\tau} \quad \text{(M2)}$$

For market model (M1), we then compute *NSKEW* as the negative skewness of W, *DUVOL* as the natural logarithm of the ratio of the variances of down-week to up-week firm-specific weekly returns, and *CRASH* as an indicator for a crash event during the fiscal year. Here, the down and up weeks are those with W below and above, respectively, its annual mean; a fiscal year experiences a crash event if at least one value of W over the fiscal year falls 3.09 or more standard deviations below its annual mean.

NSKEW2, *DUVOL2* and CRASH2 are obtained similarly for firm-specific weekly returns under market model (M2).

Operating flexibility measures

We define firm j's operating flexibility in fiscal year t as $FLEX_{j,t} = 1/INFLEX_{j,t}$, where $INFLEX_{j,t}$ is the maximum level of operational costs over sales scaled by the volatility of the sales over assets annual growth rates, over the 20-year rolling window prior to fiscal year t. FLEX2 is obtained similarly but uses the window from the firm's beginning to fiscal year t; on the other hand, FLEX3 uses the firm's entire sample period as the estimation window.

Control variables

SIGMA and *RET* are the standard deviation and mean, respectively, of the firm-specific weekly returns, under market model (M1), over the 12-month period ending three months after the fiscal year-end. *l.NSKEW* is the lagged value of *NSKEW*. *SIGMA2*, *RET2* and *l.NSKEW2* are the corresponding variables under market model (M2).

DTURN is the average monthly share turnover over the current fiscal year minus the average monthly share turnover over the previous fiscal year. The monthly share turnover is calculated as the monthly trading volume divided by the total number of shares outstanding at the end of the month.

SIZE is the natural logarithm of the market value of equity (csho×prcc_f, Compustat variable names, hereafter).

MB is the market value of equity divided by the book value of equity (ceq).

LEV is the total long-term debt (dltt) scaled by total assets (at).

ROA is the income before extraordinary items (ib) divided by total assets (at).

ACCM is the absolute value of discretionary accruals estimated from the modified Jones model following the procedure of Hutton et al. (2009). The definition of total accruals follows the balance sheet approach of Dechow et al. (2008).

Conditioning variables

TobinQ is Tobin's Q ratio defined as (at+ csho×prcc_f-ceq)/at.

GPOA is the ratio of gross profits (gp) to total assets (at).

QFC is the quasi-fixed costs estimated according to equation (9) of Gu et al. (2018).

OPCS is the ratio of operational costs (cogs + xsga) to sales (sale).

Table C.2 reports the correlations between different measures of the major variables of interest.

Table C.2 Correlations between different measures of the major variables of interest

This table reports the correlations between different measures of operating flexibility (Panel A), and the correlations between different measures of stock price crash risk (Panel B). See Table C.1 for more details about the definition of these variables. The stars represent levels of statistical significance: *** *p<0.01*, ** *p<0.05*, * *p<0.1*.

Panel A: Correlations between measures of operating flexibility

Variables	(1)	(2)	(3)
(1) FLEX	1.00		
(2) FLEX2	0.94***	1.00	
(3) FLEX3	0.79***	0.85***	1.00

Panel B: Correlations between measures of stock price crash risk

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) NSKEW	1.00					
(2) DUVOL	0.96***	1.00				
(3) CRASH	0.56***	0.52***	1.00			
(4) NSKEW2	0.92***			1.00		
(5) DUVOL2		0.89***		0.96***	1.00	
(6) CRASH2			0.85***	0.60***	0.55***	1.00