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Financial Flexibility and Firm Resilience Under Macroeconomic Policy Uncertainty

Julien Morel [1, *], Camille Rochat [2]

[1] Faculty of Business and Economics (HEC Lausanne), University of Lausanne, Lausanne, Switzerland

[2] Centre Universitaire d'Informatique, University of Geneva, Geneva, Switzerland

[*] Corresponding Author

Abstract

Macroeconomic policy uncertainty raises the cost of external finance and the option value of waiting, which turns a firm's financial slack into a potential source of resilience. This paper examines whether, and in which form, financial flexibility helps firms withstand policy uncertainty. Financial flexibility is decomposed into cash flexibility, measured by cash holdings relative to industry peers, and debt flexibility, measured by unused debt capacity relative to the industry leverage benchmark. Using an annual panel of 12,970 firm-year observations for 2,831 U.S. non-financial listed firms over 2014–2018 and a monthly panel of 338 S&P 500 constituents over 2015–2018, combined with the news-based economic policy uncertainty (EPU) index, three results emerge. First, cash flexibility predicts stronger subsequent sales growth and investment, whereas debt flexibility predicts investment continuity and a markedly lower probability of a severe stock-price decline. Second, the stock returns of firms with greater debt flexibility respond less adversely to EPU shocks: a one-standard-deviation increase in debt flexibility adds about 0.20 percentage points to the monthly return for each one-standard-deviation rise in EPU, whereas cash flexibility provides no comparable cushion. Third, the cushioning effect is concentrated among smaller firms, consistent with a financing-constraint channel. The evidence indicates that unused borrowing capacity, rather than accumulated cash, is the form of flexibility that insulates firm value from policy shocks.

Keywords

Financial flexibility, economic policy uncertainty, firm resilience, debt capacity, cash holdings, stock returns.

1. Introduction

Uncertainty about fiscal, monetary, trade, and regulatory policy has become a defining feature of the macroeconomic environment. The newspaper-based economic policy uncertainty (EPU) index of Baker, Bloom, and Davis [1] shows that policy uncertainty in the United States fluctuates widely, with recurrent spikes around elections, fiscal standoffs, and trade disputes. A large literature documents that uncertainty shocks depress investment, hiring, and output [2–4], and recent work identifies distinct effects of uncertainty about monetary policy [5] and trade policy [6, 7]. Two mechanisms drive these effects. Under irreversibility, uncertainty raises the option value of waiting [8]; under financial frictions, uncertainty widens credit spreads and restricts access to external funds, which amplifies the real consequences [9].

At the firm level, policy uncertainty reduces corporate investment [10–12], delays mergers and acquisitions [13], raises the cost of capital [14], and contracts bank credit supply [15]; firm-level political risk has similar consequences [16]. In asset markets, policy uncertainty

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commands a risk premium and makes stock prices more volatile and more correlated [17–19]. Firms respond by building liquidity buffers, and corporate cash holdings rise with policy uncertainty in the United States and in emerging markets [20–22].

These patterns place financial flexibility, the capacity of a firm to mobilize financial resources at low cost when needed, at the center of how firms cope with policy uncertainty. Chief financial officers rank flexibility as the most important determinant of debt policy [23], and theory shows that its value rises with external financing costs and growth opportunities [24, 25]. Empirically, financial flexibility is associated with greater investment ability and better performance during financial crises [26–28] and with smaller stock-price losses during the COVID-19 collapse [29]. Two questions remain open. First, flexibility can be held in different forms, as cash on the balance sheet or as unused borrowing capacity, and these forms need not provide the same protection [30, 31]. Second, most evidence comes from rare crisis episodes, whereas policy uncertainty is a recurrent shock that fluctuates from month to month.

This paper addresses both questions by linking financial flexibility to firm resilience under policy uncertainty. Following the management literature, resilience is understood as the ability of a firm to absorb adverse shocks, limit the severity of losses, and sustain its activity [32–36]. Financial flexibility is decomposed into cash flexibility, defined as cash holdings in excess of the sector median, and debt flexibility, defined as leverage below the sector median. Two complementary designs are used. An annual panel of 2,831 U.S. non-financial firms over 2014–2018 relates flexibility to subsequent sales growth, investment, and the incidence of severe stock-price declines. A monthly panel of 338 S&P 500 firms over 2015–2018 tests whether flexibility attenuates the stock-price response to monthly EPU shocks, with month fixed effects absorbing all market-wide variation.

The results reveal a clear division of labor between the two forms of flexibility. Cash flexibility is associated with faster subsequent sales growth and higher investment, but also with a higher incidence of severe price declines. Debt flexibility supports investment, substantially reduces downside risk, and is the only component that cushions stock returns against policy uncertainty shocks. The cushioning effect is robust to alternative shock definitions, firm fixed effects, and alternative clustering, and it is concentrated among smaller firms. The paper contributes to the literature on policy uncertainty and corporate policy [10, 21] by identifying unused debt capacity as a resilience resource, and to the financial flexibility literature [29, 30] by showing that the protective role of flexibility extends beyond crisis episodes to recurrent policy shocks.

The remainder of the paper is organized as follows. Section II reviews the literature and develops the hypotheses. Section III describes the data and methodology. Section IV reports the empirical results, Section V discusses their implications, and Section VI concludes.

2. Literature Review and Hypotheses

2.1. Policy Uncertainty and Corporate Outcomes

Real options theory predicts that firms postpone irreversible investment when uncertainty about future payoffs rises [8]. Policy uncertainty adds a specific dimension: the future tax, regulatory, monetary, or trade regime that governs those payoffs. Gulen and Ion [10] show that the EPU index predicts lower corporate investment, with stronger effects for firms whose investment is more irreversible, and election-based studies confirm a causal effect of political uncertainty on investment [11, 12]. Financial channels reinforce the real-options channel. Policy uncertainty raises the cost of capital [14], tightens bank lending [15], and interacts with financial frictions to amplify downturns [9]. In equity markets, uncertainty about government policy lowers prices and raises risk premia [17, 18], and innovations in EPU carry a negative price of risk [19]. Text-based firm-level measures confirm that firms exposed to political risk retrench hiring and investment [16].

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2.2. Financial Flexibility as a Resilience Resource

Financial flexibility originates in financing frictions. When managers know more than investors, external finance is costly and firms may forgo valuable projects [37], and financing constraints make investment sensitive to internal funds [38–40]. Flexible firms preserve the option to fund future needs. One source of flexibility is cash. The precautionary motive explains why firms with riskier cash flows and more growth options hold more cash [41–43], why constrained firms save cash out of cash flow [44], and why the marginal value of cash is higher for constrained firms [45, 46]; dynamic models show that liquidity, risk management, and investment are determined jointly [47]. A second source is debt capacity. Firms keep leverage below target to preserve the option to borrow [25, 48], and bank lines of credit provide liquidity mainly to firms that maintain healthy cash flows [49]. Cash and debt capacity are not perfect substitutes: cash is the preferred hedge when cash flows are low in states in which investment opportunities arise [31].

The empirical literature confirms that flexibility is valuable. Spare debt capacity raises investment ability and firm value [26, 28]; flexible firms invest more and perform better around crises [27, 50]; and firms build flexibility in anticipation of recessions [51] and manage payouts and leverage to preserve it [52–54]. Flexibility is also priced in the cross-section of stock returns [55] and moderates the response of investment to firm-specific uncertainty [56]. Crisis studies show that liquidity and low leverage protected firm value during the 2008 credit crisis [57] and the COVID-19 shock [29, 58–60], while non-financial attributes such as social capital also contributed to resilience [61, 62].

2.3. Hypotheses

Resilience has two facets: the capacity to sustain operations and investment, and the capacity to limit losses when a shock hits [35, 36]. Financial flexibility should support both. The first hypothesis concerns the unconditional relation.

H1: Financial flexibility is associated with stronger subsequent sales growth and investment and with a lower probability of severe stock-price declines.

Policy uncertainty tightens external financing conditions precisely when funding access is most valuable [9, 15]. Firms that can raise funds at short notice face lower expected costs of underinvestment and distress when uncertainty spikes, and investors should therefore revalue such firms less adversely.

H2: Financial flexibility attenuates the adverse stock-price response to policy uncertainty shocks.

Because the value of flexibility is greatest when external finance is costly [24, 46], and uncertainty affects smaller firms more strongly [63], the attenuation should be stronger for smaller firms.

H3: The attenuation effect of financial flexibility is stronger for smaller, more financially constrained firms.

3. Data and Methodology

3.1. Data Sources and Samples

Firm-level accounting data come from a publicly available compilation of 10-K-based financial indicators for U.S. listed companies covering fiscal years 2014–2018, which also reports each stock's percentage price change over the following calendar year. Financial firms, real estate firms, and utilities are excluded because regulation shapes their leverage and liquidity. Firms with total assets below USD 10 million, non-positive revenue, or missing key variables are dropped, and continuous variables are winsorized at the 1st and 99th percentiles within each

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fiscal year. The annual sample contains 12,970 firm-year observations for 2,831 firms in eight sectors.

The monthly sample uses daily closing prices of S&P 500 constituents from February 2013 to February 2018. Month-end prices are converted into monthly returns, months with daily price changes larger than 40% are removed to eliminate split-related discontinuities, and returns are winsorized at the 0.5th and 99.5th percentiles. Each return in calendar year y is matched with flexibility measures and controls from fiscal year y−1, so that firm characteristics are publicly known before returns are realized. A pre-sample market beta is estimated for each stock from daily returns over 2013–2014 against an equal-weighted market proxy. The resulting sample covers 12,224 firm-months for 338 non-financial firms over the 37 months from January 2015 to January 2018.

Policy uncertainty is measured by the monthly news-based EPU index of Baker et al. [1], together with its categorical components for monetary policy and trade policy. Fig. 1 plots the three series. The annual average of the EPU index is 113 in 2015, rises to 145 in 2016 and 153 in 2018, and reaches 189 in 2019. Monthly spikes coincide with the Brexit referendum (June 2016), the presidential election (November 2016), the federal government shutdown (January 2019), and the escalation of the U.S.–China trade dispute (August 2019). The monthly policy uncertainty shock is the log change in the index, Sm = Δln EPUm, standardized over the estimation window.

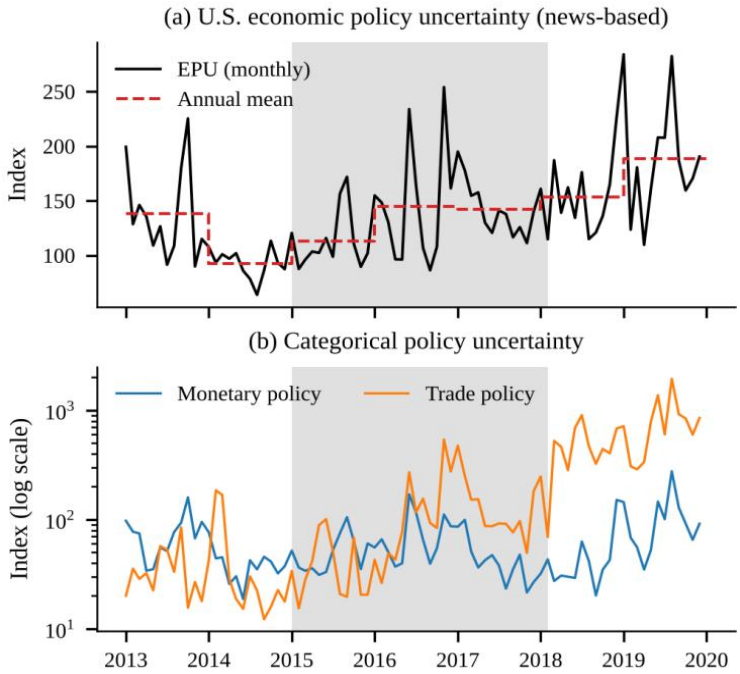

Figure 1. U.S. economic policy uncertainty, 2013–2019. Panel (a) shows the monthly news-based EPU index and its annual means; panel (b) shows the categorical monetary policy and trade policy uncertainty indices on a log scale. The shaded area marks the window of the monthly tests (January 2015–January 2018).

3.2. Measuring Financial Flexibility

Building on the spare-debt-capacity approach [26, 28] and on the joint cash–leverage view of flexibility [27, 30], two components are constructed relative to the sector-year peers s of firm i:

$$CF_{i,t} = CASH_{i,t} - Med_{s,t}(CASH) \quad (1)$$

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$$DF_{i,t} = \max\{0, Med_{s,t}(LEV) - LEV_{i,t}\} \quad (2)$$

Where CASH is cash and short-term investments over total assets and LEV is total debt over total assets. CF measures internal liquidity in excess of peers, and DF measures borrowing capacity left unused relative to the sector benchmark. The composite index FFI = CF + DF summarizes total flexibility. All flexibility measures are standardized to unit variance in the regressions.

3.3. Measuring Resilience

In the annual sample, resilience is measured over the year that follows the measurement of flexibility by three outcomes: sales growth SG_{t+1}; investment INV_{t+1}, defined as capital expenditure in t+1 scaled by total assets in t; and $CRASH_{t+1}$, an indicator equal to one if the stock price falls by more than 30% during the following year. CRASH captures the severity-of-loss dimension of resilience [35]. Sales growth and investment require next-year accounts and are therefore available for fiscal years 2014–2017. In the monthly sample, resilience is measured by the differential response of stock returns to policy uncertainty shocks.

3.4. D. Empirical Models

The annual tests estimate

$$Y_{i,t+1} = \beta_1 CF_{i,t} + \beta_2 DF_{i,t} + \gamma' X_{i,t} + \mu_s + \tau_t + \varepsilon_{i,t+1} \quad (3)$$

Where X contains firm size (log total assets), return on assets (ROA), Tobin's Q, asset tangibility (TANG), current sales growth (SGROW), R&D intensity (RD), and indicators for dividend payers (DIV) and loss-making firms (LOSS); the investment model also includes current investment. Sector fixed effects μ_s and year fixed effects τ_t absorb industry differences and common annual shocks, including the level of policy uncertainty, and standard errors are clustered by firm. The monthly tests estimate

$$R_{i,m} = \beta_1 CF_{i,y-1} + \beta_2 DF_{i,y-1} + \theta_1 CF_{i,y-1} \cdot S_m + \theta_2 DF_{i,y-1} \cdot S_m + \Sigma_k(\delta_k Z_{k,i} + \varphi_k Z_{k,i} \cdot S_m) + \mu_s + \lambda_m + \varepsilon_{i,m} \quad (4)$$

Where $R_{i,m}$ is the monthly return in percent and Z contains size, ROA, Tobin's Q, and the pre-sample beta, each also interacted with the shock. Month fixed effects λ_m absorb the market return and the main effect of the shock, so θ_1 and θ_2 are identified solely from cross-sectional differences in the response to the same EPU shock, and the beta interaction ensures that the estimates do not reflect differences in market risk. H2 predicts $\theta > 0$. Standard errors are clustered two-way by firm and month [64].

4. Empirical Results

4.1. Descriptive Statistics

Table I reports summary statistics. In the annual sample the median firm grows sales by 6.1% and invests 2.9% of assets per year, and 21.0% of firm-years are followed by a price decline of more than 30%. Cash holdings average 22.3% of assets and leverage 25.2%. CF and DF are positively correlated ($\rho = 0.36$) but far from collinear, which allows their effects to be separated. The S&P 500 firms in the monthly sample are larger and more levered than the broad sample, and 32.3% of their firm-months show positive debt flexibility. The monthly EPU shock has a standard deviation of 0.31 log points.

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4.2. Financial Flexibility and Firm Resilience

Table II reports estimates of (3). Cash flexibility is associated with stronger operating resilience. A one-standard-deviation increase in CF raises next-year sales growth by 5.5 percentage points (t = 4.16) and investment by 0.19 percentage points of assets (t = 3.65), about 4% of the sample mean. Debt flexibility is not significantly related to sales growth but raises investment by 0.13 percentage points (t = 2.14), consistent with spare debt capacity enabling investment [26, 48]. The two forms of flexibility diverge sharply in downside risk. A one-standard-deviation increase in DF lowers the probability of a severe price decline by 2.1 percentage points (t = −5.22), a 10% reduction relative to the unconditional crash rate of 21.0%. Cash flexibility, in contrast, raises the crash probability by 1.4 percentage points (t = 2.90) even after controlling for R&D intensity and losses, in line with the concentration of large cash buffers in firms with risky cash flows [41, 43]. Panel B shows that the composite index FFI predicts higher growth and investment but is unrelated to crash risk, because the opposite effects of its components offset each other. Fig. 2 visualizes the standardized effects. These results support H1 for both components with respect to investment, for cash flexibility with respect to growth, and for debt flexibility with respect to downside protection.

Table I. Descriptive Statistics

Variable	Mean	SD	P25	Median	P75
Panel A: Annual sample (12,970 firm-years; 2,831 firms)					
SG_{t+1} (%)	17.90	71.05	−3.11	6.06	18.78
INV_{t+1} (%)	4.64	5.58	1.32	2.94	5.79
$CRASH_{t+1}$ (%)	21.00	40.73	0.00	0.00	0.00
CF	0.041	0.206	−0.060	0.000	0.135
DF	0.067	0.090	0.000	0.000	0.119
CASH	0.223	0.246	0.043	0.126	0.310
LEV	0.252	0.233	0.032	0.219	0.387
SIZE	20.64	2.13	19.07	20.67	22.09
ROA	−0.040	0.230	−0.049	0.028	0.071
Q	2.02	1.94	0.90	1.39	2.35
RD	0.059	0.121	0.000	0.000	0.064
DIV	0.405	0.491	0.000	0.000	1.000
Panel B: Monthly sample (12,224 firm-months; 338 firms)					
RET (%)	0.96	7.25	−3.25	0.81	5.17
Δln EPU	0.017	0.307	−0.167	−0.012	0.137
CF	−0.030	0.169	−0.073	−0.025	0.054
DF	0.031	0.061	0.000	0.000	0.035
LEV	0.304	0.185	0.179	0.279	0.403
BETA	1.03	0.27	0.82	1.01	1.21

Notes: SG_{t+1} and INV_{t+1} are available for 10,165 and 10,183 firm-years, respectively. CF and DF are measured relative to sector-year medians of the annual sample. Statistics for Δln EPU are computed over the 37 months of the monthly sample.

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Table II. Financial Flexibility and Firm Resilience: Annual Evidence

Variable	SG_{t+1}	INV_{t+1}	$CRASH_{t+1}$
Panel A: Flexibility components			
CF	5.506*** (4.16)	0.190*** (3.65)	1.427*** (2.90)
DF	0.862 (1.08)	0.129** (2.14)	−2.123*** (−5.22)
SIZE	0.577 (1.63)	−0.037 (−1.36)	−2.289*** (−10.62)
ROA	−66.991*** (−6.99)	0.614* (1.70)	−26.083*** (−8.81)
Q	3.936*** (6.95)	0.302*** (8.69)	−1.445*** (−6.80)
TANG	−1.883 (−0.73)	3.796*** (10.25)	6.628*** (3.52)
SGROW	6.048*** (2.78)	0.125* (1.83)	1.848*** (3.12)
RD	−46.015** (−2.46)	−2.528*** (−4.26)	−7.230 (−1.28)
DIV	−4.208*** (−4.66)	−0.507*** (−5.43)	−5.213*** (−6.54)
LOSS	−0.034 (−0.02)	−0.376*** (−3.16)	4.810*** (4.56)
INVt		0.656*** (28.06)	
Sector FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	10,165	10,183	12,970
Adj. R^2	0.104	0.526	0.142
Panel B: Composite index (separate regressions, same controls)			
FFI	5.725*** (4.79)	0.264*** (5.04)	−0.123 (−0.27)

Notes: Estimates of (3). Dependent variables are in percent. CF, DF, and FFI are standardized. t-statistics based on firm-clustered standard errors are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

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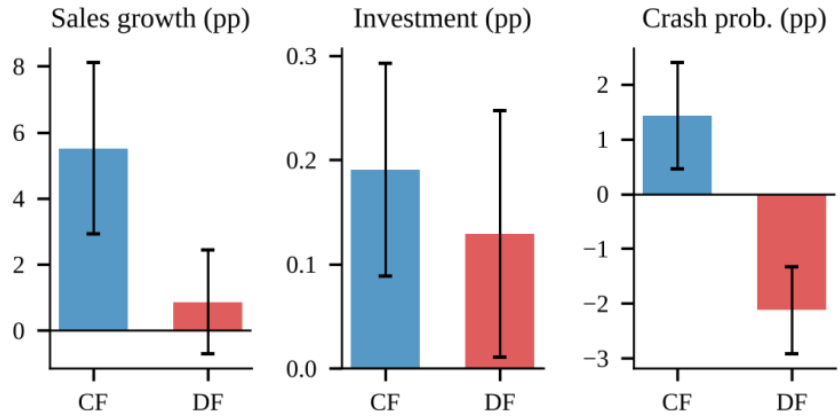

Figure 2. Effects of a one-standard-deviation increase in cash flexibility (CF) and debt flexibility (DF) on next-year sales growth, investment, and crash probability (Table II, Panel A). Error bars show 95% confidence intervals.

4.3. Policy Uncertainty Shocks and Stock-Price Resilience

Table III reports estimates of (4). Column (1) shows that the composite index earns a higher average return but does not significantly change the response to EPU shocks ($\theta = 0.109$, $t = 0.94$). Column (2) separates the two components and reveals the source of resilience. The interaction of debt flexibility with the EPU shock is 0.196 ($t = 2.60$): when EPU rises by one standard deviation, a firm with one standard deviation more debt flexibility earns a 0.20 percentage point higher return in that month. During a two-standard-deviation spike, which corresponds to an increase in EPU of roughly 85%, the differential reaches about 0.39 percentage points, which is sizable relative to the average monthly return of 0.96%. The interaction for cash flexibility is essentially zero (0.004, $t = 0.04$), even though cash-rich firms earn higher average returns over the sample period.

Columns (3) and (4) confirm the result under alternative definitions. Replacing the truncated DF by the untruncated leverage gap, which also measures how far over-levered firms are from the benchmark, yields an interaction of 0.196 ($t = 3.21$). Using as the shock the innovation from an AR(1) model of log EPU estimated over 1985–2018 yields 0.158 ($t = 2.07$). Fig. 3 provides portfolio-level evidence: the monthly return spread between firms with positive debt flexibility and the remaining firms rises with the EPU shock (slope = 1.01, HAC $t = 1.95$), so firms with spare borrowing capacity outperform when policy uncertainty jumps. These results support H2 for debt flexibility.

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Table III. Policy Uncertainty Shocks and Monthly Stock Returns

Variable	(1)	(2)	(3)	(4)
Shock S	Δln EPU	Δln EPU	Δln EPU	EPU innov.
FFI	0.350*** (3.61)			
CF		0.381*** (3.56)	0.388*** (3.71)	0.381*** (3.54)
DF		0.017 (0.23)		0.015 (0.20)
LEVGAP			−0.041 (−0.67)	
FFI×S	0.109 (0.94)			
CF×S		0.004 (0.04)	0.014 (0.13)	0.032 (0.32)
DF×S		0.196*** (2.60)		0.158** (2.07)
LEVGAP×S			0.196*** (3.21)	
Controls	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Observations	12,224	12,224	12,224	12,224
Adj. R^2	0.183	0.183	0.183	0.183

Notes: Estimates of (4). The dependent variable is the monthly return in percent. S is the standardized policy uncertainty shock; column (4) uses the AR(1) innovation of log EPU. Controls are SIZE, ROA, Q, and the pre-sample BETA, each with its interaction with S. LEVGAP is the untruncated sector-median leverage minus firm leverage. t-statistics based on standard errors clustered by firm and month are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

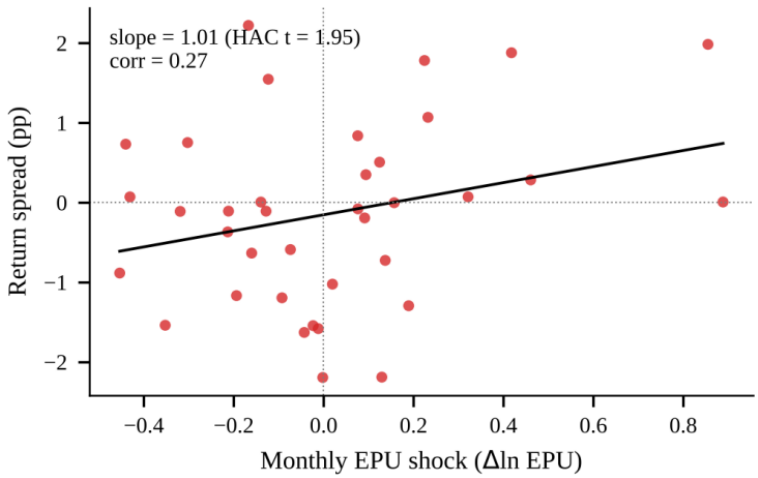

Figure 3. Monthly return spread between firms with positive debt flexibility (DF > 0) and the remaining firms against the monthly EPU shock, January 2015–January 2018. The line is the OLS fit; the t-statistic uses HAC standard errors with three lags.

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4.4. Robustness and Heterogeneity

Table IV reports further tests. Columns (1) and (2) replace the overall EPU shock by shocks to the monetary policy and trade policy uncertainty indices. The DF interactions remain positive (0.076 and 0.128) but are not statistically significant, which indicates that the cushioning effect operates mainly through the broad policy uncertainty component that combines fiscal, regulatory, monetary, and trade news. Additional specifications confirm the baseline: with firm fixed effects the interaction is 0.197 (t = 2.91), with one-way clustering by firm it is 0.196 (t = 2.93), and replacing DF by an indicator for positive debt flexibility yields 0.421 (t = 2.94).

Columns (3) and (4) split the sample at the monthly median of firm size. The interaction is 0.260 (t = 5.87) among smaller firms and 0.063 (t = 0.45) among larger firms. Smaller firms rely more heavily on credit market conditions and face tighter financing constraints [40], [63], so their unused borrowing capacity is more valuable when policy uncertainty tightens financing conditions. This pattern supports H3. Fig. 4 summarizes the estimates of the DF × S interaction across specifications.

Table IV. Robustness and Heterogeneity

Variable	(1)	(2)	(3)	(4)
Sample	All	All	Smaller	Larger
Shock S	Δln MPU	Δln TPU	Δln EPU	Δln EPU
CF	0.379***	0.380***	0.431***	0.297**
	(3.57)	(3.53)	(2.71)	(1.99)
DF	0.018	0.017	−0.055	0.129
	(0.23)	(0.21)	(−0.68)	(1.20)
CF×S	−0.012	0.023	0.017	0.006
	(−0.13)	(0.23)	(0.16)	(0.03)
DF×S	0.076	0.128	0.260***	0.063
	(0.71)	(1.20)	(5.87)	(0.45)
Controls	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Observations	12,224	12,224	6,106	6,118
Adj. R^2	0.183	0.183	0.171	0.207

Notes: Columns (1) and (2) use standardized log changes of the categorical monetary policy (MPU) and trade policy (TPU) uncertainty indices as the shock. Columns (3) and (4) split the sample at the monthly median of firm size. Other specifications follow Table III. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

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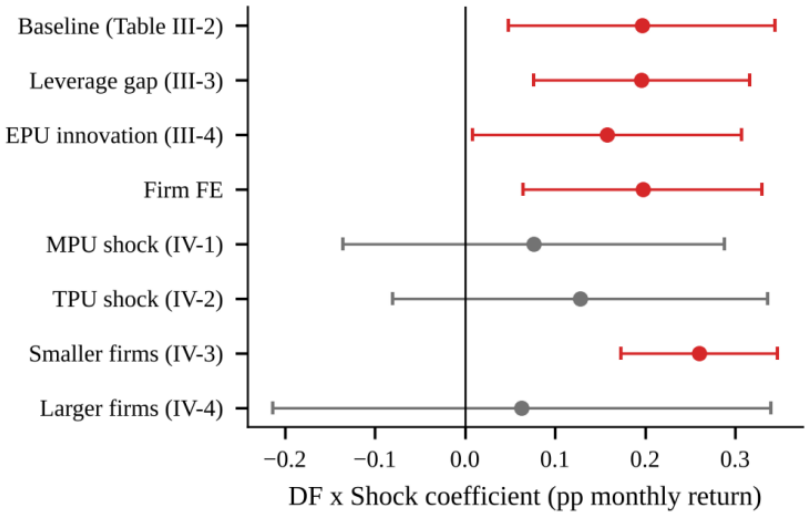

Figure 4. Estimates of the DF × S interaction across specifications with 95% confidence intervals. Red markers denote estimates significant at the 5% level.

5. Discussion

The evidence reveals an asymmetry between the two forms of financial flexibility. Cash flexibility is associated with growth: cash-rich firms expand sales and investment faster and earn higher average returns, consistent with the precautionary accumulation of cash by firms with valuable growth options [41, 43, 44]. Yet cash flexibility neither lowers crash risk nor cushions returns against policy shocks. Because large cash balances are concentrated in firms with volatile cash flows, the buffer coexists with high fundamental exposure, and the market appears to treat it as a feature of risky growth firms rather than as insurance [31, 45].

Debt flexibility, in contrast, behaves as insurance. Firms with unused borrowing capacity experience fewer severe price declines and smaller losses when policy uncertainty rises. This result is consistent with the transitory-debt view of capital structure, in which firms preserve borrowing capacity to finance needs that arise unexpectedly [25, 48], and with evidence that policy uncertainty reaches firms through the credit channel [14, 15]. When credit conditions tighten, firms already close to their debt capacity face higher refinancing costs and a greater risk of underinvestment, whereas firms with spare capacity retain access and can sustain investment. The concentration of the effect among smaller firms reinforces this interpretation.

The findings carry practical implications. For managers, policy uncertainty strengthens the case for conservative leverage: borrowing capacity held in reserve protects firm value during policy shocks more effectively than additional cash. For investors, debt flexibility is an observable characteristic that predicts relative performance when policy uncertainty rises. For policymakers, the results suggest that the real effects of policy uncertainty depend on the distribution of borrowing capacity across firms, so predictable policy communication and stable credit conditions are complementary tools for containing its costs [5, 6].

6. Conclusion

This paper examines how financial flexibility shapes firm resilience under macroeconomic policy uncertainty. Using annual data for 2,831 U.S. non-financial firms and monthly data for 338 S&P 500 firms, combined with the EPU index, the analysis distinguishes cash flexibility from debt flexibility. Cash flexibility supports subsequent sales growth and investment, whereas debt flexibility supports investment, reduces the probability of severe stock-price declines, and attenuates the negative stock-price response to policy uncertainty shocks. The attenuation is robust across shock definitions and estimation choices and is strongest for

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smaller firms. Resilience to policy uncertainty therefore depends not only on how much financial slack a firm holds but also on the form in which it is held. Future work can extend the analysis to longer horizons, other countries, and the COVID-19 period, and can examine whether firms adjust the composition of their flexibility in anticipation of policy events.

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