Coping with the Unexpected: A Forward-Looking Measure of Firm Resilience

Esther Eiling Roger J. A. Laeven Danjun Xu

University of Amsterdam

European Economics Association Bordeaux, August 26, 2025

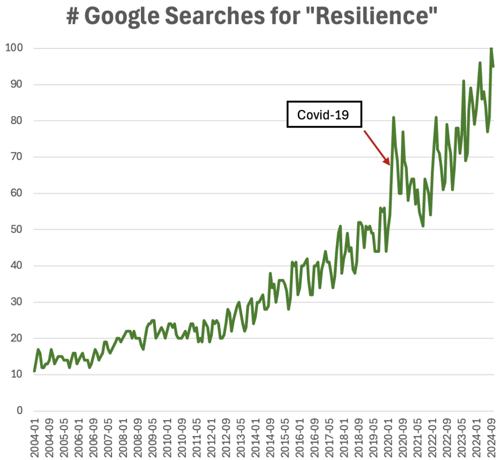
Resilience

A common definition: the ability to cope with the unexpected

- *Resilience* is conceptually different from *Risk*

In this paper, we examine the resilience of listed firms.

- Do firms bounce back after an unexpected crisis?
- How to measure firm resilience ex-ante?
- What types of firms are more resilient than others?



Key Insights of our Paper

A novel measure of firm resilience: $\Delta ReVaR$

1. Measured quarterly at the individual firm level
2. Return-based
3. Forward-looking

Empirical validation and results:

1. $\Delta ReVaR$ is distinct from other (tail) risk measures.
2. Cross-firm variation in pre-crisis $\Delta ReVaR$ relates to post-crisis ROA during the 2000 IT crisis, the 2008 GFC and the 2020 Covid outbreak.
3. Firms with lower financial leverage, more intangible assets and more innovation are significantly more resilient.

Related Literature

1. **Various forms of resilience:**
   - Psychological resilience (e.g., Masten, Best, and Garmezy, 1990; Masten and Reed, 2002; Southwick and Charney, 2018)
   - Organizational resilience (e.g., Ortiz-de-Mandojana and Bansal, 2016; Duchek, 2020)
   - Community resilience (e.g., Magis, 2010; Berkes and Ross, 2013)
   - Ecosystem resilience (e.g., Holling, 1973; Peterson, Allen, and Holling, 1998; Walker and Salt, 2012)
2. Within the field of finance, we contribute to literature on **firm resilience during Covid-19**: e.g., Albuquerque, Koskinen, Yang, and Zhang, 2020; Cheema-Fox, LaPerla, Wang, and Serafeim, 2021; Ding, Levine, Lin, and Xie, 2021; Fahlenbrach, Rageth, and Stulz, 2021; Fisher, Knesl, and Lee, 2022; Pagano, Wagner, and Zechner, 2023.
3. Our resilience measure is reminiscent of **measures of systemic risk**: e.g., **Engle and Manganelli, 2004;** Acharya, Engle, and Richardson, 2012; White, Kim, and Manganelli, 2015; **Adrian and Brunnermeier, 2016;** Acharya, Pedersen, Philippon, and Richardson, 2017; Brownlees and Engle, 2017.

Outline

- Static Version of $\Delta ReVaR$
  - Theoretical Framework and Economic Intuition
  - Estimation Method: Quantile Regressions
  - Data and Estimation Results
- Dynamic Version of $\Delta ReVaR$
- Empirical Validations and Results
- Conclusion

Theoretical Framework: *ReVaR* is Defined as a Conditional *VaR*

Concept of resilience: To what extent do firms bounce back in terms of downside risk after experiencing extreme scenarios?

1) Our resilience measure is based on the definition of the $q\%$ **Value-at-Risk**, denoted VaR_q^i:

$$Pr(X_t^i \leq VaR_q^i) = q\%,$$

where X_t^i is the return loss of firm i at time t.

2) We denote by $ReVaR_q^{i|C^i}$ firm i's q**th-quantile of return losses** conditionally upon facing a **specific scenario** C^i **in the past**:

$$Pr([X_t^i \leq ReVaR_q^{i|C^i}]|C^i) = q\%,$$

where C^i is a specific scenario that firm i experienced before time t.

Theoretical Framework: $\Delta ReVaR$ captures ReVaR Differentials

3) We distinguish between a **stress scenario (C_s^i)** and a **median (normal) scenario (C_m^i)**. $ReVaR_q^{i|C^i}$ under these two scenarios can be expressed as:

$$ReVaR_q^{i|C_s^i} = F_{X_t^i}^{-1}(q|C_s^i),$$

and

$$ReVaR_q^{i|C_m^i} = F_{X_t^i}^{-1}(q|C_m^i).$$

4) Our measure of resilience, $\Delta ReVaR_q^i$, is now defined as:

$$\Delta ReVaR_q^i = ReVaR_q^{i|C_s^i} - ReVaR_q^{i|C_m^i}.$$

$\rightarrow$ $\Delta ReVaR_q^i = 0$ **signifies that the firm's downside risk has completely bounced back to its normal state following a stress event, indicating that the firm is resilient.**

Theoretical Framework: Define Stress and Normal Scenarios

$$Pr([X_t^i \leq ReVaR_q^{i|C^i}]|C^i) = q\%,$$

5) We define C^i as scenarios in which firm i's losses exceed its **own** VaR_q^i.

Stress Scenario: $ReVaR_q^{i|C_s^i(X_{t-\tau}^i)}$ measures firm i's conditional qth-quantile of return losses at time t **after it experiences extreme loss** at time $t-\tau$.

$$Pr([X_t^i \leq ReVaR_q^{i|C_s^i(X_{t-\tau}^i)}]|[X_{t-\tau}^i \geq VaR_q^i)]) = q\%.$$

Normal Scenario: $ReVaR_q^{i|C_m^i(X_{t-\tau}^i)}$ is a benchmark that measures firm i's conditional qth-quantile of return losses at time t **after it experiences typical underperformance** at time $t-\tau$:

$$Pr([X_t^i \leq ReVaR_q^{i|C_m^i(X_{t-\tau}^i)}]|[X_{t-\tau}^i \geq VaR_{50}^i)]) = q\%.$$

A Simple Example

$$\Delta ReVaR_q^i = ReVaR_q^{i|C_s^i} - ReVaR_q^{i|C_m^i}$$

A resilient firm has a relatively low $\Delta ReVaR_q^i$.

- Firm A: $ReVaR_{q=95}^{A|C_m^i} = 5\%$ and $ReVaR_{q=95}^{A|C_s^i} = 10\% \rightarrow \Delta ReVaR_{q=95}^{A} = 10\% - 5\% = 5\%$
- Firm B: $ReVaR_{q=95}^{B|C_m^i} = 7\%$ and $ReVaR_{q=95}^{B|C_s^i} = 11\% \rightarrow \Delta ReVaR_{q=95}^{B} = 11\% - 7\% = 4\%$

$\rightarrow$ B is more resilient than A because $4\% < 5\%$.

Estimation Method: Quantile Regressions

1) First, we use quantile regression on the full sample period for each firm:

$$X^i_{q,t+\tau} = \alpha^i_{q,\tau} + \beta^i_{q,\tau} I^i_t X^i_t + \epsilon^i_{q,\tau,t},$$

where $X^i_{q,t+\tau}$ is firm i's qth quantile return loss at time $t+\tau$; X^i_t is firm i's return loss at time t; I^i_t equals 1 if $X^i_t > 0$ and 0 otherwise.

2) We can calculate $ReVaR^{i|C^i_s=VaR^i_q}_{q,\tau}$ and $ReVaR^{i|C^i_m=VaR^i_{50}}_{q,\tau}$ with the estimated coefficients:

$$ReVaR^{i|C^i_s=VaR^i_q}_{q,\tau} = \widehat{\alpha}^i_{q,\tau} + \widehat{\beta}^i_{q,\tau} I^i_q VaR^i_q,$$

$$ReVaR^{i|C^i_m=VaR^i_{50}}_{q,\tau} = \widehat{\alpha}^i_{q,\tau} + \widehat{\beta}^i_{q,\tau} I^i_{50} VaR^i_{50}.$$

3) As the last step, $\Delta ReVaR^i_{q,\tau}$ is given by:

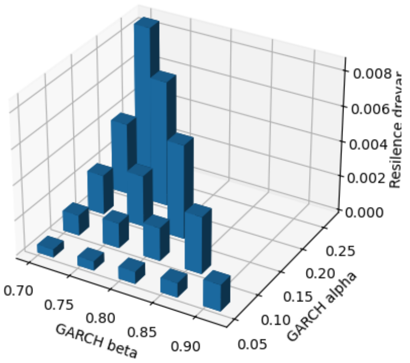
$$\Delta ReVaR^i_{q,\tau} = ReVaR^{i|VaR^i_q}_{q,\tau} - ReVaR^{i|VaR^i_{50}}_{q,\tau} = \widehat{\beta}^i_{q,\tau}(I^i_q VaR^i_q - I^i_{50} VaR^i_{50}).$$

Resilience Estimation using Simulated Data from GARCH(1,1)

$$r_t = \mu + \varepsilon_t, \qquad \varepsilon_t = \sigma_t z_t, \qquad z_t \overset{i.i.d.}{\sim} \mathcal{N}(0,1)$$

$$\sigma_t^2 = \omega + \alpha\, \varepsilon_{t-1}^2 + \beta\, \sigma_{t-1}^2$$

- GARCH(1,1) with normal errors provides a reasonable baseline model for volatility dynamics.
- α measures how today's return reacts to yesterday's shocks $\rightarrow$ *higher* α indicates stronger reaction to past information
- β measures how much of yesterday's volatility carries over to today $\rightarrow$ *higher* β indicates greater persistence of volatility
- For each parameter set, we simulate 1,000 stocks with 1,560 observations (30 years of weekly data) and compute their average level.



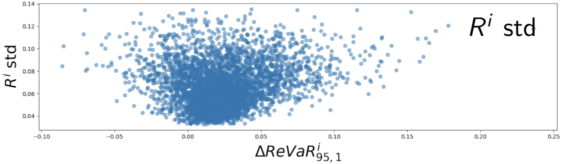
The figure shows that $\Delta ReVaR$ is **positively** associated with both GARCH parameters.

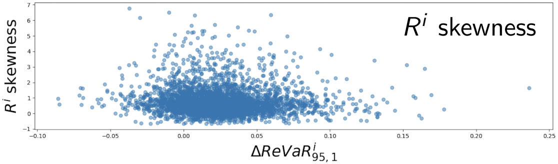
Data

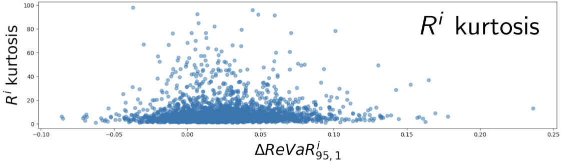
- We use weekly return data obtained from CRSP.
- Our sample comprises U.S. stocks with share code 10 and 11 from January 1, 1990 to December 31, 2022.
- We include delisted stocks and exclude small stocks with price below $1
- **3 categories of firm characteristics:** financial flexibility, organizational flexibility and firm risk
- Quarterly firm financial data including intangible assets (Compustat), patent data (Kogan, Papanikolaou, Seru, and Stoffman, 2017)

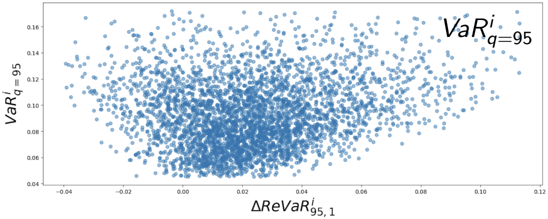
$\Delta ReVaR$ is Distinct from Other (Tail) Risk Measures

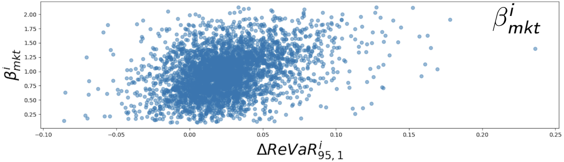
Return losses' standard deviation, skewness, kurtosis, historical VaR, market beta.











$\Delta ReVaR$ provides new information about another aspect of firms' (tail) risk, namely **Resilience**

Outline

- Static Version of $\Delta ReVaR$
- Dynamic Version of $\Delta ReVaR$
- Empirical Validations and Results
- Conclusion

Estimation of Dynamic $\Delta ReVaR$

We extend the historical VaR_q^i to time-varying $VaR_{q,t}^i$ by conditioning on state variables.

1) We estimate the following quantile regression with different state variables M_t based on the full sample period:
$$X_{q,t}^i = \alpha_q^i + \gamma_q^i M_t + \epsilon_{q,t}^i.$$

2) We can use coefficient estimates to construct $VaR_{q,t}^i$ as a linear function of M_t:
$$VaR_{q,t}^i = \widehat{\alpha}_q^i + \widehat{\gamma}_q^i M_t.$$

3) A similar estimation approach is used to calculate the benchmark $VaR_{50,t}^i$.

4) Then, we apply a similar procedure as in the static version to derive the dynamic $\Delta ReVaR$.

Estimation of Dynamic $\Delta ReVaR$

We extend the historical VaR^i_q to time-varying $VaR^i_{q,t}$ by conditioning on state variables.

1) We estimate the following quantile regression with different state variables M_t based on the full sample period:
$$X^i_{q,t} = \alpha^i_q + \gamma^i_q M_t + \epsilon^i_{q,t}.$$
2) We can use coefficient estimates to construct $VaR^i_{q,t}$ as a linear function of M_t:
$$VaR^i_{q,t} = \widehat{\alpha}^i_q + \widehat{\gamma}^i_q M_t.$$
3) A similar estimation approach is used to calculate the benchmark $VaR^i_{50,t}$.
4) Then, we apply a similar procedure as in the static version to derive the dynamic $\Delta ReVaR$.

For **state variables** M_t, we use three month yield change, the term spread change, the TED spread, the credit spread change, the value-weighted U.S. stock market return, and the VIX index.

- Overall, estimated exposures are significant for most of these state variables.

Outline

- Static Version of $\Delta ReVaR$
- Dynamic Version of $\Delta ReVaR$
- Empirical Validations and Results
- Conclusion

Ex-ante v.s. Ex-post Resilience

$$ROA^i_{event+1} = a + b\Delta ReVaR^i_{q=0.99,\tau=1,event-1} + cX^i_{event-1} + \epsilon^i_t$$

	Covid-19 (2020Q1)		Global Financial Crisis (2008Q3)		Technology Bubble (2000Q1)	
	(1) ROA (NI)	(2) ROA (EBIT)	(3) ROA (NI)	(4) ROA (EBIT)	(5) ROA (NI)	(6) ROA (EBIT)
Lag $\Delta ReVaR^i_{99,1}$	-0.030	-0.027**	-0.089***	-0.005	-0.014***	-0.017***
	(0.017)	(0.008)	(0.021)	(0.006)	(0.004)	(0.005)
Observations	1,334	1,334	1,619	1,619	1,993	1,993
Adjusted R^2	0.346	0.502	0.221	0.385	0.373	0.562
Firm Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes

- Cross-sectional regressions for three different events.
- The **negative** sign of $\widehat{b}$ indicates a **positive** relation between ex-ante resilience and post-crisis ROA.

Panel Regressions: Resilience and Firm Characteristics

	$\Delta ReVaR^i_{95,t}$		
	h=1	h=4	h=8
Leverage$_{t-h}$	0.064***	0.057***	0.068***
	(0.012)	(0.017)	(0.021)
Cash$_{t-h}$	0.345***	0.342***	0.350***
	(0.035)	(0.053)	(0.067)
R&D$_{t-h}$	-0.696*	-0.648	-0.368
	(0.398)	(0.567)	(0.717)
Number of patents$_{t-h}$	-0.046***	-0.048***	-0.047***
	(0.003)	(0.005)	(0.007)
Econ. value per patent$_{t-h}$	-0.024***	-0.023***	-0.021**
	(0.005)	(0.008)	(0.010)
$VaR_{q,t-h}$	5.217***	4.130***	2.671***
	(0.314)	(0.452)	(0.546)
Stock return vol.$_{i,t-h}$	0.016***	0.018***	0.020***
	(0.001)	(0.002)	(0.002)
Observations	216,094	211,268	202,793
Adjusted R^2	0.0413	0.0364	0.0325
Firm control variables	yes	yes	yes
Macroeconomic controls	yes	yes	yes
Industry FE	yes	yes	yes
Newey West SE lag	1	4	8

$$\Delta ReVaR^i_{q,\tau=1,t} = a + bM_{t-h} + cZ^i_{t-h} + \epsilon^i_t$$

1) As expected, **more highly leveraged firms tend to be less resilient.**

2) Using three different measures of innovation we find that **innovative firms tend to be more resilient.**

Resilience and Intangible Assets

	$\Delta ReVaR^{i}_{95,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
R&D$_{i,t-h}$	-0.444***					
	(0.029)					
Number of patents$_{i,t-h}$	-0.017**					
	(0.007)					
Economic value per patent$_{i,t-h}$	-0.035***					
	(0.010)					
Intangible assets$_{i,t-h}$		-0.030***				
		(0.001)				
Knowledge capital$_{i,t-h}$			-0.123***			
			(0.006)			
Organization capital$_{i,t-h}$				-0.096***		
				(0.005)		
Off-BS Intangible assets$_{i,t-h}$					-0.064***	
					(0.002)	
Brand Capital$_{i,t-h}$						-0.299***
						(0.019)
Observations	51,921	51,921	51,921	51,921	51,921	51,921
Adjusted R^2	0.043	0.044	0.043	0.043	0.045	0.039
Firm control variables	yes	yes	yes	yes	yes	yes
Macroeconomic control variables	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Newey West SE lag	1	1	1	1	1	1

Resilience by Industry

- Even after controlling for firm characteristics, significant cross-industry differences in resilience remain.

	$\Delta ReVaR^{i}_{95,t}$		
	Coef. (SD)	*Sample Mean (SD)*	*Firm Mean (Dispersion)*
Agriculture (Benchmark)		0.901	0.716
		1.404	1.502
Mining and Quarrying	-0.197***	0.992	0.584
	(0.071)	1.874	2.197
Construction	-0.345***	0.807	0.643
	(0.072)	1.321	1.675
Manufacturing	-0.374***	0.592	0.496
	(0.066)	1.600	2.048
TransComm & Utility Services	-0.514***	0.681	0.647
	(0.068)	1.650	2.031
Wholesale Trade	-0.306***	0.753	0.645
	(0.069)	1.746	2.041
Retail Trade	-0.466***	0.664	0.553
	(0.067)	1.735	2.083
Services	-0.216***	0.916	0.782
	(0.067)	2.164	2.625

Conclusion

- We propose a **novel** measure of resilience: $\Delta ReVaR$
  - ΔReVaR measures the extent to which firms bounce back in terms of their downside risk after experiencing extreme return losses.
- **Key advantages:** return-based and forward-looking
- **Key empirical results:**
  - Our ex-ante resilience measure helps predict post-crisis firm performance.
  - Resilience is significantly related to lagged firm characteristics, including **financial leverage, intangible assets and innovation**.