

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

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## Abstract

Do firms bounce back after an unexpected crisis? What types of firms are more resilient? We develop a new measure of ex-ante firm resilience, based on the extent to which a firm's conditional downside risk bounces back after an extreme loss. Our measure is return-based and it is forward-looking. A key advantage is that we do not need to focus on one particular crisis in order to classify firms as resilient or non-resilient. First, we show that our ex-ante resilience measure predicts cross-firm differences in post-crisis performance during three different types of crises: the 2000 Internet Bubble, the 2008 GFC and the 2020 Covid-19 outbreak. Second, panel regressions reveal that besides lower leverage, firms with more intangible assets, more knowledge capital, organization capital and brand capital, higher R&D investments, and more and higher-valued patents are significantly more resilient.

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# 1 Introduction

In a world with many uncertainties, resilience is a valuable feature both at micro- and macro-levels. Academic research across multiple disciplines examines resilience; for example, resilience as a psychological trait, organizational resilience, resilience as a feature of an energy network, ecosystem resilience, and resilience of communities or society at large. While there are many different ways to describe resilience (e.g., Bhamra, Dani, and Burnard, 2011; Logan, Aven, Guikema, and Flage, 2022), one common aspect is this: the ability to cope with the unexpected (e.g., Ducheck, 2020; Molyneaux, Brown, Wagner, and Foster, 2016).

In this paper, we examine the resilience of listed firms. Finance research traditionally studies risks that firms are exposed to. However, firms operate in an inherently uncertain environment and new types of risk or crises may emerge.<sup>1</sup> Do firms bounce back after an unexpected crisis? And what types of firms are more resilient than others?

In order to address these research questions, we first develop a novel measure of firm resilience based on the dynamics of a firm's downside risk. Our measure is return-based and it is forward-looking. Several recent studies examine the resilience of firms from an ex-post perspective. Most focus on the Covid-19 pandemic and use stock price changes or the return on assets after the start of the pandemic as a measure of firm resilience (e.g., Cheema-Fox, LaPerla, Wang, and Serafeim, 2021; Ding, Levine, Lin, and Xie, 2021; Fahlenbrach, Rageth, and Stulz, 2021). We extend this line of research by developing a forward-looking resilience measure. A key advantage is that we do not need to specify the type and timing of the crisis in order to classify firms as resilient or non-resilient.

After estimating time-varying resilience for individual U.S. listed firms, we validate our measure

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<sup>1</sup>For example, Heyerdahl-Larsen, Illeditsch, and Sinagl (2022) develop an asset pricing model where new sources of risk emerge before a recession.

by linking cross-firm variation in ex-ante resilience to post-crisis firm performance. In the final step, we run panel regressions to study how lagged firm characteristics are related to resilience. In short, besides the expected relation to leverage, we find a key role for innovation and intangible assets. Firms with higher R&D investments, more patents, a higher economic value per patent and more intangible assets (including knowledge capital, organization capital and brand capital) are significantly more resilient. Hence, while the characteristics that help firms bounce back after the Covid-19 outbreak (i.e., the ability of employees to work from home) are arguably different from characteristics that help recover from other types of crises such as the Great Financial Recession, we find that overall, innovation activities help firms cope with unexpected future extreme events. In his 2024 AFA Presidential Address, Markus Brunnermeier highlights that for a system (or a firm) to be resilient, it needs to be able to adapt after the realization of a crisis, by investing in adaptability pre-crisis. Our results suggest that innovation and intangible assets play a significant role here.<sup>2</sup>

Our resilience measure focuses on the dynamics of a firm's downside risk, based on the Value-at-Risk. We call our measure  $\Delta ReVaR$ . This resilience measure captures the extent to which a firm's conditional downside risk after an extreme loss differs from its downside risk after experiencing a typical underperformance. If the two are similar, the firm, in terms of its downside risk, bounces back after an extreme loss. In other words, the firm is resilient. By contrast, a firm whose conditional downside risk increases substantially following distress would be regarded as lacking resilience.

Our resilience measure is reminiscent of existing measures of systemic risk, such as the  $\Delta CoVaR$  measure of Adrian and Brunnermeier (2016), who develop a conditional Value-at-Risk measure to capture systemic risk across financial institutions; see also Marginal Expected Shortfall (Acharya,

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<sup>2</sup>The Presidential Address focuses mostly on resilience at the aggregate level, in the context of macro-finance models. In contrast, we study resilience at the firm level.

Engle, and Richardson, 2012; Acharya, Pedersen, Philippon, and Richardson, 2017) and SRISK (Brownlees and Engle, 2017). Instead, we construct our measure at the individual firm level.<sup>3</sup> Our resilience measure also relates to the literature on time-varying quantiles, e.g., using autoregressive processes, such as conditional autoregressive Value-at-Risk (CAViaR) of Engle and Manganelli (2004) and extended to a multivariate setting in White, Kim, and Manganelli (2015).<sup>4</sup> Rather than analyzing time-varying quantiles, our resilience measure captures conditional Value-at-Risk differentials, by conditioning upon two different loss scenarios.

More specifically, we first estimate a firm’s Value-at-Risk using return losses; the  $q\%$  Value-at-Risk of firm  $i$ , denoted by  $VaR_q^i$ , implies that there is a  $q\%$  probability that firm  $i$  will not experience losses exceeding  $VaR_q^i$ . Next, we construct conditional Value-at-Risk measures, to account for the fact that the distribution of a firm’s returns and risks may vary across different scenarios, which is not captured by an unconditional  $VaR_q^i$ . We focus on two types of historical scenarios, denoted by  $C^i$ . First, we consider a stress scenario  $C_s^i$  in which the firm’s return losses exceed its historical 95% or 99% Value-at-Risk. Second, we use a so-called median scenario  $C_m^i$ , where its losses exceed the firm’s 50% Value-at-Risk. Consequently, we denote by  $ReVaR_q^{i|C_s^i}$  the conditional  $VaR_q^i$  when firm  $i$  is in a stress scenario, and by  $ReVaR_q^{i|C_m^i}$  the conditional  $VaR_q^i$  when firm  $i$  is in a typical underperformance scenario.

Finally, we define  $\Delta ReVaR_q^i$  as the disparity (or increment) of conditional downside risks; i.e., the difference between  $ReVaR_q^{i|C_s^i}$  and  $ReVaR_q^{i|C_m^i}$ . When measuring resilience, we are interested in how much a stress scenario would increase the firm’s downside risk conditional upon an extreme stress scenario compared to that of a normal scenario. Hence, a firm with a low  $\Delta ReVaR_q^i$  is considered to be resilient. In this case, the conditional  $VaR_q^i$  does not vary much, suggesting

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<sup>3</sup>The  $\Delta CoVaR$  measure of Adrian and Brunnermeier (2016) captures how the conditional Value-at-Risk of banks change after an extreme loss of one of the other banks. Instead of the cross-sectional dimension, our resilience measure focuses on an individual firm and captures how its conditional Value-at-Risk varies after the firm itself experiences an extreme loss.

<sup>4</sup>The autoregressive nature of large shocks is also recognized in Ait-Sahalia, Cacho-Diaz, and Laeven (2015).

that an extreme scenario has the same implications for the Value-at-Risk of the firm as a typical underperformance. Loosely speaking, the firm’s downside risk bounces back to its normal state even after a stress event.

We use quantile regressions to estimate the conditional Value-at-Risk measures that form the basis of  $\Delta ReVaR$ . This estimation method has been widely applied to estimate conditional Value-at-Risk (e.g., Adrian and Brunnermeier, 2016; Chernozhukov and Du, 2006; Chernozhukov and Umantsev, 2001; Koenker and Bassett, 1978). Quantile regressions allow us to estimate the relation between a firm’s current losses and its future extreme losses, and can be used to estimate the firm’s future downside risk conditional upon a given current scenario.

In our empirical analysis, we estimate firm-level resilience for all U.S. listed stocks, using weekly return data from January 1990 to December 2022. We first assess the cross-firm dispersion of our resilience estimates and how they relate to traditional measures of firm risk. To this end, we employ a static version of  $\Delta ReVaR$ , estimated for each stock over the full sample period. Our findings reveal substantial cross-firm variation in  $\Delta ReVaR$ . Furthermore, we show that  $\Delta ReVaR$  is distinct from other (tail) risk measures, including historical  $VaR$ , volatility, skewness, kurtosis and the CAPM market beta. Next, to capture changes in firms’ resilience levels over time, we introduce a dynamic time-varying version of  $\Delta ReVaR$ , using several state variables, such as the term spread, TED spread and the VIX index.

We proceed by validating our dynamic resilience measure using three distinct crises: the Covid-19 outbreak in 2020, the Global Financial Crisis in 2008 and the Technology Bubble in 2000. We find that firms with a higher ex-ante resilience measure have significantly higher ex-post Return on Assets as well. Interestingly, the relation is statistically significant for all three crises, which are each unique and of a very different nature. It is noteworthy that we estimate a firm’s  $\Delta ReVaR$  solely using pre-crisis returns data, signifying that  $\Delta ReVaR$  as a pre-crisis resilience measure helps

predict cross-firm differences in post-crisis performance.

After having validated our novel measure of firm-level resilience, in the final and main part of the empirical analysis we can examine what types of firms are more resilient than others. To this end, we conduct panel regressions where we regress firm-level quarterly resilience measures on lagged firm characteristics. We include industry fixed effects and as such analyze within-industry differences in firm resilience. We consider three categories of firm characteristics. First, we include measures of financial flexibility: market leverage and cash holdings. In the second category we consider variables related to organizational flexibility, including measures of innovation and different types of intangible assets. Third, we include traditional measures of firm risk: return volatility and Value-at-Risk. We also include firm-level and aggregate control variables.

First, we find a positive and statistically significant relationship between financial leverage and resilience, consistent with existing literature (Ding, Levine, Lin, and Xie, 2021; Fahlenbrach, Rageth, and Stulz, 2021), although we do not find a similar relationship for cash holdings. Second and importantly, we detect a key role of firm characteristics related to organizational flexibility. To start, we find that three measures of firm innovation activities are highly significant in the panel regressions: firms with higher levels of R&D investment, a larger number of patents and firms with a higher economic value per patent are significantly more resilient. Further, using Peters and Taylor (2017)'s measures of intangible assets (see also, e.g., Eisfeldt and Papanikolaou, 2013; and Eisfeldt, Kim, and Papanikolaou, 2020), we find that firms with more intangible capital are significantly more resilient. This relationship holds for different types of intangible assets, including externally purchased intangible assets, knowledge capital, organization capital and brand capital (based on a measure by Belo, Lin, and Vitorino, 2014).

Finally, we show that even after accounting for differences in firm resilience due to firm characteristics, cross-industry wedges in firm resilience remain. The industry fixed effect estimates in our

panel regressions are highly significant and suggest that firms in the transportation and communication industries are most resilient, while firms in the services, mining and agriculture industries are least resilient.

Our paper contributes to a long-standing literature that studies various forms of resilience, such as psychological resilience (e.g., Masten, Best, and Garmezy, 1990; Masten and Reed, 2002; Southwick and Charney, 2018), organizational resilience (e.g., Ducheck, 2020; Ortiz-de-Mandojana and Bansal, 2016), community resilience (e.g., Berkes and Ross, 2013; Magis, 2010) and ecosystem resilience (e.g., Holling, 1973; Peterson, Allen, and Holling, 1998; Walker and Salt, 2012). In these domains, researchers have extensively studied how to measure resilience and have identified strategies to enhance resilience in different contexts. Within the field of finance, our paper contributes to the nascent literature on firm resilience during Covid-19 (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).

Our results suggest that innovation plays a significant role in shaping resilience. The relation between innovation and firm risks and returns has been extensively examined (Hsu, Tian, and Xu, 2014; Kogan and Papanikolaou, 2014; Kogan, Papanikolaou, Seru, and Stoffman, 2017). In addition, some studies show that firms with higher innovation capacity are less likely to go bankrupt (e.g., Bai and Tian, 2020; Eisdorfer and Hsu, 2011), and have lower stock price crash risk (e.g., Ben-Nasr, Bouslimi, and Zhong, 2021; Hossain, Masum, and Xu, 2023; Jia, 2018). Further, Hasan, Taylor, and Richardson (2022) show that firms with more brand capital have lower stock price crash risk. Rather than focusing on the risk of a stock price crash, we show that after experiencing an extreme loss, innovative firms and firms with more intangible assets also tend to bounce back more in terms of their downside risk. Finally, Uddin, Hasan, and Abadi (2022) find that firms with

more intangible assets were more resilient (ex-post) during the Covid pandemic.

The remainder of this paper is organized as follows. In Section 2, we present our resilience measure  $\Delta ReVaR$ , the economic intuition and we introduce the estimation method. We first focus on a static version of  $\Delta ReVaR$ . Next, in Section 3, we introduce a dynamic time-varying version of  $\Delta ReVaR$ . Section 4 discusses the data used for estimation and presents summary statistics. We examine cross-firm variation in  $\Delta ReVaR$  estimates and the relation to return-based risk measures in Section 5. Section 6 shows our main empirical results, including a validation of  $\Delta ReVaR$  and a panel regression that links firm resilience estimates to lagged firm-level characteristics. Section 7 concludes.

## 2 A Return-Based Resilience Measure

Resilience usually refers to the ability to adapt, survive and recover from extreme and unexpected disruptions. We define resilience as the degree to which the firm's downside risk after experiencing an extreme scenario deviates from the firm's downside risk after a typical underperformance. We call our measure  $\Delta ReVaR$ .

In Section 2.1, we first introduce a basic static version of  $\Delta ReVaR$ , and we further discuss the economic intuition in Section 2.2. Next, we explain two important components for this measure: the choice of normal and stress scenarios (Section 2.3), and the horizon parameter  $\tau$  that defines the recovery period we consider after a firm experiences a stress scenario (Section 2.4). Finally, in Section 2.5, we discuss the estimation method, which is based on quantile regressions.

## 2.1 Static $\Delta ReVaR$

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

$$Pr(X_t^i \leq VaR_q^i) = q\%, \quad (1)$$

where  $X_t^i$  is the return loss of firm  $i$  at time  $t$ .<sup>5</sup> Here, similar to Adrian and Brunnermeier (2016) and many others, we use return losses rather than gains, since  $VaR_q^i$  is typically expressed as a positive value. As such, the chosen value of  $q$  is typically larger than or equal to 50% as we focus on the downside risk of a firm. From this equation, we can see that  $VaR_q^i$  is the unconditional  $q\%$  quantile of firm  $i$ 's return losses. Suppose  $q = 95$ , then  $VaR_{q=95}^i$  can be interpreted as the upper bound of firm  $i$ 's loss in 95% cases. In other words, there is a 5% chance that firm  $i$  loses more than  $VaR_{q=95}^i$ . For  $q = 50$ ,  $VaR_{q=50}^i$  is the median loss return of firm  $i$ . That is, there is a 50% probability that firm  $i$  loses more than  $VaR_{q=50}^i$  and a 50% probability that it loses less than  $VaR_{q=50}^i$ .<sup>6</sup>

Based on the definition of  $VaR$ , we define  $ReVaR$  as a conditional  $VaR$ . 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:

$$Pr([X_t^i \leq ReVaR_q^{i|C^i}]|C^i) = q\%, \quad (2)$$

where  $C^i$  is a specific scenario that firm  $i$  experienced before time  $t$ . Recall that we define resilience as the degree to which an extreme underperformance differs from a typical underperformance of a firm in terms of the firm's conditional downside risk. Therefore, we need to define an extreme underperformance and a typical underperformance. We name these two scenarios as stress scenario

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<sup>5</sup> $X_t^i$  is given by the negative value of returns. Thus, a positive value of  $X_t^i$  indicates a loss while a negative value of  $X_t^i$  signifies a gain.

<sup>6</sup>Note that  $VaR_{q=50}^i$  is the median value (with negative sign) of all returns rather than the median value of losses only.

and median (or normal) scenario, and denote them by  $C_s^i$  and  $C_m^i$ , respectively.

We denote the cumulative distribution function (CDF) of  $X_t^i$  by  $F_{X_t^i}(\cdot)$ , and thus the conditional CDF for  $q$ th-quantile by  $F_{X_t^i}(q|\cdot)$ . Then we can express  $ReVaR_q^{i|C_s^i}$  as an inverse conditional CDF  $F_{X_t^i}^{-1}(q|C_s^i)$ :

$$ReVaR_q^{i|C_s^i} = F_{X_t^i}^{-1}(q|C_s^i), \quad (3)$$

and

$$ReVaR_q^{i|C_m^i} = F_{X_t^i}^{-1}(q|C_m^i). \quad (4)$$

$ReVaR_q^{i|C_s^i}$  measures the future downside risk conditionally upon a current extreme return loss, and  $ReVaR_q^{i|C_m^i}$  measures the future extreme downside risk conditionally upon a current median loss. When talking about resilience, we are interested in by how much downside risk increases conditionally upon a stress scenario as compared to conditionally upon a normal scenario. Therefore, we measure resilience as the difference between these conditional downside risk measures. Specifically, our measure of resilience,  $\Delta ReVaR_q^i$ , is defined as:

$$\Delta ReVaR_q^i = ReVaR_q^{i|C_s^i} - ReVaR_q^{i|C_m^i}. \quad (5)$$

The next subsection discusses more economic intuition of the resilience measure.

Throughout this paper, we use Value-at-Risk as the basic measure of risk to construct our measure of resilience. There exists a large literature on alternatives to the Value-at-Risk, such as perhaps most noticeably Expected Shortfall.<sup>7</sup> Expected Shortfall and related risk measures have been used to measure systemic risk in Acharya, Engle, and Richardson (2012), Acharya, Pedersen, Philippon, and Richardson (2017), and Brownlees and Engle (2017). One could also

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<sup>7</sup>Modern classes of risk measures include coherent, convex, entropy convex, monetary, return, cash-subadditive, quasi-convex, quasi-logconvex, and star-shaped measures of risk. We refer to Ch. 4 of Föllmer and Schied (2016), Laeven, Rosazza Gianin, and Zullino (2025), and the references therein for further details.

invoke Expected Shortfall to construct (an adapted version) of our measure of resilience.<sup>8</sup> In view of the appealing statistical properties of quantiles, we restrict attention to Value-at-Risk as the basic measure of risk, and leave extensions and generalizations to future work.

## 2.2 Economic Intuition

A resilient firm has a relatively low  $\Delta ReVaR_q^i$ . In this case, the firm's conditional  $VaR_q^i$  does not change much and is similar after an extreme scenario compared to a typical underperformance scenario.

As an example, suppose firm A has  $ReVaR_{q=95}^{A|C_s^i} = 10\%$  and  $ReVaR_{q=95}^{A|C_m^i} = 5\%$ , whereas firm B has  $ReVaR_{q=95}^{B|C_s^i} = 11\%$  and  $ReVaR_{q=95}^{B|C_m^i} = 7\%$ . When both firm A and firm B experience normal underperformance, there is a 95% probability that future return losses over a certain time period are less than 5% in stock A and less than 7% in stock B. Suppose now both firm A and firm B encounter a stress scenario. The conditional  $VaR$  implies that there now is a 95% probability that stock A loses no more than 10% and that stock B loses no more than 11% in a given future time period. In both scenarios, stock B seems to be more risky in terms of downside risk than stock A. However, firm B is classified as more resilient than firm A, since its resilience measure  $\Delta ReVaR_{q=95}^B = 11\% - 7\% = 4\%$  is lower than that of firm A,  $\Delta ReVaR_{q=95}^A = 10\% - 5\% = 5\%$ . Under a stress scenario, the guaranteed maximum potential loss increases by 4 percentage points for stock B and 5 percentage points for stock A. A stress scenario presents a greater challenge to firm A compared to firm B. Therefore, we regard B as a more resilient firm than A. Here, we show that a more risky firm (B) can be more resilient than a less risky firm (A), and thus distinguish the concept of resilience from risk.

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<sup>8</sup>In fact, it is conceptually straightforward to replace Value-at-Risk by any *conditional distortion risk measure* of Dhaene, Laeven, and Zhang (2022) in the definition of our measure of resilience.

### 2.3 $C_s^i$ and $C_m^i$

We have defined  $\Delta ReVaR_q^i$  as the difference between  $ReVaR_q^i|C_s^i$  and  $ReVaR_q^i|C_m^i$ . The next step is to define the stress scenario  $C_s^i$  and the typical underperformance scenario  $C_m^i$ . In this subsection, we follow Adrian and Brunnermeier (2016) and define  $C_s^i$  as scenarios in which firm  $i$ 's losses exceed its  $VaR_q^i$ . This makes  $ReVaR$  a  $VaR$  of  $VaR$ :

$$Pr([X_t^i \leq ReVaR_q^i|C_s^i(X_{t-\tau}^i)]|[X_{t-\tau}^i \geq VaR_q^i]) = q\%, \quad (6)$$

where  $C_s^i(X_{t-\tau}^i)$  is a stress scenario that depends on  $X_{t-\tau}^i$ . Under this definition,  $ReVaR_q^i|C_s^i(X_{t-\tau}^i)$  measures firm  $i$ 's conditional  $q$ th-quantile of return losses at time  $t$  after it experiences an extreme loss at time  $t - \tau$ .

Likewise, we define  $C_m^i(X_{t-\tau}^i)$  as a benchmark scenario when firm  $i$ 's losses exceed its median loss  $VaR_{50}^i$ . In this sense,  $ReVaR_q^i|C_m^i(X_{t-\tau}^i)$  is a benchmark that measures firm  $i$ 's conditional  $q$ th-quantile of return losses at time  $t$  after it experiences typical underperformance at time  $t - \tau$ .

$$Pr([X_t^i \leq ReVaR_q^i|C_m^i(X_{t-\tau}^i)]|[X_{t-\tau}^i \geq VaR_{50}^i]) = q\%. \quad (7)$$

There are two things that need to be highlighted. First, we use the same  $q$  in  $VaR_q^i$  as in  $ReVaR_q^i|C_s^i(X_{t-\tau}^i)$  and  $ReVaR_q^i|C_m^i(X_{t-\tau}^i)$  for reasons of consistency: we aim to re-estimate the guaranteed maximum potential losses at the same probability level. Second,  $VaR_q^i$  differs per firm, indicating that the return loss that defines a stress scenario or a median scenario is specific to each firm. This allows us to better compare resilience across firms. A stress scenario of a given percentage of loss for one firm may not be a stress scenario for another firm. Suppose firm A has  $VaR_{q=95}^A = 2\%$  and  $VaR_{q=50}^A = 0\%$ , whereas firm B has  $VaR_{q=95}^B = 6\%$  and  $VaR_{q=50}^B = 2.5\%$ . In

this case, a loss of 2.5% means a stress scenario for firm A but is just a typical underperformance for firm B.

## 2.4 Horizon $\tau$

The conditioning scenarios  $C_s^i(X_{t-\tau}^i)$  and  $C_m^i(X_{t-\tau}^i)$  are taken with a lag of  $\tau$ . In other words,  $ReVaR_q^{i|C_s^i(X_{t-\tau}^i)}$  and  $ReVaR_q^{i|C_m^i(X_{t-\tau}^i)}$  are  $\tau$ -period forward-looking measures. As a result, the resilience measure  $\Delta ReVaR_{q,\tau}^i$  is also forward-looking and depends on the chosen  $\tau$ .  $\Delta ReVaR_{q,\tau}^i$  with smaller  $\tau$  indicates short-term resilience while  $\Delta ReVaR_{q,\tau}^i$  with larger  $\tau$  indicates longer-term resilience. For a firm that is slow to recover after a crisis, but eventually does recover, one can expect  $\Delta ReVaR_{q,\tau}^i$  to approach zero for a sufficiently large horizon  $\tau$ . However, it is also possible that  $\Delta ReVaR_{q,\tau}^i$  stays at a certain level that is away from zero. In that case, a stress scenario has permanently changed the firm's (tail) return distribution. This firm is thus regarded as a non-resilient firm as it does not have the ability to recover from a stress or shock.

As an alternative measure of resilience, one could consider the recovery speed: how fast does the conditional Value-at-Risk return to its normal level? Recovery speed is clearly intimately related to our measure of resilience, but we note that the conditional Value-at-Risk may never return to the previous normal level. Therefore, in this paper, resilience  $\Delta ReVaR_{q,\tau}^i$  focuses only on the gap between the tail distribution after a stress underperformance and the tail distribution after a typical underperformance at a given horizon. That is to say, we do not explicitly relate resilience to the speed at which this gap reduces to zero (or a stable level). Lastly, we choose  $\tau = 1$  week throughout this paper. More details are discussed in Section 5.

## 2.5 Estimation Method: Quantile Regressions

In Section 2.3, we have related  $VaR$  to  $ReVaR$  by defining a stress scenario  $C_s^i$  and a normal scenario  $C_m^i$ , using  $VaR_q^i$  and  $VaR_{q=50}^i$  as benchmarks. To estimate  $ReVaR$ , we use quantile regressions as our main estimation method. Quantile regressions offer various advantages (Bassett and Koenker, 1978; Chernozhukov, Fernández-Val, and Kaji, 2017; Koenker and Bassett, 1978) and have been widely applied in the estimation of conditional Value-at-Risk (e.g., Adrian and Brunnermeier, 2016; Chernozhukov and Du, 2006; Chernozhukov and Umantsev, 2001).

In this subsection, we first estimate the static  $\Delta ReVaR$  based on the full sample period. In the following section, we extend our resilience measure to a dynamic specification. As a starting point, we use the following quantile regression:

$$X_{q,t+\tau}^i = \alpha_{q,\tau}^i + \beta_{q,\tau}^i I_t^i X_t^i + \epsilon_{q,\tau,t}^i, \quad (8)$$

where  $X_{q,t+\tau}^i$  is firm  $i$ 's  $q$ th quantile return loss at time  $t + \tau$ ;  $X_t^i$  is firm  $i$ 's return loss at time  $t$ ; and  $I_t^i$  equals 1 if  $X_t^i > 0$  and 0 otherwise.  $\alpha_{q,\tau}^i$  is a firm  $i$ , horizon  $\tau$  and probability  $q$ -specific constant;  $\beta_{q,\tau}^i$  quantifies the extent to which future extreme losses can be accounted for by current losses; and  $\epsilon_{q,\tau,t}^i$  is the error term.

There are several reasons why we introduce  $I_t^i$  into our regression equation. First, generally there is a relatively weak extreme-quantile correlation between  $X_{q,t+\tau}^i$  and  $X_t^i$ .<sup>9</sup> Baur, Dimpfl, and Jung (2012) use major European stocks and find the same pattern. They ascribe this to high variance of returns in extreme quantiles. Thus, a quantile regression that uses only  $X_t^i$  as independent variable is not suitable since insignificant coefficient estimates will result in unreliable

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<sup>9</sup>When estimating  $X_{q,t+\tau}^i = \alpha_{q,\tau}^i + \beta_{q,\tau}^i X_t^i + \epsilon_{q,\tau,t}^i$ , we find the estimated coefficients  $\hat{\beta}_{q,\tau}^i$  are overall insignificant when we take  $q \geq 90\%$ . Using both daily data and weekly data, we observe significant  $\hat{\beta}_{q,\tau}^i$  for only 3%-9% of the 500 largest stocks.

and noisy estimates of  $\Delta ReVaR_{q,\tau}^i$ .

Furthermore, using  $I_t^i X_t^i$  rather than  $X_t^i$  as regressor also fits our research design. Our idea of using a quantile regression is to predict future extreme losses, based on the current information set. By introducing  $I_t^i$ , we allow only current losses, not gains, to change the distribution of future extreme losses, which is natural when measuring resilience.

We can now calculate  $ReVaR_{q,\tau}^{i|C_s^i=VaR_q^i}$  with the estimated coefficients obtained from Equation (8):

$$ReVaR_{q,\tau}^{i|C_s^i=VaR_q^i} = \hat{\alpha}_{q,\tau}^i + \hat{\beta}_{q,\tau}^i VaR_q^i, \quad (9)$$

where  $I_q^i = 1$  because, in our empirical setting, we always have  $VaR_q^i > 0$  whenever we take  $q\% \geq 90\%$ .  $VaR_q^i$  is estimated as the quantile value using all firm  $i$ 's historical returns. The subscript  $\tau$  in  $ReVaR_{q,\tau}^{i|VaR_q^i}$  indicates the length of the forward-looking period. Suppose we use daily data, then  $ReVaR_{q,\tau=1}^{i|VaR_q^i}$  designates the conditional  $q$ th-quantile of firm  $i$  over the next day, and  $ReVaR_{q,\tau=20}^{i|VaR_q^i}$  denotes the conditional  $q$ th-quantile over the next month.

Likewise, we calculate  $ReVaR_{q,\tau}^{i|C_m^i=VaR_{50}^i}$  by plugging in  $VaR_{50}^i$ :

$$ReVaR_{q,\tau}^{i|VaR_{50}^i} = \hat{\alpha}_{q,\tau}^i + \hat{\beta}_{q,\tau}^i I_{50}^i VaR_{50}^i, \quad (10)$$

where  $I_{50}^i$  is equal to 1 if  $VaR_{50}^i > 0$  and equals 0 otherwise.

As the last step,  $\Delta ReVaR_{q,\tau}^i$  is obtained as:

$$\Delta ReVaR_{q,\tau}^i = ReVaR_{q,\tau}^{i|VaR_q^i} - ReVaR_{q,\tau}^{i|VaR_{50}^i} = \hat{\beta}_{q,\tau}^i (VaR_q^i - I_{50}^i VaR_{50}^i). \quad (11)$$

In general,  $VaR_{50}^i \approx 0$ . This gives a simplification of Equation (11):  $\Delta ReVaR_{q,\tau}^i \approx \hat{\beta}_{q,\tau}^i VaR_q^i$ .

### 3 Dynamic $\Delta ReVaR$

In Section 2, we have related  $C_s^i$  and  $C_m^i$  to  $VaR_q^i$  and  $VaR_{50}^i$ , and have estimated  $\Delta ReVaR_{q,\tau}^i$  on the basis of the quantile relation between current return losses and future return losses. As a key component of  $\Delta ReVaR_{q,\tau}^i$ ,  $ReVaR_{q,\tau}^{i|VaR_q^i}$  captures the  $q$ th-quantile of future return losses conditionally upon current  $VaR_q^i$ . For simplicity, we have used the quantile value based on all firm  $i$ 's historical returns as  $VaR_q^i$ .

This method is simple and intuitive as it defines stress scenarios as scenarios in which the firm's losses exceed its  $VaR_q^i$ . However, this method does not allow for variation in firms' downside risk over time. To address the limitations of static  $\Delta ReVaR$ , we now introduce a dynamic time-varying version. Following Adrian and Brunnermeier (2016), we extend the historical  $VaR_q^i$  to time-varying  $VaR_{q,t}^i$  by conditioning on state variables. In this section, we present the details of the estimation method for our time-varying  $\Delta ReVaR$ .

#### 3.1 Estimation Method: Quantile Regressions

To start with, we estimate the following quantile regression with different aggregate factors  $M_t$  based on the full sample period:

$$X_{q,t}^i = \alpha_q^i + \gamma_q^i M_t + \epsilon_{q,t}^i. \quad (12)$$

In this regression, we examine the contemporaneous relation between extreme losses  $X_{q,t}^i$  at quantile  $q$  and a vector of state variables  $M_t$ .  $\gamma_q^i$  is the vector of risk exposures of extreme losses to each state variable. Here, we do not impose any restrictions on  $\gamma_q^i$ , and thus the sign of  $\gamma_q^i$  can be different for each firm.

We can then use coefficient estimates to construct  $VaR_{q,t}^i$  as a linear function of  $M_t$ :

$$VaR_{q,t}^i = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_t. \quad (13)$$

In the static measures discussed in Section 2, we use  $VaR_q^i$ , calculated as the quantile value of all firm  $i$ 's historical returns. Here,  $VaR_{q,t}^i$  is time-varying through  $M_t$ .

Similar to the previous setting, we further set  $q = 50\%$  and run the following regression to obtain a benchmark measure of a firm's normal state:

$$X_{50,t}^i = \alpha_{50}^i + \gamma_{50}^i M_t + \epsilon_{50,t}^i, \quad (14)$$

and

$$VaR_{50,t}^i = \hat{\alpha}_{50}^i + \hat{\gamma}_{50}^i M_t. \quad (15)$$

Equations (12) to (15) have different interpretations compared to related expressions in Adrian and Brunnermeier (2016). In their paper, Adrian and Brunnermeier (2016) use lagged state variables  $M_{t-1}$  to capture time variation in the conditional moments of asset returns. Instead, we use contemporaneous  $M_t$  to model a firm's extreme loss. For example, if we use excess market return as  $M_t$ ,  $\hat{\gamma}_q^i$  measures how firm  $i$ 's quantiles of return losses at time  $t$  are exposed to market risk at time  $t$ .

Next, we estimate the following quantile regression:

$$X_{q,t+\tau}^i = \alpha_{q,\tau}^i + \beta_{q,\tau}^i I_t^i X_t^i + \delta_{q,\tau}^i M_t + \epsilon_{q,\tau,t}^i. \quad (16)$$

This quantile regression has the same role as Equation (8). The only difference is that Equation (16) contains  $M_t$  as control variables. These control variables are essential because we will subsequently

employ dynamic, time-varying  $VaR_{q,t}^i$  based on the control variables instead of static  $VaR_q^i$  as a component of our resilience measure.

Using the estimators, we obtain  $ReVaR_{q,\tau,t}^{i|VaR_{q,t}^i}$  and  $ReVaR_{q,\tau,t}^{i|VaR_{50,t}^i}$  as follows:

$$ReVaR_{q,\tau,t}^{i|VaR_{q,t}^i} = \hat{\alpha}_{q,\tau}^i + \hat{\beta}_{q,\tau}^i VaR_{q,t}^i + \hat{\delta}_{q,\tau}^i M_t, \quad (17)$$

and

$$ReVaR_{q,\tau,t}^{i|VaR_{50,t}^i} = \hat{\alpha}_{q,\tau}^i + \hat{\beta}_{q,\tau}^i I[VaR_{50,t}^i > 0] VaR_{50,t}^i + \hat{\delta}_{q,\tau}^i M_t. \quad (18)$$

$ReVaR_{q,\tau,t}^{i|VaR_{q,t}^i}$  indicates the  $q$ th-quantile of firm's  $i$  future return losses conditional upon stress scenarios represented by  $VaR_{q,t}^i$  that are exposed to factors  $M_t$ . Likewise,  $ReVaR_{q,\tau,t}^{i|VaR_{50,t}^i}$  indicates the  $q$ th-quantile of firm's  $i$  future return losses conditional upon a typical underperformance represented by  $VaR_{50,t}^i$  that can be described by factors  $M_t$ .<sup>10</sup>

Lastly, we can compute  $\Delta ReVaR_{q,\tau,t}^i$  for each firm as:

$$\begin{aligned} \Delta ReVaR_{q,\tau,t}^i &= ReVaR_{q,\tau,t}^{i|VaR_{q,t}^i} - ReVaR_{q,\tau,t}^{i|VaR_{50,t}^i} \\ &= \hat{\beta}_{q,\tau}^i (VaR_{q,t}^i - I[VaR_{50,t}^i > 0] VaR_{50,t}^i) \\ &= \hat{\beta}_{q,\tau}^i (\hat{\alpha}_q^i + \hat{\gamma}_q^i M_t - I[VaR_{50,t}^i > 0] (\hat{\alpha}_{50}^i + \hat{\gamma}_{50}^i M_t)). \end{aligned} \quad (19)$$

In general,  $VaR_{50,t}^i \approx 0$ . This gives a simplification of Equation (19):  $\Delta ReVaR_{q,\tau,t}^i \approx \hat{\beta}_{q,\tau}^i VaR_{q,t}^i = \hat{\beta}_{q,\tau}^i (\hat{\alpha}_q^i + \hat{\gamma}_q^i M_t)$ . We can see that the  $\Delta ReVaR_{q,\tau,t}^i$  depends primarily on four components. First, the sensitivity of future extreme losses to current losses, which is measured by  $\hat{\beta}_{q,\tau}^i$ . Since the term  $(VaR_{q,t}^i - I[VaR_{50,t}^i > 0] VaR_{50,t}^i)$  is positive, a lower sensitivity  $\hat{\beta}_{q,\tau}^i$  is related with lower  $\Delta ReVaR_{q,\tau,t}^i$  and thus higher resilience. This means resilient firms are those with stable quantiles

<sup>10</sup>In Expression (17), the indicator  $I[VaR_{q,t}^i > 0] = 1$  is omitted as  $VaR_{q,t}^i$  at an extreme quantile level  $q$  is empirically positive.

of future return losses, regardless of today’s losses.

The second component,  $\widehat{\alpha}_q^i$ , may be viewed as firms’ idiosyncratic risks when  $M_t$  stays constant. The third component,  $\widehat{\gamma}_q^i$ , measures the sensitivity of firms’ extreme losses to contemporaneous changes in  $M_t$ . The last component is  $M_t$ , which is the same for all firms.

## 4 Data

Our analysis relies on three types of data: firm-level stock return data, used to estimate firm-level resilience, aggregate financial and macroeconomic variables used as state variables for the conditional Value-at-Risk measures, and finally, firm-level characteristics that we use to examine what types of firms are more resilient than others.

### 4.1 Firm-level stock return data

We obtain daily firm-level stock return data from CRSP, and transform the daily returns to continuously compounded returns on a weekly basis. We focus on weekly returns since it provides more observations than monthly data. Compared to daily data, weekly data provides a more effective means of capturing the information we require, given our expectation of firms experiencing recovery over the course of weeks rather than days. Our sample comprises U.S. stocks with share code 10 and 11 from January 1, 1990 to December 31, 2022. Our sample begins in 1990 as this is the start of the VIX index, one of the state variables. To mitigate survivorship bias, we incorporate delisted stocks in our sample. We exclude small stocks whose prices have fallen below 1 dollar at any point during our sample period. Following previous literature, we exclude observations with Book-to-Market that is negative. We also exclude regulated utilities (Standard Industrial Classification codes 4900–4999), financial firms (6000–6999), and companies classified under public services, international affairs, or non-operating establishments (9000+).

## 4.2 State variables

In order to estimate dynamic  $\Delta ReVaR$  with Equations (12) and (14), we need to introduce state variables  $M_t$ . Similar to Adrian and Brunnermeier (2016), we focus on six macroeconomic variables: the 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. The three month yield change is calculated as the weekly change of the average three-month treasury bill secondary market rate (DTB3). The term spread change is the weekly change of the average ten-year treasury constant maturity minus three-month treasury constant maturity (T10Y3M). The TED spread is the spread between the three-month LIBOR and three-month treasury bill before January 2022, and the spread between the secured overnight financing rate (SOFR) and the three-month treasury bill after January 2022. The credit spread change is the weekly change of the spread between Moody's seasoned Baa corporate bond yield and the ten-year treasury rate (DTB10). The VIX index is the CBOE volatility index (VIXCLS). The stock market return is obtained from Kenneth French's website, and the other macro variables are from the Federal Reserve Bank of St. Louis. Summary statistics of these weekly variables from January 1, 1990 to December 31, 2022 are shown in Table 1.

[Insert Table 1]

## 4.3 Firm characteristics

In Section 6, we analyze the relation between our firm-level resilience measures and firm characteristics to assess which types of firms are more resilient. We consider three categories of firm characteristics. First, we consider measures of a firm's financial flexibility, including market leverage and cash holdings. We obtain quarterly firm financial data from Compustat. Market leverage is calculated as the sum of long-term and short-term debt divided by the firm's market value of equity. Cash and cash equivalents are scaled by total assets.

Second, we include variables related to a firm’s organizational flexibility; different categories of intangible assets and measures of firm innovation. We obtain five measures of firms’ intangible assets. The first four are based on Peters and Taylor (2017), where the data is provided directly by Compustat through WRDS. First, we include intangible assets that are reported on the firm’s balance sheet, representing externally purchased intangible capital of the firm. Next, Peters and Taylor (2017) define the stock of internal intangible capital (i.e., off balance sheet intangible assets) as the sum of knowledge capital and organization capital. In brief, knowledge capital is developed through spending on R&D, and therefore is calculated as the accumulating past R&D spending using the perpetual inventory method. Similarly, organizational capital is based on past selling, general and administrative (SG&A) spending, using a similar perpetual inventory method (see also, e.g., Eisefeldt and Papanikolaou, 2013). In different specifications, we include knowledge capital and organization capital separately as well as combined (i.e., off-balance sheet intangible assets). Fifth, we include a measure of brand capital, following Belo, Lin, and Vitorino (2014) and Hasan, Taylor, and Richardson (2022), which we construct as:

$$BC_{it} = (1 - \delta)BC_{it-1} + Adv_{it}, \quad (20)$$

where  $BC_{it}$  is the brand capital of firm  $i$  at time  $t$ .  $Adv_{it}$  is the advertising expenses of firm  $i$  at time  $t$ .  $BC_{i0}$  is initialized as  $Adv_{i0}/(g + \delta)$ , using the first observation of  $Adv_{i0}$  in Compustat. The average growth rate  $g$  is estimated as the average real growth of advertising expense by each firm. The depreciation rate of  $\delta$  is set to be 0.5.

We also consider three measures of firm innovation activities. To capture innovation input, we include R&D expenses scaled by total assets, based on Compustat data. To measure innovation output, we use patent data from Kogan, Papanikolaou, Seru, and Stoffman (2017). As the first to

exploit this dataset at a large scale, Kogan, Papanikolaou, Seru, and Stoffman (2017) collect and use patent data dated back to 1926 and provide PERMNO as firm identifier to match with other firm-level datasets. For patent-related variables, we use two main measures. The first one is the number of patents, defined as the total number of patents issued in the past five years (i.e., twenty quarters). The other measure is the average economic value of firm patents, computed as the total economic value of patents in the past five years divided by the patent number during the same period. Kogan, Papanikolaou, Seru, and Stoffman (2017) construct the measure of economic value by using three-day market reactions around patent announcement days while adjusting for noise, and define economic value as a measure of investors' valuation. In other words, economic value is defined as the change in stock price, based on the assumption that stock prices reflect the value investors assign to the technological innovation or intellectual property represented by the patent.

The third category of firm characteristics includes traditional risk measures: stock return volatility, based on the standard deviation of the firm's stock returns in the past 12 months, and the time-varying Value-at-Risk obtained from Equation (17).

Finally, we include as firm-level control variables firm size (the natural logarithm of total assets), the book-to-market ratio and the Return on Assets (ROA). ROA is calculated as net income divided by total assets. Alternatively, we use EBITDA and EBIT as numerators in the calculation of ROA.

The measures of intangible assets are available at an annual frequency, all other independent variables are available at the quarterly frequency. We therefore run panel regressions both at the quarterly and at the annual frequencies.

Summary statistics of all firm-level variables, except for the Value-at-Risk are reported in Table 2. Summary statistics of the Value-at-Risk estimates, along with those for the other components of the resilience measures, are reported in Table 4, which we discuss later.

[Insert Table 2]

## 5 Estimation Results

There are several parameter choices in the estimation procedure (Section 3.1). First, in line with common practice, we adopt both  $q = 95\%$  and  $q = 99\%$  to assess tail risk. As discussed in Section 2.4, we use  $\tau = 1$  week as forward-looking horizon in the following analysis. When applying the estimation method in the U.S. equity market, we find  $\tau = 1$  gives statistically significant  $\beta$  estimates for more stocks compared to other values of  $\tau$ .

We begin with the static  $\Delta ReVaR$  to examine cross-firm variation and we compare it to other risk measures. Next, we use the dynamic  $\Delta ReVaR$  in cross-sectional and panel regressions to explore the relation between resilience and firm characteristics.

### 5.1 Static $\Delta ReVaR$

Section 2.5 introduces quantile regression as an estimation method for the static  $\Delta ReVaR$ . As a first step, we estimate Equation (8) and obtain  $\widehat{\beta}_{95}^i$ , which measures the extent to which future extreme losses can be accounted for by current losses.<sup>11</sup> Figure 1 Panel A displays the relation between  $\widehat{\beta}_{95}^i$  and its  $t$ -value. In this figure, 1% outliers of all variables are winsorized.

[Insert Figure 1]

We find that 46% of all firm-level  $\widehat{\beta}_{95}^i$  estimates is statistically significant at at least the 10% level. The figure shows that  $\widehat{\beta}_{95}^i$  is typically both economically important and statistically significant. Moreover, even though the vast majority of  $\widehat{\beta}_{95}^i$  estimates is positive, highlighting that past losses positively predict extreme future losses, we observe a small number of negative  $\widehat{\beta}_{95}^i$  estimates.

We obtain  $\Delta ReVaR_{95}^i$  using Equation (11), where  $VaR_{95}^i$  and  $VaR_{50}^i$  are calculated as the quantile values of all of firm  $i$ 's historical returns. Panel B shows substantial cross-firm variation

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<sup>11</sup>For ease of exposition, we write  $\widehat{\beta}_{95}^i$  instead of  $\widehat{\beta}_{95,1}^i$  since we use  $\tau = 1$  week throughout this paper.

in both  $\widehat{\beta}_{95}^i$ , ranging from  $-0.4$  to about  $1.0$ , and in  $\Delta ReVaR_{95}^i$ , ranging from  $-4\%$  to  $12\%$ . This dispersion across firms is essential for our follow-up analysis where we relate differences in resilience to different firm characteristics.

Panel C plots the relationship between  $\Delta ReVaR_{95}^i$  and its component  $VaR_{95}^i$ . As there is no one-to-one relationship between  $\Delta ReVaR_{95}^i$  and  $VaR_{95}^i$ , the figure highlights that our resilience measure  $\Delta ReVaR$  is different from a historical  $VaR$  and provides information about another aspect of firms' tail risk.

[Insert Figure 2]

Further, we compare  $\Delta ReVaR$  to other (tail) risk measures. Figure 2 Panels A, B and C present scatter plots between  $\Delta ReVaR$  and higher moments of historical returns  $R^i$ . We also obtain  $\beta_{mkt}^i$  from CAPM and show its relation with  $\Delta ReVaR$  in Panel D. In short, we do not find a significant positive or negative relation between  $\Delta ReVaR$  and  $\beta_{mkt}^i$  or higher moments.

In sum, we show that there is substantial variation of  $\Delta ReVaR$  across firms, which enables us to conduct further cross-sectional analyses. Furthermore,  $\Delta ReVaR$  is different from other (tail) risk measures, including historical Value-at-Risk ( $VaR$ ), market beta ( $\beta_{mkt}^i$ ) from CAPM, and higher moments of historical returns. This evidence shows that  $\Delta ReVaR$  provides new information about another aspect of firms' (tail) risk, namely *Resilience*.

## 5.2 Dynamic $\Delta ReVaR$

We now turn to the dynamic  $\Delta ReVaR$  estimates as our main measure of resilience. As discussed in Section 3, time variation in the components of  $\Delta ReVaR$  is driven by several state variables, such as stock market returns, the VIX and the term spread.

We first estimate, for each stock, the quantile regression where we use the stock's  $q\%$  quantile weekly returns as dependent variable and the contemporaneous weekly state variables as indepen-

dent variables as in Equations (12) and (14). We also estimate the quantile regression of (16), where the independent variables are the one-week lagged state variables, along with the one-week lagged return losses of the stock.

[Insert Table 3]

Table 3 presents the average absolute  $t$ -values of state variable exposures. We report the average absolute  $t$ -statistics because the exposures to state variables of each stock might have different signs and here we are interested in evaluating the statistical significance rather than the sign of the estimated risk exposure. According to Equations (12) and (14),  $\hat{\gamma}^i$  measures how much the quantile returns are exposed to the state variable. Overall, we find that the estimated exposures are on average significant for most of the state variables. Particularly, quantile returns  $X_{95,t}^i$  and  $X_{99,t}^i$  (i.e., extreme losses) are most exposed to the VIX index, the market return and the TED spread. Quantile returns  $X_{50,t}^i$  (i.e., median returns) are most exposed to the market return. When we include lagged state variables as control variables in the quantile regressions on the stock's own lagged losses (Equation (16)), we find that the average absolute  $t$ -values for  $\hat{\delta}_{q,1}^i$  are above one for all state variables and above two for the three-month yield change and the VIX index.

[Insert Table 4]

Table 4 presents summary statistics of dynamic firm-level resilience estimates. In total, our sample includes 4,046 stocks and 3,279,885 observations on a weekly basis. Our key measure  $\Delta ReVaR_{95,t+1}^i$  ranges from  $-3.96\%$  (p1%) to  $6.86\%$  (p99%), and the average value is  $0.708\%$ . The economic intuition is that a stress scenario will increase the weekly 95% Value-at-Risk of a stock by  $0.708\%$  point on average. Similarly, a stress scenario will increase the 99% Value-at-Risk of a stock by  $2.495\%$  point on average. At the same time, these numbers highlight that there is substantial variation in resilience estimates, which we will exploit in the next section.

## 6 Resilience and Firm Characteristics

Before linking resilience to firm characteristics, we first validate our measure by showing a significant relation between ex-ante dynamic  $\Delta ReVaR$  and the post-crisis Return on Assets (ROA), which can be viewed as an ex-post resilience measure of the firm. In Section 6.2, we conduct panel regressions that relate resilience to lagged firm-level characteristics to better understand what types of firms are more resilient than others.

### 6.1 Ex-Ante v.s. Ex-Post Resilience

Several recent finance studies use stock price changes after crisis as an ex-post measure of firm resilience (e.g., Cheema-Fox, LaPerla, Wang, and Serafeim, 2021; Ding, Levine, Lin, and Xie, 2021; Fahlenbrach, Rageth, and Stulz, 2021). By this definition, firms with lower cumulative stock return losses since a crisis are regarded as resilient firms. Alternatively, ROA is also applied as it measures the financial performance of a firm. That is, higher Return on Assets (ROA) after a crisis means the firm has the ability to maintain its business activity and is thus regarded as more resilient. As our resilience measure is already return-based, we focus on ROA as a post-crisis outcome measure. Specifically, in this section, we link our measure  $\Delta ReVaR$  estimated using pre-crisis data to ex-post ROA in three different crises: the Covid-19 outbreak in 2020Q1, the Global Financial Crisis in 2008Q3 and the Technology Bubble in 2000Q1.

To avoid a look-ahead bias, we estimate ex-ante resilience using pre-crisis data only. That is, we use data from January 1 1990 to December 31 2019, from January 1 1990 to December 31 2007, and from January 1 1990 to December 31 1999 for the above three crisis events, respectively. Following the estimation methods in Sections 3.1 and 5.2, we obtain weekly  $\Delta ReVaR$  for each estimates pre-crisis sub sample period. Next, we average the weekly  $\Delta ReVaR$  within each quarter, and use the quarterly  $\Delta ReVaR$  in 2019Q4, 2008Q2, and 1999Q4, respectively, as pre-crisis  $\Delta ReVaR$  for

the three events. To measure post-crisis performance, we use the Return on Assets in quarters 2020Q2, 2008Q4 and 2000Q2, respectively. We compute ROA in three different ways using NI, EBITDA and EBIT as numerators. We then run the following cross-sectional regressions:

$$ROA_{event+1}^i = a + b\Delta ReVaR_{q=0.99,\tau=1,event-1}^i + cX_{event-1}^i + \epsilon_t^i \quad (21)$$

We include industry fixed effects and clustered standard errors by industry level. We also control for pre-crisis firm-level characteristics, including lagged ROA, in all regressions. As a larger value of  $\Delta ReVaR_{q=0.99,\tau=1,event-1}^i$  indicates a less resilient firm, a negative sign of  $\hat{b}$  should be interpreted as a positive relation between ex-ante resilience and post-crisis ROA. Table 5 shows the results.

[Insert Table 5]

In all regressions, we can observe negative signs of  $\hat{b}$ , indicating that firms with lower  $\Delta ReVaR$  before the crisis tend to have higher ROA after the crisis. As mentioned earlier, we conduct the tests with three alternative measures of ROA. For all crises, we find that the relation between ROA and  $\Delta ReVaR$  is statistically significant for one, two or three of the specifications: during the Covid-19 outbreak (Columns 1-3) based on EBITDA and EBIT, during the Global Financial Crisis (Columns 4-6) based on NI, and during the Technology Bubble (Columns 7-9) based on all three ROA measures. Recall that in all regressions we control for multiple pre-crisis firm characteristics as well as industry fixed effects. In Table 5 we focus on  $\Delta ReVaR_{q=0.99}^i$ , but results are qualitatively similar when we use  $\Delta ReVaR_{q=0.95}^i$ .<sup>12</sup>

In sum, these results carry two noteworthy implications. Each of these three crises is unique and arguably of a very distinct nature. Yet, our return-based ex-ante resilience estimates  $\Delta ReVaR$

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<sup>12</sup>When using  $\Delta ReVaR_{q=0.95}^i$  as explanatory variable, the coefficient estimate is again negative in all specifications, indicating that firms with higher ex-ante resilience (i.e., lower  $\Delta ReVaR$ ) tend to have higher ex-post ROA. The coefficients are statistically significant only for the Global Financial Crisis.

have significant predictive power for which firms turn out to be ex-post resilient during each of these crises. Across all three crises examined, we estimate a firm’s  $\Delta ReVaR$  solely from pre-crisis data. This suggests that  $\Delta ReVaR$  captures a firm’s prospective capacity to sustain its business operations during unforeseen crises. In essence, it serves as an indicator of the firm’s preparedness to navigate through unexpected disruptions, thereby providing valuable insights into its resilience potential. Second,  $\Delta ReVaR$  extracts information concerning a firm’s fundamental performance using stock return data.

## 6.2 Panel Regression Results

After validating our resilience measure, we investigate which firm characteristics are related to cross-sectional differences in firm resilience. As discussed in Section 4, most firm characteristics are available at the quarterly frequency. As such, we start with quarterly panel regressions. Our measures of different types of intangible assets, however, are only available at the annual frequency. We therefore perform the panel regressions with intangible assets at the annual frequency. To this end, we first need to convert our weekly firm-level resilience estimates to quarterly and annual resilience measures, by averaging all weekly estimates for a firm within the quarter or year. Note that, different from the validation exercise in the previous subsection, here we use the full sample period with all available data to estimate time-varying weekly firm-level resilience, as discussed in Section 5.2.

We conduct the following panel regressions:

$$\Delta ReVaR_{q,\tau=1,t}^i = a + bM_{t-h} + cZ_{t-h}^i + \epsilon_t^i, \quad (22)$$

where  $h$  is the forecast horizon,  $M_{t-h}$  are lagged macro variables, and  $Z_{t-h}^i$  are lagged firm-level

variables. For our quarterly panel regressions, we consider  $h = 1, 4,$  and 8 quarters. For the annual panel regressions we only consider  $h = 1$  year. We report results for both  $\Delta ReVaR_{95, \tau=1}^i$  and  $\Delta ReVaR_{99, \tau=1}^i$ . Recall that a higher  $\Delta ReVaR_{q, \tau=1, t}^i$  implies that a firm is less resilient. Therefore, in the above equation, a negative sign of  $\hat{c}$  indicates a positive relation between firm characteristics  $Z_{t-h}^i$  and firm resilience and a positive sign indicates a negative relation. We include industry fixed effects and adopt Newey-West standard errors with  $h$  lags.

We classify a firm as resilient when, loosely speaking, it can “bounce back” after an unexpected extreme negative shock. Hence, different from traditional risk management, resilience management is more naturally related to a firm’s agility or flexibility. As discussed in Section 4, we consider three categories of firm characteristics: financial flexibility, organizational flexibility and firm stock return risk.

We also include firm-level control variables (size, book-to-market and ROA) and aggregate control variables (changes in the three-month yield, term spread, TED spread, credit spread, stock market returns and the VIX).

Note that we include industry fixed effects, and as such explore variation in resilience across firms within an industry. In the final subsection, we briefly discuss the estimated industry fixed effects, to see whether, controlling for the effect of firm characteristics, there are unconditional cross-industry differences in firm resilience.

### 6.2.1 Quarterly Panel Regressions

We start with quarterly panel regressions, where we can include all firm characteristics except for the variables related to intangible assets that are available at the annual frequency only. The results are displayed in Table 6.

[Insert Table 6]

First, as expected, the coefficient estimates of leverage are highly significant and positive, implying that firms with lower market leverage tend to be more resilient. For  $q = 95\%$ , we find that a 1% decrease in lagged leverage level is associated with a 57 to 68 percentage point decrease in  $\Delta ReVaR$ , and hence a 57 to 68 percentage point increase in the resilience level. The coefficient estimate is significant in regressions with different parameters  $q$  and different lagged horizons  $h$ . This finding is consistent with existing literature indicating that firms with higher leverage tend to have worse performance during Covid-19 (Ding, Levine, Lin, and Xie, 2021; Fahlenbrach, Rageth, and Stulz, 2021).

This literature also concludes that firms with more cash holdings performed better during Covid-19, while we do not find such a link between cash and time-varying firm resilience. The coefficient estimates of cash holdings are positive and significant, suggesting a negative relation between cash and resilience. A potential explanation is that the types of extreme negative shocks that underlay our resilience measure go beyond negative cash flow shocks, for which cash buffers as a source of precautionary savings would be sufficient. In addition, holding excess cash entails high opportunity cost. This potentially impedes a firm's ability to enhance its resilience through, for instance, investments in organizational flexibility, which play a key role as we discuss next.

Second and importantly, we find significant linkages between measures of firm innovation and firm resilience. The results indicate that firms with more R&D spending, and especially a higher number of patents and a higher economic value per patent tend to be more resilient. This suggests that an innovative firm tends to be more adaptable to changes in the business environment and can quickly adjust itself in response to unexpected shocks. Moreover, innovation can create competitive advantages for firms, enabling them to preserve during market disruptions.

Our third category includes two traditional measures of firm risk. Both are statistically significant: firms with more volatile past stock returns and firms with a higher Value-at-Risk tend to be

less resilient.

Finally, the firm-level control variables suggest that that small firms tend to be more resilient. Yet, the portrait of resilient firms is more likely to be mid-sized firms since very small firms are not included in our sample. While larger firms could be perceived as more resilient, a concept often referred to as “too big to fail”, we find that in terms of downside risk, small firms bounce back more. Furthermore, we find that firms with higher book-to-market (BM) value are associated with lower  $\Delta ReVaR$ , suggesting that value firms tend to be more resilient. These results are in line with Hasan, Taylor, and Richardson (2022), who find that a firm’s crash risk (i.e., its negative return skewness) is associated with larger size and lower BM. Note that resilience is conceptually different from skewness, as it captures to what extent its downside risk after an extreme negative shock (measured as conditional Value at Risk) returns to the median downside risk, rather than the level of downside risk itself.

### **6.2.2 Annual Panel Regressions including Intangible Assets**

Next, we examine the relationship between firm resilience and various measures of firms’ intangible assets. These measures, obtained from Peters and Taylor (2017), capture various dimensions of intangible capital, including knowledge capital, organizational capital, and brand-related intangible assets, as detailed in Section 4. Since these measures are available only at an annual frequency, we perform the panel regressions using annual data. Specifically, we set  $h$  to one year in Equation( 22), allowing us to assess how firms’ resilience responds to changes in intangible asset accumulation over time.

[Insert Table 7]

Table 7 reports the results. First, in column 1 we repeat the analysis from Table 6 at the annual frequency to confirm that previously identified characteristics including innovation measures

continue to remain significant at the annual frequency. Now we also find a highly significant coefficient estimate of R&D expenses. This suggests that the resilience-enhancing effects of innovation activities persist over time and are not merely driven by short-term fluctuations.

Next, we document strong linkages between all types of intangible assets and firm resilience measures. Columns 2 to 6 show that the coefficient estimates of (acquired) intangible assets, knowledge capital, organization capital, off-balance-sheet intangibles, and brand capital, are all negative and statistically significant. The negative coefficients suggest that firms with higher intangible capital tend to be more resilient. Knowledge capital, derived from R&D investments, enables firms to maintain competitiveness, while organization capital reflects stronger managerial capabilities and operational flexibility. The resilience benefits of off-balance-sheet intangibles highlight the economic importance of unrecorded intellectual assets, while brand capital provides firms with pricing power and customer loyalty, helping them withstand downturns.

In sum, our panel regressions point towards two important types of firm characteristics that relate to firm resilience: financial flexibility (leverage) and organizational flexibility (intangible assets and innovation). Moreover, while resilience is intrinsically different from risk, we do find that firms with more volatile past returns and more downside risk tend to be less resilient.

### **6.3 Cross-Industry Difference in Firm Resilience**

The above analysis shows that resilience varies substantially across firms and over time, and part of this variation can be linked variation in firm financial flexibility, organizational flexibility and risk. One follow-up question is whether there are an cross-industry differences in resilience that remain after accounting for the effect of these firm characteristics. Are some industries inherently more resilient than others? In a preliminary analysis, we consider cross-industry differences by examining the industry fixed effects estimates from our panel regressions. Table 8 reports the results.

[Insert Table 8]

First, we report the average firm resilience for all firms within each industry (i.e., column "Firm Mean"). We find that on average, firms in the manufacturing and retail industries have the lowest  $\Delta ReVaR$  estimates and firms in the agriculture and in the services industries have the highest average  $\Delta ReVaR$  estimates. However, the high levels of dispersion in average firm resilience indicate that there is substantial cross-firm variation in resilience within industries.

Further, some of the differences across industries are likely related to cross-industry differences in firm innovation activities, firm size, leverage and other characteristics that relate to resilience, as identified in the panel regressions. By examining the estimates of the industry fixed effects from the panel regressions, we essentially control for the role of these firm characteristics for resilience, and see whether there are some (yet) unexplained differences in unconditional average resilience across industries. Table 8 shows that this is indeed the case. We focus on the industry fixed effects estimates from the quarterly panel regressions. For  $q = 95\%$ , all industry fixed effects are highly statistically significant and for  $q = 99\%$ , all but three are significant. We use the agriculture industry as a benchmark. For  $q = 95\%$ , the coefficient estimate of the Transportation and Communication industry is most negative, suggesting that controlling for cross-industry differences due to the firm characteristics, firms in the transportation and communication industries are most resilient. Based on the fixed effects estimates, the findings suggest that firms in the agriculture, mining and services industries are least resilient. In follow-up work we aim to examine in more detail the potential drivers of these wedges in industry resilience.

## 7 Conclusion

While resilience is widely studied across many different disciplines, within finance the concept of resilience is nascent. Rather than studying how firms are exposed to different sources risk, we study their resilience. Commonly, resilience is described as the ability to cope with the unexpected. After being hit by an unexpected negative shock, do firms bounce back? And what are the characteristics of firms that are resilient?

To address these questions, we first propose a novel measure of resilience, namely  $\Delta ReVaR$ .  $\Delta ReVaR$  captures the extent to which a firm's conditional downside risk after an extreme loss differs from its conditional downside risk after a typical underperformance of that firm. If the two are similar, an extreme scenario has the same implications for the conditional return distribution and hence Value-at-Risk of the firm as a typical underperformance. In other words, the firm is resilient. Loosely speaking, the firm's downside risk bounces back to its normal state even after a stress event.

A key advantage of  $\Delta ReVaR$  is that the measure is return-based and forward-looking. This means that we do not need to specify the type and timing of the crisis in order to classify firms as resilient or non-resilient.

Using weekly stock returns of U.S. listed firms and employing quantile regressions as our estimation method, we compute both a static and dynamic version of  $\Delta ReVaR$ . The dynamic version accounts for changes in firms' downside risk over time, and is thereby used as the primary measure in subsequent empirical analyses. Our initial assessment reveals substantial cross-firm variation in  $\Delta ReVaR$ . Furthermore, we show that  $\Delta ReVaR$  is distinct from other (tail) risk measures, including historical  $VaR$ , volatility, skewness, kurtosis and the CAPM market beta.

Next, we validate the dynamic resilience measure using three distinct crises: the Covid-19

outbreak in 2020, the Global Financial Crisis in 2008 and the Technology Bubble in 2000. We find that firms with a higher ex-ante resilience measure have higher ex-post Return on Assets as well. The relation is statistically significant for all three crises, even though they are each of a very different nature.

Lastly, we examine the relation between firm resilience and lagged firm characteristics using panel regressions. We consider three categories of variables, related to financial flexibility, organizational flexibility and traditional measures of firm risk. Besides the expected relation to leverage, we find that innovation and intangible assets matter significantly. Firms with higher R&D investments, a greater number of patents and a higher economic value per patent are significantly more resilient. Also, firms with more intangible assets, more knowledge capital, organization capital and brand capital are significantly more resilient. Hence, while the characteristics that help firms bounce back after the Covid-19 outbreak (i.e., the ability of employees to work from home) are arguably different from characteristics that help recover from other types of crises such as the Great Financial Recession, we find that overall, organizational flexibility, i.e., a firm's key talent and workers and the firm's innovation activities help cope with unexpected future extreme events.

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Figure 1: **Static Resilience Estimates**

These figures plot static  $\Delta ReVaR_{95,1}^i$  and related estimates using a sample of U.S. stocks from 1980 to 2022. Panel A plots  $\beta_{95,1}^i$  ( $x$ -axis) and  $t$ -value ( $y$ -axis). The two horizontal lines indicate  $t$ -values of 1.65 and -1.65. Panel B plots resilience measure  $\Delta ReVaR_{95,1}^i$  ( $x$ -axis) and  $\beta_{95,1}^i$  ( $y$ -axis). Panel C plots  $\Delta ReVaR_{95,1}^i$  ( $x$ -axis) and  $VaR_{q=95}^i$  ( $y$ -axis).

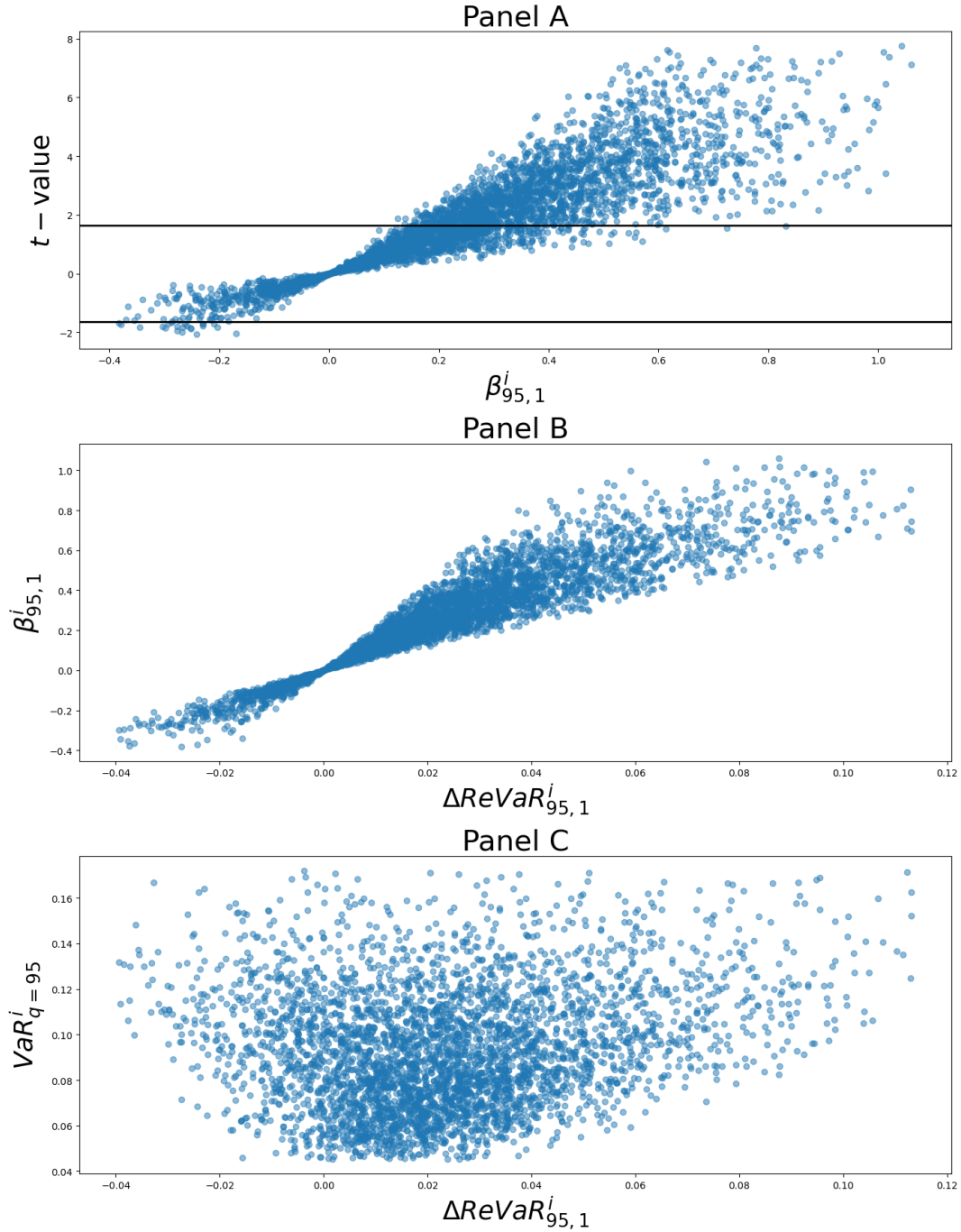


Figure 2:  $\Delta ReVaR$  and Risk-Related Measurements

These figures plot static  $\Delta ReVaR_{95,1}^i$  and other risk-related measurements. Panel A plots  $\Delta ReVaR_{95,1}^i$  ( $x$ -axis) and standard deviations of weekly returns  $R^i$  ( $y$ -axis). Panel B plots  $\Delta ReVaR_{95,1}^i$  ( $x$ -axis) and skewness of weekly returns  $R^i$  ( $y$ -axis). Panel C plots  $\Delta ReVaR_{95,1}^i$  ( $x$ -axis) and kurtosis of weekly returns  $R^i$  ( $y$ -axis). Panel D plots  $\Delta ReVaR_{95,1}^i$  ( $x$ -axis) and  $\beta_{mkt}^i$  ( $y$ -axis) from CAPM.

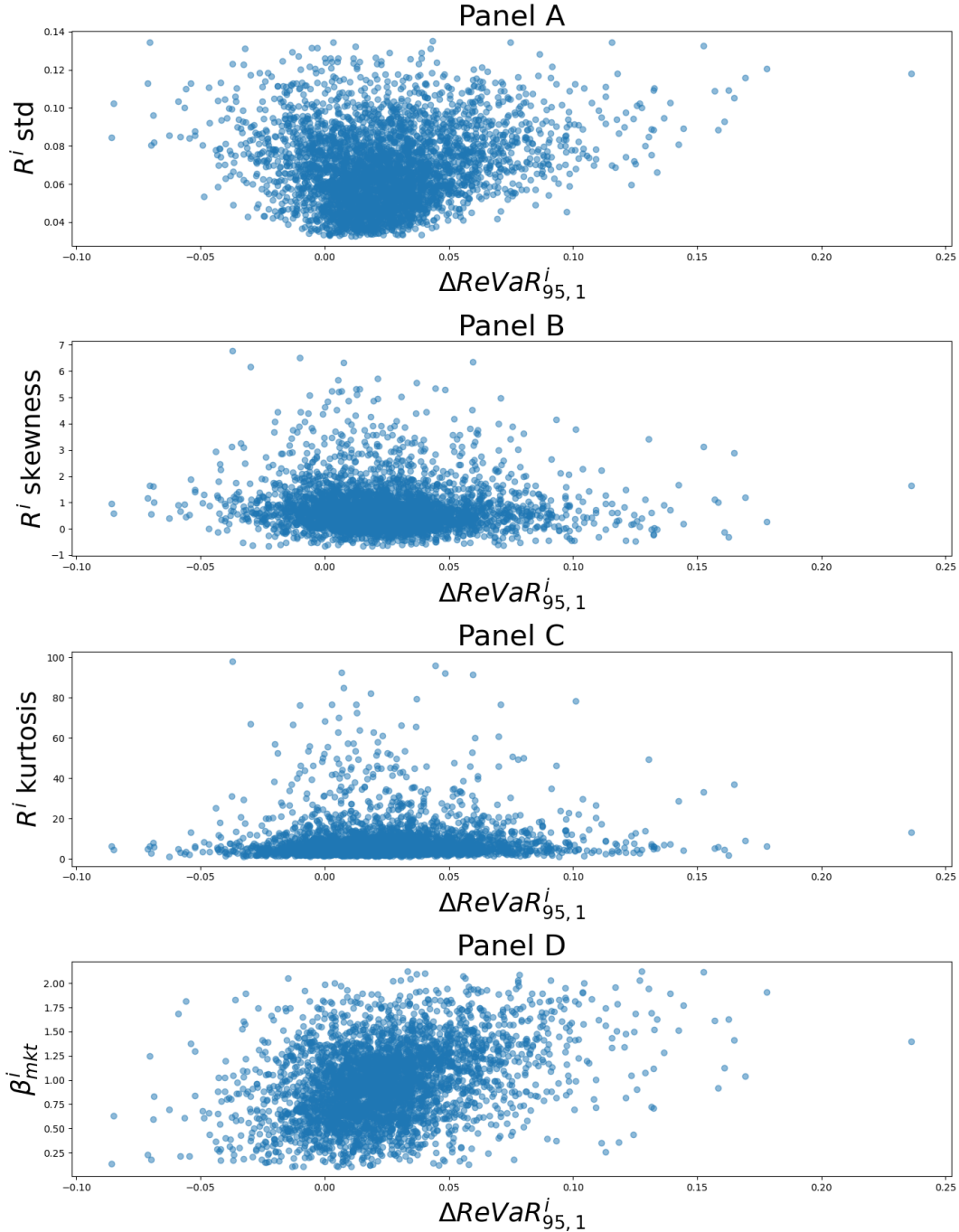


Table 1: **Summary Statistics of State Variables**

This table presents summary statistics for the state variables  $M_t$ , based on weekly data from 1990 to 2022. Market returns are obtained from Kenneth French’s website, while the remaining macroeconomic variables are obtained from the Federal Reserve Bank of St. Louis. The change in the three-month yield is calculated as the weekly difference in the average three-month Treasury bill secondary market rate (DTB3). The term spread change represents the weekly difference between the average ten-year Treasury constant maturity rate and the three-month Treasury constant maturity rate (T10Y3M). The TED spread measures the difference between the three-month LIBOR and the three-month Treasury bill before January 2022, and the difference between the Secured Overnight Financing Rate (SOFR) and the three-month Treasury bill after January 2022. The credit spread change reflects the weekly difference between Moody’s seasoned Baa corporate bond yield and the ten-year Treasury rate (DTB10). Lastly, the VIX refers to the CBOE Volatility Index (VIXCLS).

	Obs.	Mean	Median	p99	p1	SD	Skewness	Kurtosis
Three month yield change (%)	1,717	0.802	0.084	67.111	-50.000	14.640	1.151	11.547
Term spread change (%)	1,717	0.135	-0.368	104.324	-100.000	22.018	0.383	14.039
Ted spread (%)	1,717	44.529	37.000	188.400	-0.444	32.462	1.840	7.540
Credit spread change (%)	1,717	0.008	-0.110	7.582	-6.145	2.303	0.372	4.155
Market return (%)	1,717	0.219	0.320	6.424	-6.443	2.189	-0.224	3.969
VIX	1,717	19.661	17.838	48.375	10.188	7.877	2.067	10.495

Table 2: **Summary Statistics of Stock-Level Variables**

This table presents summary statistics for firm characteristics, with data obtained from Compustat. Panel A reports all variables that are available at a quarterly frequency, and Panel B reports variables that are only available at a yearly frequency. Leverage is defined as the ratio of total debt (dlttq + dlcq) to market value of equity (cshoq \* prccq). Cash holdings are measured as cash and equivalents (cheq) divided by total assets (atq). R&D intensity is measured as research and development expenditures (xrdq) divided by total assets (atq). Patent data is obtained from Kogan et al. (2017). Number of patents refers to the total number of patents issued in the past five years (i.e., twenty quarters). Average economic value per patent is calculated as the total economic value of patents over the past five years, divided by the number of patents issued in the same period. Stock return volatility is measured as the standard deviation of past 12-month stock returns (trt1m). Size is measured as the natural logarithm of total assets (log(atq)). The book-to-market ratio is calculated as the ratio of common equity (ceqq) to market value, determined by shares outstanding times price (cshoq \* prccq). Return on assets (ROA) is calculated as net income (niq) divided by total assets (atq). Alternatively, EBITDA and EBIT are also used as net income in the calculation of ROA. In Panel B, Intangible assets, knowledge capital, organization capital and off balance sheet intangible assets are obtained from Peters and Taylor (2017). Brand capital is estimated from Belo, Lin, and Vitorino (2014). Summary statistics are calculated over all quarter- (or year-) firm observations.

	Obs.	Mean	Median	p99	p1	Stdev.	Skewness	Kurtosis
Panel A: Quarterly Panel								
Leverage	217,648	0.377	0.165	0.000	3.724	0.611	3.188	15.013
Cash	217,648	0.156	0.083	0.000	0.796	0.181	1.631	5.164
R&D	217,648	0.009	0.000	0.000	0.094	0.018	2.605	10.493
Patent number	217,648	1.519	0.000	0.000	7.636	2.023	1.230	3.496
Average economic value of patent	217,648	1.054	0.000	0.000	5.270	1.394	1.180	3.378
Stock Volatility	217,648	11.522	10.083	3.312	34.930	6.050	1.449	5.489
Size	217,648	6.558	6.483	2.526	11.346	1.945	0.203	2.557
Book-to-market	217,648	0.567	0.457	0.038	2.346	0.427	1.720	6.657
ROA (NI)	217,648	0.010	0.013	-0.139	0.082	0.030	-2.018	10.948
ROA (EBITDA)	217,648	0.032	0.032	-0.102	0.131	0.033	-0.711	6.857
ROA (EBIT)	217,648	0.021	0.022	-0.097	0.104	0.030	-0.761	6.402
Panel B: Yearly Panel								
Intangible assets	54,556	2.011	0.251	0.000	42.933	5.856	5.151	32.251
Knowledge capital	54,556	0.321	0.004	0.000	9.549	1.231	5.967	41.046
Organizational Capital	54,556	0.651	0.108	0.000	12.230	1.704	4.857	29.390
Off-BS Intangible assets	54,556	1.027	0.162	0.000	21.903	2.942	5.304	34.020
Brand capital	54,556	0.085	0.000	0.000	2.745	0.356	5.964	40.714

Table 3: Average absolute  $t$ -statistics of State Variable Exposures

This table presents the average absolute  $t$ -statistic values from dynamic measurement estimations. The first column reports  $\widehat{\gamma}_{50}^i$  from Equation (14) ( $X_{50,t}^i = \alpha_{50}^i + \gamma_{50}^i M_t + \epsilon_{50,t}^i$ ). The second and fourth columns present the average absolute  $t$ -statistics of estimates from Equation 12 ( $X_{q,t}^i = \alpha_q^i + \gamma_q^i M_t + \epsilon_{q,t}^i$ ) with  $q$  equals to 95 and 99 respectively. The third and fifth columns report average absolute  $t$ -statistics of estimates from Equation (16) ( $X_{q,t+\tau}^i = \alpha_{q,\tau}^i + \beta_{q,\tau}^i I_t^i X_t^i + \delta_{q,\tau}^i M_t + \epsilon_{q,t+\tau}^i$ ).

	$\widehat{\gamma}_{50}^i$	<b><math>q=95</math></b>		<b><math>q=99</math></b>	
		$\widehat{\gamma}_{95}^i$	$\widehat{\delta}_{95,1}^i$	$\widehat{\gamma}_{99}^i$	$\widehat{\delta}_{99,1}^i$
Three month yield change	1.107	1.464	2.058	1.693	1.950
Term spread change	1.290	1.697	1.529	2.734	2.317
Ted spread	0.947	2.000	1.667	2.146	1.755
Credit spread change	0.972	1.024	1.099	1.202	1.220
Market return	10.673	4.713	1.148	2.673	1.318
VIX	0.884	2.877	3.010	2.699	2.898

Table 4: Summary Statistics of Dynamic Resilience Estimates

This table presents summary statistics of dynamic resilience estimates, calculated on a weekly frequency from 1990 to 2022. The variable  $X_t^i$  represents weekly losses.  $VaR_{95,t}^i$  and  $VaR_{99,t}^i$  are conditional Value-at-Risk ( $VaR$ ) estimates based on Equation (13) ( $VaR_{q,t}^i = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_t$ ), while  $VaR_{50,t}^i$  is based on Equation (15) ( $VaR_{50,t}^i = \hat{\alpha}_{50}^i + \hat{\gamma}_{50}^i M_t$ ).  $ReVaR_{95,t+1}^{i|VaR_{95,t}^i}$  and  $ReVaR_{99,t+1}^{i|VaR_{99,t}^i}$  represent conditional tail risk based on Equation (17) ( $ReVaR_{q,t+\tau}^{i|VaR_{q,t}^i} = \hat{\alpha}_{q,\tau}^i + \hat{\beta}_{q,\tau}^i VaR_{q,t}^i + \hat{\delta}_{q,\tau}^i M_t$ ).  $ReVaR_{95,t+1}^{i|VaR_{50,t}^i}$  and  $ReVaR_{99,t+1}^{i|VaR_{50,t}^i}$  are benchmarks, calculated using Equation (18) ( $ReVaR_{q,t+\tau}^{i|VaR_{50,t}^i} = \hat{\alpha}_{q,\tau}^i + \hat{\beta}_{q,\tau}^i I[VaR_{50,t}^i > 0] VaR_{50,t}^i + \hat{\delta}_{q,\tau}^i M_t$ ). Finally,  $\Delta ReVaR_{95,t+1}^i$  and  $\Delta ReVaR_{99,t+1}^i$  are the final resilience measures, defined by Equation (19) ( $\Delta ReVaR_{q,t+\tau}^i = ReVaR_{q,t+\tau}^{i|VaR_{q,t}^i} - ReVaR_{q,t+\tau}^{i|VaR_{50,t}^i}$ ).

	Obs.	Mean	Median	p99	p1	SD	Skewness	Kurtosis
$X_t^i$ (%)	3,279,885	-0.334	0.000	17.038	-21.242	6.009	-0.383	4.981
$VaR_{50,t}^i$ (%)	3,279,885	-0.062	-0.083	7.076	-6.402	2.104	0.291	4.978
<b>q=95</b>								
$\beta_{95,1}^i$	3,279,885	0.105	0.095	0.710	-0.416	0.218	0.258	3.195
$\beta_{95,1}^i$ t-value	3,279,885	0.949	0.749	6.190	-2.809	1.780	0.549	3.292
$VaR_{95,t}^i$ (%)	3,279,885	7.926	7.282	21.960	1.025	3.942	1.017	4.355
$ReVaR_{95,t+1}^{i VaR_{50,t}^i}$ (%)	3,279,885	8.696	8.091	21.086	3.244	3.439	1.090	4.460
$ReVaR_{95,t+1}^{i VaR_{95,t}^i}$ (%)	3,279,885	9.406	8.724	23.938	3.175	3.945	1.163	4.740
$\Delta ReVaR_{95,t+1}^i$ (%)	3,279,885	0.708	0.554	6.855	-3.962	1.757	0.601	4.838
<b>q=99</b>								
$\beta_{99,1}^i$	3,095,057	0.188	0.116	1.766	-0.667	0.466	0.917	4.122
$\beta_{99,1}^i$ t-value	3,095,057	1.006	0.484	9.98	-2.828	2.235	1.522	6.122
$VaR_{99,t}^i$ (%)	3,095,057	13.54	12.502	35.881	3.437	6.168	1.088	4.524
$ReVaR_{99,t+1}^{i VaR_{50,t}^i}$ (%)	3,095,057	14.416	13.385	35.699	5.2	5.825	1.134	4.63
$ReVaR_{99,t+1}^{i VaR_{99,t}^i}$ (%)	3,095,057	16.946	14.758	56.635	3.54	9.487	1.649	6.593
$\Delta ReVaR_{99,t+1}^i$ (%)	3,095,057	2.495	1.203	32.679	-11.586	6.975	1.562	7.227

Table 5: **Events: ROA Prediction**

This table presents the results of cross sectional regressions ( $ROA_{event+1}^i = a + b\Delta ReVaR_{q=0.99, \tau=1, event-1}^i + cZ_{event-1}^i + \epsilon_t^i$ ) for three major events: the Covid-19 pandemic (Columns 1-3), the Global Financial Crisis (Columns 4-6), and the Technology Bubble (Columns 7-9). The resilience estimates are based on expanding samples from 1990 to 2019, 1990 to 2007, and 1990 to 1999, respectively. The independent variables (Lag  $\Delta ReVaR_{99, \tau=1}^i$  and other Lag firm-level characteristics denoted by  $Z$ ) are measured as of 2019Q4, 2008Q2, and 1999Q4 for the three events. The dependent variable, ROA, is measured at 2020Q2, 2008Q4, and 2000Q2, respectively. Lagged ROA is also included as an independent variable. All regressions account for industry fixed effects. Standard errors clustered at industry level are reported in parentheses. Significance levels are indicated as follows: \* $p < .10$ ; \*\* $p < .05$ ; \*\*\* $p < .01$ .

	<i>Covid</i>			<i>Global Financial Crisis</i>			<i>Technology Bubble</i>		
	(1) ROA (NI)	(2) ROA (EBITDA)	(3) ROA (EBIT)	(4) ROA (NI)	(5) ROA (EBITDA)	(6) ROA (EBIT)	(7) ROA (NI)	(8) ROA (EBITDA)	(9) ROA (EBIT)
Lag $\Delta ReVaR_{99,1}^i$	-0.030 (0.017)	-0.023** (0.007)	-0.027** (0.008)	-0.089*** (0.021)	-0.004 (0.009)	-0.005 (0.006)	-0.014*** (0.004)	-0.013* (0.006)	-0.017** (0.005)
Lag size	0.001 (0.001)	0.001 (0.000)	0.000 (0.001)	0.005* (0.002)	-0.000 (0.001)	0.000 (0.000)	0.003* (0.002)	0.003*** (0.001)	0.002* (0.001)
Lag BM	-0.006 (0.004)	-0.007 (0.004)	-0.007* (0.003)	-0.102*** (0.012)	-0.016*** (0.004)	-0.013** (0.004)	-0.003 (0.004)	-0.005 (0.004)	-0.005 (0.004)
Lag leverage	-0.005** (0.002)	-0.003** (0.001)	-0.003** (0.001)	0.007* (0.003)	0.002 (0.002)	0.002 (0.002)	-0.004 (0.003)	-0.001 (0.001)	-0.001 (0.001)
Lag cash	-0.019** (0.006)	-0.017*** (0.004)	-0.015*** (0.002)	0.058*** (0.008)	-0.013** (0.004)	-0.006 (0.003)	-0.017 (0.018)	-0.013 (0.010)	-0.017 (0.011)
Lag ROA	0.381*** (0.040)	0.640*** (0.069)	0.619*** (0.070)	0.644*** (0.025)	0.584*** (0.058)	0.705*** (0.061)	0.373*** (0.059)	0.572*** (0.043)	0.559*** (0.054)
Lag R&D	-0.332*** (0.081)	-0.198** (0.074)	-0.201** (0.074)	-0.821*** (0.149)	-0.479*** (0.067)	-0.369*** (0.066)	-0.225 (0.139)	-0.185 (0.109)	-0.175 (0.112)
Lag patent number	0.001* (0.000)	0.000 (0.000)	0.000 (0.001)	-0.004* (0.002)	0.001* (0.001)	0.000 (0.000)	0.001 (0.001)	-0.001 (0.001)	0.001 (0.001)
Lag EV per patent	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	0.003 (0.003)	0.003 (0.002)	0.003* (0.002)	0.000 (0.001)	0.000 (0.001)	-0.001 (0.001)
Observations	1,334	1,334	1,334	1,619	1,619	1,619	1,993	1,993	1,993
Adjusted $R^2$	0.346	0.488	0.502	0.221	0.331	0.385	0.373	0.493	0.562
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table 6: Resilience and Firm Characteristics

This table presents the results of quarterly panel regressions ( $\Delta ReVaR_{q,\tau=1,t}^i = a + bM_{t-h} + cZ_{t-h}^i + \epsilon_t^i$ ) using data from 1990 to 2022. The dependent variables are resilience measurements  $\Delta ReVaR_{95,t}^i$  in Columns 1 to 3 and  $\Delta ReVaR_{99,t}^i$  in Columns 4 to 6. The independent variables are 1-quarter lag in Columns 1 and 4, 4-quarter lag in Columns 2 and 5, and 8-quarter lag in Columns 3 and 6. The lagged  $VaR_q$  is component of the lagged dependent variable  $\Delta ReVaR_{q,t}^i$ . Financial variables are obtained from Compustat and are winsorized at 1% level. Patent data is obtained from Kogan et al. (2017). Macroeconomic variables consist of six state variables used in the estimation of  $\Delta ReVaR_{q,t}^i$ . All regressions include industry fixed effects. Newey-West standard errors are reported in brackets. Significance levels are indicated as follows: \* $p < .10$ ; \*\* $p < .05$ ; \*\*\* $p < .01$ .

	$\Delta ReVaR_{95,t}^i$			$\Delta ReVaR_{99,t}^i$		
	(1) $h=1$	(2) $h=4$	(3) $h=8$	(4) $h=1$	(5) $h=4$	(6) $h=8$
Leverage $_{i,t-h}$	0.064*** (0.012)	0.057*** (0.017)	0.068*** (0.021)	0.114** (0.046)	0.109 (0.067)	0.148* (0.083)
Cash $_{i,t-h}$	0.345*** (0.035)	0.342*** (0.053)	0.350*** (0.067)	0.072 (0.152)	0.112 (0.226)	0.236 (0.286)
R&D $_{i,t-h}$	-0.696* (0.398)	-0.648 (0.567)	-0.368 (0.717)	0.260 (1.724)	1.724 (2.464)	3.452 (3.132)
Number of patents $_{i,t-h}$	-0.046*** (0.003)	-0.048*** (0.005)	-0.047*** (0.007)	-0.028* (0.015)	-0.040* (0.023)	-0.041 (0.030)
Economic value per patent $_{i,t-h}$	-0.024*** (0.005)	-0.023*** (0.008)	-0.021** (0.010)	-0.030 (0.022)	-0.024 (0.034)	-0.025 (0.044)
$VaR_{i,q,t-h}$	5.217*** (0.314)	4.130*** (0.452)	2.671*** (0.546)	26.433*** (0.769)	23.964*** (1.110)	20.483*** (1.344)
Stock return volatility $_{i,t-h}$	0.016*** (0.001)	0.018*** (0.002)	0.020*** (0.002)	0.009* (0.005)	0.014** (0.007)	0.020*** (0.008)
Size $_{i,t-h}$	0.172*** (0.004)	0.165*** (0.006)	0.152*** (0.007)	0.356*** (0.015)	0.341*** (0.022)	0.305*** (0.029)
BM $_{i,t-h}$	-0.124*** (0.016)	-0.140*** (0.023)	-0.130*** (0.029)	-0.470*** (0.063)	-0.517*** (0.092)	-0.544*** (0.115)
ROA $_{i,t-h}$	-0.169 (0.181)	-0.168 (0.240)	-0.091 (0.291)	0.295 (0.793)	0.516 (1.059)	0.953 (1.292)
3-month yield change $_{t-h}$	0.217*** (0.057)	0.007 (0.055)	-0.093 (0.062)	0.220 (0.248)	-0.245 (0.246)	-0.439 (0.268)
Term spread change $_{t-h}$	-0.053*** (0.014)	0.003 (0.012)	-0.073*** (0.013)	-0.131** (0.057)	0.006 (0.051)	-0.195*** (0.056)
Ted spread $_{t-h}$	0.090*** (0.019)	0.107*** (0.027)	0.073*** (0.028)	0.080 (0.080)	0.162 (0.115)	0.055 (0.121)
Credit spread change $_{t-h}$	0.680* (0.400)	1.446*** (0.369)	-0.401 (0.326)	-0.931 (1.684)	-0.112 (1.554)	-5.200*** (1.371)
Market return $_{t-h}$	0.556 (0.803)	3.182*** (0.902)	1.495 (0.969)	15.548*** (3.210)	25.933*** (3.509)	20.640*** (3.687)
VIX $_{t-h}$	-0.000 (0.001)	-0.005*** (0.001)	-0.009*** (0.002)	-0.032*** (0.004)	-0.044*** (0.005)	-0.054*** (0.006)
Observations	216,094	211,268	202,793	216,094	211,268	202,793
Adjusted $R^2$	0.0413	0.0364	0.0325	0.0376	0.0328	0.0274
Industry FE	yes	yes	yes	yes	yes	yes
Newey-West SE lag	1	4	8	1	4	8

Table 7: **Resilience and Intangible Assets**

This table presents the results of annually panel regressions ( $\Delta ReVaR_{q,\tau=1,t}^i = a + bM_{t-h} + cZ_{t-h}^i + \epsilon_t^i$ ) using data from 1990 to 2022. The dependent variables are resilience measurements  $\Delta ReVaR_{95,t}^i$ . The independent variables are 1-year lag. The lagged  $VaR_q$  is component of the lagged dependent variable  $\Delta ReVaR_{q,t}^i$ . Financial variables are obtained from Compustat and are winsorized at 1% level. Patent data is obtained from Kogan et al. (2017). Intangible assets, knowledge capital, organization capital and off balance sheet intangible assets are obtained from Peters and Taylor (2017). Brand capital is estimated from Belo, Lin, and Vitorino (2014). Macroeconomic variables consist of six state variables used in the estimation of  $\Delta ReVaR_{q,t}^i$ . All regressions include industry fixed effects. Newey-West standard errors are reported in brackets. Significance levels are indicated as follows: \* $p < .10$ ; \*\* $p < .05$ ; \*\*\* $p < .01$ .

	$\Delta ReVaR_{95,t}^i$					
	(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)
Leverage $_{i,t-h}$	0.064*** (0.022)	0.066*** (0.021)	0.075*** (0.021)	0.067*** (0.022)	0.068*** (0.021)	0.079*** (0.022)
Cash $_{i,t-h}$	0.370*** (0.065)	0.252*** (0.064)	0.309*** (0.064)	0.247*** (0.064)	0.295*** (0.064)	0.236*** (0.064)
$VaR_{i,q,t-h}$	0.054*** (0.006)	0.050*** (0.006)	0.052*** (0.006)	0.047*** (0.006)	0.050*** (0.006)	0.048*** (0.006)
Stock return volatility $_{i,t-h}$	0.014*** (0.002)	0.014*** (0.002)	0.014*** (0.002)	0.014*** (0.002)	0.014*** (0.002)	0.014*** (0.002)
Size $_{i,t-h}$	0.189*** (0.008)	0.190*** (0.007)	0.173*** (0.007)	0.184*** (0.007)	0.192*** (0.007)	0.156*** (0.006)
BM $_{i,t-h}$	-0.132*** (0.029)	-0.108*** (0.030)	-0.123*** (0.030)	-0.117*** (0.030)	-0.119*** (0.029)	-0.124*** (0.030)
ROA $_{i,t-h}$	-0.035 (0.108)	-0.062 (0.107)	-0.002 (0.107)	-0.048 (0.107)	-0.024 (0.107)	-0.017 (0.107)
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
Macroeconomic variable Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Newey west SE lag	1	1	1	1	1	1

Table 8: **Resilience by Industry**

This table presents  $\Delta ReVaR_{q,\tau=1,t}^i$  across nine different industries using data from 1990 to 2022. The coefficients of the industry effect are estimated from quarterly panel regressions ( $\Delta ReVaR_{q,\tau=1,t}^i = a + bM_{t-h} + cZ_{t-h}^i + \epsilon_t^i$ ) with  $h = 1$ . Newey-West standard errors are reported in brackets. Significance levels are indicated as follows: \* $p < .10$ ; \*\* $p < .05$ ; \*\*\* $p < .01$ . The full estimated results are reported in Table 6. The sample mean and standard deviation over the whole sample are reported in the second columns. In the third columns, the firm mean and dispersion are computed in two steps. First, we calculate the average  $\Delta ReVaR_{q,\tau=1,t}^i$  for each firm. Then, we determine the mean and standard deviation of these firm-level averages. The resulting standard deviation represents the dispersion of  $\Delta ReVaR_{q,\tau=1,t}^i$ .

	$\Delta ReVaR_{95,t}^i$			$\Delta ReVaR_{99,t}^i$		
	<i>Coef. (SD)</i>	<i>Sample Mean (SD)</i>	<i>Firm Mean (Dispersion)</i>	<i>Coef. (SD)</i>	<i>Sample Mean (SD)</i>	<i>Firm Mean (Dispersion)</i>
Agriculture (Benchmark)		0.901	0.716		2.315	1.707
		1.404	1.502		4.318	3.829
Mining and Quarrying	-0.197*** (0.071)	0.992	0.584	-0.222 (0.230)	3.052	1.836
		1.874	2.197		7.049	7.951
Construction	-0.345*** (0.072)	0.807	0.643	-0.358 (0.251)	2.747	1.989
		1.321	1.675		6.558	6.286
Manufacturing	-0.374*** (0.066)	0.592	0.496	-0.875*** (0.212)	2.136	2.206
		1.600	2.048		7.312	8.991
TransComm & Utility Services	-0.514*** (0.068)	0.681	0.647	-1.293*** (0.223)	1.809	1.487
		1.650	2.031		6.695	7.497
Wholesale Trade	-0.306*** (0.069)	0.753	0.645	-0.488** (0.226)	2.576	2.496
		1.746	2.041		6.601	7.521
Retail Trade	-0.466*** (0.067)	0.664	0.553	-0.809*** (0.220)	2.432	2.761
		1.735	2.083		7.244	9.238
Services	-0.216*** (0.067)	0.916	0.782	-0.139 (0.217)	3.471	3.340
		2.164	2.625		9.572	11.050