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

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Abstract

This paper analyzes the resilience of U.S. listed firms. The environment in which firms operate is inherently uncertain and new types of risk or crises may emerge. Do firms bounce back after an unexpected crisis? And what types of firms are more resilient than others? We first develop a novel measure of firm resilience. 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. Our resilience measure captures the extent to which a firm's conditional downside risk after an extreme loss differs from its downside risk after a typical underperformance loss. If the two are similar, the firm, in terms of its downside risk, bounces back after experiencing an extreme loss. In other words, the firm is resilient. Using weekly stock return data, we estimate time-varying firm resilience and document substantial cross-firm variation. We validate our measure by linking cross-firm variation in ex-ante resilience to post-crisis firm performance, focusing on three different types of crises: the 2000 Internet Bubble, the 2008 Great Financial Crisis and the 2020 Covid-19 outbreak. Finally, we relate resilience to lagged firm characteristics. Besides the expected link with leverage, we find a key role of innovation. Firms with higher R&D investments, more patents and a higher economic value per patent are significantly more resilient.

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1 Introduction

Resilience is important and relevant in many different settings. For example, resilience as a psychological trait, resilience as a feature of an ecosystem or an energy network, organizational resilience or resilience of communities. 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., Duchek, 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.[1] 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. Our measure is return-based and it is forward-looking. Several recent studies examine 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 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,

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

besides the expected relation to leverage, we find that innovation matters. Firms with higher R&D investments, more patents and a higher economic value per patent 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 plays a significant role here.[2]

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 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; cf. also Marginal Expected Shortfall (Acharya, 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.[3] Our resilience

[2]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.

[3]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.

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).[4] 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 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.

[4] The autoregressive nature of large shocks is also recognized in Aït-Sahalia, Cacho-Diaz, and Laeven (2015).

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 tend to have higher ex-post Return on Assets as well. The relation is statistically significant for both the Covid-19 crisis as well as the Global Financial Crisis, two very different types of crises. 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 can predict a firm's post-crisis performance.

In the final part of the analysis, we examine how firm resilience relates to firm characteristics. To this end, we conduct panel regressions where we regress firm-level quarterly resilience measures on lagged firm characteristics. 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). Second and importantly, we detect a key role of innovation. We find that 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.

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., Duchek, 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; Wu and Lai, 2020). We add to this literature by showing that after experiencing an extreme loss, innovative firms also tend to bounce back more in terms of their downside risk.

The remainder of this paper is organized as follows. In Section 2, we present our resilience measure, 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 an extreme scenario deviates from a typical underperformance of a firm in terms of the firm's conditional downside risk. 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 τ 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:

$$Pr(X_t^i \leq VaR_q^i) = q\%, \tag{1}$$

where X_t^i is the return loss of firm i at time t.[5] 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 $VaR_{q=50}^i$. Note that $VaR_{q=50}^i$ is the median value (with negative sign) of all returns rather than the median value of losses only.

Based on the definition of VaR, we define $ReVaR$ as a conditional VaR. We denote by $ReVaR_q^{i|C^i}$ firm i's qth-quantile of return losses conditionally upon facing a specific scenario C^i in the past:

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

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 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 qth-quantile by $F_{X_t^i}(q|\cdot)$. Then we can express $ReVaR_q^{i|C^i}$ as an inverse conditional CDF

[5] 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.

$F^{-1}_{X^i_t}(q|C^i)$:

$$ReVaR_q^{i|C_s^i} = F^{-1}_{X^i_t}(q|C^i_s), \tag{3}$$

and

$$ReVaR_q^{i|C_m^i} = F^{-1}_{X^i_t}(q|C^i_m). \tag{4}$$

$ReVaR_q^{i|C_s^i}$ 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:

$$\Delta ReVaR_q^i = ReVaR_q^{i|C_s^i} - ReVaR_q^{i|C_m^i}. \tag{5}$$

As the benchmark scenario C_m^i and corresponding $ReVaR_q^{i|C_m^i}$ are firm specific, we can compare resilience across firms, controlling for possible different levels of normal downside risks. 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.[6] 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

[6]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 (2023), and the references therein for further details.

invoke Expected Shortfall to construct (an adapted version) of our measure of resilience.[7] 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 $\Delta ReVaR^i_q$. In this case, the firm's conditional VaR^i_q does not change much and is similar after an extreme scenario compared to a typical underperformance scenario.

As an example, suppose firm A has $ReVaR^{A|C^i_s}_{q=95} = 10\%$ and $ReVaR^{A|C^i_m}_{q=95} = 5\%$, whereas firm B has $ReVaR^{B|C^i_s}_{q=95} = 11\%$ and $ReVaR^{B|C^i_m}_{q=95} = 7\%$. 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 they are now 95% sure that they would lose no more than 10% in stock A and lose no more than 11% in stock B in a certain 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 $\Delta ReVaR^B_{q=95} = 11\% - 7\% = 4\%$ is lower than that of firm A, $\Delta ReVaR^A_{q=95} = 10\% - 5\% = 5\%$. 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.

[7] 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:

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

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 qth-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 qth-quantile of return losses at time t after it experiences typical underperformance at time $t-\tau$.

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

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. In other words, 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 τ

The conditioning scenarios $C_s^i(X_{t-\tau}^i)$ and $C_m^i(X_{t-\tau}^i)$ are taken with a lag of τ. 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 τ-period forward-looking measures. As a result, the resilience measure $\Delta ReVaR_{q,\tau}^i$ is also forward-looking and depends on the chosen τ. $\Delta ReVaR_{q,\tau}^i$ with smaller τ indicates short-term resilience while $\Delta ReVaR_{q,\tau}^i$ with larger τ 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 τ. 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:

$$X^i_{q,t+\tau} = \alpha^i_{q,\tau} + \beta^i_{q,\tau} I^i_t X^i_t + \epsilon^i_{q,\tau,t}, \tag{8}$$

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; and I^i_t equals 1 if $X^i_t > 0$ and 0 otherwise. $\alpha^i_{q,\tau}$ is a firm i, horizon τ and probability q-specific constant; $\beta^i_{q,\tau}$ quantifies the extent to which future extreme losses can be accounted for by current losses; and $\epsilon^i_{q,\tau,t}$ is the error term.

There are several reasons why we introduce I^i_t into our regression equation. First, generally there is a relatively weak extreme-quantile correlation between $X^i_{q,t+\tau}$ and X^i_t.[8] 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^i_t as independent variable is not suitable since insignificant coefficient estimates will result in unreliable and noisy estimates of $\Delta ReVaR^i_{q,\tau}$.

Furthermore, using $I^i_t X^i_t$ rather than X^i_t 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^i_t, we allow only current losses, not gains, to change the distribution of future

[8] In our initial estimation of $X^i_{q,t+\tau} = \alpha^i_{q,\tau} + \beta^i_{q,\tau} X^i_t + \epsilon^i_{q,\tau,t}$, we find the estimated coefficients $\widehat{\beta}^i_{q,\tau}$ are overall insignificant when we take $q \geq 90\%$. Using both daily data and weekly data, we observe significant $\widehat{\beta}^i_{q,\tau}$ for only 3%-9% of the 500 largest stocks.

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):

$$ReVaR_{q,\tau}^{i|C_s^i=VaR_q^i} = \widehat{\alpha}_{q,\tau}^i + \widehat{\beta}_{q,\tau}^i VaR_q^i, \tag{9}$$

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 τ 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 qth-quantile of firm i over the next day, and $ReVaR_{q,\tau=20}^{i|VaR_q^i}$ denotes the conditional qth-quantile over the next month.

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

$$ReVaR_{q,\tau}^{i|VaR_{50}^i} = \widehat{\alpha}_{q,\tau}^i + \widehat{\beta}_{q,\tau}^i I_{50}^i VaR_{50}^i, \tag{10}$$

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:

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

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

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 qth-quantile of future return losses conditionally upon current VaR^i_q. For simplicity, we have used the quantile value based on all firm i's historical returns as VaR^i_q.

This method is simple and intuitive as it defines stress scenarios as scenarios in which the firm's losses exceed its VaR^i_q. 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^i_q to time-varying $VaR^i_{q,t}$ 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:

$$X^i_{q,t} = \alpha^i_q + \gamma^i_q M_t + \epsilon^i_{q,t}. \tag{12}$$

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

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

$$VaR^i_{q,t} = \widehat{\alpha}^i_q + \widehat{\gamma}^i_q M_t. \tag{13}$$

In the static measures discussed in Section 2, we use VaR^i_q, calculated as the quantile value of all firm i's historical returns. Here, $VaR^i_{q,t}$ 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:

$$X^i_{50,t} = \alpha^i_{50} + \gamma^i_{50} M_t + \epsilon^i_{50,t}, \tag{14}$$

and

$$VaR^i_{50,t} = \widehat{\alpha}^i_{50} + \widehat{\gamma}^i_{50} M_t. \tag{15}$$

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, $\widehat{\gamma}^i_q$ 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:

$$X^i_{q,t+\tau} = \alpha^i_{q,\tau} + \beta^i_{q,\tau} I^i_t X^i_t + \delta^i_{q,\tau} M_t + \epsilon^i_{q,\tau,t}. \tag{16}$$

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 $VaR^i_{q,t}$ based on the control variables instead of static VaR^i_q as X^i_t.

Using the estimators, we obtain $ReVaR^{i|VaR^i_{q,t}}_{q,\tau,t}$ and $ReVaR^{i|VaR^i_{50,t}}_{q,\tau,t}$ as follows:

$$ReVaR^{i|VaR^i_{q,t}}_{q,\tau,t} = \widehat{\alpha}^i_{q,\tau} + \widehat{\beta}^i_{q,\tau} VaR^i_{q,t} + \widehat{\delta}^i_{q,\tau} M_t, \tag{17}$$

and

$$ReVaR^{i|VaR^i_{50,t}}_{q,\tau,t} = \widehat{\alpha}^i_{q,\tau} + \widehat{\beta}^i_{q,\tau} I[VaR^i_{50,t} > 0] VaR^i_{50,t} + \widehat{\delta}^i_{q,\tau} M_t. \tag{18}$$

$ReVaR^{i|VaR^i_{q,t}}_{q,\tau,t}$ indicates the qth-quantile of firm's i future return losses conditional upon stress scenarios represented by $VaR^i_{q,t}$ that are triggered by factors M_t. Likewise, $ReVaR^{i|VaR^i_{50,t}}_{q,\tau,t}$ indicates the qth-quantile of firm's i future return losses conditional upon a typical underperformance represented by $VaR^i_{50,t}$ that can be described by factors M_t. In Equation (17), the indicator $I[VaR^i_{q,t} > 0] = 1$ is omitted as $VaR^i_{q,t}$ at an extreme quantile level q is empirically positive.

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

$$\begin{aligned}\Delta ReVaR^i_{q,\tau,t} &= ReVaR^{i|VaR^i_{q,t}}_{q,\tau,t} - ReVaR^{i|VaR^i_{50,t}}_{q,\tau,t} \\ &= \widehat{\beta}^i_{q,\tau}(VaR^i_{q,t} - I[VaR^i_{50,t} > 0]VaR^i_{50,t}) \\ &= \widehat{\beta}^i_{q,\tau}(\widehat{\alpha}^i_q + \widehat{\gamma}^i_q M_t - I[VaR^i_{50,t} > 0](\widehat{\alpha}^i_{50} + \widehat{\gamma}^i_{50} M_t)).\end{aligned} \tag{19}$$

In general, $VaR^i_{50,t} \approx 0$. This gives a simplification of Equation (19): $\Delta ReVaR^i_{q,\tau,t} \approx \widehat{\beta}^i_{q,\tau} VaR^i_{q,t} = \widehat{\beta}^i_{q,\tau}(\widehat{\alpha}^i_q + \widehat{\gamma}^i_q M_t)$. We can see that the $\Delta ReVaR^i_{q,\tau,t}$ depends primarily on four components. First, the sensitivity of future extreme losses to current losses, which is measured by $\widehat{\beta}^i_{q,\tau}$. Since the term $(VaR^i_{q,t} - I[VaR^i_{50,t} > 0]VaR^i_{50,t})$ is positive, a lower sensitivity $\widehat{\beta}^i_{q,\tau}$ is related with lower $\Delta ReVaR^i_{q,\tau,t}$ and thus higher resilience. This means resilient firms are those with stable quantiles of future return losses, regardless of today's losses.

The second component, $\widehat{\alpha}^i_q$, may be viewed as firms' idiosyncratic risks when M_t stays constant. The third component, $\widehat{\gamma}^i_q$, 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

We focus on weekly return data 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. We obtain daily stock return data from CRSP, and transform the daily returns to continuously compounded returns on a weekly basis. Our sample comprises U.S. stocks with share code 10 and 11 from January 1, 1990 to December 31, 2022.[9] 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. In our context, the reliability of resilience estimates for small stocks may be weakened due to the influence of other non-fundamental factors on their stock prices.

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]

[9] Our sample begins in 1990 as this is the start of the VIX index, one of the state variables.

In Section 6, we analyze the relation between our resilience measures and firm characteristics to assess which types of firms are more resilient. We obtain quarterly firm financial data from Compustat. As firm characteristics, we use size, book-to-market ratio, leverage, cash, Return on Assets (ROA) and R&D investment. Size is calculated as the natural logarithm of total assets. Leverage is calculated as the sum of long-term and short-term debt divided by total assets. Cash, ROA and R&D investment are all scaled by total assets.

Moreover, we study how resilience relates to firm innovation by using patent data from Kogan, Papanikolaou, Seru, and Stoffman (2017) as measures of innovation output. 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. Summary statistics of all firm-level variables are reported in Table 2.

[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 β estimates for more stocks compared to other values of τ.

We estimate two versions of the resilience measure: a static one (Section 2) and a dynamic measure (Section 3). Here, we begin with the static $\Delta ReVaR$ to examine cross-firm variation and we contrast it with 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 $\widehat{\beta^i_{95}}$, which measures the extent to which future extreme losses can be accounted for by current losses.[10] Figure 1 Panel A displays the relation between $\widehat{\beta^i_{95}}$ 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 $\widehat{\beta^i_{95}}$ estimates is statistically significant at at least the 10% level. The figure shows that $\widehat{\beta^i_{95}}$ is both economically important and statistically significant. Moreover, even though the vast majority of $\widehat{\beta^i_{95}}$ estimates is positive, highlighting that past losses positively predict extreme future losses, we observe a small number of negative $\widehat{\beta^i_{95}}$ estimates.

We obtain $\Delta ReVaR^i_{95}$ using Equation (11), where VaR^i_{95} and VaR^i_{50} are calculated as the

[10]For ease of exposition, we write $\widehat{\beta^i_{95}}$ instead of $\widehat{\beta^i_{95,1}}$ since we use $\tau = 1$ week throughout this paper.

quantile values of all firm i's historical returns. Panel B shows substantial cross-firm variation in both β^i_{95}, ranging from -0.5 to 1.5, and $\Delta ReVaR^i_{95}$, ranging from -5% to 15%. 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 $\Delta ReVaR^i_{95}$ and its component VaR^i_{95}. As there is no one-to-one relationship between $\Delta ReVaR^i_{95}$ and VaR^i_{95}, 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 do not find a significant positive or negative relation between $\Delta ReVaR$ and these higher moments. We also obtain β^i_{mkt} from CAPM and show its relation with $\Delta ReVaR$ in Panel D. The correlation between these two variables is as low as 0.3 and the scatter plot shows a high dispersion within the sample.

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 (β^i_{mkt}) 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.

[Insert Table 3]

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 independent 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.

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), $\widehat{\gamma}^i$ measures how much the quantile returns are exposed to the state variable. Overall, we find that the estimated exposures are significant for most of the state variables. Particularly, quantile returns $X^i_{95,t}$ and $X^i_{99,t}$ (i.e., extreme losses) are most exposed to the VIX index, the market return and the TED spread. Quantile returns $X^i_{50,t}$ (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 estimates of $\widehat{\delta}^i_{q,1}$ are also significant for most state variables.

[Insert Table 4]

Table 4 presents summary statistics of dynamic firm-level resilience estimates. In total, our sample includes $6,319$ stocks and thus $4,867,067$ observations on a weekly basis. Our key measure $\Delta ReVaR^i_{95,t+1}$ ranges from -3.93% to 6.64%, and the average value is 0.642%. The economic intuition is that a stress scenario will increase the weekly 95% Value-at-Risk of a stock by 0.642%

point on average. Similarly, a stress scenario will increase the 99% Value-at-Risk of a stock by 2.298% 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 Return on Assets (ROA), which can be viewed as an ex-post resilience measure. In Section 6.2, we conduct a panel regression that relates resilience to lagged firm-level characteristics.

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 returns-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. Alternatively, we use three types of firm financial performance (i.e., NI, EBITDA and EBIT) as numerator to compute ROA. We then run the following cross-sectional regressions:

$$ROA^i_{event+1} = a + b\Delta ReVaR^i_{q=0.99,\tau=1,event-1} + cX^i_{event-1} + \epsilon^i_t. \tag{20}$$

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

[Insert Table 5]

In all regressions, we can observe negative signs of $\widehat{b}$, indicating that firms with lower $\Delta ReVaR$ before the crisis tend to have higher ROA after the crisis. The relation between ROA and $\Delta ReVaR$ is statistically significant during the Covid-19 outbreak (Columns 1-3) and the Global Financial Crisis (Columns 4-6), while the sign are negative but lack statistical significance during the Technology Bubble (Columns 7-9). For the first two crises, the relation is significant after controlling for multiple pre-crisis firm characteristics and for all three types of ROA measures.

In sum, these results carry two noteworthy implications. First, $\Delta ReVaR$ as a pre-crisis resilience measure can predict cross-sectional differences in firms' post-crisis performance. 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 higher levels of firm resilience. To do so, we use weekly estimates of dynamic $\Delta ReVaR$ using the full sample period, as discussed in Section 5.2, and convert them into quarterly estimates by taking the average weekly value within the quarter. Finally, we conduct the following panel regression:

$$\Delta ReVaR^i_{q,\tau=1,t} = a + bM_{t-h} + cZ^i_{t-h} + \epsilon^i_t, \tag{21}$$

where h is the forecast horizon in quarters, M_{t-h} are lagged macro variables, and Z^i_{t-h} are lagged firm-level variables. In this equation, a negative sign of $\widehat{c}$ indicates a positive relation between firm characteristics Z^i_{t-h} and resilience and a positive sign indicates a negative relation. We adopt $h = 1, 4, 8$ to see how quarter t resilience of a firm is related to its characteristics one quarter, one year and two years ago. We include industry fixed effects and adopt Newey-West standard errors with h lags. The regression results with different values of h and q are displayed in Table 6.

[Insert Table 6]

In Table 6, two firm characteristics stand out: leverage and innovation. The most statistically significant result is the relation between lagged leverage and $\Delta ReVaR$. For $q = 95\%$, we find that a 1% increase in lagged leverage level is associated with a 41 to 45 percentage point decrease in resilience level. This negative relation between financial leverage and $\Delta ReVaR$ 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 conclude that firms with more cash performed better during Covid-19, while we do not find a positive and significant relation between cash and resilience. A potential explanation is cash holdings do not always play a positive role during different types of crises. In rapidly changing markets, a resilient firm should equip itself with diversified buffers, rather than solely relying on cash, to withstand crises. Holding excess cash entails high opportunity cost, potentially impeding a firm's ability to enhance its resilience and sending a negative signal that the firm lacks the capacity to allocate its resources effectively (Cortes, 2021).

Second, we find a significant relation between innovation and resilience. We use three different measures of innovation, including R&D as innovation input, the number of patents issued in the past five years as innovation output, and the economic value of patents issued from Kogan et al. (2017) as a measure for the patent value. The results indicate that firms with more innovation input, more innovation output and 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.

In terms of size, our results imply that small firms are 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.

In sum, our panel regressions point towards two important firm characteristics that relate to firm resilience: leverage and innovation. Firms with higher financial leverage tend to be less resilient. Furthermore, resilience is related to several measures of firm innovation. Overall, our findings suggest that firms may enhance their ability to cope with unexpected future shocks and uncertainties by maintaining low debt levels and engaging in innovative activities.

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 tend to have higher ex-post Return on Assets as well. The relation is statistically significant for both the Covid-19 crisis as well as the Global Financial Crisis, two very different types of crises.

Lastly, we examine the relation between firm resilience and lagged firm characteristics using panel regressions. Besides the expected relation to leverage, we find that innovation matters significantly. Firms with higher R&D investments, a greater number of patents and a higher economic value per patent 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.

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Figure 1: **Static Resilience Estimates**

These figures plot static $\Delta ReVaR^i_{95,1}$ and related estimates using a sample of U.S. stocks from 1980 to 2022. Panel A plots $\beta^i_{95,1}$ (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 $\Delta ReVaR^i_{95,1}$ (x-axis) and $\beta^i_{95,1}$ (y-axis). Panel C plots $\Delta ReVaR^i_{95,1}$ (x-axis) and VaR^i_{95} (y-axis).

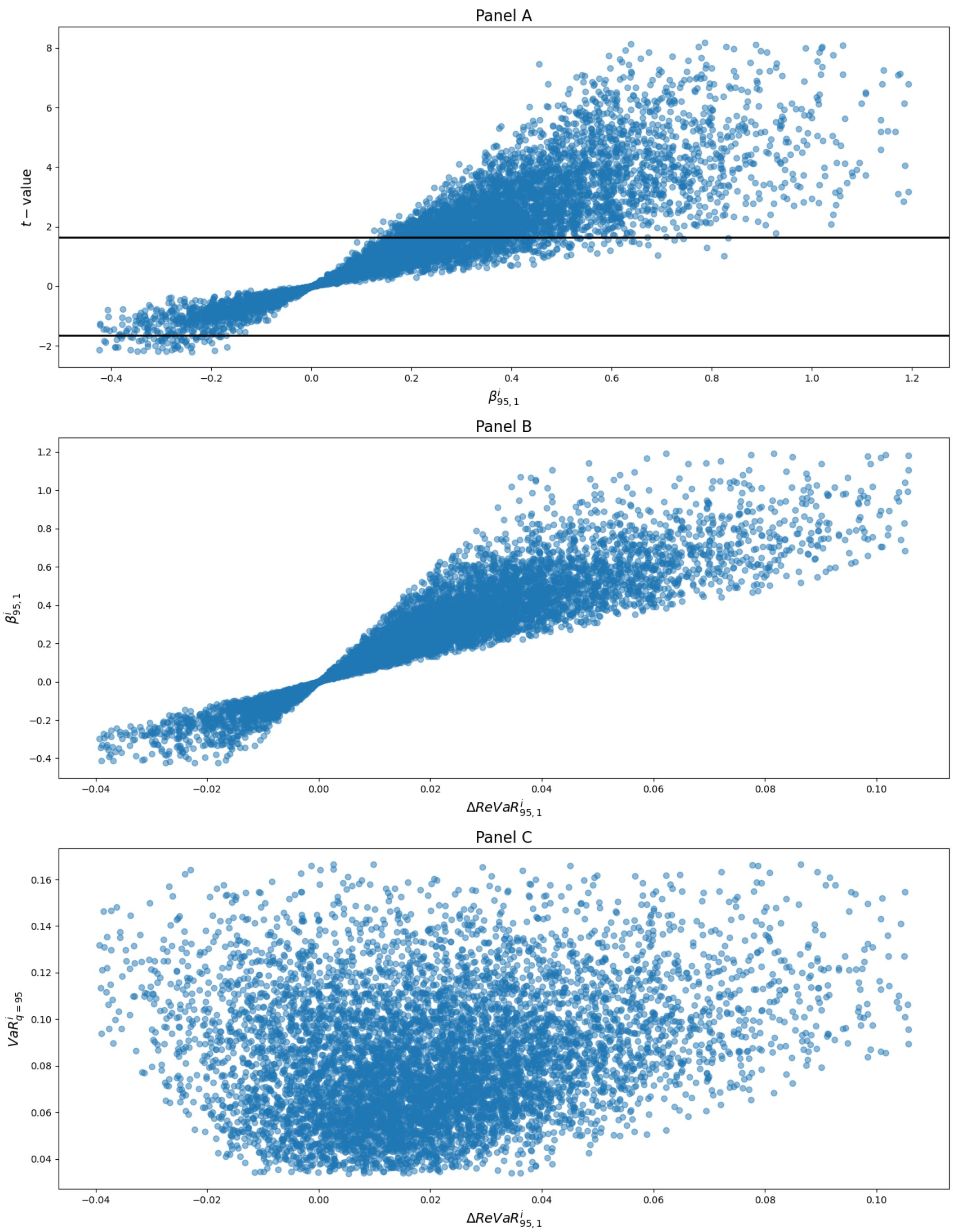

Figure 2: $\Delta ReVaR$ **and Risk-Related Measurements**

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

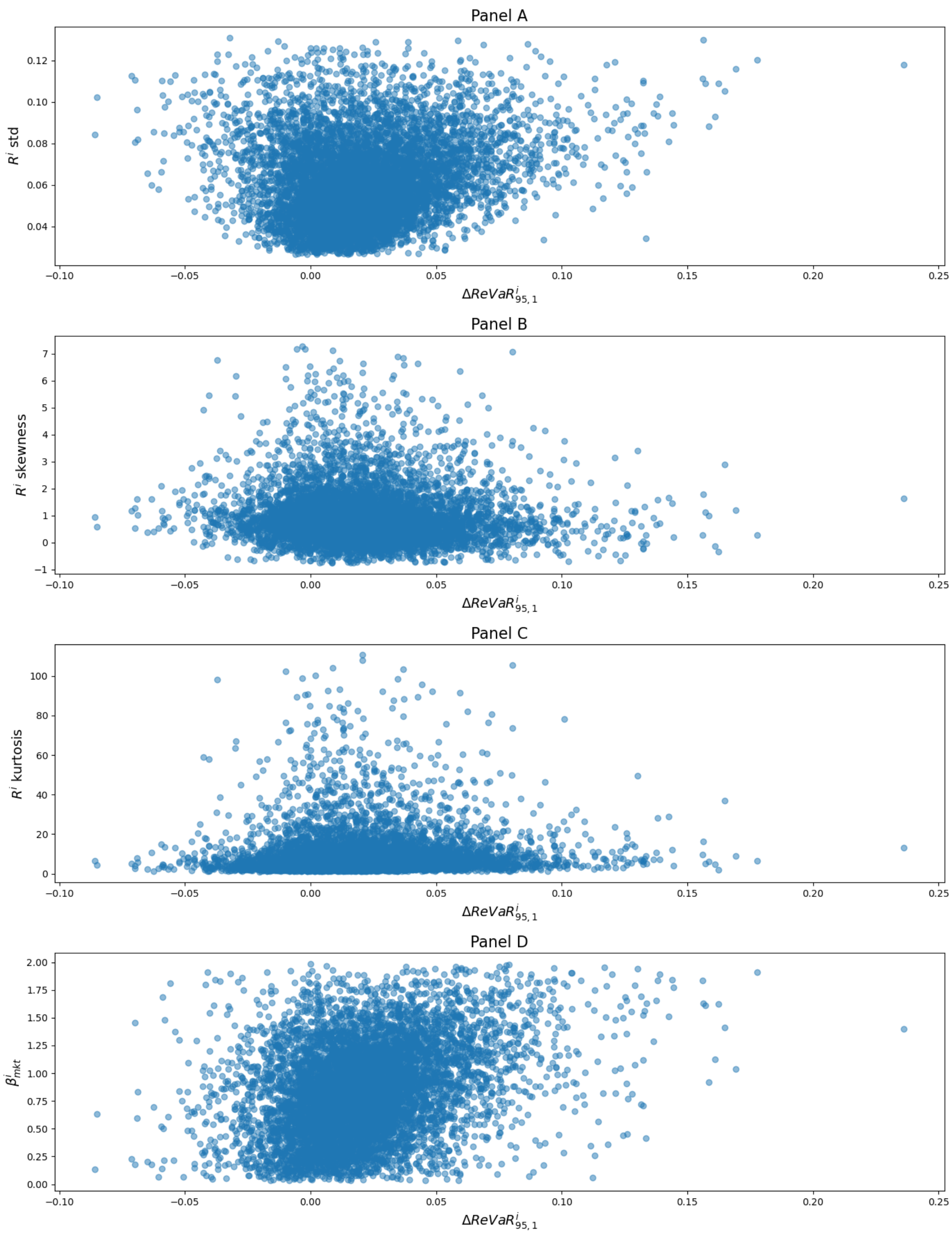

Table 1: **Summary Statistics of State Variables**

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	0.230	0.084	67.111	-50.000	49.219	-27.753	1,050.862
Term spread change (%)	1,717	-2.173	-0.368	104.324	-100.000	142.299	0.514	420.541
Ted spread (%)	1,717	45.155	37.000	188.400	-0.444	36.276	3.122	21.177
Credit spread change (%)	1,717	0.030	-0.110	7.582	-6.145	2.514	1.202	12.518
Market return (%)	1,717	0.209	0.320	6.424	-6.443	2.393	-0.542	8.799
VIX	1,717	19.661	17.838	48.375	10.188	7.877	2.067	10.495

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

This table presents summary statistics for quarterly firm characteristics, with data obtained from Compustat. 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). Leverage is defined as the ratio of total debt (dlttq + dlcq) to total assets (atq). Cash holdings are measured as cash and equivalents (cheq) divided by total assets (atq). Return on assets (ROA) is calculated as net income (niq) 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). Patent number refers to the total number of patents issued in the past five years (i.e., twenty quarters). The average economic value of patents 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.

	Obs.	Mean	Median	p99	p1	SD	Skewness	Kurtosis
Size	355,965	6.742	6.645	2.508	11.872	1.998	0.238	2.701
Book-to-market	355,965	0.605	0.517	-0.140	2.380	0.442	1.426	5.847
Leverage	355,965	0.212	0.173	0.000	0.867	0.195	1.008	3.721
Cash	355,965	0.146	0.067	0.000	0.844	0.186	1.912	6.235
ROA (NI)	355,965	0.007	0.008	-0.150	0.078	0.030	-2.300	12.768
ROA (EBITDA)	355,965	0.025	0.025	-0.119	0.126	0.034	-0.753	7.266
ROA (EBIT)	355,965	0.017	0.016	-0.116	0.103	0.030	-0.973	7.868
R&D	355,965	0.007	0.000	0.000	0.099	0.017	3.125	13.688
Patent number	355,965	1.040	0.000	0.000	7.197	1.769	1.753	5.164
Average economic value of patent	355,965	0.770	0.000	0.000	5.138	1.289	1.646	4.731

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 $\widehat{\gamma}^i_{50}$ from Equation (14) ($X^i_{50,t} = \alpha^i_{50} + \gamma^i_{50} M_t + \epsilon^i_{50,t}$). The second and forth columns present the average absolute $t-$statistics of estimates from Equation 12 ($X^i_{q,t} = \alpha^i_q + \gamma^i_q M_t + \epsilon^i_{q,t}$) with q equals to 95 and 99 respectively. The third and fifth columns report average absolute $t-$statistics of estimates from Equation (16) ($X^i_{q,t+\tau} = \alpha^i_{q,\tau} + \beta^i_{q,\tau} I^i_t X^i_t + \delta^i_{q,\tau} M_t + \epsilon^i_{q,t+\tau}$).

	$\widehat{\gamma}^i_{50}$	***q=95***		***q=99***	
		$\widehat{\gamma}^i_{95}$	$\widehat{\delta}^i_{95,1}$	$\widehat{\gamma}^i_{99}$	$\widehat{\delta}^i_{99,1}$
Three month yield change	1.167	1.472	2.168	1.746	2.009
Term spread change	1.240	1.760	1.519	2.812	2.256
Ted spread	0.944	2.001	1.697	2.156	1.780
Credit spread change	0.977	1.027	1.084	1.194	1.205
Market return	9.822	4.599	1.157	2.779	1.322
VIX	0.863	3.026	3.092	2.934	3.057

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) ($VaR_{q,t}^i = \widehat{\alpha}_q^i + \widehat{\gamma}_q^i M_t$), while $VaR_{50,t}^i$ is based on Equation (15) ($VaR_{50,t}^i = \widehat{\alpha}_{50}^i + \widehat{\gamma}_{50}^i M_t$). $ReVaR_{95,t+1}^{i|VaR_{95,t}^i}$ and $ReVaR_{99,t+1}^{i|VaR_{99,t}^i}$ represent conditional tail risk based on Equation (17) ($ReVaR_{q,t+\tau}^{i|VaR_{q,t}^i} = \widehat{\alpha}_{q,\tau}^i + \widehat{\beta}_{q,\tau}^i VaR_{q,t}^i + \widehat{\delta}_{q,\tau}^i M_t$). $ReVaR_{95,t+1}^{i|VaR_{50,t}^i}$ and $ReVaR_{99,t+1}^{i|VaR_{50,t}^i}$ are benchmarks, calculated using Equation (18) ($ReVaR_{q,t+\tau}^{i|VaR_{50,t}^i} = \widehat{\alpha}_{q,\tau}^i + \widehat{\beta}_{q,\tau}^i I[VaR_{50,t}^i > 0] VaR_{50,t}^i + \widehat{\delta}_{q,\tau}^i M_t$). 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 (%)	4,867,067	-0.355	-0.000	16.129	-20.000	6.499	-5.840	631.757
$VaR_{50,t}^i$ (%)	4,867,067	-0.067	-0.086	6.655	-5.998	2.209	0.828	18.163
q=95								
$\beta_{95,1}^i$	4,867,067	0.102	0.092	0.732	-0.473	0.241	0.278	4.106
$\beta_{95,1}^i$ t-value	4,867,067	0.942	0.710	6.856	-3.106	2.006	1.039	8.058
$VaR_{95,t}^i$ (%)	4,867,067	7.366	6.600	21.079	0.901	4.210	2.139	20.092
$ReVaR_{95,t+1}^{i\|VaR_{50,t}^i}$ (%)	4,867,067	8.051	7.355	20.320	2.653	3.785	2.063	26.746
$ReVaR_{95,t+1}^{i\|VaR_{95,t}^i}$ (%)	4,867,067	8.693	7.913	23.111	2.434	4.350	2.136	23.466
$\Delta ReVaR_{95,t+1}^i$ (%)	4,867,067	0.642	0.486	6.639	-3.925	1.892	1.273	15.879
q=99								
$\beta_{99,1}^i$	4,536,898	0.185	0.113	1.777	-0.726	0.501	1.409	8.535
$\beta_{99,1}^i$ t-value	4,536,898	1.050	0.459	10.302	-2.955	2.942	8.079	191.574
$VaR_{99,t}^i$ (%)	4,536,898	12.532	11.277	34.500	2978	6.723	2.699	36.847
$ReVaR_{99,t+1}^{i\|VaR_{50,t}^i}$ (%)	4,536,898	13.368	12.173	34.428	4.344	6.467	3.149	65.168
$ReVaR_{99,t+1}^{i\|VaR_{99,t}^i}$ (%)	4,536,898	15.666	13.327	53.221	2.575	10.240	3.280	41.426
$\Delta ReVaR_{99,t+1}^i$ (%)	4,536,898	2.298	1.041	29.699	-11.140	7.478	3.375	54.054

Table 5: **Events: ROA Prediction**

This table presents the results of cross sectional regressions ($ROA^i_{event+1} = a + b\Delta ReVaR^i_{q=0.99,\tau=1,event-1} + cZ^i_{event-1} + \epsilon^i_t$) 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 $\Delta ReVaR^i_{99,\tau=1}$ 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: $^*p < .10$; $^{**}p < .05$; $^{***}p < .01$.

	Covid			*Global Financial Crisis*			*Technology Bubble*		
	(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 $\Delta ReVaR^i_{99,1}$	-0.030**	-0.015***	-0.017**	-0.086***	-0.022*	-0.024**	-0.004	-0.002	-0.005
	(0.010)	(0.004)	(0.006)	(0.016)	(0.011)	(0.010)	(0.003)	(0.005)	(0.005)
Lag size	0.002**	0.001*	0.001**	0.007***	0.001	0.001	0.002	0.001	0.001
	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lag BM	-0.009***	-0.008***	-0.009***	-0.046*	-0.010**	-0.008***	-0.006***	-0.006*	-0.004
	(0.002)	(0.002)	(0.002)	(0.025)	(0.003)	(0.002)	(0.001)	(0.003)	(0.003)
Lag leverage	-0.030***	-0.015*	-0.015*	-0.007	-0.005	-0.005	-0.009**	0.001	0.001
	(0.006)	(0.007)	(0.007)	(0.010)	(0.010)	(0.011)	(0.004)	(0.004)	(0.005)
Lag cash	-0.013	-0.017*	-0.014*	0.032*	-0.023***	-0.020***	-0.018	-0.012	-0.016
	(0.010)	(0.008)	(0.007)	(0.015)	(0.004)	(0.005)	(0.016)	(0.012)	(0.012)
Lag ROA	0.322***	0.477***	0.450***	0.635***	0.617***	0.724***	0.341***	0.497***	0.512***
	(0.033)	(0.079)	(0.081)	(0.107)	(0.072)	(0.068)	(0.037)	(0.020)	(0.024)
Lag R&D	-0.422***	-0.229**	-0.252**	-0.230	-0.165*	-0.038	-0.296*	-0.255**	-0.214*
	(0.094)	(0.079)	(0.080)	(0.254)	(0.082)	(0.079)	(0.139)	(0.095)	(0.098)
Lag patent number	0.000	0.000	0.000	-0.006**	0.001	-0.000	0.001	-0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Lag EV per patent	0.000	0.000	0.001	0.003	0.002	0.003	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Observations	2,081	2,081	2,081	2,142	2,142	2,142	2,697	2,697	2,697
Adjusted R^2	0.357	0.437	0.440	0.162	0.322	0.365	0.363	0.472	0.534
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 ($\Delta ReVaR^i_{q,\tau=1,t} = a + bM_{t-h} + cZ^i_{t-h} + \epsilon^i_t$) using data from 1990 to 2022. The dependent variables are resilience measurements $\Delta ReVaR^i_{95,t}$ in Columns 1 to 3 and $\Delta ReVaR^i_{99,t}$ 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 $\Delta ReVaR^i_{q,t}$. 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 $\Delta ReVaR^i_{q,t}$. All regressions include industry fixed effects. Newey-West standard errors are reported in brackets. Significance levels are indicated as follows: *$p < .10$; **$p < .05$; ***$p < .01$.

	$\Delta ReVaR^i_{95,t}$			$\Delta ReVaR^i_{99,t}$		
	(1) *h=1*	(2) *h=4*	(3) *h=8*	(4) *h=1*	(5) *h=4*	(6) *h=8*
$VaR_{q,t-h}$	0.089***	0.077***	0.064***	0.263***	0.241***	0.205***
	(0.003)	(0.004)	(0.005)	(0.007)	(0.010)	(0.012)
Size$_{t-h}$	0.166***	0.159***	0.150***	0.354***	0.339***	0.302***
	(0.003)	(0.004)	(0.006)	(0.012)	(0.018)	(0.023)
BM$_{t-h}$	-0.092***	-0.115***	-0.109***	-0.322***	-0.402***	-0.422***
	(0.013)	(0.018)	(0.023)	(0.049)	(0.071)	(0.089)
Leverage$_{t-h}$	0.414***	0.429***	0.448***	0.227**	0.319*	0.481**
	(0.027)	(0.042)	(0.054)	(0.109)	(0.166)	(0.216)
Cash$_{t-h}$	0.366***	0.380***	0.397***	-0.000	0.056	0.218
	(0.034)	(0.050)	(0.064)	(0.152)	(0.226)	(0.287)
ROA$_{t-h}$	0.287	0.177	0.180	1.213	1.056	0.821
	(0.181)	(0.244)	(0.299)	(0.833)	(1.149)	(1.442)
R&D$_{t-h}$	-2.640***	-2.169***	-1.520**	-3.276*	-1.285	1.494
	(0.403)	(0.589)	(0.750)	(1.847)	(2.728)	(3.476)
Patent number$_{t-h}$	-0.045***	-0.048***	-0.049***	-0.044***	-0.054**	-0.062*
	(0.004)	(0.006)	(0.007)	(0.016)	(0.024)	(0.032)
Economic value per patent$_{t-h}$	-0.012**	-0.013*	-0.015	-0.023	-0.029	-0.035
	(0.005)	(0.007)	(0.010)	(0.020)	(0.031)	(0.040)
3-month yield change$_{t-h}$	0.001***	0.001***	-0.000	0.004***	-0.001	-0.004***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Term spread change$_{t-h}$	-0.000***	0.000***	-0.001***	-0.001***	-0.000	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ted spread$_{t-h}$	0.000*	0.001***	0.000	0.002**	0.002**	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Credit spread change$_{t-h}$	0.000	0.009***	-0.007**	-0.002	0.038***	-0.007
	(0.003)	(0.003)	(0.003)	(0.014)	(0.014)	(0.012)
Market return$_{t-h}$	0.045***	0.074***	0.057***	0.189***	0.285***	0.222***
	(0.007)	(0.008)	(0.008)	(0.028)	(0.031)	(0.033)
VIX$_{t-h}$	-0.002**	-0.007***	-0.011***	-0.033***	-0.045***	-0.054***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.005)	(0.005)
Observations	354,491	335,727	310,767	350,026	331,257	306,298
Adjusted R^2	0.043	0.038	0.033	0.036	0.031	0.027
Industry FE	yes	yes	yes	yes	yes	yes
Newey-West SE lag	1	4	8	1	4	8