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CORPORATE INNOVATION AND RESILIENCE IN THE UNITED STATES

September 2025

Marco Fanno Working Papers – 326

dSEA DIPARTIMENTO DI SCIENZE ECONOMICHE E AZIENDALI 'MARCO FANNO'

UNIVERSITÀ DEGLI STUDI DI PADOVA

Corporate Innovation and Resilience in the United States

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Abstract

This paper examines how corporate innovation affects resilience. We use the financial statements and weekly stock price data of over 900 publicly traded companies in the United States, finding that the stock prices of companies reporting research and development (R&D) expenses before the crisis caused by the COVID–19 pandemic increased by 10%, on average, in its aftermath. We propose two new measures of resilience—impact resistance and recovery speed—to explicate the mechanisms by which innovation enhances resilience. Our findings suggest that R&D spenders were less likely to incur a loss due to the crisis and recovered faster, *ceteris paribus*.

Keywords: crisis; innovation; resilience
JEL codes: E32; M21; O32

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An earlier version of this paper was presented at the paper development workshop of the *Academy of Management Journal* in Rome, Italy (October 12–13, 2022), and two international conferences: the Annual Meeting of the Academy of Management in Boston, United States (August 4–8, 2023), and the Annual Conference of the Society for Institutional and Organizational Economics in Frankfurt, Germany (August 24–26, 2023). Shakhmuradyan would like to thank the organizers of these events, in particular Alessandro Zattoni (LUISS Guido Carli University), Marc Gruber (Ecole Polytechnique Fédérale de Lausanne), Elena Novelli (Bayes Business School), and Guido Friebel (Goethe University Frankfurt) for selecting the paper for presentation, as well as Anne ter Wal (Imperial College London) and three anonymous reviewers for their feedback. The receipt of a doctoral scholarship from the Italian Ministry of University and Research and a conference travel grant from the Hirair Hovnanian Family Foundation is also gratefully acknowledged. Both authors would like to thank Enrico Rettore, head of the Ph.D. Program in Economics and Management at the University of Padua, and Martina Gianecchini, the co–supervisor of Shakhmuradyan's doctoral research, for their feedback on earlier drafts of this paper. Any errors are our own.

1 Introduction

Recurrent crises and adversities necessitate the development of organizational capabilities to manage risk and uncertainty (van der Vegt et al. 2015; Bundy et al. 2017; Hardy et al. 2020). While the increased frequency and magnitude of exogenous perturbations to socio–economic systems render traditional contingency planning frameworks obsolete, the concept of resilience—originating in natural sciences and introduced into administrative science by Meyer (1982)—has gained paramount importance in the fields of economics, management, and finance (Acemoglu, Ozdaglar, and Tahbaz–Salehi 2015; Mithani 2020; Grossman, Helpman, and Lhuillier 2023; Pagano, Wagner, and Zechner 2023; Brunnermeier 2024; Grossman, Helpman, and Sabal 2024; Acemoglu and Tahbaz–Salehi 2025). [1] In the field of management, it has come to constitute an overarching notion of organizational capabilities to cope with environmental turbulence, as scholars associate resilience with crisis anticipation and response, as well as post–crisis recovery (Sutcliffe and Vogus 2003; Weick and Sutcliffe 2015; Linnenluecke 2017; Williams et al. 2017; Hillmann and Guenther 2021; Shepherd and Williams 2023).

The current paper contributes to the literature on resource endowments constituting organizational resilience (Williams et al. 2017), as well as to the literature on antecedents of resilience (Hillmann and Guenther 2021) by empirically examining the role innovation plays in fostering resilience. We build on the seminal work of Meyer (1982), who studied the adaptation of hospitals to a doctors' strike, as well as extend the literature on business resilience during the global financial crisis (Ahn, Mortara, and Minshall 2018; Bertschek, Polder, and Schulte 2019; Aghion et al. 2021) and the COVID–19 pandemic (Ding et al. 2021; Krammer 2022; Calza, Lavopa, and Zagato 2023; Copestake, Estefania–Flores, and Furceri 2024). Specifically, we speak to recent studies examining the link between innovation and resilience (Li et al. 2021; Bergami et al. 2022; Capodistrias et al. 2022) and

[1] A review by Alexander (2013) on the historical evolution of the concept of resilience in natural and social sciences suggests that its first scientific use was in the field of mechanics by William J. M. Rankine (*A Manual of Applied Mechanics*, 1867), who referred to the resistance properties of solid materials such as steel. Batabyal (1998) reviews the early literature in economics.

consider other factors that contribute to resilience (Fahlenbrach, Rageth, and Stulz 2021; Smith et al. 2024).

Despite different research contexts and methodological approaches, prior evidence in the field of management suggests that organizations allocating resources to innovation, i.e., engaging in the development of new products, processes, and ways of organization, are more resilient. However, there is theory and substantial empirical evidence in economics (Bernanke 1983; McDonald and Siegel 1986; Dixit and Pindyck 1994; Bloom, Bond, and Van Reenen 2007; Bloom 2009; Kellogg 2014; Baker, Bloom, and Davis 2016; Kumar, Gorodnichenko, and Coibion 2023)—reflected in the literature on real options in the field of management (Driouchi and Bennett 2012; Trigeorgis and Reuer 2017)—suggesting that firms would postpone capital investment decisions, including research and development (R&D), under uncertainty, and reduce such investment during protracted periods of crisis, such as recessions (Mezzanotti and Simcoe 2023). Thus, whether and how innovation affects resilience is a matter of further empirical examination. We provide such an examination and contribute to the fields of economics and management in two primary ways.

First, this paper offers a new theoretical framework on how innovation affects resilience. Specifically, we build on the literature at the intersection of organizational adaptation and crisis management (Meyer 1982; Wildavsky 1988; Weick and Sutcliffe 2015; Linnenluecke 2017; Williams et al. 2017) and advance a continuous–time dynamic model composed of three phases—*anticipation, response*, and *recovery*. Furthermore, based on conceptions from the fields of ecology and engineering (Holling 1973, 1996; Rose 2007; Hillmann and Guenther 2021), resilience is operationalized as crisis *impact resistance* and *recovery speed*. Crucially, it is argued that innovation at the crisis anticipation phase enables resilience as crisis impact resistance, while innovation at the crisis response phase enables resilience as recovery speed—a distinction that has not been made in the prior literature. By studying the relationship between innovation and resilience across three phases of a crisis, we thus incorporate a time dimension into organizational theory on resilience (Abbott 2001; Langley et al. 2013; Blagoev et al. 2024; Hernes et al. 2024). More importantly, while prior empirical research suggests links between innovation and resilience at each of the crisis management phases in isolation (e.g., Meyer (1982) focuses on crisis anticipation, Ahn, Mortara, and Minshall (2018) and Bertschek, Polder, and Schulte (2019) focus on crisis response, and Li et al. (2021) focus on crisis recovery), we offer a unifying framework that examines the relative importance of the allocation of resources to innovation across all phases. Overall, the framework offered in this study is characterized by simplicity and generality (Langley 1999), thus enabling the provision of actionable implications for management practice.

Second, this paper provides quantitative evidence—through a high–frequency quasi–experimental research design—that the relationship between innovation and resilience is causal. Prior studies on resource endowments constituting resilience are either based on a small number of case studies that cannot be easily generalized (Bergami et al. 2022; Sonenshein and Nault 2024; Smith et al. 2024) or use cross–sectional survey data that do not enable drawing causal inferences (Calza, Lavopa, and Zagato 2023). This paper, in contrast, studies the COVID–19 pandemic as an exogenous crisis and estimates difference–in–differences regression models using panel data of over 900 publicly traded companies. Our observation window comprises 156 weeks over three years, and it includes both pre–crisis and post–crisis periods, thus enabling the testing of the main identifying assumption in difference–in–differences estimates, i.e., parallel trends (Borusyak, Jaravel, and Spiess 2024), as well as the observation of post–crisis trajectories (Swider, Yang, and Wang 2024). A key finding from these estimates is that while companies reporting R&D expenses and those not reporting such expenses followed a similar trajectory prior to the crisis induced by the pandemic, their paths diverged in its aftermath. The observed effect is positive and significant, especially for companies in service industries, suggesting that innovation is an antecedent of resilience.

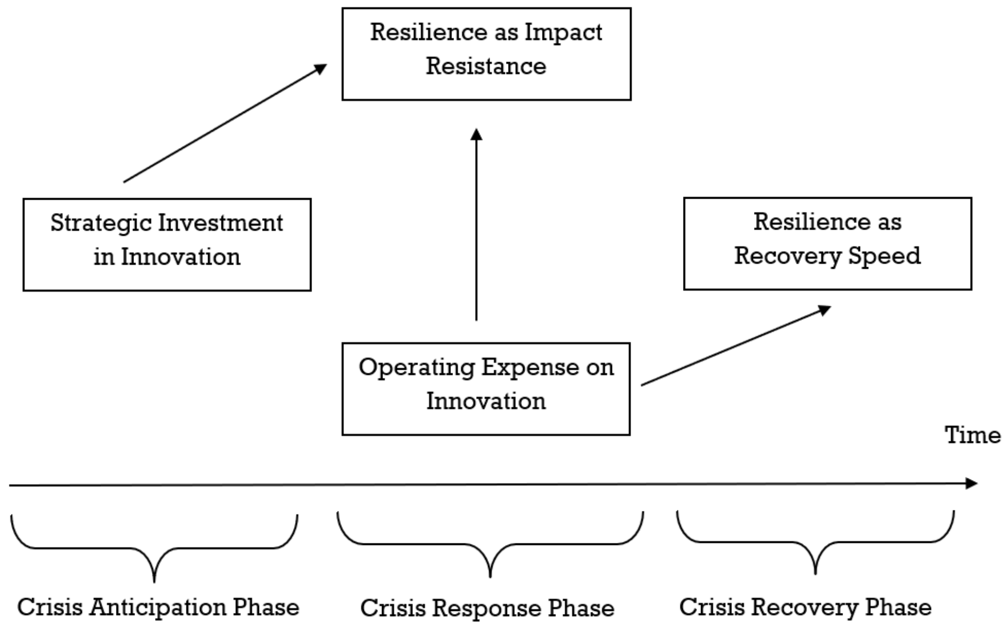
The rest of the paper is organized as follows: Section 2 below lays out the theoretical framework of our research and advances testable hypotheses. It is followed by Section 3, which describes the empirical setting and data we use; Section 4 discusses our measures and estimation methods; Section 5 provides the results; Section 6 discusses the results in relation to the extant literature; and Section 7 concludes. Additional statistics are provided in the appendices.

2 Theoretical Framework and Hypotheses

Organizational adaptation and resilience research streams in the management literature often delineate three phases of crisis management: *anticipation, response*, and *recovery* (Meyer 1982; Bundy et al. 2017; Linnenluecke 2017; Williams et al. 2017). From a temporal perspective (Blagoev et al. 2024), these phases entail actions taken *before*, *during*, and *after* crises. As noted by one of the earliest contributors to the literature on organizational adaptation (Thompson 1967, p. 21): *"Under norms of rationality, organizations seek to anticipate and adapt to environmental changes which cannot be buffered or leveled."* Similarly, Weick and Sutcliffe (2015, p. 12, emphasis added) note that high–reliability organizations "develop capabilities to *detect, contain* and *bounce back* from those inevitable errors that are part of an indeterminate world." Finally, Wildavsky (1988, p. 77) defines resilience as *"learning to bounce back"* and argues that *"To learn from error (as opposed to avoiding error altogether) and to implement that learning through fast negative feedback, which dampens oscillations, are at the forefront of operating resiliently"* (p. 120).

We build on the crisis management literature and advance a three–period dynamic model that formalizes the relationship between innovation and resilience (see Figure 1 for a graphical representation). Specifically, we observe both innovation and resilience across continuous time (Abbott 2001). Organizations may allocate resources to innovation before a crisis (at the crisis anticipation phase), as well as during a crisis (at the crisis response phase): there is conceptual distinction between the two, corresponding to business practice (Cohen and Levinthal 1989, 1990), and the former is denoted as *strategic investment in innovation*, while the latter is denoted as *operating expense on innovation.* Based on ecological and engineering foundations of the concept (Holling 1973, 1996; Rose 2007; Hillmann and Guenther 2021), resilience in the model is operationalized as crisis *impact resistance* and *recovery speed*: the former denotes whether an organization incurs a loss due to a crisis, while the latter denotes the time it takes to recover to pre–crisis levels for those organizations that incur a loss due to a crisis. Essentially, what we propose is a process model whereby boxes represent different states of resilience, while arrows represent relations of precedence (Langley et al. 2013).

Figure 1: Theoretical Framework on How Innovation Affects Resilience



Based on the framework advanced above, we argue that innovation affects resilience through three channels: first, strategic investment in innovation at the crisis anticipation phase increases the likelihood that an organization will not incur a loss during an exogenous crisis. The identification of this channel is grounded in the conceptual–theoretical literature on organizational *surveillance* (Thompson 1967), *foresight* (Turner 1976), *future search* (Linnenluecke and Griffiths 2010), and *weak signals* (Weick and Sutcliffe 2015). The latter has its origins in the field of sociology, in particular Vaughan (2002)'s research, which suggests that crisis events are preceded by incubation periods containing early warning signs—clear in retrospect but ignored or misinterpreted at the time decisions are made. Our observation is also aligned with the seminal empirical research on organizational resilience, i.e., Meyer (1982, p. 528), who finds that: *"[T]he potential for a strike was detected earlier by hospitals that marketed their services more innovatively, spanned their boundaries more extensively, and whose administrators devoted more attention to their environments."* More specifically, we advance our first hypothesis as follows:

Hypothesis 1 *Strategic investment in innovation at the crisis anticipation phase enables resilience as impact resistance.*

The second channel through which innovation affects resilience relates to the first, but it relies on the variation in resource allocation across crisis management phases. Specifically, we argue that operating expense on innovation during the crisis response phase is expected to increase the likelihood of not incurring a loss during a crisis. This channel is supported by several case studies (Bergami et al. 2022; Capodistrias et al. 2022), as well as quantitative evidence based on firm surveys during the global financial crisis (Ahn, Mortara, and Minshall 2018; Bertschek, Polder, and Schulte 2019) and the COVID–19 pandemic (Calza, Lavopa, and Zagato 2023). For instance, Bergami et al. (2022) provide cases of how Italian companies recombined their capabilities to manufacture products that were not in their core business but were essential for effectively responding to the COVID–19 pandemic. More generally and at a conceptual level, our second channel relates to recent research by Shepherd and Williams (2023), who argue—drawing from the field of psychology—that there are different *response paths* to organizational resilience: organizations may respond to the same crisis event differently, thus emerging from it either weakened or strengthened. Hence, our second hypothesis is stated as follows:

> **Hypothesis 2** *Operating expense on innovation at the crisis response phase enables resilience as impact resistance.*

The literature on investment under uncertainty (Bernanke 1983; Dixit and Pindyck 1994; Bloom, Bond, and Van Reenen 2007; Bloom 2009) suggests that Hypothesis 1 may be stronger than Hypothesis 2, i.e., the allocation of resources to innovation before a crisis would matter more for resilience than the allocation of resources during a crisis. This is because heightened uncertainty induces a reduction in innovation financing and reallocation of resources (Barrero, Bloom, and Davis 2020; Barrero et al. 2021), thus negatively affecting both firm–level and aggregate productivity (Bloom et al. 2025).

Finally, the conceptual distinction between two states of resilience—resilience as impact resistance and resilience as recovery speed—enables us to hypothesize that the allocation of resources to innovation during a crisis shortens the time required to attain pre–crisis levels of performance after a crisis has subsided. Prior research on the global financial crisis (Ahn, Mortara, and Minshall 2018) suggests that *retrenchment*, i.e., employment cuts and reduction of innovation financing during an economic downturn, may save resources in the short term and thus help firms endure a crisis; however, such a strategy results in a loss of innovation capability in the long term, thus making it more difficult to recover after a downturn. Relatedly, Sonenshein and Nault (2024) study organizational responses to the COVID–19 pandemic, arguing that resourcefulness—a key contributor to resilience—entails a capacity to seek opportunities amidst crises rather than cutting back on employment. Thus, we advance our third and final hypothesis as follows:

> **Hypothesis 3** *Operating expense on innovation at the crisis response phase enables resilience as recovery speed.*

3 Empirical Setting and Data

3.1 Empirical Setting

The empirical setting in which we examine corporate resilience in the United States (US) is the COVID–19 pandemic. According to the National Bureau of Economic Research (NBER) Business Cycle Dating Committee announcement of June 8, 2020, the peak in monthly economic activity prior to the recession caused by the pandemic occurred in February 2020; the peak in quarterly economic activity occurred in Q4–2019 (National Bureau of Economic Research 2020). The Committee announcement of July 19, 2021, states that the trough in monthly economic activity occurred in April 2020, and it was followed by an expansion starting in May 2020; the quarterly trough occurred in Q2–2020, thus making the recession induced by the pandemic the shortest on record in US history (National Bureau of Economic Research 2021). Despite its brevity, the recession was severe, as real gross domestic product contracted at an annualized rate of 28.1%—the largest quarterly decline since the series began in 1947—in Q2–2020 (Bureau of Economic Analysis 2025). [2]

3.2 Data

Our aim was to construct a panel data set linking financial statements, stock prices, and other corporate characteristics, such as industry and location, of companies traded in the US before and after the declaration of a national emergency due to the COVID–19 pandemic on March 13, 2020 (Federal Register 2020; World Health Organization 2020). Therefore, we match data from several sources, as elaborated below.

Our first data source is the *Company Tickers* static file provided by the US Securities and Exchange Commission (SEC), which contains the universe of publicly traded companies in the country (United States Securities and Exchange Commission 2025a). As of November 9, 2024, the file contained 10,077 tickers and 7,913 unique Central Index Keys (CIKs). The latter are permanent identifiers assigned by the SEC to each filing entity, and we

[2] Advance estimates released in July 2020 suggested a contraction rate of 32.9% (Bureau of Economic Analysis 2020). See also Council of Economic Advisers (2020).

use these to match companies with their quarterly financial statements. Compiled by the SEC Division of Economic and Risk Analysis, the *Submissions* files in quarterly financial statement data sets contain additional company information, such as business addresses, fiscal year end dates, and standard industrial classification (SIC) codes (United States Securities and Exchange Commission 2025d). Financial statements are available for all 12 quarters of interest to us, i.e., from Q1–2019 to Q4–2021, for 3,680 companies. [3] We exclude companies not incorporated in the US (n = 461) and companies operating in financial industries (SIC two–digit codes 60–67, $n = 907$), as the financial ratios of companies in these industries, including their liquidity ratios, are not directly comparable with the financial ratios of companies in other industries (Fama and French 1992). We are able to match financial statements with CIKs of 1,936 companies (match rate of 84%).

Second, we obtain weekly stock price data of all companies traded on the two US stock exchanges, i.e., the New York Stock Exchange (NYSE) and the Nasdaq Stock Exchange, from the LSEG Workspace (formerly Refinitiv Eikon database) (London Stock Exchange Group 2025). As of mid–November 2024, price data were available for 5,814 companies; 766 of these are not incorporated in the US, as identified by the first two letters of the alpha–numeric International Securities Identification Number (ISIN), and are therefore excluded. We also exclude one company with a duplicated ISIN in the combined data set of the two stock exchanges, as well as companies with missing price data in any of the weeks between W1–2019 and W52–2021 (n = 1,709). The median price of the remaining companies (n = 3,338) was USD 28.48, and we exclude companies the stocks of which traded below USD 1.60 (1$^{\text{st}}$ percentile) and above USD 1,623.83 (99$^{\text{th}}$ percentile) in any of the observed weeks. This further reduces the sample by 166 and 54 companies, respectively; thus, we are left with a cross–section of 3,118 companies, the matching of which with quarterly financial statements using tickers results in a strongly balanced panel data set of 1,463 companies

[3] We choose to start in Q1–2019, as the availability of data one year before the crisis quarter enables us to test the parallel trends assumption in difference–in–differences estimates and calculate the first measure of resilience (see below). Quarters following Q4–2021 are excluded due to the war in Ukraine (started in February 2022, i.e., Q1–2022), as it would confound our results focused on the COVID–19 pandemic.

observed over 156 weeks (228,228 company–week observations). [4]

Finally, we obtain annual financial statements from Application Programming Interfaces (API) of the SEC Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system (United States Securities and Exchange Commission 2025c). We need annual data for two primary reasons: first, we exclude companies reporting negative or zero net income in 2019 to ensure that losses incurred during the crisis induced by the pandemic are due to its impact, rather than other, company–specific factors (Altman 1968). The data frame for net income in 2019 contains values for 6,178 companies, of which slightly more than half ($n =$ 3,251) are negative, and 18 are zero. We match companies reporting positive net income in 2019 with the panel obtained above using CIKs and retain only those companies that appear in both data sets; therefore, our final data set is a balanced panel of 925 companies. Second, a non–negligible share of companies report R&D expenses—our measure of innovation—at annual but not quarterly frequency. [5] Therefore, the identification of a company as an R&D spender based solely on quarterly data would induce a measurement error in our independent variable. Using the yearly financial statements, we identify that 401 companies in the final sample (43.35%) reported R&D expenses in 2019, i.e., before the pandemic; therefore, these are classified as innovative. [6]

[4]The fact that 2020 was a leap year and included an additional day (29 February) does not affect our week count for that year, as the statistical software we use (Stata) has a convention that all years have 52 weeks irrespective of the number of days. See Cox (2022) for further details.

[5]For instance, the EDGAR data frame for R&D expenses in 2019 contains values for 2,542 companies, of which 2,501 are positive. This compares with 1,696 companies contained in the data frame for Q1–2019; 1,686 companies in the data frame for Q2–2019, and 1,718 companies in the data frame for Q3–2019.

[6]Total R&D expenses in our sample of 401 companies amount to USD 222,122 million. Total domestic business R&D in the US in 2019 was USD 492,956 million, of which around 90% (USD 441,223 million) was performed by large companies with more than 250 employees (National Center for Science and Engineering Statistics 2022). Therefore, the sample used in analyses reported in this paper is representative of around 45% of total domestic business R&D and 50% of large–company R&D in the US in 2019. Total R&D expenses of all companies for which 2019 annual data are available from the EDGAR API amount to USD 401,119 million, i.e., around 91% of total large–company R&D in the US.

To reiterate, the results reported below are based on a panel data set of publicly traded companies that satisfy the following four conditions: *a)* are incorporated in the US; *b)* operate in non–financial industries; *c)* have complete close price data for all weeks between the first week of 2019 and the last week of 2021; and *d)* report positive net income in 2019. Overall, we have a balanced panel of 144,300 company–week observations ($n = 925 \times T = 156$). Appendix A provides descriptive statistics, including the distribution of the sample by industries (SIC divisions and major groups) and locations (Census Bureau regions and states). As the NBER Business Cycle Dating Committee identifies only monthly and quarterly dates of peaks and troughs in economic activity, we perform additional analyses with weekly prices averaged at monthly (N = 33,300 company–month observations) and quarterly (N = 11,100 company–quarter observations) frequencies. The results based on alternative frequencies are reported in Appendix B.

4 Measures and Econometric Estimation

4.1 Resilience Measures

In line with ecological and engineering conceptions of resilience (Holling 1973, 1996; Rose 2007; Hillmann and Guenther 2021), we measure resilience by two variables that are new to the economic literature: *impact resistance* and *recovery speed*. Impact resistance (IR) is a binary variable, such that, when measured with stock price (P):

$$IR = \begin{cases} 1 & \text{if } P_t \geq P_{t-s} \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

In Equation 1 above, t indicates time, and s is a difference operator: for weekly data, it equals 52, i.e., the number of weeks in a typical calendar year; for monthly and quarterly observations, $s = 12$ and $s = 4$, respectively.

Recovery speed (RS) is a count variable corresponding to the number of weeks, months, or quarters it takes to recover the stock price to its pre–crisis levels:

$$RS \in \mathbb{N}. \tag{2}$$

In the context of the pandemic–induced recession in the US, whereby the trough of the recession using weekly data can be dated to W12–2020 (see Figure A1), and there are observations up to W52–2021, the following is true:

$$1 \leq RS \leq 92. \tag{3}$$

For monthly and quarterly data in the same context, the maximum values for RS are 20 and 6, respectively. RS is not defined for companies that did not incur a loss throughout the crisis (i.e., $IR = 1$ in all weeks, months, or quarters).

4.2 Innovation Measures

We measure innovation by R&D expenses. As opposed to patents, which capture the output of innovative activities of firms, R&D expenses capture the input of such activities and have been widely used in the innovation and productivity literature (Griliches 1998; Smith 2006; Cohen 2010). More importantly, R&D expenses are a better measure of the theoretical construct we aim to operationalize, i.e., the *allocation of resources* to innovation (Arrow 1962).

Besides the binary variable of being an R&D spender (equal to one if a company reported R&D expenses in 2019 and zero otherwise), we have two measures of innovation that enable us to test the hypotheses advanced above: *strategic investment in innovation* and *operating expense on innovation.* The former is measured by pre–crisis R&D intensity, i.e., R&D expenses in 2019 divided by sales revenues in 2019; the latter is measured by crisis R&D intensity, i.e., R&D expenses in 2020 divided by revenues in the same year. More formally,

$$\textit{R\&D Intensity} = \frac{\textit{R\&D Expenses}}{\textit{Revenues}}. \tag{4}$$

4.3 Econometric Estimation

We adopt three econometric approaches to examine whether more innovative companies are more resilient and how innovation affects resilience. Each approach is elaborated below.

First, we estimate a two–way fixed effects difference–in–differences (TWFE DID) model (Cameron and Trivedi 2022) to quantify the differential effect of being an R&D spender during the crisis induced by the pandemic:

$$\ln(Price_{it}) = \phi_i + \gamma_t + \alpha RDS_i \times Crisis_t + \epsilon_{it}, \tag{5}$$

where i denotes companies, and t denotes time (156 weeks spanning from W1–2019 to W52–2021 inclusive). *RDS* is a binary variable equal to one if a company reported R&D expenses before the crisis (in calendar year 2019) and zero otherwise. [7] *Crisis* is a binary variable equal to one during the crisis period (starting in W12–2020) and zero otherwise; ϕ_i denotes company fixed effects; γ_t stands for week fixed effects, and ϵ_{it} is an error term clustered at the company level. Our interest lies in estimating the parameter α, and it is identified if the assumption of parallel trends holds. We test this assumption and provide appropriate test statistics and diagnostic graphs. [8]

Second, we estimate a binary outcome (logit) regression model for panel data (Cameron and Trivedi 2005, 2022) to gauge the effect of innovation on our first measure of resilience, i.e., *impact resistance*. Our baseline specification is as follows:

$$\Pr(IR_{it} = 1 \mid RDI_{it}, \alpha_i) = \Lambda(\alpha_i + \beta RDI_{it}), \tag{6}$$

where IR_{it} is the crisis impact resistance of company i at time t; RDI_{it} is its R&D intensity—measured before or during the crisis; and α_i is a random effect (RE).

[7] Corporate fiscal year end dates may not necessarily correspond to the calendar year end date, as some companies, including those in our sample, end fiscal years not on 31 December but on other dates (e.g., 30 June). We account for this heterogeneity in additional analyses reported in Section 5.1.

[8] All analyses were carried out with Stata 18 software and reproduced using Stata 19. Specifically, we utilized the `xtdidregress`, `estat ptrends`, and `estat trendplots` commands (StataCorp 2025).

The augmented specification with controls (see Section 4.4) has the following form:

$$\Pr(IR_{it} = 1 \mid RDI_{it}, x_{it}, \alpha_i) = \Lambda(\alpha_i + \beta RDI_{it} + \boldsymbol{x}'_{it}\boldsymbol{\gamma}). \tag{7}$$

We expect the β coefficient in both Equations 6 and 7 to be positive, i.e., greater R&D intensity increases crisis impact resistance, *ceteris paribus*.

Third, we estimate a Poisson regression model (Cameron and Trivedi 2005; Wooldridge 2010; Cameron and Trivedi 2022) for only those companies that incurred a loss due to the crisis and subsequently recovered:

$$\mathrm{E}(RS_{it} \mid RDI_{it}, \alpha_i) = \exp(\alpha_i + \beta RDI_{it}), \tag{8}$$

where RS_i is the recovery speed of company i at time t; RDI_{it} is its R&D intensity in 2020; and α_i is a random effect.

The augmented specification has the following form:

$$\mathrm{E}(RS_{it} \mid RDI_{it}, x_{it}, \alpha_i) = \exp(\alpha_i + \beta RDI_{it} + \boldsymbol{x}'_{it}\boldsymbol{\gamma}). \tag{9}$$

We expect the β coefficient in both Equations 8 and 9 to be negative, i.e., greater R&D intensity shortens the time to recovery, *ceteris paribus*.

4.4 Controls

The augmented specifications of RE logit and Poisson regression models, as specified above, control for several factors that affect both innovation and resilience (see Appendix Table A1 for summary statistics and Table A2 for t–test statistics). First, we control for *liquidity* and *profitability*, as financially less constrained and better performing companies are more likely to allocate resources to innovation (O'Sullivan 2006; Hall and Lerner 2010), as well as withstand and rebound from crises (Williams et al. 2017; DesJardine, Bansal, and Yang 2019; Fahlenbrach, Rageth, and Stulz 2021). Liquidity is measured by the pre–crisis current ratio, i.e., current assets in 2019 divided by current liabilities in the same year; profitability is measured by the pre–crisis return on assets, i.e., net income in 2019 divided by total assets in the same year. [9]

Second, we control for *age*, as older companies are more likely to allocate resources to innovation (Akcigit, Hanley, and Stantcheva 2022) and have experience of prior crises (Smith et al. 2024). Age is measured by years since incorporation. Third, we control for *industry*, as there are differences in the allocation of resources to innovation across industries, with some being more R&D–intensive than others (Malerba 2006; Smith 2006), and the impact of the COVID–19 pandemic was uneven: industries that enabled work from home to a greater extent were less affected by the pandemic than other industries (Dingel and Neiman 2020; Guerrieri et al. 2022; Bloom et al. 2025; Cirelli and Gertler 2025). Industry is identified by the SIC section in which a company operates (Occupational Safety and Health Administration 2025). Our sample is representative of eight SIC divisions [10] and 57 major groups in both manufacturing and service industries (see Tables A3 and A4).

Finally, we control for *location*, as there are geographic disparities in the allocation of resources to innovation across the US (Jaffe, Trajtenberg, and Henderson 1993; Audretsch and Feldman 1996; Chikis, Kleinman, and Prato 2025), with some states, such as California, attracting more employment and investment in R&D–intensive industries; in addition, the economic impact of the pandemic was spatially uneven due to different policies implemented by state and local governments (Barrot et al. 2024; Minniti, Rodriguez, and Williams 2024). Location is identified by the Census Bureau region and state (United States Census Bureau 2025) in which a company is headquartered: our sample is representative of all four regions and 45 states (see Table A5).

[9] We prefer liquidity as a measure of financial constraints instead of leverage due to the reason (as noted in Section 3.1 above) that the recession induced by the pandemic was very short, and it therefore did not materially affect the long–run financial condition of most companies.

[10] There are ten SIC divisions in total, and we excluded Division H (Finance, Insurance, and Real Estate) at the research design stage. No companies operate under Division J (Public Administration).

5 Results

5.1 TWFE DID Regression Results

The two–way fixed effects regression results based on the analysis of the full sample (see Table 1, column 1 below) suggest that the coefficient of the interaction term *R&D spender* $\times$ *Crisis* is positive and significant at the 1% level ($\alpha = 0.103, se = 0.023$); this means that the stock prices of R&D spenders increased by 10%, on average, in the weeks following W12–2020. The parallel trends assumption holds ($F = 1.26$), as can be observed also from Panel A of Figure 2. Disaggregation of the sample by industries (see Table 1, columns 2 and 3 below) suggests that there is effect heterogeneity: specifically, the coefficient estimate is smaller but significant at the 5% level for manufacturing companies ($\alpha = 0.082, se = 0.035$); it is larger for companies operating in service industries ($\alpha = 0.139, se = 0.057$). The parallel trends assumption holds for both industry subsamples ($F = 0.31$ and 0.03, respectively; see Panels A and B of Figure 3).

As noted in Section 4.3 above, corporate fiscal year end dates may not correspond to the calendar year end date. Therefore, we perform an additional analysis using the subsample of companies for which the fiscal year ends in December, i.e., the majority ($n = 674$). [11] The estimated effect for this subsample (see Table 2, column 1 below) is greater than for the full sample and significant at the 1% level ($\alpha = 0.117, se = 0.028$); the parallel trends assumption holds ($F = 0.24$; see also Panel B of Figure 2 below). We further split the sample based on exchange (see Table 2, columns 2 and 3). The estimates for companies traded on NYSE ($\alpha = 0.080, se = 0.027$) are comparable to the estimates for companies operating in manufacturing industries (see Table 1, column 2), while the estimates for companies traded on Nasdaq ($\alpha = 0.118, se = 0.038$) are comparable to those obtained for companies with December fiscal year ends.

[11] The EDGAR API documentation (United States Securities and Exchange Commission 2025c) states that data frames are *"assembled by the dates that best align with a calendar quarter or year."* The financial statement data sets we use (United States Securities and Exchange Commission 2025d) contain 12 fiscal year end dates (one for each month), including 31 December.

Table 1: TWFE DID Regression Results

	All	Manufacturing	Services
	($n = 925$)	($n = 446$)	($n = 183$)
R&D spender × *Crisis*	0.103	0.082	0.139
	(0.023)	(0.035)	(0.057)
	[0.058; 0.148]	[0.014; 0.150]	[0.027; 0.251]
Company FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
n (non–spender)	524	120	123
n (R&D spender)	401	326	60
N (company–week obs.)	144,300	69,576	28,548
Parallel trends test	$F_{(1,924)} = 1.26$	$F_{(1,445)} = 0.31$	$F_{(1,182)} = 0.03$

Notes: The dependent variable in all columns is the natural logarithm of the weekly close price, obtained from the LSEG Workspace (London Stock Exchange Group 2025), and the time spans from W1–2019 to W52–2021, for a total of 156 weeks. The classification of a company as an R&D spender is based on 2019 annual financial statements, obtained from the SEC EDGAR API (United States Securities and Exchange Commission 2025c). "Crisis" indicates weeks after COVID–19 was declared an emergency by the presidential decree, i.e., W12–2020 onward (Federal Register 2020). Manufacturing companies are those operating under SIC Division D; service companies are those operating under SIC Division I (Occupational Safety and Health Administration 2025). Robust standard errors clustered at the company level in parentheses below coefficient estimates; 95% confidence intervals in brackets. The null hypothesis for the parallel trends test is that linear trends in the pre–crisis period are parallel.

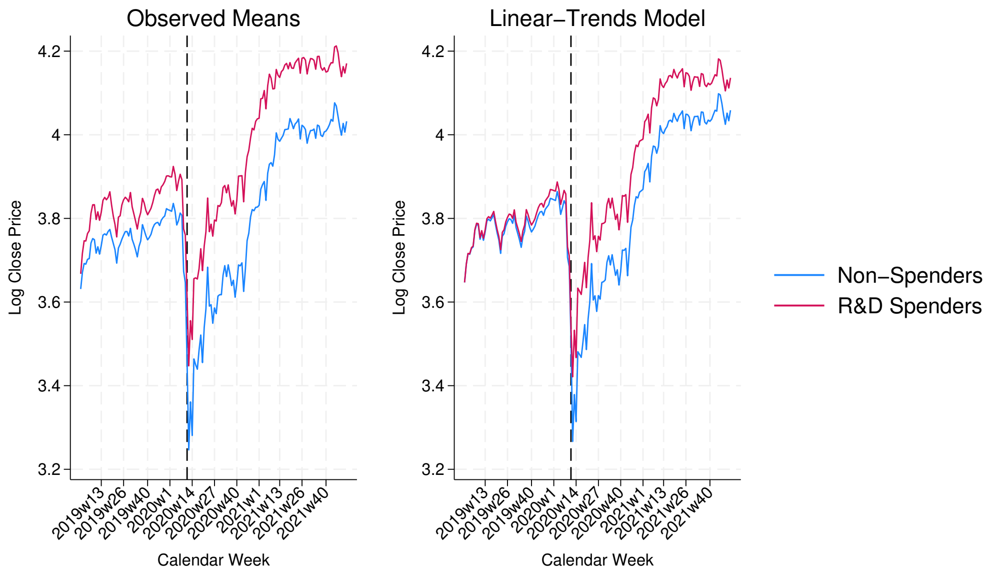
Table 2: TWFE DID Regression Results Accounting for Heterogeneity

	December FYE	NYSE	Nasdaq
	(n = 674)	(n = 509)	(n = 416)
R&D spender × *Crisis*	0.117	0.080	0.118
	(0.028)	(0.027)	(0.038)
	[0.063; 0.172]	[0.028; 0.133]	[0.044; 0.192]
Company FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
n (non–spender)	387	304	220
n (R&D spender)	287	205	196
N (company–week obs.)	105,144	79,404	64,896
Parallel trends test	$F_{(1,673)} = 0.24$	$F_{(1,508)} = 0.48$	$F_{(1,415)} = 4.57$

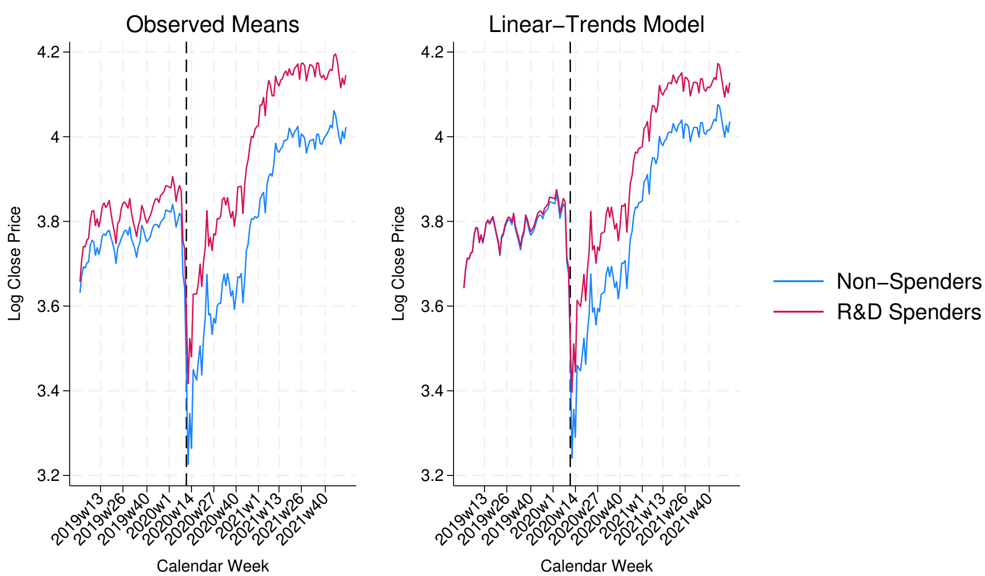
Notes: The dependent variable in all columns is the natural logarithm of the weekly close price, obtained from the LSEG Workspace (London Stock Exchange Group 2025), and the time spans from W1–2019 to W52–2021, for a total of 156 weeks. The classification of a company as an R&D spender is based on 2019 annual financial statements, obtained from the SEC EDGAR API (United States Securities and Exchange Commission 2025c). December FYE indicates companies whose fiscal year ends in December (United States Securities and Exchange Commission 2025d); "Crisis" indicates weeks after COVID–19 was declared an emergency by the presidential decree, i.e., W12–2020 onward (Federal Register 2020). NYSE and Nasdaq refer to companies traded on the two exchanges, respectively (United States Securities and Exchange Commission 2025b). Robust standard errors clustered at the company level in parentheses below coefficient estimates; 95% confidence intervals in brackets. The null hypothesis for the parallel trends test is that linear trends in the pre–crisis period are parallel.

Figure 2: Graphical Diagnostics for Parallel Trends

(a) All Companies



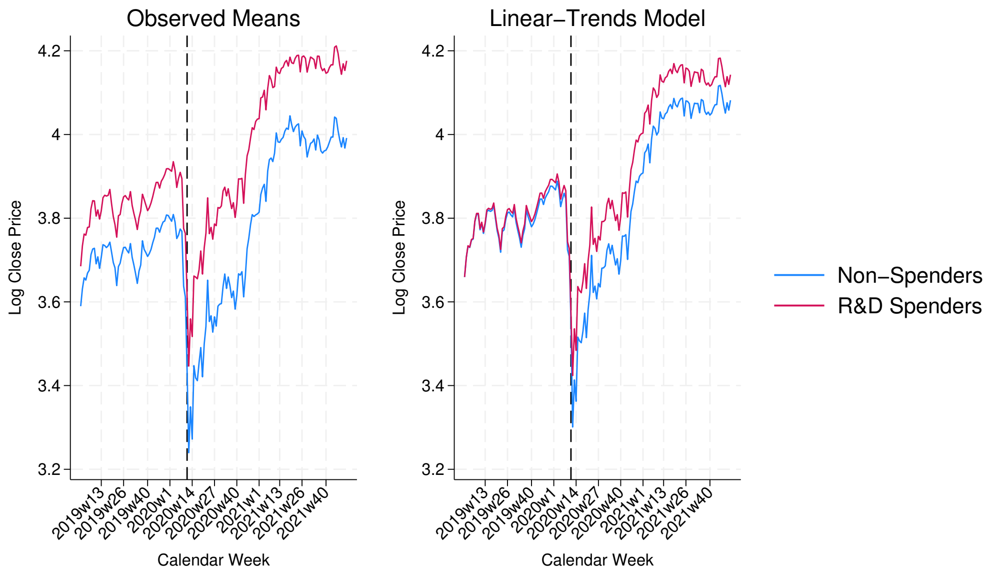
(b) Companies with December Fiscal Year End Dates



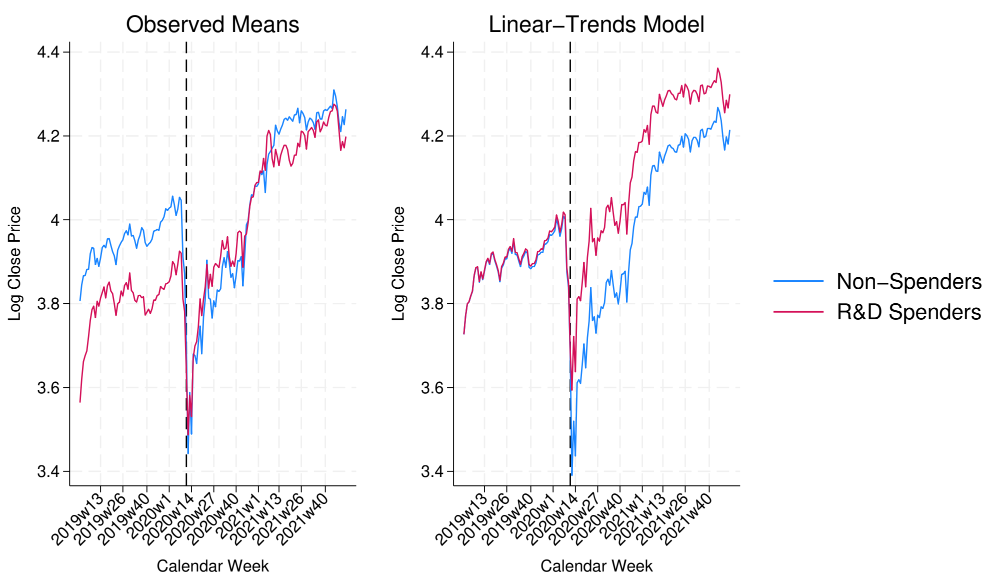
Notes: Panel A is based on TWFE DID regression estimates for the full sample (925 companies, of which 401 are R&D spenders); Panel B is based on TWFE DID regression estimates for the subsample that has December fiscal year ends (674 companies, of which 287 are R&D spenders).

Figure 3: Graphical Diagnostics for Parallel Trends Based on Industry

(a) Manufacturing Companies



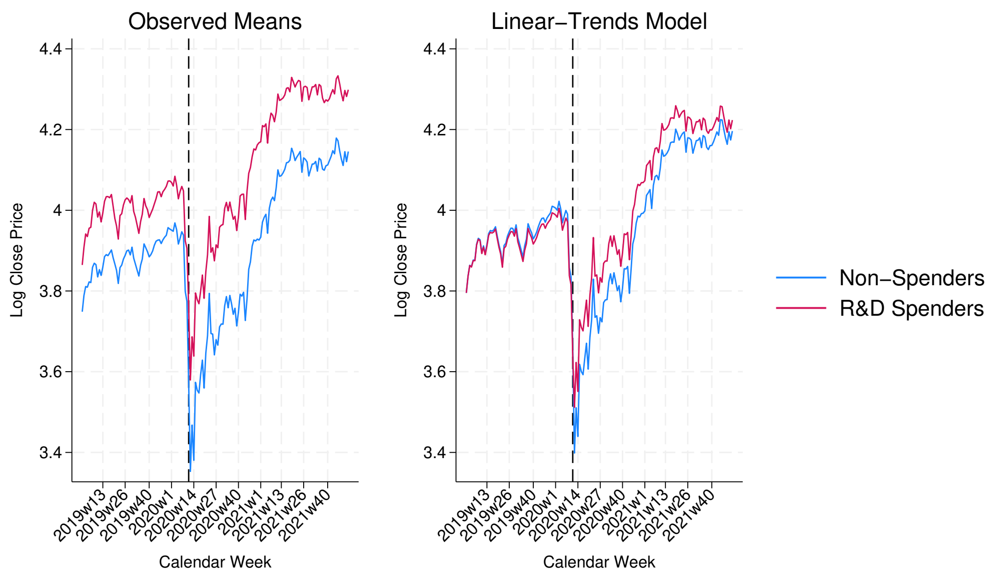
(b) Service Companies



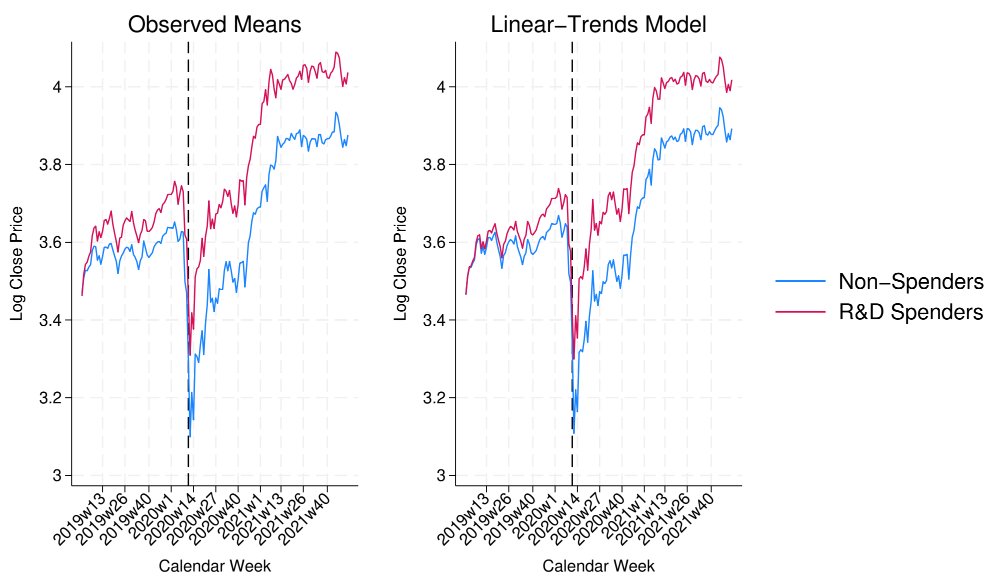
Notes: Panel A is based on TWFE DID regression estimates for the subsample in manufacturing industries (446 companies, of which 326 are R&D spenders); Panel B is based on TWFE DID regression estimates for the subsample in service industries (183 companies, of which 60 are R&D spenders).

Figure 4: Graphical Diagnostics for Parallel Trends Based on Exchange

(a) NYSE Companies



(b) Nasdaq Companies



Notes: Panel A is based on TWFE DID regression estimates for the subsample traded on NYSE (509 companies, of which 205 are R&D spenders); Panel B is based on TWFE DID regression estimates for the subsample traded on Nasdaq (416 companies, of which 196 are R&D spenders).

5.2 RE Logit Regression Results

Descriptive statistics provided in Table A1 suggest that R&D intensity slightly decreased over the observed period (from 0.078 in 2019 to 0.076 in 2020), i.e., some companies in the sample reduced R&D expenses as a share of revenues during the pandemic. This observation is in line with the literature on investment under uncertainty (Bernanke 1983; Dixit and Pindyck 1994; Bloom, Bond, and Van Reenen 2007; Bloom 2009) and makes the testing of Hypotheses 1 and 2 meaningful.

RE logit regressions testing for the baseline effect of strategic investment in innovation (see Table 3, column 1) suggest that higher pre–crisis R&D intensity leads to greater crisis impact resistance ($\beta = 0.181, se = 0.044$). Exponentiation of the coefficient ($e^{0.181} \approx 1.198$) implies that a one–unit increase in log R&D intensity before the crisis increases the odds of impact resistance by around 19.8%. This effect is significant at the 1% level, and it holds as various controls, including industry and location fixed effects, are added to the regression specification (see Table 3, columns 2–6): for instance $\beta = 0.159$ ($se = 0.054$) when controlling for both industry (at the SIC division level) and location (at the region level) fixed effects, as well as financial variables (liquidity and profitability) and age. The inclusion of industry fixed effects at the SIC major group level and location fixed effects at the state level (see Table 3, columns 7 and 8, respectively) weakens the coefficient ($\beta = 0.145$), but it retains its significance at the 5% level.

RE logit regressions testing for the effect of operating expense (see Table 4, column 1) suggest that R&D intensity during the crisis has a stronger association with crisis impact resistance ($\beta = 0.212, se = 0.043$). Similar to the regression estimates for the effect of strategic investment in innovation, the effect of operating expense holds as control variables are added to the regression specification (see Table 4, columns 2–6): e.g., $\beta = 0.170$ ($se = 0.056$) when controlling for both industry (at the SIC division level) and location (at the region level), as well as financial variables (liquidity and profitability) and age. Again, the inclusion of industry fixed effects at the SIC major group level and location fixed effects at the state level (see Table 4, columns 7 and 8) weakens the coefficient ($\beta = 0.181$ and $\beta = 0.173$, respectively), but it retains its significance at the 1% level.

5.3 RE Poisson Regression Results

Poisson regression results, as reported in Table 5 below, suggest that higher R&D intensity is associated with a shorter time to recovery ($\beta = -0.052, se = 0.022$; see column 1). Exponentiation of the coefficient ($e^{-0.052} \approx 0.949$) suggests that a one–unit increase in log R&D intensity during the crisis is associated with a 5.1% decrease in the expected number of recovery weeks. This association is significant at the 5% level, and it strengthens as the two financial controls are added to the regression specification ($\beta = -0.068, se = 0.024$; see column 2). Similarly, the effect holds when age is controlled for ($\beta = -0.067, se = 0.024$; see column 3). However, the coefficient on R&D intensity weakens and becomes insignificant at the 10% level when industry fixed effects are included in the regression specification ($\beta = -0.044, se = 0.027$; see column 4). The inclusion of both industry and location fixed effects reduces the coefficient estimate further ($\beta = -0.039, se = 0.028$), suggesting that these factors are a stronger predictor of faster recovery from the crisis than R&D expense.

Table 3: RE Logit Regression Results Testing for the Effect of Strategic Investment

	Baseline	Augmented						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log *R&D Intensity*$_{2019}$	0.181	0.200	0.180	0.179	0.166	0.159	0.145	0.145
	(0.044)	(0.045)	(0.047)	(0.052)	(0.049)	(0.054)	(0.061)	(0.050)
Log *Liquidity*		-0.121	-0.187	-0.207	-0.193	-0.205	-0.243	-0.244
		(0.101)	(0.107)	(0.108)	(0.107)	(0.108)	(0.113)	(0.102)
Log *Profitability*		0.169	0.210	0.208	0.212	0.210	0.199	0.206
		(0.069)	(0.073)	(0.073)	(0.072)	(0.072)	(0.069)	(0.068)
Age			-0.014	-0.015	-0.015	-0.015	-0.014	-0.014
			(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Industry (Division) FE				✓		✓		
Industry (Major Group) FE							✓	
Location (Region) FE					✓	✓		
Location (State) FE								✓
Constant	2.318	2.968	3.604	3.505	3.738	3.452	3.357	2.682
	(0.182)	(0.305)	(0.340)	(0.348)	(0.364)	(0.412)	(0.375)	(0.246)
Observations	61,932	61,464	61,464	61,464	61,464	61,464	61,464	61,308
Log pseudo–L	-28,268.05	-28,023.17	-28,001.70	-28,000.42	-27,998.94	-27,997.93	-27,976.89	-27,971.52
Wald χ^2	17.08	24.30	49.72	71.05	54.32	70.85	—	—

Notes: The dependent variable in all columns is crisis impact resistance, as defined in Equation 1. Column 1 estimates Equation 6, while columns 2–8 estimate Equation 7. Robust standard errors clustered at the company level are reported in parentheses below coefficient estimates. See Appendix A for descriptive statistics, including the distribution of companies across industries and locations.

Table 4: RE Logit Regression Results Testing for the Effect of Operating Expense

	Baseline	Augmented						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log *R&D Intensity*$_{2020}$	0.212	0.227	0.207	0.195	0.191	0.170	0.181	0.173
	(0.043)	(0.045)	(0.047)	(0.056)	(0.048)	(0.056)	(0.068)	(0.048)
Log *Liquidity*		-0.111	-0.169	-0.190	-0.178	-0.190	-0.235	-0.197
		(0.104)	(0.109)	(0.111)	(0.110)	(0.111)	(0.117)	(0.105)
Log *Profitability*		0.202	0.238	0.237	0.240	0.240	0.233	0.243
		(0.071)	(0.075)	(0.075)	(0.074)	(0.074)	(0.071)	(0.070)
Age			-0.013	-0.014	-0.014	-0.014	-0.014	-0.013
			(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Industry (Division) FE				✓		✓		
Industry (Major Group) FE							✓	
Location (Region) FE					✓	✓		
Location (State) FE								✓
Constant	2.401	3.124	3.709	2.302	3.807	2.097	2.186	2.815
	(0.183)	(0.314)	(0.351)	(0.470)	(0.371)	(0.520)	(0.552)	(0.252)
Observations	60,126	59,748	59,748	59,748	59,748	59,748	59,748	59,592
Log pseudo–L	-27,633.41	-27,387.64	-27,368.42	-27,366.24	-27,365.83	-27,363.63	-27,342.88	-27,337.28
Wald χ^2	24.20	32.65	52.17	—	55.79	—	—	—

Notes: The dependent variable in all columns is crisis impact resistance, as defined in Equation 1. Column 1 estimates Equation 6, while columns 2–8 estimate Equation 7. Robust standard errors clustered at the company level are reported in parentheses below coefficient estimates. See Appendix A for descriptive statistics, including the distribution of companies across industries and locations.

Table 5: RE Poisson Regression Results

	Baseline	Augmented						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log *R&D Intensity*$_{2020}$	-0.052	-0.068	-0.067	-0.044	-0.066	-0.039	-0.029	-0.062
	(0.022)	(0.024)	(0.024)	(0.027)	(0.024)	(0.028)	(0.033)	(0.027)
Log *Liquidity*		0.109	0.113	0.097	0.116	0.097	0.120	0.145
		(0.054)	(0.055)	(0.055)	(0.054)	(0.054)	(0.060)	(0.055)
Log *Profitability*		-0.101	-0.103	-0.108	-0.107	-0.113	-0.126	-0.112
		(0.038)	(0.039)	(0.039)	(0.038)	(0.038)	(0.041)	(0.043)
Age			0.001	0.001	0.001	0.000	0.001	0.001
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Industry (Division) FE				✓		✓		
Industry (Major Group) FE							✓	
Location (Region) FE					✓	✓		
Location (State) FE								✓
Constant	3.192	2.754	2.722	3.618	2.642	3.640	3.664	2.468
	(0.091)	(0.173)	(0.183)	(0.227)	(0.190)	(0.259)	(0.260)	(0.152)
Observations	10,469	10,395	10,395	10,395	10,395	10,395	10,395	10,395
Log pseudo–L	-29,593.69	-29,390.21	-29,390.03	-29,387.77	-29,388.28	-29,385.62	-29,368.88	-29,370.49
Wald χ^2	12,102.91	12,532.59	12,612.82	1,648.55	12,793.71	1,688.36	2,163.81	1,504.37

Notes: The dependent variable in all columns is recovery speed, as defined in Equation 3. Column 1 estimates Equation 8, while columns 2–8 estimate Equation 9. Robust standard errors clustered at the company level are reported in parentheses below coefficient estimates. See Appendix A for descriptive statistics, including the distribution of companies across industries and locations.

6 Discussion

Innovation has long been identified as a source of economic growth (Schumpeter 1942; Romer 1990; Aghion and Howitt 1992; Grossman and Helpman 1994). This paper offers a framework suggesting that innovation is also a source of economic resilience. We find support for this proposition based on high–frequency data of a large sample of companies in both manufacturing and service industries in the US during the COVID–19 pandemic. Our main results are consistent with prior evidence (Dingel and Neiman 2020; Bloom et al. 2025; Cirelli and Gertler 2025) that service industries were less affected by the pandemic than manufacturing industries due to enabling remote work; however, our primary contribution is that we conceptualize the phenomenon of economic resilience by drawing on interdisciplinary knowledge and insights from across the natural and social sciences, including administrative science (Meyer 1982), ecology (Holling 1973), engineering (Holling 1996), political science (Wildavsky 1988), and sociology (Vaughan 2002).

In our conception, resilience is a phenomenon managed over time (Rose 2007; Langley et al. 2013; Weick and Sutcliffe 2015), i.e., across the phases of crisis anticipation, response, and recovery. It manifests itself as the ability to withstand a crisis (*impact resistance*), as well as in the ability to recover faster from a crisis (*recovery speed*). Innovation enhances resilience by increasing the probability of not incurring a loss due to a crisis, as well as by shortening the time required to attain performance levels comparable to the pre–crisis period. Importantly, a key assumption underlying our framework is that organizations are open and rational systems (Thompson 1967) in constant search of knowledge about the environment in which they operate (Cohen and Levinthal 1989, 1990): organizations may act proactively by sending, receiving, and interpreting signals about threats and opportunities in the business environment (Daft and Weick 1984; Miles and Snow 1978), or they may fail to do so—with negative ramifications for various stakeholders, such as employees, buyers, suppliers, and the society at large (Brunnermeier 2021). Although the assumption of rationality may be questioned by invoking such phenomena as myopia (Levinthal and March 1993), the latter observation leads to the practical implications of our research, as elaborated below.

First, recent evidence (Graham et al. 2023) suggests that employees bear substantial costs, both short– and long–term, from corporate bankruptcy, i.e., absence of resilience as crisis impact resistance: annual earnings of individuals whose employers file for bankruptcy decrease by more than ten percent in the first year of such an event, and the present value of their earnings falls short of pre–bankruptcy levels in the following six years. Second, there is influential and growing literature (Acemoglu et al. 2012; Acemoglu, Ozdaglar, and Tahbaz–Salehi 2015; Elliott, Golub, and Leduc 2022; Grossman, Helpman, and Sabal 2024; Acemoglu and Tahbaz–Salehi 2025) underscoring the importance of network effects in the propagation of economic crises: the failure of one business enterprise may lead to the failure of other enterprises that are related to it as buyers or suppliers. Relatedly, there is literature on the microeconomic origins of aggregate fluctuations (Gabaix 2011; Acemoglu, Ozdaglar, and Tahbaz–Salehi 2017), suggesting that shocks to individual firms and sectors, especially if those are large and constitute an important share of total output, may reverberate throughout the economy; thus, developing corporate resilience is key to developing macroeconomic resilience. Finally, innovation and resilience are intertwined in the sustainable development agenda (United Nations Department of Economic and Social Affairs 2025b), and fostering both is crucial for mitigating global challenges such as climate change (United Nations Department of Economic and Social Affairs 2025a).

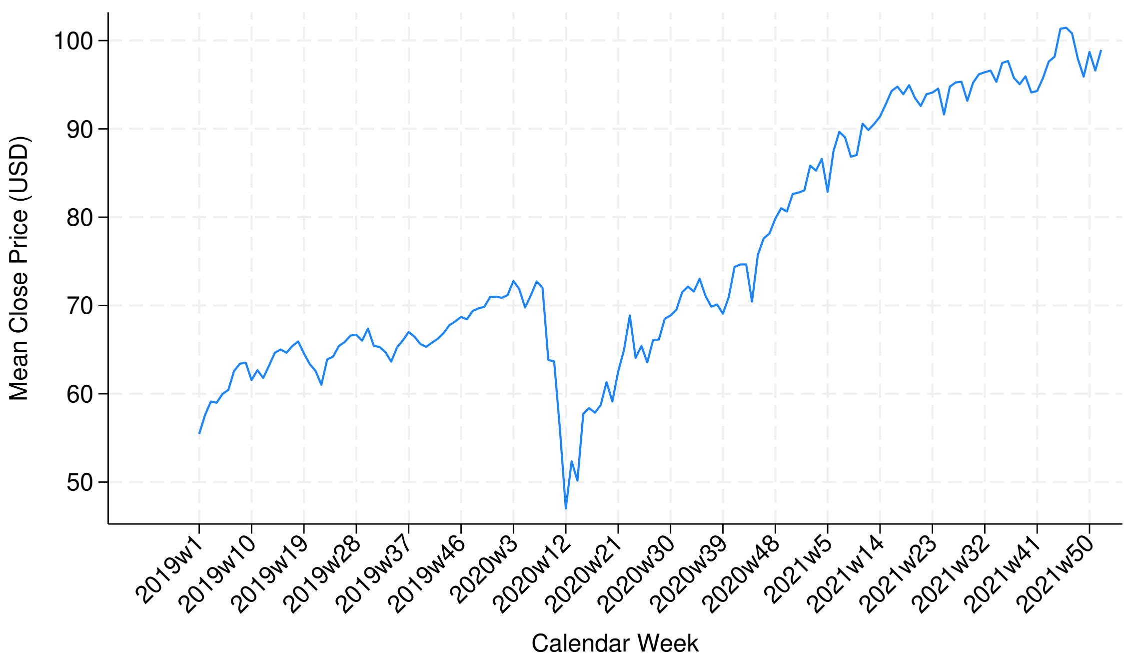
The role of innovation in fostering resilience has been a subject of research aimed at business practitioners since the early 2000s (Hamel and Välikangas 2003; Reinmoeller and van Baardwijk 2005; Teixeira and Werther 2013). Nevertheless, we are positioned to provide further insights based on our research: looking at the relationship between the two phenomena across three phases of a crisis, we find that the allocation of resources to innovation enables resilience as impact resistance and recovery speed; therefore, innovation is a resilience strategy, enabling anticipation and response to threats and opportunities in the business environment. Our research has implications also for public policy, as R&D tax credits are an important component of government support to innovative enterprises both in the US and other developed economies (Bloom, Van Reenen, and Williams 2019; Organization for Economic Cooperation and Development 2025): we find that R&D spenders have greater crisis impact resistance and recover faster if having incurred a loss due to an exogenous crisis; therefore, the extension of R&D tax incentives during a crisis would constitute an effective policy response aimed at restoring the growth path of an economy.

7 Conclusion

This paper provided empirical evidence on how innovation affects resilience by drawing on a large sample of publicly traded companies in the United States. We utilized the setting of the economy–wide crisis caused by the COVID–19 pandemic and found, using corporate financial statements and stock price data, that companies reporting research and development expenses and those not reporting such expenses followed a similar trajectory prior to the crisis; their paths diverged in its aftermath, suggesting that innovation is an antecedent of resilience. Furthermore, we conceptualized resilience in two ways—as crisis impact resistance and recovery speed—revealing that companies allocating resources to innovation before and during the pandemic were less likely to incur a loss due to it, as well as recovered faster if having incurred a loss; therefore, innovation is a resilience strategy.

A Appendix 1

Figure A1: Time Series of Weekly Stock Prices



Notes: The sample includes 925 publicly traded companies in the United States observed for 156 weeks from W1–2019 to W52–2021.

Table A1: Summary Statistics

Variable	Obs.	Mean	SD	Percentiles				
				5^{th}	25^{th}	50^{th}	75^{th}	95^{th}
Impact resistance	144,300	0.777	0.416	0	1	1	1	1
Recovery speed	27,506	42.069	15.712	14	32	45	50	68
R&D intensity$_{2019}$	61,932	0.078	0.100	0.003	0.015	0.037	0.113	0.259
R&D intensity$_{2020}$	60,216	0.076	0.097	0.003	0.015	0.037	0.107	0.235
Liquidity	139,620	2.380	3.155	0.608	1.099	1.693	2.782	5.792
Profitability	144,300	0.088	0.563	0.010	0.031	0.055	0.090	0.179
Age	144,300	34.8	28.335	5	17	27	41	97

Notes: The sample includes 925 publicly traded companies in the United States observed weekly from W1–2019 to W52–2021. Impact resistance is a binary variable equal to one if the stock price of a company in a given week is greater than or equal to its 52–week difference and zero otherwise. Recovery speed is a count variable corresponding to the number of weeks it takes to recover the stock price to its pre–crisis levels, and it is calculated only for companies that incurred a loss on or after W12–2020 ($n = 876$). R&D intensity is computed by dividing R&D expenses in 2019 (2020) by revenues in the same year. Liquidity is measured by the pre–crisis current ratio, i.e., current assets in 2019 divided by current liabilities in the same year. Profitability is measured by the pre–crisis return on assets, i.e., net income in 2019 divided by total assets in 2019. Age is measured by years since incorporation.

Table A2: t–test Statistics

Variable	Group	Obs.	Mean	SD	Difference	p–value
Impact resistance	Non–spenders	81,744	0.7624	0.4256	-0.0334	0.0000
	R&D spenders	62,556	0.7958	0.4031		
Recovery speed	Non–spenders	16,698	43.4464	15.5709	3.5047	0.0000
	R&D spenders	10,808	39.9417	15.6925		
Liquidity	Non–spenders	77,532	1.8914	1.9707	-1.0978	0.0000
	R&D spenders	62,088	2.9891	4.2081		
Profitability	Non–spenders	81,744	0.0605	0.0522	-0.0627	0.0000
	R&D spenders	62,556	0.1232	0.8517		
Age	Non–spenders	81,744	33.0840	26.8399	-3.9584	0.0000
	R&D spenders	62,556	37.0424	30.0296		

Notes: The sample includes 925 publicly traded companies in the United States observed weekly from W1–2019 to W52–2021, of which 401 are R&D spenders based on 2019 annual financial statements. Variable definitions provided in Table A1 above. Unequal variances are assumed. Four decimal digits are reported due to greater precision in differences.

Table A3: Distribution of the Sample by Industries: Manufacturing and Services

SIC Division and Major Group	All Companies	R&D Spenders
Division D: Manufacturing	*48.22*	*81.30*
Major Group 20: Food and Kindred Products	3.35	4.24
Major Group 21: Tobacco Products	0.22	0.50
Major Group 22: Textile Mill Products	0.43	0.50
Major Group 23: Apparel and Other Finished Products Made from Fabrics and Similar Materials	1.19	0.00
Major Group 24: Lumber and Wood Products, except Furniture	0.97	0.25
Major Group 25: Furniture and Fixtures	0.54	1.00
Major Group 26: Paper and Allied Products	0.65	1.25
Major Group 27: Printing, Publishing, and Allied Industries	0.54	0.50
Major Group 28: Chemicals and Allied Products	8.22	14.96
Major Group 29: Petroleum Refining and Related Industries	1.08	1.25
Major Group 30: Rubber and Miscellaneous Plastics Products	1.19	2.24
Major Group 31: Leather and Leather Products	0.43	0.00
Major Group 32: Stone, Clay, Glass, and Concrete Products	0.32	0.50
Major Group 33: Primary Metal Industries	1.51	2.00
Major Group 34: Fabricated Metal Products, except Machinery and Transportation Equipment	2.27	4.24
Major Group 35: Industrial and Commercial Machinery and Computer Equipment	6.49	12.97
Major Group 36: Electronic and Other Electrical Equipment and Components, except Computer Equipment	8.22	16.21
Major Group 37: Transportation Equipment	4.11	6.98
Major Group 38: Measuring, Analyzing, and Controlling Instruments; Photographic, Medical and Optical Goods; Watches and Clocks	5.30	9.23
Major Group 39: Miscellaneous Manufacturing Industries	1.19	2.49
Division I: Services	*19.78*	*14.96*
Major Group 70: Hotels, Rooming Houses, Camps, and Other Lodging Places	1.62	0.00
Major Group 72: Personal Services	0.54	0.25
Major Group 73: Business Services	11.57	12.47
Major Group 75: Automotive Repair, Services, and Parking	0.22	0.00
Major Group 78: Motion Pictures	0.32	0.25
Major Group 79: Amusement and Recreation Services	0.86	0.25
Major Group 80: Health Services	1.51	0.25
Major Group 81: Legal Services	0.11	0.00
Major Group 82: Educational Services	0.97	0.25
Major Group 87: Engineering, Accounting, Research, Management, and Related Services	2.05	1.25

Notes: The sample includes 925 publicly traded companies in the United States, of which 401 are R&D spenders based on 2019 annual financial statements. Numbers denote the percent of total within the full sample and within the subsample of R&D spenders, respectively.

Table A4: Distribution of the Sample by Industries: Non–Manufacturing and Services

SIC Division and Major Group	All Companies	R&D Spenders
Division A: Agriculture, Forestry, and Fishing	*0.43*	*0.00*
Major Group 01: Agricultural Production Crops	0.11	0.00
Major Group 07: Agricultural Services	0.32	0.00
Division B: Mining	*2.92*	*0.25*
Major Group 10: Metal Mining	0.22	0.25
Major Group 12: Coal Mining	0.54	0.00
Major Group 13: Oil and Gas Extraction	1.73	0.00
Major Group 14: Mining and Quarrying of Nonmetallic Minerals, except Fuels	0.43	0.00
Division C: Construction	*2.92*	*0.50*
Major Group 15: Building Construction General Contractors and Operative Builders	1.41	0.25
Major Group 16: Heavy Construction other than Building Construction Contractors	0.86	0.25
Major Group 17: Construction Special Trade Contractors	0.65	0.00
Division E: Transportation, Communications, Electric, Gas and Sanitary Services	*12.54*	*1.00*
Major Group 40: Railroad Transportation	0.32	0.00
Major Group 42: Motor Freight Transportation and Warehousing	1.19	0.00
Major Group 44: Water Transportation	0.22	0.00
Major Group 45: Transportation by Air	1.19	0.00
Major Group 46: Pipelines, except Natural Gas	0.32	0.00
Major Group 47: Transportation Services	0.86	0.00
Major Group 48: Communications	2.05	0.00
Major Group 49: Electric, Gas, and Sanitary Services	6.38	1.00
Division F: Wholesale Trade	*4.86*	*1.25*
Major Group 50: Wholesale Trade—Durable Goods	2.70	0.50
Major Group 51: Wholesale Trade—Non–Durable Goods	2.16	0.75
Division G: Retail Trade	*8.32*	*0.75*
Major Group 52: Building Materials, Hardware, Garden Supply, and Mobile Home Dealers	0.54	0.00
Major Group 53: General Merchandise Stores	1.08	0.00
Major Group 54: Food Stores	0.43	0.00
Major Group 55: Automotive Dealers and Gasoline Service Stations	1.62	0.00
Major Group 56: Apparel and Accessory Stores	0.76	0.50
Major Group 57: Home Furniture, Furnishings, and Equipment Stores	0.32	0.00
Major Group 58: Eating and Drinking Places	2.16	0.25
Major Group 59: Miscellaneous Retail	1.41	0.00

Notes: The sample includes 925 publicly traded companies in the United States, of which 401 are R&D spenders based on 2019 annual financial statements. Numbers denote the percent of total within the full sample and within the subsample of R&D spenders, respectively.

Table A5: Distribution of the Sample by Locations

Census Bureau Region	State	All Companies	R&D Spenders
Region 1: Northeast		*23.78*	*23.94*
	Connecticut (CT)	2.38	3.24
	Maine (ME)	0.22	0.25
	Massachusetts (MA)	4.32	7.23
	New Hampshire (NH)	0.54	0.25
	New Jersey (NJ)	3.46	3.49
	New York (NY)	7.03	6.48
	Pennsylvania (PA)	5.30	6.48
	Rhode Island (RI)	0.43	0.75
	Vermont (VT)	0.11	0.00
Region 2: Midwest		*21.41*	*28.18*
	Illinois (IL)	4.97	5.24
	Indiana (IN)	1.73	2.24
	Iowa (IA)	0.43	0.25
	Kansas (KS)	0.32	0.25
	Michigan (MI)	2.38	2.74
	Minnesota (MN)	3.46	4.49
	Missouri (MO)	1.08	1.50
	Nebraska (NE)	0.32	0.25
	Ohio (OH)	4.00	3.24
	South Dakota (SD)	0.22	0.25
	Wisconsin (WI)	2.49	3.49
Region 3: South		*31.78*	*19.95*
	Alabama (AL)	0.54	0.25
	Arkansas (AR)	0.86	0.25
	Delaware (DE)	0.43	0.25
	District of Columbia (DC)	0.43	0.50
	Florida (FL)	3.57	1.00
	Georgia (GA)	3.46	2.74
	Kentucky (KY)	0.97	1.00
	Louisiana (LA)	0.43	0.00
	Maryland (MD)	1.08	1.25
	North Carolina (NC)	2.49	2.24
	Oklahoma (OK)	0.86	0.50
	South Carolina (SC)	0.54	0.75
	Tennessee (TN)	0.73	1.25
	Texas (TX)	10.70	5.49
	Virginia (VA)	3.57	2.49
	West Virginia (WV)	0.11	0.00
Region 4: West		*23.03*	*27.93*
	Arizona (AZ)	1.84	1.25
	California (CA)	13.84	20.95
	Colorado (CO)	2.05	1.75
	Hawaii (HI)	0.11	0.00
	Idaho (ID)	0.11	0.00
	Nevada (NV)	1.08	0.50
	Oregon (OR)	0.86	0.50
	Utah (UT)	1.08	2.00
	Washington (WA)	2.05	1.00

Notes: The sample includes 925 publicly traded companies in the United States, of which 401 are R&D spenders. Numbers denote the percent of total within the full sample and within the subsample of R&D spenders, respectively.

B Appendix 2

Table B1: TWFE DID Regression Results Based on Monthly Frequency

	All	Manufacturing	Services
	(n = 925)	(n = 446)	(n = 183)
R&D spender × *Crisis*	0.098	0.078	0.132
	(0.023)	(0.034)	(0.057)
	[0.053; 0.142]	[0.011; 0.146]	[0.020; 0.243]
Company FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
n (non–spender)	524	120	123
n (R&D spender)	401	326	60
N (company–month obs.)	33,300	16,056	6,588
Parallel trends test	$F_{(1,924)} = 3.23$	$F_{(1,445)} = 0.84$	$F_{(1,182)} = 0.31$

Notes: The dependent variable in all columns is the natural logarithm of the monthly close price, obtained by averaging weekly stock prices obtained from the LSEG Workspace (London Stock Exchange Group 2025), and the time spans from M1–2019 to M12–2021, for a total of 36 months. The classification of a company as an R&D spender is based on 2019 annual financial statements, obtained from the SEC EDGAR API (United States Securities and Exchange Commission 2025c). "Crisis" indicates months after COVID–19 was declared an emergency by the presidential decree in March 2020 (Federal Register 2020). Manufacturing companies are those operating under SIC Division D; service companies are those operating under SIC Division I (Occupational Safety and Health Administration 2025). Robust standard errors clustered at the company level in parentheses below coefficient estimates; 95% confidence intervals in brackets. The null hypothesis for the parallel trends test is that linear trends in the pre–crisis period are parallel.

Table B2: TWFE DID Regression Results Based on Quarterly Frequency

	All	Manufacturing	Services
	(n = 925)	(n = 446)	(n = 183)
R&D spender × Crisis	0.099	0.079	0.135
	(0.023)	(0.034)	(0.057)
	[0.055; 0.144]	[0.012; 0.147]	[0.022; 0.247]
Company FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
n (non–spender)	524	120	123
n (R&D spender)	401	326	60
N (company–quarter obs.)	11,100	5,352	2,196
Parallel trends test	$F_{(1,924)} = 1.72$	$F_{(1,445)} = 0.47$	$F_{(1,182)} = 0.08$

Notes: The dependent variable in all columns is the natural logarithm of the quarterly close price, obtained by averaging weekly stock prices obtained from the LSEG Workspace (London Stock Exchange Group 2025), and the time spans from Q1–2019 to Q4–2021, for a total of 12 quarters. The classification of a company as an R&D spender is based on 2019 annual financial statements, obtained from the SEC EDGAR API (United States Securities and Exchange Commission 2025c). "Crisis" indicates quarters after COVID–19 was declared an emergency by the presidential decree in Q1–2020 (Federal Register 2020). Manufacturing companies are those operating under SIC Division D; service companies are those operating under SIC Division I (Occupational Safety and Health Administration 2025). Robust standard errors clustered at the company level in parentheses below coefficient estimates; 95% confidence intervals in brackets. The null hypothesis for the parallel trends test is that linear trends in the pre–crisis period are parallel.

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