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ESSAYS ON INNOVATION AS A RESILIENCE STRATEGY

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CONTENTS

ABSTRACT

This dissertation examines innovation as a resilience strategy. It consists of three interrelated chapters that study how innovation affects corporate resilience in the United States, the Euro Area, and the United Kingdom. In the first chapter, co–authored with my supervisor, I advance a new theoretical framework on how innovation affects resilience. Specifically, I build on prior literature in the field of management, arguing that the relationship between innovation and resilience can be conceived across the three phases of crisis management: anticipation, response, and recovery. Innovation at the crisis anticipation phase enables resilience as impact resistance, and innovation at the crisis response phase enables resilience as recovery speed. I use the financial statements and stock price data of 925 publicly traded companies in the United States to test the hypotheses advanced in the first chapter. The second chapter builds on the first chapter, arguing that the relationship between innovation and resilience varies across countries that are institutionally different and implement different policies during crises—a proposition that is supported by the literature on institutions and economic growth. I use data of 1,209 companies in the 19 Euro Area member states—countries that are in a monetary union but do not form a fiscal union. I find that the relationship between innovation and resilience is stronger in civil law countries that provide tax incentives for innovation under crisis conditions, such as Germany. Finally, the third chapter argues that due to public policy, the relationship between innovation and resilience also varies within the same country. I use data of 313 companies headquartered across 12 regions in the United Kingdom—a country that is characterized by disparities in regional development. I find that innovation has a stronger impact on resilience in regions that receive greater funding for research and innovation. Overall, this dissertation provides a comparative examination of how innovation affects resilience over time and space: I use high–frequency data of around 2,500 companies headquartered in 21 advanced economies, with around 380,000 company–week observations before and during the COVID–19 pandemic.

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Finally, I would like to thank my family for supporting my decision to move and carry out my doctoral research in Italy—a country I love. The second chapter of the dissertation benefited from thorough feedback from my colleague, Dr. Lorenzo Mori.

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PREFACE

Each of the three chapters constituting this dissertation has seven sections: introduction; theoretical framework and hypotheses; empirical setting and data; measures and econometric estimation; results; discussion; and conclusion. In addition, three appendices supplement each of the chapters, providing descriptive statistics. The chapters build on each other, and, therefore, should be read sequentially. Many references are common across chapters; thus, the dissertation has one bibliography. The primary field of the dissertation is Business Economics (*JEL* classification code M2), although its contents span across several fields, including Public Economics and Regional Economics. The first two chapters of the dissertation have been released as *Marco Fanno* working papers 326 and 327, respectively (Shakhmuradyan 2025; Shakhmuradyan and Campagnolo 2025).

Theoretically, the first chapter is grounded in the field of business administration, as it delineates three phases of crisis management (anticipation, response, and recovery), as well as distinguishes between strategic investment versus operating expense on innovation. The second chapter is grounded in the field of institutional economics, as its key arguments are the role of institutions and public policies in fostering resilience. The third chapter synthesizes extant literature in business administration and regional economics, offering a theoretical framework and empirical evidence on how policies implemented at the regional level affect resilience at the organizational level.

Methodologically, all chapters entail panel data analysis of corporate financial statements and weekly stock price data. The two measures of resilience (*impact resistance* and *recovery speed*) were developed in Fall 2022 and are used in all chapters; additionally, the second chapter has regression specifications that include interaction terms with fiscal policy. Throughout the dissertation, I report coefficient estimates and robust standard errors clustered at the company level, refraining from cutoff values for statistical significance and corresponding notations with asterisks (e.g., *** if $p < 0.01$). The results section in each chapter includes statements on the economic significance, i.e., effect size, of coefficient estimates, thereby following best practice in the fields of economics and management.

CHAPTER 1
CORPORATE INNOVATION AND RESILIENCE IN THE UNITED STATES

1.1 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

[*]The extended abstract of the paper on which this chapter is based was presented at the paper development workshop of the *Academy of Management Journal*, held at LUISS Guido Carli University in Rome, Italy (12–13 October 2022). I would like to thank the local organizer of the workshop, Professor Alessandro Zattoni, as well as the Editor, Professor Marc Gruber (Ecole Polytechnique Fédérale de Lausanne), for selecting me as a participant; Professor Anne ter Wal (Imperial College London), Associate Editor of the *Journal* at the time, provided feedback on the paper during the workshop. The full paper was presented at the internal seminar of the Department of Economics and Management, University of Padua, Italy (10 May 2023), as well as two international conferences: the Annual Meeting of the Academy of Management (AOM) in Boston, United States (4–8 August 2023), and the Annual Conference of the Society for Institutional and Organizational Economics (SIOE) in Frankfurt, Germany (24–26 August 2023). I would like to thank Professor Elena Novelli (Bayes Business School), the Program Chair of the AOM Technology and Innovation Management Division at the time, and Professor Guido Friebel (Goethe University Frankfurt), the SIOE President, for selecting the paper for presentation at the conferences; three anonymous reviewers provided feedback on an earlier version of the paper.

Chapter keywords: crisis; innovation; resilience; strategy.
JEL classification codes: E32; M21; O32.

2024; Grossman, Helpman, and Sabal 2024; Acemoglu and Tahbaz–Salehi 2025). [1] In the field of management, resilience has come to constitute an overarching notion of organizational capabilities to cope with environmental turbulence, as scholars associate it 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 chapter 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. 2021a; Bergami et al. 2022; Capodistrias et al. 2022) and 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 greater 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

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.

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 chapter offers a new theoretical framework on how innovation affects resilience. Specifically, we build on the established research on organizational adaptation and crisis management (Meyer 1982; Wildavsky 1988; Weick and Sutcliffe 2015; Linnenluecke 2017; Williams et al. 2017), advancing a continuous–time dynamic model composed of three phases—*anticipation, response*, and *recovery.* Furthermore, based on conceptions derived 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 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. (2021a) 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 chapter is characterized by simplicity and generality (Langley 1999), thus enabling the provision of actionable implications for management practice.

Second, this chapter 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 chapter, 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.

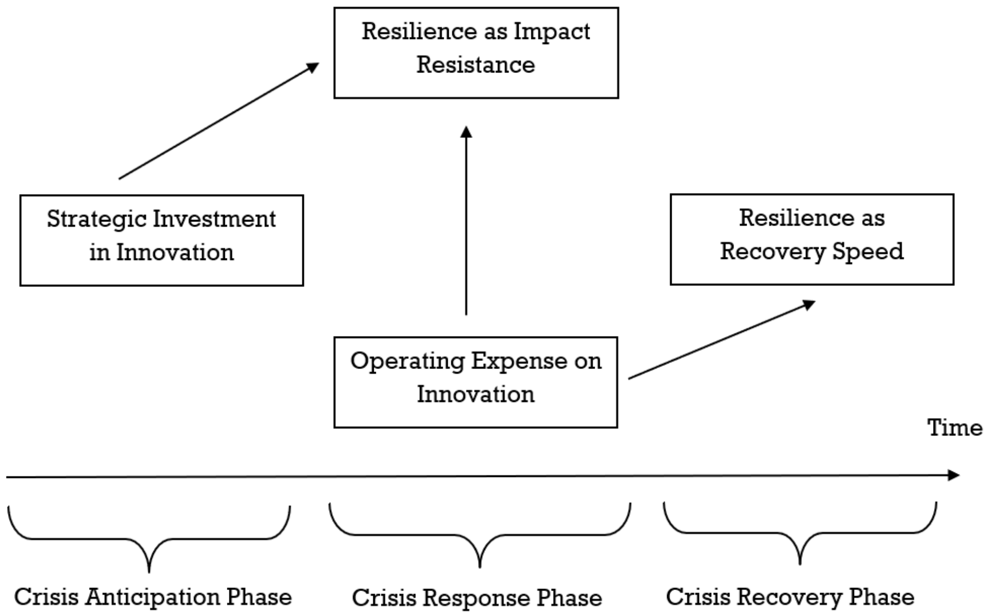
The rest of the chapter is organized as follows: Section 1.2 below lays out the theoretical framework of our research and advances testable hypotheses. It is followed by Section 1.3, which describes the empirical setting and data we use; Section 1.4 discusses our measures and estimation methods; Section 1.5 provides the results; Section 1.6 discusses the results in relation to the extant literature; and Section 1.7 concludes. Additional details are provided in the appendix to this chapter (Supplement Section A1).

1.2 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 1.1 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 1.1: Theoretical Framework on How Innovation Affects Resilience



Source: Own elaboration.

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.*

1.3 Empirical Setting and Data

1.3.1 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 8 June 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 19 July 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]

1.3.2 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 13 March 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 9

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).

November 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 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;

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 Section 1.4 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.

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 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]

To reiterate, the results reported below are based on a panel data set of publicly traded

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.

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 × T = 156). Supplement Section A1 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 available in the working paper version of this chapter (Shakhmuradyan and Campagnolo 2025).

1.4 Measures and Econometric Estimation

1.4.1 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):

$$IR = \begin{cases} 1 & \text{if } P_t \geq P_{t-s} \\ 0 & \text{otherwise.} \end{cases} \tag{1.1}$$

In Equation 1.1 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:

$$RS \in \mathbb{N}. \tag{1.2}$$

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:

$$1 \leq RS \leq 92. \tag{1.3}$$

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).

1.4.2 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,

$$\textit{R\&D Intensity} = \frac{\textit{R\&D Expenses}}{\textit{Revenues}}. \tag{1.4}$$

1.4.3 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:

$$\ln(Price_{it}) = \phi_i + \gamma_t + \alpha RDS_i \times Crisis_t + \epsilon_{it}, \tag{1.5}$$

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:

$$\Pr(IR_{it} = 1 \mid RDI_{it}, \alpha_i) = \Lambda(\alpha_i + \beta RDI_{it}), \tag{1.6}$$

where IR_{it} is the crisis impact resistance of company i at time t; RDI_{it} is its R&D

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 1.5.

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).

intensity—measured before or during the crisis; and α_i is a normally–distributed random effect (RE). The augmented specification with controls (see Section 1.4.4 below) has the following form:

$$\Pr(IR_{it} = 1 \mid RDI_{it}, x_{it}, \alpha_i) = \Lambda(\alpha_i + \beta RDI_{it} + \boldsymbol{x}'_{it}\boldsymbol{\gamma}). \tag{1.7}$$

We expect the β coefficient in both Equations 1.6 and 1.7 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:

$$\mathrm{E}(RS_{it} \mid RDI_{it}, \alpha_i) = \exp(\alpha_i + \beta RDI_{it}), \tag{1.8}$$

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:

$$\mathrm{E}(RS_{it} \mid RDI_{it}, x_{it}, \alpha_i) = \exp(\alpha_i + \beta RDI_{it} + \boldsymbol{x}'_{it}\boldsymbol{\gamma}). \tag{1.9}$$

We expect the β coefficient in both Equations 1.8 and 1.9 to be negative, i.e., greater R&D intensity shortens the time to recovery, *ceteris paribus*.

1.4.4 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 and 57 major groups in both manufacturing and service industries (see Tables A3 and A4). [10]

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 1.3.1 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).

1.5 Results

1.5.1 TWFE DID Regression Results

The two–way fixed effects regression results based on the analysis of the full sample (see Table 1.1, column 1 below) suggest that the interaction term *R&D spender* × *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 1.2. Disaggregation of the sample by industries (see Table 1.1, 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 subsamples ($F = 0.31$ and 0.03, respectively; see Panels A and B of Figure 1.3).

As noted in Section 1.4.3 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 1.2, 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 1.2 below). We further split the sample based on exchange (see Table 1.2, 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 1.1, 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 SEC 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 1.1: TWFE DID Regression Results, United States

	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.

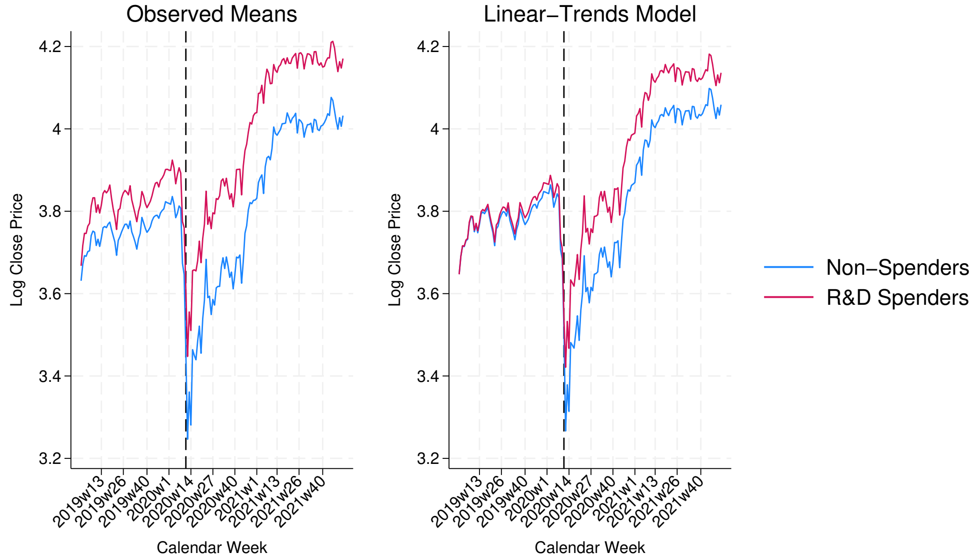
Table 1.2: TWFE DID Regression Results Accounting for Heterogeneity

	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	$F_{(1,673)} = 0.24$	$F_{(1,508)} = 0.48$	$F_{(1,415)} = 4.57$

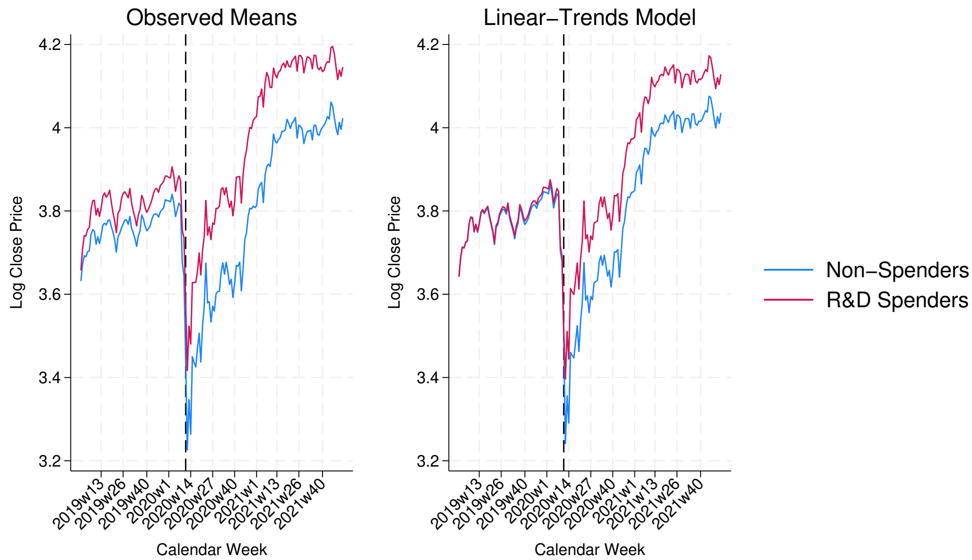
Notes: The dependent variable in all columns is the natural logarithm of the weekly close price, obtained from the LSEG Workspace (London Stock Exchange Group 2025), and the time spans from W1–2019 to W52–2021, for a total of 156 weeks. The classification of a company as an R&D spender is based on 2019 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 1.2: Graphical Diagnostics for Parallel Trends, United States

(a) All Companies



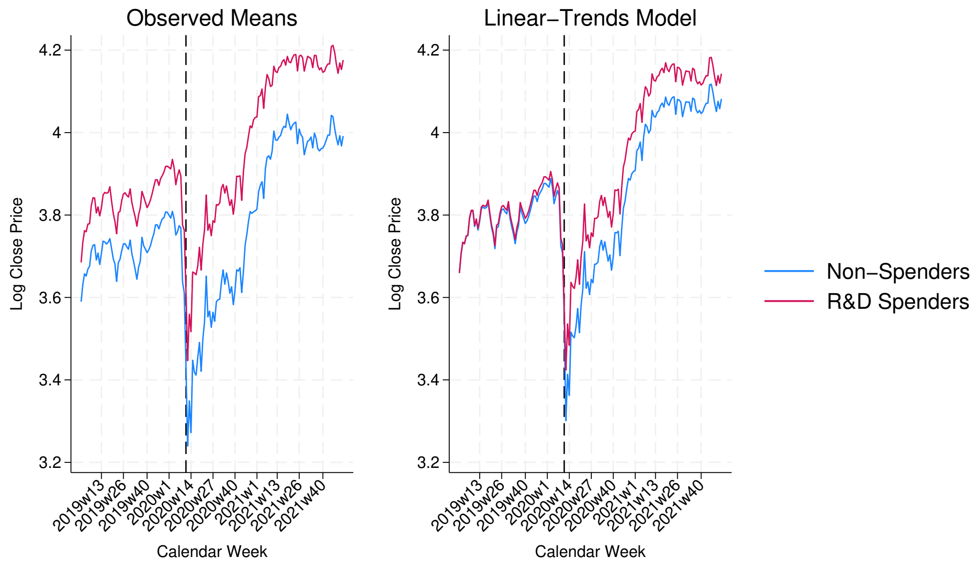
(b) Companies with December Fiscal Year End Dates



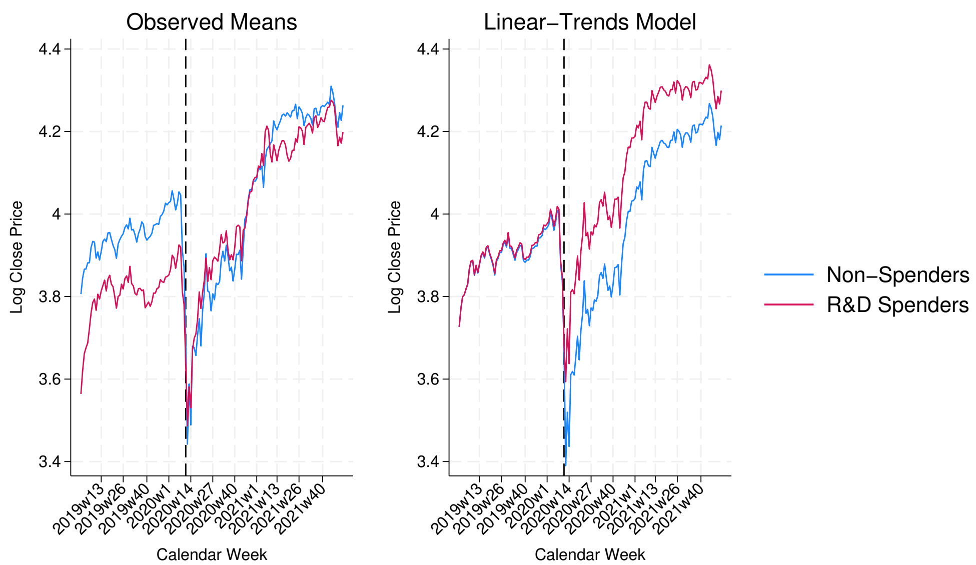
Notes: Panel A is based on TWFE DID regression estimates for the full sample (925 companies, of which 401 are R&D spenders); Panel B is based on TWFE DID regression estimates for the subsample that has December fiscal year ends (674 companies, of which 287 are R&D spenders).

Figure 1.3: Graphical Diagnostics for Parallel Trends Based on Industry, United States

(a) Manufacturing Companies



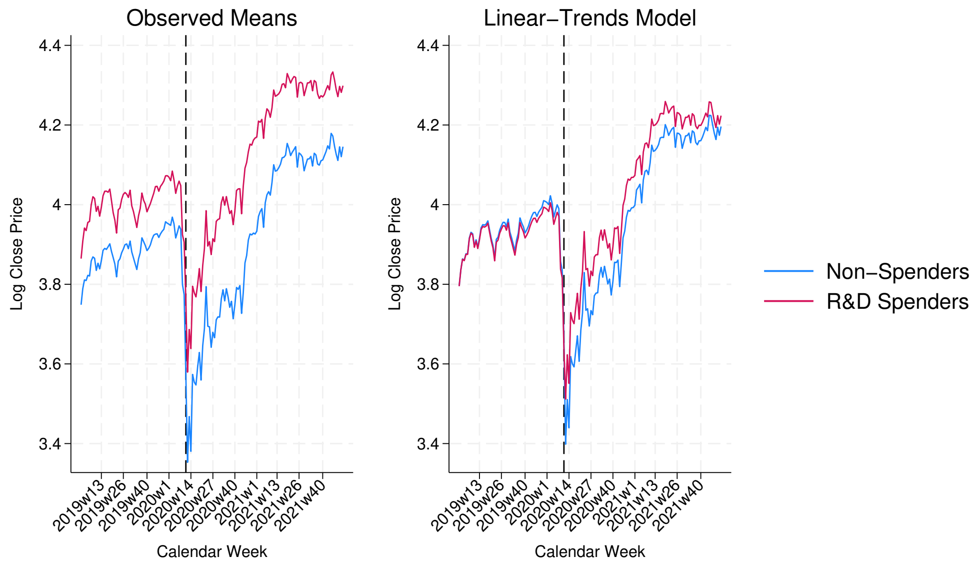
(b) Service Companies



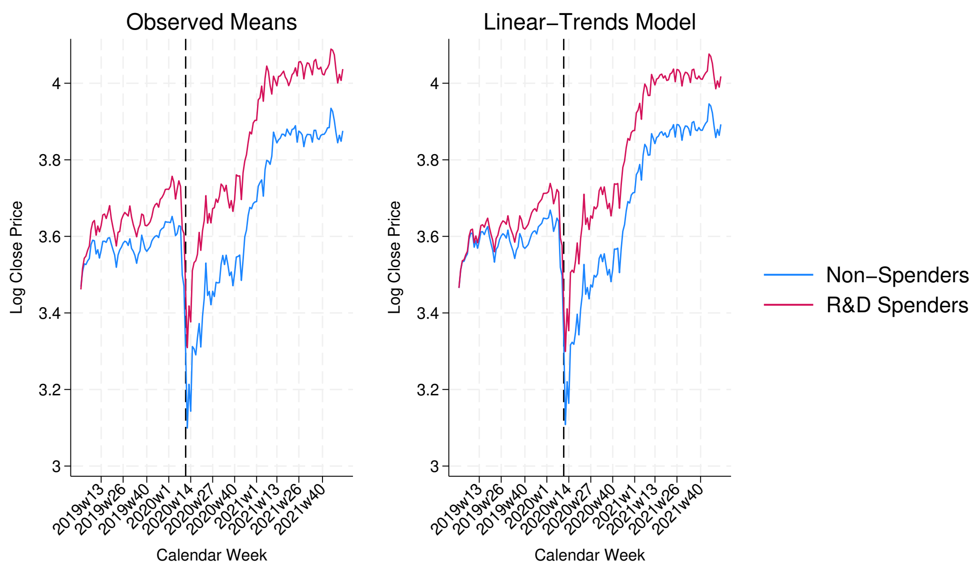
Notes: Panel A is based on TWFE DID regression estimates for the subsample in manufacturing industries (446 companies, of which 326 are R&D spenders); Panel B is based on TWFE DID regression estimates for the subsample in service industries (183 companies, of which 60 are R&D spenders).

Figure 1.4: Graphical Diagnostics for Parallel Trends Based on Exchange, United States

(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).

1.5.2 RE Logit Regression Results

Descriptive statistics provided in Table A1 suggest that average 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.

The RE logit regression model testing for the baseline effect of strategic investment in innovation (see Table 1.3, column 1) suggests 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 1.3, 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 1.3, columns 7 and 8, respectively) weakens the coefficient ($\beta = 0.145$), but it retains its significance at the 5% level.

The RE logit regression model testing for the baseline effect of operating expense (see Table 1.4, column 1) suggests 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, the effect of operating expense holds as control variables are added to the regression specification (see Table 1.4, 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. The inclusion of industry fixed effects at the SIC major group level and location fixed effects at the state level (see Table 1.4, columns 7 and 8) weakens the coefficient ($\beta = 0.181$ and $\beta = 0.173$, respectively), but it retains its significance at the 1% level.

1.5.3 RE Poisson Regression Results

Poisson regression results, as reported in Table 1.5 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 stronger predictors of faster recovery from the crisis than R&D expense.

Table 1.3: 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 1.1. Column 1 estimates Equation 1.6, while columns 2–8 estimate Equation 1.7. Robust standard errors clustered at the company level are reported in parentheses below coefficient estimates. See Appendix A1 for descriptive statistics, including the distribution of companies across industries and locations.

Table 1.4: 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 1.1. Column 1 estimates Equation 1.6, while columns 2–8 estimate Equation 1.7. Robust standard errors clustered at the company level are reported in parentheses below coefficient estimates. See Appendix A1 for descriptive statistics, including the distribution of companies across industries and locations.

Table 1.5: RE Poisson Regression Results, United States

	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 1.3. Column 1 estimates Equation 1.8, while columns 2–8 estimate Equation 1.9. Robust standard errors clustered at the company level are reported in parentheses below coefficient estimates. See Appendix A1 for descriptive statistics, including the distribution of companies across industries and locations.

1.6 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 chapter 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) 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 2025b): 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.

1.7 Conclusion

This chapter 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.

CHAPTER 2
CORPORATE INNOVATION AND RESILIENCE IN THE EURO AREA

2.1 Introduction

The question of what fosters resilience, i.e., the ability of economic agents to withstand and rebound from crises, is of both academic and policy relevance. Interest in resilience within the field of economics arose largely in the aftermath of the global financial crisis (Acemoglu, Ozdaglar, and Tahbaz–Salehi 2015), and it has recently been revived due to the COVID–19 pandemic (Pagano, Wagner, and Zechner 2023; Brunnermeier 2024; Copestake, Estefania–Flores, and Furceri 2024; Eichengreen, Park, and Shin 2024). In particular, scholars have studied supply chain resilience due to the unprecedented disruptions in global supply chains caused by the pandemic (Grossman, Helpman, and Lhuillier 2023; Grossman,

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Helpman, and Sabal 2024; Acemoglu and Tahbaz–Salehi 2025). [1] Less attention has been devoted to inherent company characteristics that contribute to resilience, such as culture, structure, and governance (Aghion et al. 2021; Ding et al. 2021; Li et al. 2021b).

In this paper, I address two interrelated research questions: *Does innovation enhance corporate resilience?* and *Do institutions and government policies implemented during crises affect corporate resilience?* These are important questions to address due to the uncertainty and volatility associated with the current business environment, as well as the aim of governments to design cost–effective measures supporting businesses affected by economic crises. Based on the endogenous growth theory (Schumpeter 1942; Arrow 1962; Romer 1990; Grossman and Helpman 1991; Aghion and Howitt 1992), I hypothesize that companies allocating resources to innovation, i.e., reporting research and development (R&D) expenses, are more resilient. Specifically, I conceive of resilience as crisis *impact resistance* and *recovery speed*, arguing that innovation enhances resilience in two ways: first, it makes companies less likely to incur a loss due to an exogenous crisis, and second, it enables the faster recovery of those companies that incur a loss. Furthermore, drawing on the literature on institutions as a source of economic growth (North 1990; Hall and Jones 1999; Acemoglu, Johnson, and Robinson 2005; Acemoglu 2025), law and finance (La Porta et al. 1998), and tax policy and investment (Hall and Jorgenson 1967; Bloom, Griffith, and Van Reenen 2002; Hassett and Hubbard 2002; Zwick and Mahon 2017), I hypothesize that institutions and government policies matter for corporate resilience: the observed impact of innovation on resilience is greater in countries that provide a more favorable environment for business innovation in general and tax incentives for innovation under crisis conditions in particular.

I observe innovation and resilience using financial statements and stock prices of a large sample of companies traded in the euro area (EA) member states—a group of 20 economies that have formed a monetary union since 1999 but retain autonomy over business taxation,

1. Notably, the National Bureau of Economic Research hosted two conferences on the resilience of supply chains in 2024 (Spring and Fall), featuring 14 papers in total. See National Bureau of Economic Research (2024a, 2024b) for further details.

and therefore, implemented different fiscal policies in response to the COVID–19 pandemic. Specifically, my baseline sample includes all EA member states as of 1 January 2019 (thereby excluding Croatia, which adopted the euro on 1 January 2023) and around 1,200 companies operating across different industries and locations. To examine the role of fiscal policy in enhancing resilience, I restrict the sample to 17 member states that are also members of the Organization for Economic Cooperation and Development (OECD), as data on corporate income tax rates and incentives, especially those implemented during the COVID–19 pandemic, are provided by the OECD. Finally, to examine the role of institutions, I restrict the sample to 11 member states that have been classified by La Porta et al. (1998) as belonging to either of the four legal origins (English, French, German, and Scandinavian): in major part, those are the member states that formed the EA on 1 January 1999 and founded the OECD in 1960. Overall, I have panel data of around 190,000 company–week observations starting in 2019 and ending in 2021. [2]

By examining the relationship between corporate innovation and resilience, I contribute to several strands of economic literature. First and most importantly, I contribute to the growing literature on economic resilience. Although I am not the first to examine whether more innovative companies are more resilient (see Ahn, Mortara, and Minshall (2018) and Bertschek, Polder, and Schulte (2019) for earlier evidence), this paper is the first—to the best of my knowledge—to utilize the setting of a monetary union in the absence of a fiscal union (Farhi and Werning 2017) to examine whether the impact of innovation on resilience varies depending on different institutional environments and crisis response policies implemented by national governments. Analogously to La Porta et al. (1998, p. 1114), who asked whether being a shareholder in France gives investors the same privileges as being a shareholder in, for instance, the United States, I ask and provide an answer to the following question: Does being an innovator in France enable the same capacity

2. Upon recommendation of the World Health Organization, the pandemic ceased to be an emergency in the EA in May 2023 (World Health Organization 2025). However, I exclude the years 2022 and 2023 due to the war in Ukraine, which constitutes another exogenous crisis affecting its member states starting in February 2022. As noted by Ramey (2016, p. 75), in the presence of two exogenous shocks, it is not possible to identify the *unique causal effects* of one relative to another.

for resilience as being an innovator in, for instance, Germany? In other words, *Does innovation contribute equally to corporate resilience in countries that are institutionally different and implement different policies during crises?* The answer is “no”, as I find that institutions and policies do matter for resilience, and they do so in countries that are comparable along many dimensions relevant to economic outcomes (i.e., founding members of the EA and the OECD), as well as in the process of economic convergence (member states that joined the EA during the early– and mid–2000s). [3]

Secondly, I contribute to the literature on tax policy and business investment, which, dating to Hall and Jorgenson (1967) and as reviewed by Hassett and Hubbard (2002), suggests that tax incentives are cost–effective in stimulating private investment. Most prior research in this area, including the recent contributions by Zwick and Mahon (2017), Guceri and Liu (2019), Dechezleprêtre et al. (2023), and Lichter et al. (2025), has focused on tax incentives provided during growth periods, while economic theory (Bernanke 1983; Dixit and Pindyck 1994; Bloom 2009) and the extant empirical evidence on recessions (Guceri and Albinowski 2021; Link et al. 2024) suggest that tax incentives are not effective under uncertainty due to high capital adjustment costs which reduce investment. [4] Studying the extension of the R&D tax credit in Germany in June 2020 and its role in fostering the resilience of innovative companies during the COVID–19 pandemic, I argue that fiscal policy plays a key role in macroeconomic stabilization during crises (Blanchard 2025; Eichenbaum 2025), enabling faster recovery than would otherwise take place. Besides

3. The answer would most probably have been “yes” if one were to overlook the role of institutions and policies in affecting resilience, as has been the case in recent research examining other factors. For instance, Copestake, Estefania–Flores, and Furceri (2024) study digitization and resilience in a heterogeneous group of 75 economies without considering either the institutional environment of these countries before the pandemic or public policies implemented in response to it. They re–estimate their baseline regression equation excluding one country or region at a time and conclude that the “results are not dependent on any specific country or group of countries” (p. 8). Aizenman et al. (2025) consider institutions but not policies and without reference to La Porta et al. (1998).

4. Bloom, Bond, and Van Reenen (2007, p. 411) note that “increases in uncertainty around major shocks, like September 11, 2001 and the 1970’s oil shocks, could seriously reduce the responsiveness of investment to monetary or fiscal policy.” Similarly, Bloom et al. (2018, p. 1062) note that “uncertainty shocks not only impact the economy directly, but also indirectly change the response of the economy to any potential reactive stabilization policy.”

extending the literature on the effectiveness of R&D tax credits in OECD countries (Hall and Van Reenen 2000; Bloom, Griffith, and Van Reenen 2002; Thomson 2017), I thereby contribute to the literature on the growth impact of discretionary fiscal policy during a recessionary period in the EA (Coenen, Straub, and Trabandt 2012, 2013; Devereux et al. 2020).

Finally, I contribute to the literature on monetary–fiscal policy interactions in monetary unions with heterogeneous fiscal space (Beetsma and Jensen 2005; Davig and Leeper 2011; Bellifemine, Couturier, and Jamilov 2025). Having its origins in the literature on optimal currency areas (Mundell 1961; McKinnon 1963; Kenen 1969; Alesina and Barro 2002; Alesina, Barro, and Tenreyro 2002), this literature finds that diverging fiscal policies may jeopardize the integrity and sustainability of a monetary union such as the EA. My findings suggest that the impact of innovation on resilience is stronger in EA member states that were compliant with the Maastricht Treaty before the pandemic, i.e., had debt–to–GDP ratios not exceeding 60%. Thus, the maintenance of fiscal rules (European Commission 2025c) is of paramount importance in an incomplete economic union.

The rest of the chapter is organized as follows: Section 2.2 below outlines the theoretical framework of my research; Section 2.3 describes the empirical setting and the data I use; Section 2.4 elaborates on my measures and econometric approaches; Section 2.5 provides the results, Section 2.6 discusses the results in relation to the extant literature; and Section 2.7 concludes. Descriptive statistics are provided in the appendix to this chapter (Supplement Section A2).

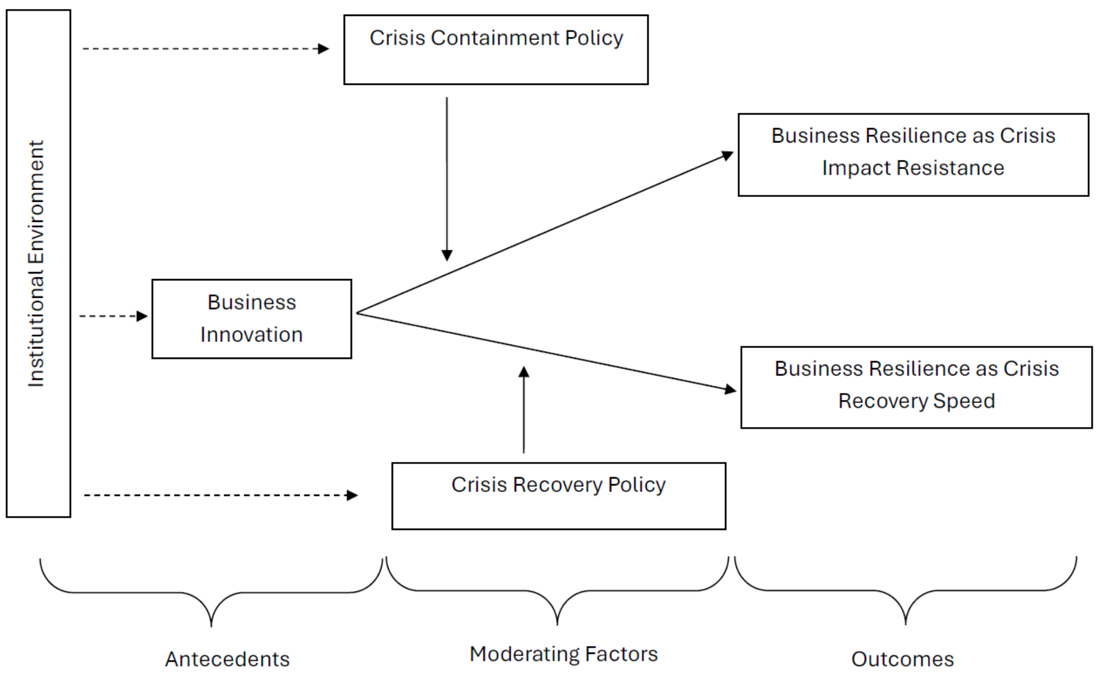
2.2 Theoretical Framework and Hypotheses

This chapter builds on the framework advanced in Chapter 1, offering a new framework on how innovation affects resilience under institutional and policy variation (see Figure 2.1 below). Specifically, I establish the relationship between innovation, resilience, institutions, and policies through a causal moderation model composed of three layers: *antecedents, moderating factors*, and *outcomes*. Institutions are fundamental to economic growth (Acemoglu, Johnson, and Robinson 2005; Acemoglu 2025), affecting both innovation before crises and policies implemented during crises. Innovation before crises is an antecedent of resilience, conceived as crisis impact resistance and recovery speed (Holling 1973, 1996). Policies implemented during crises moderate the relationship between innovation and resilience, as tax credits and subsidies for R&D vary across countries, thereby differentially affecting firm incentives to innovate (Bloom, Griffith, and Van Reenen 2002; Hassett and Hubbard 2002). Two testable hypotheses may be derived from the framework:

Hypothesis 1. *Crisis containment policy moderates the relationship between innovation and resilience as impact resistance.*

Hypothesis 2. *Crisis recovery policy moderates the relationship between innovation and resilience as recovery speed.*

Figure 2.1: Theoretical Framework on How Innovation Affects Resilience under Institutional and Policy Variation



Source: Own elaboration.

Notes: Solid lines indicate hypotheses tested in this study; dashed lines indicate relationships assumed based on prior research in the field of economics and not tested in this study.

2.3 Empirical Setting and Data

2.3.1 Empirical Setting

The empirical setting in which I examine corporate resilience in the EA is the COVID–19 pandemic. In its Fall 2020 statement, dated 29 September 2020, the Euro Area Business Cycle Dating Committee of the Centre for Economic Policy Research (CEPR) declared that the expansion that had started in Q2–2013 reached its peak in Q4–2019, and the EA entered a recession in Q1–2020 (Euro Area Business Cycle Network 2020). In its Fall 2021 statement, dated 9 November 2021, the Committee declared that the EA recession that had started after Q4–2019 reached its trough in Q2–2020; therefore, the pandemic–induced recession lasted for only two quarters, the shortest on record (Euro Area Business Cycle Network 2021). Despite its brevity, the recession was severe, as the seasonally adjusted gross domestic product (GDP) in the EA contracted at a rate of 11.8% in Q2–2020, the largest decline since the series was first observed in 1995 (Eurostat 2020).

2.3.2 Data

To address my first research question, i.e., whether innovation fosters resilience, I construct a panel data set linking financial statements, stock prices, and other characteristics (e.g., industry and location) of companies traded in the EA member states before, during, and after COVID–19 was declared a pandemic on 11 March 2020 (World Health Organization 2025). To examine the role of institutions and policies in fostering resilience and thereby address the second research question, I study public policy responses in individual member states from January 2020 to December 2021. [5] In particular, I study fiscal policies related to the corporate income tax (CIT), as those affect all incorporated businesses in an economy, and incentives for innovation, such as R&D tax credits, which affect innovative

5. Besides the confounding effect of the war in Ukraine, as noted in the introduction to this chapter, the end of the observation window in 2021 is appropriate as the OECD data on tax policy measures during the pandemic were last updated in April 2021. Similarly, the IMF data on COVID–19 policy responses were last updated in July 2021.

enterprises. I gather and match data from several sources, as elaborated below.

Financial Statements and Stock Prices: First, I obtain identifiers of publicly traded companies in the EA from the Bureau van Dijk (BvD) Orbis database. Specifically, I start the data collection with International Securities Identification Numbers (ISINs), i.e., standardized 12–digit alphanumeric codes, the first two digits of which correspond to the two–letter ISO country code in which a company is incorporated (e.g., DE for Germany and FR for France). I retain only companies incorporated in 19 member states constituting the EA as of 1 January 2019 (European Union 2025). [6] From the population of 3,286 companies, [7] I exclude financial companies, i.e., those operating under NACE Rev.2 sections K (finance and insurance) and L (real estate) (Eurostat 2008), as the financial ratios of companies in these industries are not directly comparable with the financial ratios of companies in other industries (Fama and French 1992). [8] Thus, I obtain a sample of 2,495 companies.

Second, I gather financial statement data of all companies in the sample. In particular, I obtain data on net income in 2019, i.e., in the pre–crisis year. I exclude companies with missing net income ($n = 367$), as well as companies reporting negative ($n = 662$) and zero ($n = 18$) net income. This is meant to ensure that losses incurred during the crisis are due to its impact rather than other, company–specific factors (Altman 1968). Thus, my sample is reduced to 1,448 companies. In addition, I obtain data on R&D expenses in 2019 to classify companies as either R&D spenders or non–spenders pre–crisis, as this enables me to claim exogeneity of the independent variable of innovation with respect to the dependent variables of resilience (see Section 2.4.1 below). Non–missing non–zero

6. The countries are, in alphabetical order, the following: Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Portugal, Slovakia, Slovenia, and Spain.

7. The version of the database I use is 357, last updated 15 January 2025.

8. These sections include divisions 64–66 and 68, respectively. NACE is an abbreviation in French, standing for *Nomenclature statistique des activités économiques dans la Communauté européenne* and translated as "Statistical classification of economic activities in the European Community." Rev.2 indicates the second edition of the classification.

values for R&D are available for 411 companies, and therefore, these are classified as R&D spenders. [9] For both R&D spenders and non–spenders, I gather additional financial data from both balance sheets and profit–loss accounts, e.g., total assets, current assets, and current liabilities, as these enable me to calculate measures that serve as controls in econometric estimation (see Section 2.4.5 below).

Finally, I gather stock price data of all companies incorporated in 19 EA member states from the LSEG Workspace (formerly Refinitiv Eikon database). Price data for all weeks between W1–2019 and W52–2021 are available for 2,642 companies. Given the median price of EUR 9 and to ensure that extreme observations do not bias my estimates, I exclude companies the stocks of which traded below the 1^{st} percentile (EUR 0.022) and above the 99^{th} percentile (EUR 3,920) of the distribution in any of the weeks ($n = 53$ and $n = 34$, respectively). The matching of the resulting panel with the cross–section of 1,448 companies obtained above using the ISINs and retention of only those companies that appear in both data sets results in a strongly balanced panel of 1,209 companies observed over 156 weeks, i.e., 188,604 company–week observations. In this panel, 379 companies ($\approx 31\%$) are R&D spenders, and it constitutes the basis for most statistical analyses reported below. Supplement Section A2 provides the distribution of companies by industries (NACE Rev.2 sections and divisions) and locations (EA member states and NUTS 1 regions), for the sample as a whole, as well as separately for R&D spenders and non–spenders. [10]

Government Policies: I obtain data on government policy responses to the pandemic from three sources: the Oxford University COVID–19 Government Response Tracker (OxCGRT) (Hale et al. 2021; Blavatnik School of Government 2023), the International Monetary Fund's (IMF) COVID–19 Policy Tracker (International Monetary Fund 2021),

9. The Orbis database has data on R&D expenses reported in both Global Standard and Global Detailed formats. My classification is based on the detailed format.

10. NUTS stands for "*Nomenclature des unités territoriales statistiques*," i.e., Nomenclature of Territorial Units for Statistics. See Eurostat (2025).

and the OECD Tax Policy Reforms report (Organization for Economic Cooperation and Development 2021). Data on corporate tax rates and incentives for innovation before and during the pandemic are from two additional sources: the OECD Corporate Tax Statistics Database (Organization for Economic Cooperation and Development 2024b) and the InnoTax Portal, maintained as a part of the European Commission (EC)–OECD Science, Technology, and Innovation Policy (STIP) Compass (Organization for Economic Cooperation and Development 2025c). Each of these five data sources is outlined below.

Oxford Tracker: The most recent version of the OxCGRT data set, available as a GitHub repository since June 2023, provides a systematic record of government responses to COVID–19 in 185 countries and territories (as well as sub–national jurisdictions in eight countries) for three years from 1 January 2020 to 31 December 2022. [11] Overall, it includes 25 indicators organized in five groups: closure and containment, economic, health, vaccine, and miscellaneous; these are combined into four indices: Government Response Index (GRI), Stringency Index (SI), Containment and Health Index (CHI), and Economic Support Index (ESI). All EA member states are in the data set; however, the ESI, as acknowledged by the project team, “does not include support to firms or businesses and does not take into account the total fiscal value of economic support,” although it has income support indicators for “payments to firms if explicitly linked to payroll/salaries” (Hale et al. 2023, pp. 10, 53). Therefore, from this data set, I retain only SI and CHI values from 1 January 2020 to 31 December 2021, and I obtain data on fiscal policy related to CIT from IMF and OECD sources, as elaborated below. [12] The time series of both indices is daily, and I use a monthly series with values taken on the first day of each month.

IMF Tracker: The IMF Policy Tracker (last updated 2 July 2021) provides an overview of government policies aimed at containing the spread, as well as the economic impact of the COVID–19 pandemic. Besides containment (lockdown and vaccination) policies,

11. See https://github.com/OxCGRT/covid-policy-tracker.

12. GRI and SI are highly correlated, as there is an 87.5% overlap in the underlying indicators. See Hale et al. (2023, pp. 97–104) for further details.

it covers fiscal, monetary, and macro–financial policies implemented in 197 economies, including individual member states of the EA and the EA as a whole. Due to the common monetary policy in the latter, I focus on the fiscal policy sections of the tracker. In particular, I retain data on the size of the fiscal stimulus package as a share of each country's 2019 GDP (e.g., 12.6% for Austria).

OECD Report: The 2021 edition of the annual Tax Policy Reforms report published by the OECD is focused on the COVID–19 pandemic, providing an analysis of tax policy measures in around 70 jurisdictions. An Excel spreadsheet associated with the report, last updated 22 April 2021, contains details on tax policies (e.g., type of tax concerned and date of legislation) in each jurisdiction, and all EA member states—except Cyprus and Malta—have corresponding entries, as these two economies are neither members nor partners of the OECD. [13] Therefore, in further analyses, I focus on 17 EA member states that are also members of the OECD.

OECD Database: The OECD Corporate Tax Statistics Database, last updated 11 July 2024, provides data on corporate income tax rates in OECD member states and partner economies. In particular, it has statistics on statutory and effective tax rates, as well as R&D tax incentives. Data are available at an annual frequency, and I obtain time series for three years (2019–2021) for two indicators in each of the 17 EA member states that are also members of the OECD: effective tax rates and implied tax subsidy rates on R&D (see Section A2). For the former, I consider both effective average and effective marginal tax rates; for the latter, consistently with my sample selection, I consider only the rates for large profitable firms. [14] Since 2019, the OECD has published an annual Corporate Tax Statistics report based on the database, and I refer to 2019–2021 editions for qualitative information on tax rates and incentives (see Organization for Economic Cooperation and Development (2024a) for the latest edition and references to earlier editions).

13. The spreadsheet is available for download from https://www.oecd.org/tax/covid-19-tax-policy-and-other-measures.xlsm; the author retains a copy. The list of current OECD members and partners is available at https://www.oecd.org/en/about/members-partners.html.

14. Data are available also for small and medium enterprises and loss–making firms.

EC–OECD Compass: I supplement the OECD corporate tax data with more detailed information on R&D tax credits in each country from the InnoTax Portal of the STIP Compass. Expect four countries (Estonia, Finland, Latvia, and Luxembourg), all EA member states that are also members of the OECD had expenditure–based tax credits for R&D as of 1 January 2020 (see Supplement Section A2). [15] The oldest is the French R&D tax credit *(crédit d'impôt recherche, CIR)*, in force since 1983, and three countries (Greece, Slovakia, and Slovenia) allowed for full (100%) deduction of R&D from taxable income both before and during the pandemic.

Institutions: Based on extensive background research in the field of law, La Porta et al. (1998) classify 49 economies as belonging to four legal origins: English, French, German, and Scandinavian. The overlap between the economies they classify and my sample of EA–OECD member states that provided R&D tax incentives during the pandemic is 11. These economies are representative of all four legal origins, as listed below:

1. English: Ireland;
2. French: Belgium, France, Greece, Italy, the Netherlands, Portugal, and Spain;
3. German: Austria and Germany;
4. Scandinavian: Finland.

English and Scandinavian legal origins are each represented by only one country in my sample (Ireland and Finland, respectively); therefore, I focus on the distinction between countries belonging to French and German origins. La Porta et al. (1998) find that, on average, countries belonging to the German civil law origin provide greater protection to

15. Chapter 5 of the OECD Corporate Tax Statistics report (Organization for Economic Cooperation and Development 2024a) provides a discussion of expenditure–based vs. income–based tax incentives for R&D. Estonia and Luxembourg have never had tax incentives, and therefore, there are no profiles for either country in the InnoTax Portal. Finland introduced an expenditure–based tax credit in 2021. The tax credit in Latvia, introduced in 2014, ceased to be in force in 2018. See https://stip.oecd.org/innotax/countries/Finland and https://stip.oecd.org/innotax/countries/Latvia for further details.

investors than those belonging to the French civil law origin. Similarly, I expect to find a stronger impact of innovation on corporate resilience in Austria and Germany as compared to the seven countries belonging to the French civil law origin. More narrowly, I expect to find a stronger impact of innovation on corporate resilience in Germany than in France.

Among the post–socialist economies that La Porta et al. (1998) did not classify, but the classification of which is possible due to their subsequent research (La Porta, Lopez–de–Silanes, and Shleifer 2008), Lithuania belongs to the French origin, while Slovakia and Slovenia belong to the German origin. I report the results below without these countries and include them in additional analyses reported in the working paper version of this chapter (Shakhmuradyan 2025).

2.4 Measures and Econometric Estimation

2.4.1 Resilience Measures

Originating in natural sciences, the concept of resilience has been adopted in several social sciences over the past centuries (Alexander 2013), including business administration and management (Meyer 1982; Linnenluecke 2017; Hillmann and Guenther 2021). According to Holling (1996, p. 33), the conception of resilience that may serve as a basis for its definition in economics, termed *engineering resilience*, focuses on “stability near an equilibrium steady state, where resistance to disturbance and speed of return to the equilibrium are used to measure the property.” Holling (1996) contrasts the engineering conception of resilience to *ecological resilience* (Holling 1973), arguing that the latter “emphasizes conditions far from any equilibrium steady state, where instabilities can flip a system into another regime of behavior—that is, to another stability domain.”

In line with the engineering conception, I 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):

$$IR = \begin{cases} 1 & \text{if } P_t \geq P_{t-s} \\ 0 & \text{otherwise.} \end{cases} \tag{2.1}$$

When calculated with weekly data, s in Equation 2.1 above 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 the stock price to recover to its pre–crisis levels:

$$RS \in \mathbb{N}. \tag{2.2}$$

In the context of the pandemic–induced recession in the EA, whereby the trough of the recession using weekly data can be dated to W12–2020 (see Appendix Figure B4), and there are observations up to W52–2021, the following is true:

$$1 \leq RS \leq 92. \tag{2.3}$$

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).

2.4.2 Innovation Measures

I 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). More importantly, R&D expenses are a better measure of the theoretical construct I aim to operationalize, i.e., the *allocation of resources* to innovation (Arrow 1962).

As noted in Section 2.3.2 above, the BvD Orbis database provides data on corporate R&D expenses. Therefore, my first measure of innovation, *R&D spender* (RDS), equals one if a company reported R&D expenses in 2019 and zero otherwise. For most companies that report R&D, I calculate a second measure of innovation, *R&D intensity* (RDI), equal to R&D expenses in 2019 divided by operating revenues (turnover) in the same year:

$$RDI = \frac{\textit{R\&D Expenses}}{\textit{Revenues}}. \tag{2.4}$$

I report the results below using *RDS* as the independent variable, while the results based on *RDI* are provided in the working paper version of this chapter (Shakhmuradyan 2025). [16]

2.4.3 Fiscal Policy Measures

In line with the resilience measures, I adopt two measures of fiscal policy: *containment tax cut* (CTC) and *recovery tax cut* (RTC). Both are binary variables, calculated based on the effective average tax rate (EATR). Specifically,

$$CTC = \begin{cases} 1 & \text{if } EATR_{2020} < EATR_{2019} \\ 0 & \text{otherwise.} \end{cases} \tag{2.5}$$

Similarly:

$$RTC = \begin{cases} 1 & \text{if } EATR_{2021} < EATR_{2020} \\ 0 & \text{otherwise.} \end{cases} \tag{2.6}$$

The OECD Corporate Tax Statistics Database suggests that EATR in 2020 was lower than a year before in only five EA member states: Austria, Belgium, Finland, France, and Germany (see Appendix Table B7, column 1). Among these, the generosity of R&D incentives, as measured by the implied tax subsidy rate (ITSR), increased in only two

16. It is important to note that BvD data on R&D expenses are incomplete, as R&D costs that are incurred but do not meet the recognition criteria of the *International Accounting Standard (IAS) 38: Intangible Assets* (International Financial Reporting Standards 2025) are reported in narrative sections of corporate reports rather than financial statements. I performed a textual analysis of annual reports filed in 2019 to ascertain whether a company allocates resources to innovation.

countries: Finland and Germany (see Appendix Table B7, column 3). The Finnish case is special as the R&D tax credit was introduced in 2021 (legislated in 2020), and therefore, the ITSR turned to zero in 2020 and 2021 from its negative (-0.01) value in 2019. The German R&D tax credit (*Forschungszulage*) was in place before the pandemic (legislated on 14 December 2019; in force from 1 January 2020), and the rate increased from -0.02 in 2019 to 0.19 in 2020 and 2021. Notably, following the adoption of a fiscal stimulus package on 3 June 2020, the maximum amount of expenses qualifying for the R&D tax credit increased from EUR 2 million to EUR 4 million, and this extension is effective for the six–year period between 1 July 2020 and 30 June 2026 (Federal Government of Germany 2020).

The OECD database further suggests that EATR in 2021 was lower than EATR in 2020 in four EA member states: France, Germany, Greece, and Italy (see Appendix Table B7, column 1). ITSR in 2021 was higher than in 2020 in two countries: Belgium and Italy. Notably, the generosity of the French R&D tax credit was lower during the pandemic than before it, as the ITSR decreased in both observed years: from 0.43 to 0.39 in 2020 and from 0.39 to 0.37 in 2021, respectively (see Appendix Table B7, column 3).

2.4.4 Econometric Estimation

I adopt three econometric approaches to examine whether more innovative companies are more resilient and whether fiscal policy enhances corporate resilience. First, I estimate binary outcome (logit) regression models for panel data to test the relationship between being an R&D spender and my first measure of resilience, *impact resistance* (Cameron and Trivedi 2022, pp. 1139–1190). Second, I estimate count data (Poisson) regression models for panel data to examine the relationship between being an R&D spender and my second measure of resilience, *recovery speed* (Ibid.). In each case, I have one baseline specification and two augmented specifications including firm–level controls and country–level fiscal policy variables. Third, to examine the role of fiscal policy in fostering corporate resilience in the country that extended its existing R&D tax credit during the pandemic (Germany), I estimate a two–way fixed effects difference–in–differences (TWFE DID) regression model. Each approach is elaborated below.

Binary Outcome Models: My measure of impact resistance is a binary variable, and it equals one if a company does not incur a loss due to a crisis in a specific week. Therefore, I estimate the following logit model as a baseline:

$$\Pr(IR_{it} = 1 \mid RDS_i, \alpha_i) = \Lambda(\alpha_i + \beta RDS_i), \tag{2.7}$$

where IR_{it} is the crisis impact resistance of firm i at time t; RDS_i is its status in terms of R&D expense (spender or non–spender); and α_i is a random effect (RE).

The augmented specification with controls (see Section 2.4.5) has the following form:

$$\Pr(IR_{it} = 1 \mid RDS_i, x_i, \alpha_i) = \Lambda(\alpha_i + \beta RDS_i + \boldsymbol{x}_i'\boldsymbol{\gamma}). \tag{2.8}$$

The specification including a fiscal policy variable has an interaction term:

$$\begin{aligned} &\Pr(IR_{it} = 1 \mid RDS_i \times CTC_c, x_i, \alpha_i) \\ &\quad = \Lambda(\alpha_i + \boldsymbol{x}_i'\boldsymbol{\gamma} + \delta RDS_i \times CTC_c), \end{aligned} \tag{2.9}$$

where CTC is an indicator equal to one for each country c that implemented a containment tax cut during the pandemic and zero otherwise.

I expect the β coefficient in both Equations 2.7 and 2.8 to be positive, i.e., R&D spenders are less likely to incur a loss due to the crisis, *ceteris paribus*. Additionally, I expect the δ coefficient in Equation 2.9 to be greater for R&D spenders, i.e., a containment tax cut matters more for the crisis impact resistance of R&D spenders than non–spenders.

Count Data Models: My measure of recovery speed is a count variable equal to the number of weeks it takes for a company that has incurred a loss due to a crisis to recover to pre–crisis levels. Therefore, I estimate an RE Poisson regression model for only those companies that incurred a loss due to the crisis and subsequently recovered:

$$\mathrm{E}(RS_{it} \mid RDS_i, \alpha_i) = \exp(\alpha_i + \beta RDS_i), \tag{2.10}$$

where RS_{it} is the recovery speed of firm i at time t; RDS_i is its status in terms of R&D expense (spender or non–spender); and α_i is a random effect.

The augmented specification with controls has the following form:

$$\mathrm{E}(RS_{it} \mid RDS_i, x_i, \alpha_i) = \exp(\alpha_i + \beta RDS_i + \boldsymbol{x}_i' \boldsymbol{\gamma}). \tag{2.11}$$

The specification including a fiscal policy variable has an interaction term:

$$\begin{aligned} &\mathrm{E}(RS_{it} \mid RDS_i \times RTC_c, x_i, \alpha_i) \\ &= \exp(\alpha_i + \boldsymbol{x}_i' \boldsymbol{\gamma} + \delta RDS_i \times RTC_c), \end{aligned} \tag{2.12}$$

where RTC is an indicator equal to one for each country c that implemented a recovery tax cut during the pandemic and zero otherwise.

I expect the β coefficient in both Equations 2.10 and 2.11 to be negative, i.e., R&D spenders affected by the crisis recover faster than non–spenders, *ceteris paribus*. Additionally, I expect the δ coefficient in Equation 2.12 to be greater for R&D spenders, i.e., a recovery tax cut matters more for the crisis recovery speed of R&D spenders than non–spenders.

TWFE DID Model: For publicly traded companies in Germany, I estimate the following model to quantify the differential impact of fiscal policy on the stock prices of R&D spenders:

$$\ln(Price_{it}) = \phi_i + \gamma_t + \alpha D_{it} + \epsilon_{it}, \tag{2.13}$$

where i denotes companies, and t denotes time (156 weeks spanning from W1–2019 to W52–2021 inclusive). D is a binary variable equal to one for R&D spenders in the post–legislation period following the extension of the R&D tax credit (starting in W27–2020) 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. My interest lies in estimating the parameter α, i.e., the average treatment effect on the treated (ATET). This parameter is identified if the two assumptions of parallel trends and Granger causality hold. I test both assumptions and provide appropriate test statistics and diagnostic graphs. [17]

2.4.5 Controls

While estimating RE logit and Poisson regression models, as specified above, I control for several factors that simultaneously affect corporate innovation and resilience. First and most importantly, I control for *industry*, as there are differences in the allocation of resources to innovation across industries, some being more R&D–intensive than others (Malerba 2006; Smith 2006), and the impact of the COVID–19 pandemic was uneven across industries: those that enabled work from home to a greater extent were less affected by the pandemic than other industries (del Rio–Chanona et al. 2020; Dingel and Neiman 2020; Guerrieri et al. 2022; Bloom et al. 2025; Cirelli and Gertler 2025). Industry is identified by the NACE Rev.2 section in which a company operates: most companies in my sample operate in manufacturing industries, i.e., Section C (see Appendix Figure B1), and R&D spenders have a greater representation in these industries; however, the sample overall is representative of 17 NACE Rev.2 sections and 74 divisions within those sections (see Appendix Tables B1–B3). [18]

Second, I control for *location*, as there are geographic disparities in the allocation of resources to innovation across and within the EA member states (European Commission 2025b, 2025d), and the impact of the pandemic was spatially uneven, varying depending on socio–economic characteristics and crisis response policies (Muggenthaler, Schroth, and Sun 2021; Cancedda et al. 2024). Location is identified by the country in which a company

17. All analyses were carried out with Stata 18 software and reproduced using Stata 19. Specifically, I utilized the `xtdidregress` command to estimate the ATET, as well as the `estat ptrends` and `estat granger` commands to obtain test statistics on the validity of parallel trends and Granger causality assumptions. Figures were obtained using `estat trendplots` and `estat grangerplot` commands, respectively. See StataCorp (2025) for further details.

18. There are 21 NACE Rev.2 sections in total, and I excluded two sections (K and L) at the research design stage (see Section 2.3.2 above). No publicly traded companies operate in sections T and U.

is incorporated, as well as the region of the corporate headquarters within a country. Most companies in the sample are located in France and Germany (see Appendix Table B4); Île–de–France is the region with the largest share of companies, followed by Bayern, while the sample overall is representative of 53 NUTS 1 regions (see Appendix Table B5).

Third, I control for *liquidity*, as financially less constrained firms are more likely to allocate resources to innovation (O'Sullivan 2006; Hall and Lerner 2010) and withstand exogenous crises (Williams et al. 2017; 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. [19] Appendix Table B6 provides t–test statistics, suggesting that R&D spenders have greater liquidity and crisis impact resistance than non–spenders, on average, as well as recover faster.

Finally, I 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: the mean age in my sample is 46, and R&D spenders are older, on average, than non–spenders.

19. I prefer liquidity as a measure of financial constraints instead of leverage due to the reason (as noted in Section 2.3.1 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.

2.5 Results

2.5.1 Main Results

RE logit regression results, as reported in Table 2.1 below, suggest that R&D spenders were less likely to incur a loss due to the crisis induced by the pandemic, *ceteris paribus*. The baseline coefficient estimate (see column 1, $\beta = 0.256, se = 0.081$) increases in size and retains its significance at the 1% level when industry fixed effects for NACE Rev.2 sections are included in the regression specification (see column 2, $\beta = 0.282, se = 0.086$). It weakens but remains significant when both industry and location fixed effects are included (see column 3, $\beta = 0.216, se = 0.092$), suggesting that cross–country heterogeneity is an important factor affecting the relationship between innovation and resilience in the EA. Interpretation of this coefficient after exponentiation ($e^{0.216} \approx 1.241$) implies that, holding constant the industry in which a company operates, as well as its location, being an R&D spender is associated with approximately 24% higher odds of not incurring a loss due to the crisis. The coefficient estimate when other controls are included is also positive and significant (see column 4, $\beta = 0.242, se = 0.108$); the inclusion of industry fixed effects for NACE Rev.2 divisions and location fixed effects for NUTS regions (see columns 5 and 6, respectively) weakens the coefficient, but it retains its significance at conventional levels.

The inclusion of interaction terms with fiscal policy in impact resistance regressions (see Table 2.2 below) yields expected results: the estimated coefficient of the interaction term *R&D spender* $\times$ *CTC* without controls (see column 1, $\delta = 0.322, se = 0.100$) is more than three times larger than the coefficient of the interaction term *Non–spender* $\times$ *CTC* ($\delta = 0.103, se = 0.088$). Exponentiation of the coefficient ($e^{0.322} \approx 1.380$) implies that, as compared to the baseline (*Non–spender* $\times$ *No CTC*), being an R&D spender in a country that implemented a containment tax cut is associated with approximately 38% higher odds of being crisis impact resistant. The coefficient increases in size and retains significance at the 1% level when industry fixed effects for NACE Rev.2 sections and other controls are included in the regression specification (see columns 2–3).

RE Poisson regression results, as reported in Table 2.3 below, suggest that R&D spenders that incurred a loss due to the crisis recovered faster than non–spenders, on average (see column 1, $\beta = -0.158, se = 0.035$). Exponentiation of the coefficient ($e^{-0.158} \approx 0.854$) suggests that being an R&D spender is associated with approximately 15% reduction in the expected number of recovery weeks. The coefficient weakens when control variables are included, but it retains significance at the 5% level throughout different specifications (see columns 2–5). Similar to the impact resistance regressions, the inclusion of interaction terms with fiscal policy in recovery regressions (see Table 2.4 below) yields expected results: the estimated coefficient of the interaction term *R&D spender* × *RTC* ($\delta = -0.226, se = 0.047$) is around four times larger than the coefficient of the interaction term *Non–spender* × *RTC* ($\delta = -0.060, se = 0.036$). Its exponentiation ($e^{-0.226} \approx 0.798$) suggests that being an R&D spender in a country that implemented a recovery tax cut is associated with around 20% reduction in the expected number of recovery weeks. The coefficient of the interaction term weakens in size but retains significance at the 5% level when control variables are included (see Table 2.4, columns 2–4).

TWFE DID regression results suggest that fiscal policy has a causal effect on resilience: the interaction term *R&D spender* × *Post* for all companies in Germany (see Table 2.5, column 1 below) is positive and significant at the 5% level ($\alpha = 0.100, se = 0.045$), suggesting that the stock prices of R&D spenders increased by 10%, on average, in the post–legislation period following the extension of the R&D tax credit, i.e., starting 1 July 2020. The parallel trends and Granger causality assumptions hold ($F = 0.09$ and $F = 2.31$, respectively), as can be observed also from panels A and B of Figure 2.2 below. The coefficient is slightly larger and still significant at the 5% level for manufacturing companies (see Table 2.5, column 2, $\alpha = 0.155, se = 0.057$), but it is marginally insignificant for companies in service industries (see Table 2.5, column 3, $\alpha = 0.123, se = 0.076$).

Table 2.1: RE Logit Regression Results, Euro Area

	Baseline	Augmented				
	(1)	(2)	(3)	(4)	(5)	(6)
R&D spender	0.256	0.282	0.216	0.242	0.231	0.159
	(0.081)	(0.086)	(0.092)	(0.108)	(0.087)	(0.086)
Industry (NACE section) FE		✓	✓	✓		
Industry (NACE division) FE					✓	
Location (country) FE			✓	✓		
Location (NUTS region) FE						✓
Other controls				✓		
Constant	1.267	1.558	1.019	0.709	1.537	1.024
	(0.048)	(0.286)	(0.301)	(0.413)	(0.318)	(0.201)
n (companies)	1,209	1,209	1,209	1,193	1,209	1,209
N (company–week obs.)	188,604	188,604	188,604	186,108	188,604	188,604
Log pseudo–L	-97,859.56	-97,833.51	-97,807.75	-96,384.50	-97,790.96	-97,811.63
Wald χ^2	9.95	183.19	246.57	131.58	—	—

Notes: The dependent variable in all columns is impact resistance, as specified in Equation 2.1. Column 1 estimates the regression model specified in Equation 2.7, while columns 2–6 estimate the regression model specified in Equation 2.8. Robust standard errors clustered at the company level in parentheses below coefficient estimates. Other controls include liquidity and age. See Supplement Section A2 for descriptive statistics, including the distribution of companies across industries and locations.

Table 2.2: RE Logit Regression Results Accounting for Fiscal Policy

	(1)	(2)	(3)	(4)	(5)
Non–spender × *CTC*	0.103	0.083	0.161	0.070	2.041
	(0.088)	(0.089)	(0.102)	(0.088)	(1.005)
R&D spender × *No CTC*	0.272	0.310	0.183	0.216	0.183
	(0.157)	(0.156)	(0.183)	(0.155)	(0.162)
R&D spender × *CTC*	0.322	0.330	0.490	0.285	2.194
	(0.100)	(0.104)	(0.124)	(0.104)	(1.010)
Industry (NACE section) FE		✓	✓		
Industry (NACE division) FE				✓	
Location (NUTS region) FE					✓
Other controls			✓		
Constant	1.214	1.549	2.281	1.535	-1.014
	(0.067)	(0.286)	(0.357)	(0.317)	(1.025)
n (companies)	1,209	1,209	1,193	1,209	1,209
N (company–week obs.)	188,604	188,604	186,108	188,604	188,604
Log pseudo–L	-97,858.84	-97,833.07	-96,409.47	-97,790.54	-97,808.43
Wald χ^2	11.59	163.94	114.47	—	—

Notes: The dependent variable in all columns is impact resistance, as specified in Equation 2.1, and all columns estimate the regression model specified in Equation 2.9, with (columns 2–5) and without (column 1) controls. CTC stands for containment tax cut, as defined in Equation 2.5. Robust standard errors clustered at the company level in parentheses below coefficient estimates. Other controls include liquidity and age. See Supplement Section A2 for descriptive statistics, including the distribution of companies across industries and locations.

Table 2.3: RE Poisson Regression Results, Euro Area

	Baseline	Augmented				
	(1)	(2)	(3)	(4)	(5)	(6)
R&D spender	-0.158	-0.128	-0.083	-0.086	-0.122	-0.104
	(0.035)	(0.038)	(0.039)	(0.040)	(0.040)	(0.037)
Industry (NACE section) FE		✓	✓	✓		
Industry (NACE division) FE					✓	
Location (country) FE			✓	✓		
Location (NUTS region) FE						✓
Other controls				✓		
Constant	3.709	3.455	3.476	3.465	3.505	3.707
	(0.018)	(0.178)	(0.198)	(0.201)	(0.186)	(0.111)
n (companies)	1,120	1,120	1,120	1,105	1,120	1,120
N (company–week obs.)	43,551	43,551	43,551	42,985	43,551	43,551
Log pseudo–L	-127,314.56	-127,296.65	-127,277.32	-125,602.78	-127,263.66	-127,278.09
Wald χ^2	57,955.26	91,083.64	90,000.94	289,131.92	1,501.86	1,798.52

Notes: The dependent variable in all columns is recovery speed, as specified in Equation 2.3. Column 1 estimates the regression model specified in Equation 2.10, while columns 2–6 estimate the regression model specified in Equation 2.11. Robust standard errors clustered at the company level in parentheses below coefficient estimates. Other controls include liquidity and age. See Supplement Section A2 for descriptive statistics, including the distribution of companies across industries and locations.

Table 2.4: RE Poisson Regression Results Accounting for Fiscal Policy

	(1)	(2)	(3)	(4)	(5)
Non–spender × *RTC*	-0.060	-0.037	-0.035	-0.034	-1.202
	(0.036)	(0.038)	(0.038)	(0.039)	(0.490)
R&D spender × *No RTC*	-0.149	-0.107	-0.090	-0.094	-0.053
	(0.056)	(0.060)	(0.061)	(0.064)	(0.060)
R&D spender × *RTC*	-0.226	-0.182	-0.195	-0.177	-1.338
	(0.047)	(0.050)	(0.051)	(0.053)	(0.492)
Industry (NACE section) FE		✓	✓		
Industry (NACE division) FE				✓	
Location (NUTS region) FE					✓
Other controls			✓		
Constant	3.746	3.461	3.427	3.508	3.680
	(0.028)	(0.174)	(0.176)	(0.182)	(0.114)
n (companies)	1,120	1,120	1,105	1,120	1,120
N (company–week obs.)	43,551	43,551	42,985	43,551	43,551
Log pseudo–L	-127,313.16	-127,295.76	-125,620.79	-127,262.73	-127,275.25
Wald χ^2	58,330.80	90,056.32	99,252.96	153,830.94	279.73

Notes: The dependent variable in all columns is recovery speed, as specified in Equation 2.3, and all columns estimate the regression model specified in Equation 2.12, with (columns 2–5) and without (column 1) controls. RTC stands for recovery tax cut, as defined in Equation 2.6. Robust standard errors clustered at the company level in parentheses below coefficient estimates. Other controls include liquidity and age. See Supplement Section A2 for descriptive statistics, including the distribution of companies across industries and locations.

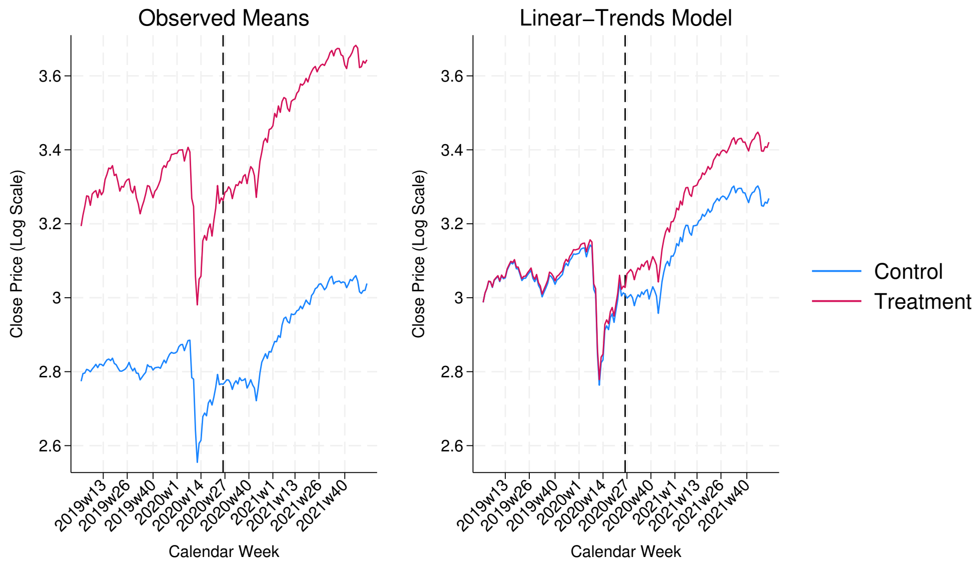
Table 2.5: TWFE DID Regression Results, Germany

	All	Manufacturing	Non–Manufacturing
ATET: *R&D spender* × *Post*	0.100	0.155	0.123
	(0.045)	(0.057)	(0.076)
	[0.012; 0.187]	[0.041; 0.269]	[-0.028; 0.273]
Company FE	✓	✓	✓
Week FE	✓	✓	✓
n (all companies)	246	126	120
n (control group)	121	38	83
n (treatment group)	125	88	37
N (company–week obs.)	38,376	19,656	18,720
Parallel trends test	$F_{(1,245)} = 0.09$	$F_{(1,125)} = 1.74$	$F_{(1,119)} = 1.07$
Granger causality test	$F_{(77,245)} = 2.31$	$F_{(77,125)} = 9.03$	$F_{(77,119)} = 5.63$

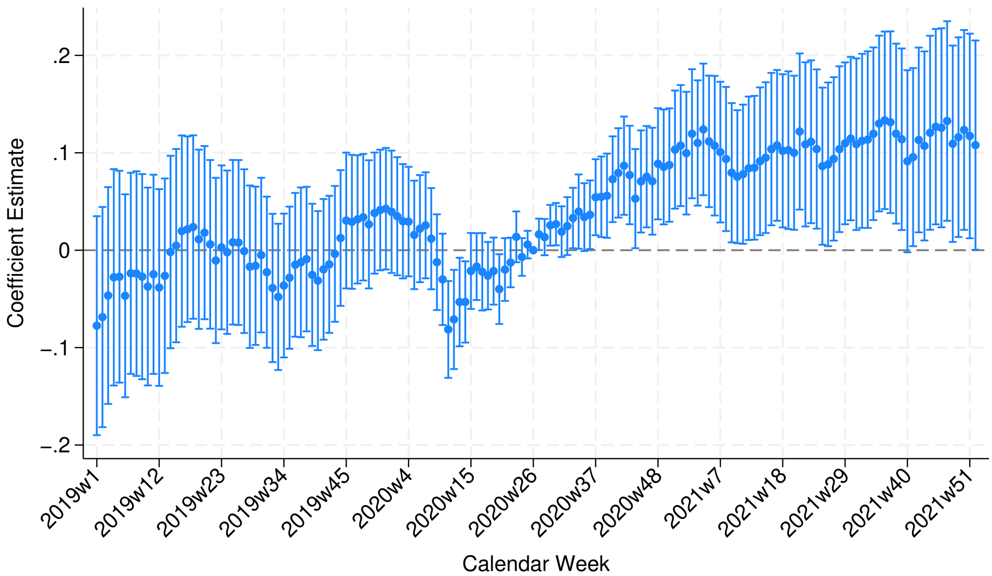
Notes: The dependent variable in all columns is the natural logarithm of company stock price, and all columns estimate the regression model specified in Equation 2.13. The classification of a company as an R&D spender is based on the BvD Orbis database; "post" indicates weeks after the legislation on the extension of the R&D tax credit took effect, i.e., W27–2020 onward. Manufacturing companies are those operating under Section C of the NACE Rev.2 classification; non–manufacturing companies are those operating under other sections (see Supplement Section A2). 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–treatment time period are parallel; the null hypothesis for the Granger causality test is that there is no effect in anticipation of treatment.

Figure 2.2: Graphical Diagnostics for Parallel Trends and Granger Causality, Germany

(a) Parallel Trends



(b) Granger Causality



Notes: The sample includes 246 publicly traded companies incorporated in Germany; of these, 125 are R&D spenders according to the BvD Orbis data classification. Treatment is defined as being an R&D spender after the legislation on the extension of the R&D tax credit took effect, i.e., W27–2020 onward.

2.5.2 Heterogeneity Analyses

Legal Origins: Tables 2.6 and 2.7 below provide heterogeneity analyses of RE logit and Poisson regressions by legal origins. As noted in Section 2.3.2 above, the French civil law origin includes seven countries (Belgium, France, Greece, Italy, the Netherlands, Portugal, and Spain), while the German civil law origin includes two countries (Austria and Germany). There are more companies located in the combined sample of seven countries ($n = 716$) than in the combined sample of two countries ($n = 278$); therefore, and due to the balanced nature of the panel, the number of company–week observations in the former group is substantially larger ($N = 111{,}696$) than in the latter ($N = 43{,}368$), and any differences in coefficient estimates cannot be attributed to sample size.

The baseline estimate for resilience as crisis impact resistance in French civil law countries (see Table 2.6, Panel A, column 1 below) is positive but insignificant ($\beta = 0.173, se = 0.114$); it stays insignificant as additional controls are added to the regression specification (see Table 2.6, Panel A, columns 2–3). By contrast, the baseline estimate for resilience as impact resistance in German civil law countries (see Table 2.6, Panel B, column 1 below) is positive and significant at the 10% level ($\beta = 0.271, se = 0.150$); it increases—in both size and significance—as additional controls are added to the regression specification (see Table 2.6, Panel B, columns 2–3 below): for instance, $\beta = 0.352$ ($se = 0.186$) in the specification controlling for industry fixed effects, company age, and liquidity.

The baseline estimate for resilience as crisis recovery speed in French civil law countries (see Table 2.7, Panel A, column 1 below) is negative but insignificant ($\beta = -0.071, se = 0.046$); it stays insignificant as additional controls are added to the regression specification (see Table 2.7, Panel A, columns 2–3). By contrast, the baseline coefficient estimate for resilience as recovery speed in German civil law countries (see Table 2.7, Panel B, column 1 below) is negative and significant at the 5% level ($\beta = -0.166, se = 0.070$); it increases—in both size and significance—as additional controls are added to the regression specification (see Table 2.7, Panel B, columns 2–3 below): for instance, $\beta = -0.216$ ($se = 0.084$) in the specification controlling for liquidity and industry fixed effects.

Fiscal Space and Stimulus: Government debt was below 60% of GDP in nine EA member states before the pandemic: Estonia, Germany, Ireland, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, and Slovakia (see Appendix Table B9, column 1). These countries were compliant with the debt criterion of sustainable fiscal policy, as set out in the Maastricht Treaty (European Parliament 2025), as well as the Stability and Growth Pact; therefore, their governments had more fiscal space for effective crisis response (Romer and Romer 2019). Heterogeneity analyses provided in Table 2.8 suggest that the relationship between innovation and resilience as crisis impact resistance is much stronger in countries with lower pre–crisis debt–to–GDP ratios.

The average size of the fiscal stimulus package implemented in 19 EA member states in response to the pandemic, as measured by the change in the primary budget balance from 2019 to 2020 (Muggenthaler, Schroth, and Sun 2021), was 6.4% of GDP (median: 6.7%) (see Appendix Table B9, column 4). Countries that implemented larger than average packages include Austria, Belgium, Cyprus, France, Greece, Italy, Lithuania, Malta, Slovenia, and Spain. Heterogeneity analyses (see Table 2.9 below) suggest that the impact of innovation on resilience as crisis impact resistance is stronger in countries that implemented *below* average stimulus packages; therefore, it is the targeted nature of fiscal policy enhancing innovation, as discussed in the preceding section, that mattered during the response phase of the pandemic, rather than its size.

Regression results for resilience as recovery speed (see Table 2.10 below) suggest that R&D spenders in countries implementing larger stimulus packages recovered faster than non–spenders, on average; however, this relationship does not hold once industry differences are accounted for. Similar to the impact resistance regressions, the relationship holds for countries implementing below average stimulus packages, and this is robust to the inclusion of industry fixed effects.

Non–Fiscal Policy Responses: As discussed in Section 2.3.2, non–fiscal policy responses to the pandemic included closure, containment, and vaccination policies. I proxy these with the OxCGRT *Stringency* and *Containment and Health* indices, respectively (Hale et al. 2021; Hale et al. 2023). The former includes eight indicators, while the latter includes 14 indicators, as laid out below:

- Stringency Index (SI): school closure; workplace closure; cancellation of public events; restrictions on gatherings; public transport closure; stay at home requirements; restrictions on internal movement; and restrictions on international travel.
- Containment and Health Index (CHI): all eight indicators above, in addition to: public information campaigns; testing policy; contact tracing; facial covering; vaccination policy; and protection of the elderly.

Both indices are standardized, ranging from zero to 100. SI values in 2020 were above the median (50.00) in six countries: France, Germany, Ireland, Italy, Portugal, and Spain; SI values in 2021 were above the median in all but four countries of the EA (Estonia, Finland, Lithuania, and Luxembourg). CHI values in 2020 were above the median in only two countries: France and Italy; similar to the SI, CHI values in 2021 were above the median in all but three countries (Estonia, Finland, and Latvia). Heterogeneity analyses for resilience as impact resistance (see Table 2.11 below) suggest that R&D spenders were less likely to incur a loss in countries that had more stringent crisis response policies.

Table 2.6: Heterogeneity Analysis by Legal Origins for Resilience as Impact Resistance

	Panel A. French Civil Law			Panel B. German Civil Law		
	(1)	(2)	(3)	(1)	(2)	(3)
R&D spender	0.173	0.156	0.271	0.271	0.407	0.352
	(0.114)	(0.115)	(0.154)	(0.150)	(0.168)	(0.186)
Industry (NACE section) FE		✓	✓		✓	✓
Other controls			✓			✓
Constant	1.190	1.134	1.684	1.272	1.365	3.152
	(0.055)	(0.436)	(0.534)	(0.113)	(0.168)	(0.453)
n (companies)	716	716	711	278	278	270
N (company–week obs.)	111,696	111,696	110,916	43,368	43,368	42,120
Log pseudo–L	-60,109.66	-60,093.75	-59,708.04	-21,881.73	-21,863.95	-21,161.28
Wald χ^2	2.29	134.51	41.49	3.26	–	1.61e+08

Notes: The dependent variable in all columns is impact resistance, as specified in Equation 2.1. In both panels, column 1 estimates the regression model specified in Equation 2.7, while columns 2 and 3 estimate the regression model specified in Equation 2.8. French civil law includes seven countries: Belgium, France, Greece, Italy, the Netherlands, Portugal, and Spain; German civil law includes two countries: Austria and Germany. Robust standard errors clustered at the company level in parentheses below coefficient estimates. See Supplement Section A2 for descriptive statistics, including the distribution of companies across industries and locations.

Table 2.7: Heterogeneity Analysis by Legal Origins for Resilience as Recovery Speed

	Panel A. French Civil Law			Panel B. German Civil Law		
	(1)	(2)	(3)	(1)	(2)	(3)
R&D spender	-0.071	-0.042	-0.045	-0.166	-0.209	-0.216
	(0.046)	(0.048)	(0.049)	(0.070)	(0.080)	(0.084)
Industry (NACE section) FE		✓	✓		✓	✓
Other controls			✓			✓
Constant	3.728	3.642	3.631	3.670	2.982	2.839
	(0.021)	(0.318)	(0.318)	(0.050)	(0.080)	(0.139)
n (companies)	669	669	665	259	259	251
N (company–week obs.)	27,342	27,342	27,192	9,339	9,339	9,066
Log pseudo–L	-80,209.13	-80,196.20	-79,738.20	-27,097.78	-27,089.62	-26,293.61
Wald χ^2	41,345.22	84,668.49	90,195.55	10,554.63	6,804.71	6,738.99

Notes: The dependent variable in all columns is recovery speed, as specified in Equation 2.3. In both panels, column 1 estimates the regression model specified in Equation 2.10, while columns 2 and 3 estimate the regression model specified in Equation 2.11. French civil law includes seven countries: Belgium, France, Greece, Italy, the Netherlands, Portugal, and Spain; German civil law includes two countries: Austria and Germany. Robust standard errors clustered at the company level in parentheses below coefficient estimates. See Supplement Section A2 for descriptive statistics, including the distribution of companies across industries and locations.

Table 2.8: Heterogeneity Analysis by Fiscal Space for Resilience as Impact Resistance

	Panel A. Narrow Fiscal Space			Panel B. Wide Fiscal Space		
	(1)	(2)	(3)	(1)	(2)	(3)
R&D spender	0.172	0.165	0.155	0.327	0.482	0.516
	(0.101)	(0.104)	(0.134)	(0.141)	(0.152)	(0.170)
Industry (NACE section) FE		✓	✓		✓	✓
Other controls			✓			✓
Constant	1.241	1.598	2.253	1.335	1.508	2.701
	(0.055)	(0.166)	(0.268)	(0.098)	(0.452)	(0.515)
n (companies)	813	813	803	396	396	390
N (company–week obs.)	126,828	126,828	125,268	61,776	61,776	60,840
Log pseudo–L	-67,133.49	-67,116.45	-66,263.73	-30,722.09	-30,705.39	-30,114.96
Wald χ^2	2.92	192.35	48.69	5.37	38.68	53.85

Notes: The dependent variable in all columns is impact resistance, as specified in Equation 2.1. In both panels, column 1 estimates the regression model specified in Equation 2.7, while columns 2 and 3 estimate the regression model specified in Equation 2.8. Fiscal space is measured by the pre–crisis (2019) debt–to–GDP ratio. Countries with narrow fiscal space (having debt over 60% of GDP) are Austria, Belgium, Cyprus, Finland, France, Greece, Italy, Portugal, Slovenia, and Spain; countries with wide fiscal space are Estonia, Germany, Ireland, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, and Slovakia. Robust standard errors clustered at the company level in parentheses below coefficient estimates. See Supplement Section A2 for descriptive statistics, including the distribution of companies across industries and locations, as well as government finance statistics.

Table 2.9: Heterogeneity Analysis by Fiscal Stimulus for Resilience as Impact Resistance

	Panel A. Limited Fiscal Stimulus			Panel B. Broad Fiscal Stimulus		
	(1)	(2)	(3)	(1)	(2)	(3)
R&D spender	0.385	0.491	0.487	0.040	0.042	0.057
	(0.128)	(0.143)	(0.157)	(0.106)	(0.107)	(0.162)
Industry (NACE section) FE		✓	✓		✓	✓
Other controls			✓			✓
Constant	1.335	1.459	2.018	1.234	1.626	2.765
	(0.089)	(0.551)	(0.610)	(0.057)	(0.140)	(0.995)
n (companies)	469	469	462	740	740	731
N (company–week obs.)	73,164	73,164	72,072	115,440	115,440	114,036
Log pseudo-L	-35,953.66	-35,938.10	-35,236.76	-61,898.05	-61,881.60	-61,137.08
Wald χ^2	9.06	44.96	66.03	0.14	167.54	23.93

Notes: The dependent variable in all columns is impact resistance, as specified in Equation 2.1. In both panels, column 1 estimates the regression model specified in Equation 2.7, while columns 2 and 3 estimate the regression model specified in Equation 2.8. Fiscal stimulus is measured by the change in primary budget balance from 2019 to 2020. Countries that implemented limited (with respect to the average of 6.4% of GDP) fiscal packages include the following: Estonia, Finland, Germany, Ireland, Latvia, Luxembourg, the Netherlands, Portugal, and Slovakia; countries that implemented broad fiscal packages include Austria, Belgium, Cyprus, France, Greece, Italy, Lithuania, Malta, Slovenia, and Spain. Robust standard errors clustered at the company level in parentheses below coefficient estimates. See Supplement Section A2 for descriptive statistics, including the distribution of companies across industries and locations, as well as government finance statistics.

Table 2.10: Heterogeneity Analysis by Fiscal Stimulus for Resilience as Recovery Speed

	Panel A. Limited Fiscal Stimulus			Panel B. Broad Fiscal Stimulus		
	(1)	(2)	(3)	(1)	(2)	(3)
R&D spender	-0.197	-0.206	-0.203	-0.082	-0.048	-0.047
	(0.057)	(0.065)	(0.066)	(0.044)	(0.046)	(0.047)
Industry (NACE section) FE		✓	✓		✓	✓
Other controls			✓			✓
Constant	3.667	3.709	3.683	3.728	3.164	3.129
	(0.036)	(0.257)	(0.262)	(0.021)	(0.167)	(0.162)
n (companies)	431	431	424	689	689	681
N (company–week obs.)	15,456	15,456	15,171	28,095	28,095	27,814
Log pseudo–L	-44,932.06	-44,925.31	-44,083.14	-82,372.98	-82,356.02	-81,521.69
Wald χ^2	16,748.76	41,764.10	39,948.26	42,640.54	87,522.09	91,870.35

Notes: The dependent variable in all columns is recovery speed, as specified in Equation 2.3. In both panels, column 1 estimates the regression model specified in Equation 2.10, while columns 2 and 3 estimate the regression model specified in Equation 2.11. Fiscal stimulus is measured by the change in primary budget balance from 2019 to 2020. Countries that implemented limited (with respect to the average of 6.4% of GDP) fiscal packages include the following: Estonia, Finland, Germany, Ireland, Latvia, Luxembourg, the Netherlands, Portugal, and Slovakia; countries that implemented broad fiscal packages include Austria, Belgium, Cyprus, France, Greece, Italy, Lithuania, Malta, Slovenia, and Spain. Robust standard errors clustered at the company level in parentheses below coefficient estimates. See Supplement Section A2 for descriptive statistics, including the distribution of companies across industries and locations, as well as government finance statistics.

Table 2.11: Heterogeneity Analysis by Non–Fiscal Policy Responses

	Panel A. Less Stringent			Panel B. More Stringent		
	(1)	(2)	(3)	(1)	(2)	(3)
R&D spender	0.121	0.119	-0.062	0.314	0.340	0.452
	(0.148)	(0.157)	(0.225)	(0.097)	(0.104)	(0.119)
Industry (NACE section) FE		✓	✓		✓	✓
Other controls			✓			✓
Constant	1.458	1.636	2.599	1.178	1.377	2.273
	(0.098)	(0.357)	(0.575)	(0.054)	(0.395)	(0.701)
n (companies)	406	406	399	803	803	794
N (company–week obs.)	63,336	63,336	62,224	125,268	125,268	123,864
Log pseudo–L	-31,603.14	-31,589.73	-31,051.26	-66,248.04	-66,232.92	-65,346.06
Wald χ^2	0.66	74.81	40.86	10.47	100.57	86.25

Notes: The dependent variable in all columns is impact resistance, as specified in Equation 2.1. In both panels, column 1 estimates the regression model specified in Equation 2.7, while columns 2 and 3 estimate the regression model specified in Equation 2.8. Stringency is measured by the OxCGRT 2020 Stringency Index. Countries that implemented less stringent policies include the following: Austria, Belgium, Cyprus, Estonia, Finland, Greece, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Slovakia, and Slovenia; countries that implemented more stringent policies include France, Germany, Ireland, Italy, Portugal, and Spain. Robust standard errors clustered at the company level in parentheses below coefficient estimates. See Supplement Section A2 for descriptive statistics, including the distribution of companies across industries and locations, as well as non–fiscal policy response statistics.

2.6 Discussion

The analyses carried out and presented in this chapter suggest that innovation enhances corporate resilience, and this relationship is moderated by fiscal policies aimed at crisis containment and recovery. Most notably, I find that the impact of innovation on resilience—defined as crisis impact resistance and recovery speed—is stronger in countries that provided fiscal incentives for innovation during the COVID–19 pandemic, such as Germany. My findings are aligned with the long–standing literature on the effectiveness of tax incentives for business investment and innovation (Hall and Jorgenson 1967; Hassett and Hubbard 2002; Zwick and Mahon 2017; Dechezleprêtre et al. 2023) but contrast with economic theory and recent evidence suggesting that tax incentives are not effective during crises (Bloom, Bond, and Van Reenen 2007; Bloom 2009; Guceri and Albinowski 2021; Link et al. 2024). More importantly, my research on innovation and resilience brings a novel insight into the field of macroeconomics: the provision of tax incentives for innovation during a recession may contain its severity as well as enable faster recovery.

This chapter complements several recent papers on economic resilience. Specifically, it relates to research examining firm–level characteristics that contribute to resilience (Aghion et al. 2021; Ding et al. 2021; Li et al. 2021b), as well as research on resilience in supply chains (Grossman, Helpman, and Lhuillier 2023; Grossman, Helpman, and Sabal 2024). My findings are in contrast to a recent study on digitization and resilience (Copestake, Estefania–Flores, and Furceri 2024), which does not find differential effects across a large number of countries and regions: I find that the impact of innovation on resilience is heterogeneous across 17 member states of the EA that are also members of the OECD, and this is largely due to fiscal policies they implement. Furthermore, I find heterogeneous effects across countries belonging to French and German legal origins.

As the absence of a fiscal union has been and remains a bottleneck in the process of European integration (European Parliament 2025), my findings support the need for greater coordination of fiscal policies in the EA. [20] There has been coordination in the realm of multinational enterprise taxation due to the OECD Base Erosion and Profit Shifting Project (Organization for Economic Cooperation and Development 2025a), as well as after the establishment of the European Fiscal Board (European Commission 2025a). However, policies on corporate income taxation in general and incentives for innovation, in particular, are set by national governments, and there is wide variation in both respects, as evidenced by effective average tax rates and implied tax subsidy rates. My findings suggest that fiscal policies before and during a union–wide recession differentially affect corporate resilience in individual member states of a monetary union; therefore, as well as due to interactions between monetary and fiscal policy (Beetsma and Jensen 2005; Reichlin et al. 2021), fiscal integration is indispensable to a long–lasting economic union.

2.7 Conclusion

This chapter provided evidence on how innovation affects corporate resilience in euro area member states—countries that are in a monetary union but do not form a fiscal union, thus retaining autonomy over business taxation and expenditure. Drawing on prior research in the field of economics, I argued and found support for the hypothesis that fiscal policies aimed at crisis containment and recovery moderate the relationship between corporate innovation and resilience: the observed impact of the allocation of resources to R&D on resilience—defined as crisis impact resistance and recovery speed—is stronger in countries that had lower effective average corporate tax rates during the COVID–19 pandemic and, at the same time, higher implied tax subsidy rates for R&D. I also found evidence on the role of institutions in the study of corporate innovation and resilience: the observed impact of innovation on resilience is greater in German civil law countries.

20. An insightful speech on this topic is the Feldstein Lecture delivered by Dr. Mario Draghi at the 2023 NBER Summer Institute. See National Bureau of Economic Research (2023).

CHAPTER 3
CORPORATE INNOVATION AND RESILIENCE IN THE UNITED KINGDOM

3.1 Introduction

Organizations, regions, and nations face economic crises—such as those caused by the recent pandemic and the war in Ukraine—that necessitate the development of capabilities to cope with uncertainty and volatility. The ability of economic agents to withstand and rebound from crises is encapsulated in the concept of *resilience*, which, originating in natural sciences (Alexander 2013), has recently gained paramount importance in economic and managerial studies (Hillmann and Guenther 2021; Brunnermeier 2024).

Although innovation scholars have long recognized the crucial role played by national and regional actors, including government agencies responsible for innovation policy and universities conducting basic research, in fostering firm applied research and development (Asheim and Gertler 2006; Edquist 1997, 2006; Mowery and Sampat 2006), the literature streams on organizational resilience and regional resilience have evolved largely in parallel, with little or no cross–fertilization. In this paper, I take a step towards synthesizing the two by offering a novel theoretical framework on how national and regional actors

*The paper on which this chapter is based was conceived in November 2024 and developed while I was a visiting doctoral researcher at the Manchester Institute of Innovation Research in Manchester, United Kingdom (February–April 2025). I would like to thank Professor Cornelia Lawson, head of the Innovation, Strategy, and Sustainability group at the Alliance Manchester Business School, and Dr. An Yu Chen, postgraduate researcher affiliated with the same group, for the invitation and a productive stay at the Institute. During the visiting research stay, I benefited from discussions with Professors Kieron Flanagan, Elvira Uyarra, Raquel Ortega–Argilés, Philip Shapira, and Philip McCann. I thank them all and acknowledge that any errors are my own.

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JEL classification codes: E32; M21; O31; R58.

interact through funding and knowledge flows in enhancing resilience at the organizational level. Furthermore, I provide empirical evidence testing the relationships identified in the framework by using data of publicly traded companies and government funding for research and innovation in the United Kingdom (UK).

Specifically, I follow Flanagan, Uyarra, and Laranja (2011) in adopting a multi–level multi–actor perspective to study how innovation affects resilience across space: my starting observation is that, acting at the national level, the government funds both basic research (carried out mostly at universities) and applied research and development (conducted to a large extent by business enterprises). The UK Research and Innovation (UKRI), established by the *Higher Education and Research Act 2017*, is a prime example of such an actor. Second, I note that there are knowledge flows between two key actors at the regional level (Feldman and Kogler 2010): on the one hand, universities train the workforce employed by business enterprises and transfer technology resulting from basic research; on the other hand, business enterprises develop and supply equipment and software used in academic research. A prime example of a flow from academia to industry is the mRNA technology used in the development of COVID–19 vaccines by Moderna and Pfizer companies, while a salient example of a flow from industry to academia is the Zoom software used for remote work and learning throughout the pandemic. Finally, the ability of business enterprises to withstand and rebound from crises, i.e., resilience as crisis impact resistance and crisis recovery speed (Holling 1973, 1996), is determined by innovation: companies allocating greater resources to innovation are less likely to incur a loss due to an exogenous crisis as well as recover faster if having incurred a loss (Shakhmuradyan 2023; Shakhmuradyan and Campagnolo 2025). Taken together, the three pieces of the framework suggest that innovation enhances corporate resilience to a greater extent in regions that benefit from more public funding for research and innovation. I find evidence supporting this hypothesis based on the analysis of financial statements and stock price data of around 300 companies traded on the London Stock Exchange before and during the COVID–19 pandemic, combined with statistics on the regional distribution of UKRI funding before the pandemic.

By studying how innovation affects resilience in a multi–level multi–actor setting, I contribute to several strands of economic literature. First and most importantly, I contribute to the growing literature on resilience. Scholars working on both organizational resilience (Williams et al. 2017; Hillmann and Guenther 2021) and regional resilience (Christopherson, Michie, and Tyler 2010; Bristow and Healy 2014; Boschma 2015; Martin and Sunley 2015) emphasize that it is determined by resources and capabilities, such as human capital and technology, which may be deployed and redeployed in response to exogenous crises. There has been recognition among scholars working on regional resilience that organizational and regional resilience are intertwined: for instance, in the introduction to a special issue on regional resilience in the *Cambridge Journal of Regions, Economy and Society*, the editors note the following: *"political and economic processes, such as those that lead to investment in one neighborhood or region and disinvestment in another, are at the core of regional resilience"* (Christopherson, Michie, and Tyler 2010, p. 4); similarly, in a theoretical elaboration on regional resilience from an evolutionary perspective, Boschma (2015, p. 736) notes that *"the long–term adaptability of regions is conditioned by its industrial, network and institutional legacy which provides opportunities but also sets limits for local actors to be resilient."* However, there is no study—to the best of my knowledge—offering a unifying perspective and empirical evidence on how policies affecting the spatial distribution of innovative economic activity at the regional level, such as funding for research and development (R&D), may foster resilience at the organizational level. [1]

Secondly, I contribute to the geography of innovation literature (Jaffe, Trajtenberg, and Henderson 1993; Audretsch and Feldman 1996, 2004; Feldman and Kogler 2010) and particularly to the research stream on regional innovation systems (Asheim and Gertler 2006). As noted by Feldman and Kogler (2010, p. 383), *"The deliberate and unintended circulation of knowledge between economic actors and the role of physical proximity and colocation are pivotal in understanding the dynamics of the innovation process."* Similarly,

1. Similarly, Martin (2012, p. 28) notes the following: *"A full explanation [of regional economic resilience] would need to analyze the reactions and adjustments of both firms and workers at the local level, as well as the reactions of local institutions and policy actors."*

Asheim and Gertler (2006, p. 292) note that *"geography is fundamental, not incidental, to the innovation process itself. ... one simply cannot understand innovation properly if one does not appreciate the central role of spatial proximity and concentration in this process."* My findings suggest that the regional distribution of funding for research and innovation plays a role in determining the strength of the relationship between innovation and resilience in the UK—a nation characterized by stark regional disparities in economic development (McCann 2016). By highlighting the links between government, business enterprises, and academia, I also relate to the triple helix model of university–industry–government relations (Etzkowitz and Leydesdorff 1997; Leydesdorff 2000).

Finally, I contribute to the literature on the complementarity between public and private expenditure on R&D. In their review of the early evidence, David, Hall, and Toole (2000) note that public and private research are complements rather than substitutes; however, prior research findings are not unequivocal, as the results often depend on the econometric specification and granularity of the data (micro studies of business enterprises versus macro studies of economy–wide aggregates) employed. My study is unique in combining company–level R&D data with regional statistics on the distribution of public funding for research and innovation. I find support for complementarity, as the relationship between corporate R&D expenditure and resilience is stronger in regions that receive greater government funding for research and innovation.

The remainder of this chapter is organized as follows: Section 3.2 below provides a review of the related literature and outlines the theoretical framework that guides my empirical analysis; Section 3.3 elaborates on the institutional setting of my research, as well as the data sources and methodology I use; Section 3.5 provides the results; Section 3.6 discusses the results in relation to the literature reviewed above; and Section 3.7 concludes.

3.2 Theoretical Framework and Hypotheses

3.2.1 Theoretical Background

In this chapter, I take a step towards synthesizing the literature streams on organizational resilience and regional economic resilience by offering an integrative framework. As noted in the introduction, the two literature streams have evolved largely in parallel: the literature on *regional resilience* is grounded in the field of economic geography (Martin 2012; Bristow and Healy 2014), while the literature on *organizational resilience* is grounded in the field of management (Williams et al. 2017; Hillmann and Guenther 2021).

Since its inception, the literature on regional resilience has recognized the interaction between institutions and organizations in fostering the adaptability of regions to exogenous crises. Most notably, Martin (2012, p. 10) proposes that *"regional economic resilience ... could be viewed as having to do with the capacity of a regional economy to reconfigure, that is adapt, its structure (firms, industries, technologies and institutions) so as to maintain an acceptable growth path in output, employment and wealth over time."* Similarly, Bristow and Healy (2014, p. 927) adopt a complex adaptive systems perspective in studying resilience, arguing that *"regional economies must be understood as broad and diverse entities driven by the decision–making of an array of different individual actors—firms, policymakers, labor, consumers, and civil society."* The organizational resilience literature, by contrast, is not explicit about how regional institutions and policies affect the ability of organizations to withstand and rebound from crises. In their seminal review of the literature, Williams et al. (2017, p. 741) note that "a dynamic perspective [on resilience] would involve an interaction between actors (i.e., organizations, individuals, and institutions) and the environment." However, and despite their emphasis on the integration between the literature streams on resilience and crisis management, there is no discussion of how organizations and institutions interact in the process of preparing for and/or responding to adversities. Two reviews concurrent with Williams et al. (2017), namely Bundy et al. (2017) and Linnenluecke (2017), survey a large body of research on crisis management and organizational resilience, respectively. Although neither refers to sources of variation in organizational resilience due to regional factors, Linnenluecke (2017, p. 25) acknowledges that *"resilience is often not determined just by organizational resources and capabilities alone, but by the interrelations and interactions that organizations have with other actors."* Finally, Hillmann and Guenther (2021, p. 33) note that innovation is an antecedent of resilience; however, they do not identify either the organizational–level mechanisms through which innovation enhances resilience or factors at the regional and national level that may affect the relationship between innovation and resilience.

3.2.2 Hypotheses

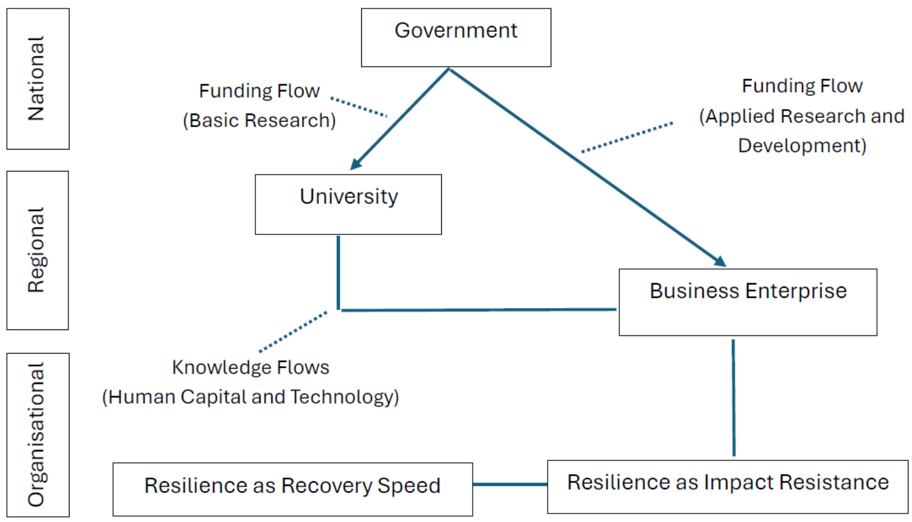
In this paper, I follow Flanagan, Uyarra, and Laranja (2011) and adopt a multi–level multi–actor perspective to study the relationship between innovation and resilience. I distinguish among three levels of analysis: *national*, *regional*, and *organizational*, and three actors: the *government*, *universities*, and *business enterprises* (see Figure 3.1 below). Based on the literature on national innovation systems (Edquist 1997, 2006), I note that the government funds both basic research (conducted mostly at universities) and applied research and development (carried out mostly by business enterprises): these are denoted as *funding flows* in the framework. The geography of innovation literature (Feldman 1994; Feldman and Kogler 2010) suggests that there are *knowledge flows* between two actors at the regional level: these may take the form of either human capital mobility (Almeida and Kogut 1999) or technology transfer (Bercovitz and Feldman 2006). Based on ecological and engineering foundations of the concept (Holling 1973, 1996; Rose 2007), resilience is observed at the organizational level as crisis *impact resistance* and *recovery speed*.

Two hypotheses may be derived from the framework:

Hypothesis 1. *Private expenditure on innovation enhances resilience to a greater extent in regions that receive more public funding for research and innovation before crises.*

Hypothesis 2. *Private expenditure on innovation enhances resilience to a greater extent in regions that receive more public funding for research and innovation during crises.*

Figure 3.1: Theoretical Framework on How Innovation Affects Resilience in a Multi–Level Multi–Actor Setting



Source: Own elaboration.

Due to the UK's exit from the European Union (EU), effective 31 January 2020, and subsequent changes in UKRI reports on the geographical distribution of funding, I test only Hypothesis 1. Regional funding data are available at both NUTS 1 and NUTS 2 levels (UK Research and Innovation 2025d), and I carry out the baseline analyses at the NUTS 1 level, matching corporate postcodes to 12 regions in the UK. [2] Section 3.3 below provides further details on the methodology and data I use, including the matching procedure.

2. As a result of the UK's exit from the EU, the Eurostat classification (*Nomenclature des unités territoriales statistiques* (NUTS) was replaced with the International Territorial Levels (ITLs). However, the UKRI funding report for FY 2018–2019 is based solely on the NUTS classification, as the replacement scheme took effect in 2021. See Office for National Statistics (2025) for further details.

3.3 Empirical Setting and Data

3.3.1 Institutional Setting

Public funding for research and innovation in the UK is administered by the UK Research and Innovation (UKRI), a non–departmental government body sponsored by the Department for Science, Innovation and Technology (UK Research and Innovation 2025a). It was established after the enactment of the *Higher Education and Research Act 2017*, on 1 April 2018, bringing together seven disciplinary research councils, including the Economic and Social Research Council and the Medical Research Council. In addition to research councils, UKRI incorporates Research England, supporting research and knowledge exchange at higher education institutions in England, and the national innovation agency, Innovate UK (UK Research and Innovation 2025f, 2025e).

UKRI funds both academic and business research (UK Research and Innovation 2025h). Funding decisions are made independently from the government and in accordance with the Haldane principle (Section 103 of the *Higher Education and Research Act 2017*), which states that *"decisions about which research projects to fund should be made through independent evaluation by experts, based on the quality and likely impact of that research"* (UK Research and Innovation 2025g). UKRI annual reports and accounts suggest that it invested a total of GBP 7.5 billion in the financial year (FY) ending on 31 March 2019 (UK Research and Innovation 2025b).

Tables 3.1 and 3.2 and Figures 3.2 and 3.3 below provide the geographical distribution of UKRI funds by NUTS 1 regions in FY 2018–2019. It can be observed that although London received the largest amount of research council funding in monetary terms (GBP 470 million), the funding per research organization has been greater in Yorkshire and The Humber region (around GBP 680 thousand), followed by Scotland (around GBP 678 thousand). The West Midlands region received the largest amount of Innovate UK funding in monetary terms (GBP 133 million), followed by the South East region (GBP 129 million); the funding per business enterprise has been greater in the West Midlands (around GBP 298), followed by the East Midlands (GBP 270).

Table 3.1: UK Research Council Funding by NUTS 1 Regions, FY 2018–2019

NUTS 1 Region	Funding Expenditure			
	GBP (million)	per research organization (GBP)	as a share of GVA (%)	per capita (GBP)
East Midlands	102	387,479	0.10	21
East of England	279	534,697	0.18	45
London	470	353,294	0.11	52
North East	104	623,157	0.20	39
North West	265	639,642	0.16	36
Northern Ireland	25	267,378	0.06	13
Scotland	248	677,628	0.18	45
South East	409	502,241	0.16	45
South West	163	386,433	0.12	29
Wales	66	476,817	0.11	21
West Midlands	128	410,998	0.10	22
Yorkshire and The Humber	191	678,916	0.16	35

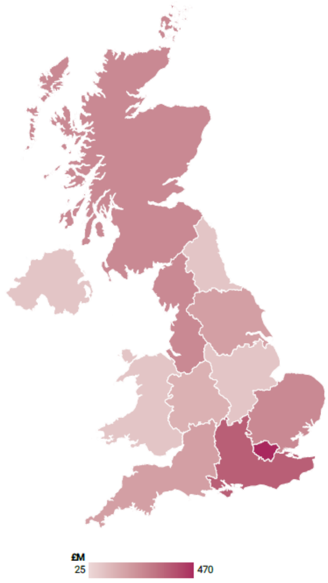
Source: UK Research and Innovation (2025d)
Note: GBP indicates the British pound, and GVA stands for gross value added.

Table 3.2: Innovate UK Funding by NUTS 1 Regions, FY 2018–2019

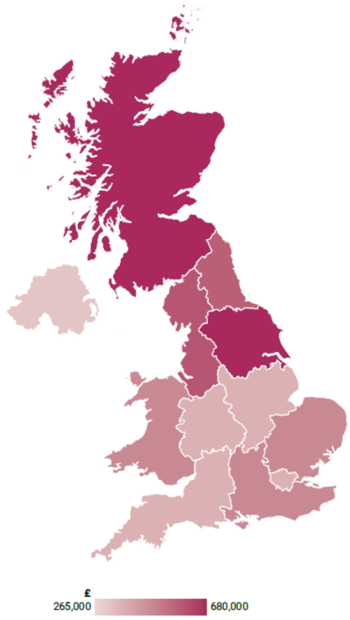
NUTS 1 Region	Funding Expenditure				
	GBP (million)	per business enterprise (GBP)	per R&D active business (GBP)	as a share of GVA (%)	per capita (GBP)
East Midlands	99	270.0	26,093	0.09	21
East of England	82	145.4	14,402	0.05	13
London	125	113.8	10,550	0.03	14
North East	39	241.6	19,665	0.07	15
North West	41	74.9	6,690	0.02	6
Northern Ireland	11	85.5	7,023	0.03	6
Scotland	57	171.0	19,376	0.04	10
South East	129	147.4	14,359	0.05	14
South West	116	212.5	26,029	0.09	21
Wales	30	148.8	14,781	0.05	9
West Midlands	133	297.6	24,447	0.10	22
Yorkshire and The Humber	79	197.9	18,504	0.07	14

Source: UK Research and Innovation (2025d)
Note: GBP indicates the British pound, and GVA stands for gross value added.

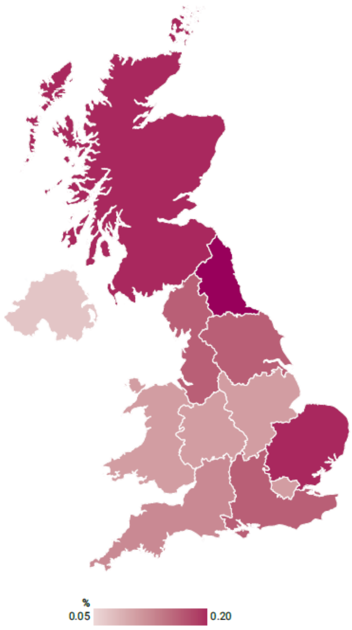
Figure 3.2: UK Research Council Funding by NUTS 1 Regions, FY 2018–2019



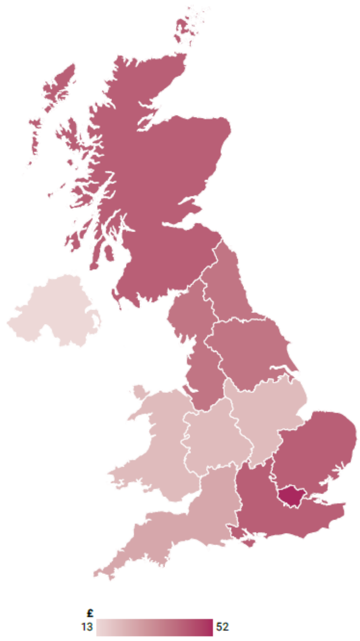
(a) Total



(b) Per Research Organization



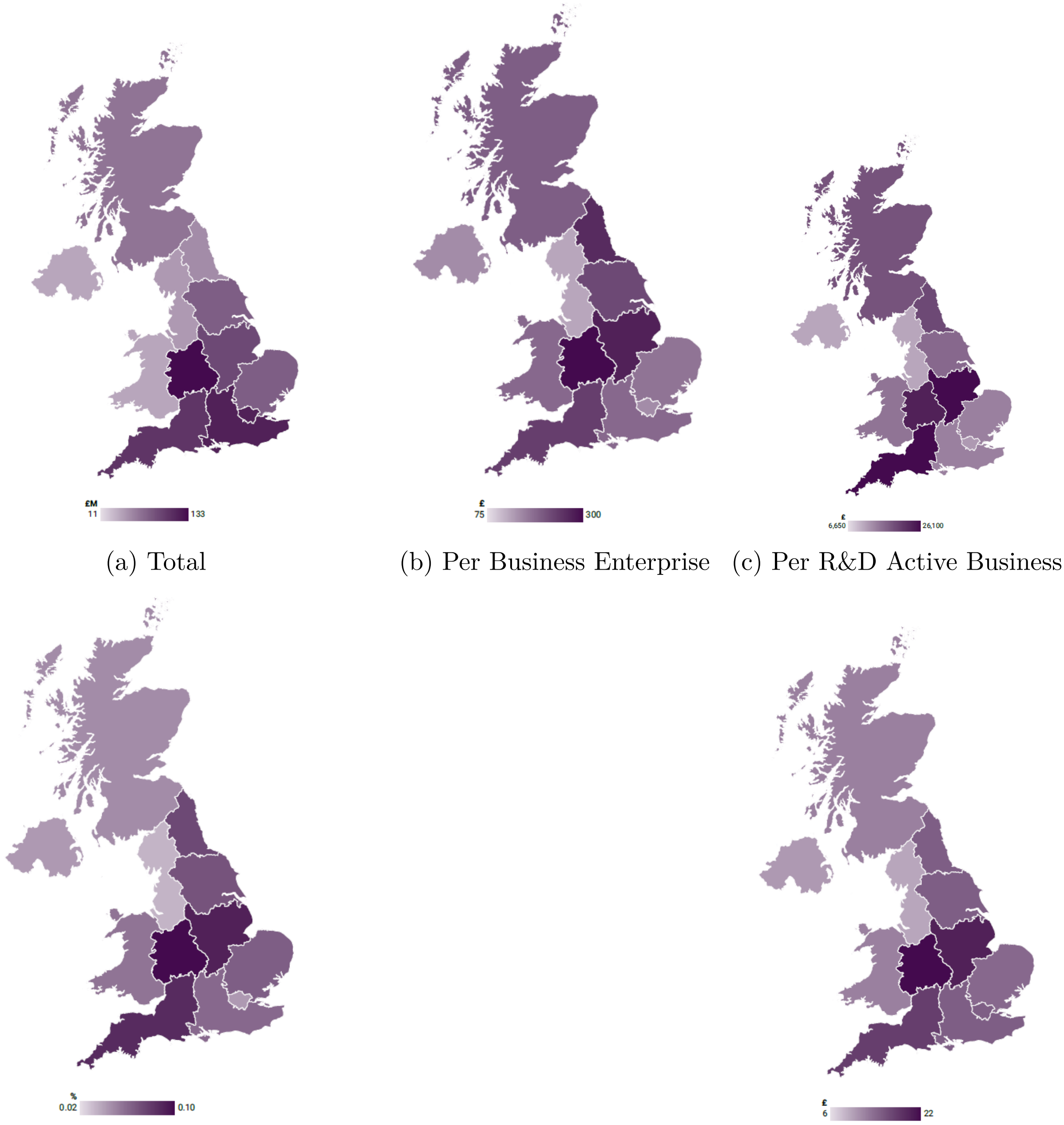
(c) Share of Regional GVA



(d) Per Capita

Source: UK Research and Innovation (2025d)

Figure 3.3: Innovate UK Funding by NUTS 1 Regions, FY 2018–2019



(a) Total (b) Per Business Enterprise (c) Per R&D Active Business

(d) Share of Local GVA (e) Per Capita

Source: UK Research and Innovation (2025d)

Note: See Appendix A3 for a map with regional designations.

3.3.2 Corporate Accounts

The corporate data used in this chapter are from the Companies House, the UK government agency responsible for maintaining company records. Each company may be identified by its eight–digit registration number, and the company registry includes data such as registered office address, incorporation date, industry classification, and annual accounts (UK Companies House 2025a). From the population of 1,695 publicly traded companies, [3] I exclude companies not incorporated in the UK ($n = 315$), as well as financial companies, i.e., those operating under Standard Industrial Classification sections K (finance and insurance, $n = 458$) and L (real estate, $n = 30$) (UK Companies House 2025b), as the financial ratios of companies in these industries are not directly comparable to the financial ratios of companies in other industries (Fama and French 1992). Thus, I obtain a sample of 892 companies.

Furthermore, I exclude companies with missing net income ($n = 124$), as well as companies reporting negative net income ($n = 352$) in 2019. This is meant to ensure that losses incurred during the crisis are due to its impact, rather than other, company–specific factors (Altman 1968). Thus, my sample is reduced to 416 companies. In addition, I obtain data on R&D expenses in 2019 to classify companies as either R&D spenders or non–spenders pre–crisis, as this enables me to claim exogeneity of the independent variable of innovation with respect to the dependent variables of resilience (see Section 3.4.1 below). Non–missing non–zero values for R&D are available for 137 companies, and therefore, these are classified as R&D spenders. For both R&D spenders and non–spenders, I gather additional financial data from both balance sheets and profit–loss accounts, e.g., total assets, current assets, and current liabilities, as these enable me to calculate measures of liquidity and profitability, which serve as controls in econometric estimation (see Section 3.4.2 below).

3. The official designation of publicly traded companies in the UK is *public limited company* (PLC); data were last accessed on 10 March 2025.

3.3.3 Stock Prices

I gather stock price data of all companies traded on the London Stock Exchange from the London Stock Exchange Group (LSEG) Workspace (formerly Refinitiv Eikon database). Price data for the calendar weeks between W1–2019 and W52–2021 are available for 1,785 companies, and similar to the procedure above, I exclude companies not incorporated in the UK ($n = 542$) and financial companies ($n = 435$). To obtain a balanced panel, I exclude companies with missing stock price data in any of the observed weeks ($n = 148$), as well as companies the stocks of which traded below the 1$^{\text{st}}$ percentile and above the 99$^{\text{th}}$ percentile of the price distribution in any of the weeks ($n = 27$). The matching of the resulting panel ($n = 633,\ T = 156$) with the cross–section of 416 companies obtained above using the registration numbers and the retention of only those companies that appear in both data sets results in a strongly balanced panel of 313 companies observed over 156 weeks, i.e., 48,828 company–week observations. In this panel, 121 companies ($\approx$ 39% of the total) are R&D spenders, and it constitutes the basis for most statistical analyses reported below. Appendix Figures C2 and C3 below provide the distribution of companies by industries, for both the sample as a whole and separately for R&D spenders and non–spenders.

3.3.4 Matching Procedure

Corporate data are matched to UKRI funding data using company postcodes. The alpha–numeric postcode used in the UK has two components—the outward code and the inward code—the former of which denotes the postcode area: for instance, the first two letters of the postcode "NE13 8BF" indicate that it belongs to the "NE" area, i.e., Newcastle upon Tyne. There are currently 121 postcode areas in the UK, and these correspond to 179 regions at the NUTS 3 level, which in turn are mapped into 41 regions at the NUTS 2 level and 12 regions at the NUTS 1 level (see Appendix Table C1). [4] The

4. The complete list of NUTS codes and names is available from the *Regional Accounts Methodology Guide*, last revised in June 2019 (Office for National Statistics 2019).

postcode area "NE" belongs to UKC22, i.e., the North East region. Using an archived version of the Eurostat correspondence tables, I match each company postcode to its postcode area and the region. [5] Appendix Figures C4 and C5 provide the distribution of companies by regions, for both the sample as a whole and separately for R&D spenders and non–spenders.

3.4 Measures and Econometric Estimation

3.4.1 Resilience Measures

Holling (1996, p. 33) notes that the conception of resilience in economic theory, termed *engineering resilience*, focuses on "stability near an equilibrium steady state, where resistance to disturbance and speed of return to the equilibrium are used to measure the property." In line with this conception, I 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):

$$IR = \begin{cases} 1 & \text{if } P_t \geq P_{t-s} \\ 0 & \text{otherwise.} \end{cases} \tag{3.1}$$

When calculated with weekly data, s in Equation 3.1 above 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:

5. Correspondence tables and data files were accessed through the Web Archive: https://web.archive.org/web/20190711160208/https://ec.europa.eu/eurostat/web/nuts/correspondence-tables/postcodes-and-nuts (last update: 2 August 2018).

$$RS \in \mathbb{N}. \tag{3.2}$$

In the context of the pandemic–induced recession in the UK, whereby the start of the recession using weekly data can be dated to W12–2020 (see Appendix Figure C6), and there are observations up to W52–2021, the following is true:

$$1 \leq RS \leq 92. \tag{3.3}$$

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).

3.4.2 Econometric Estimation

I adopt three econometric approaches to examine whether more innovative companies are more resilient and whether this effect varies across regions. First, I estimate a two–way fixed effects difference–in–differences (TWFE DID) regression model to quantify the differential effect of being an R&D spender during the crisis induced by the COVID–19 pandemic. Specifically, I estimate an equation of the following form:

$$\ln(Price)_{it} = \phi_i + \gamma_t + \alpha D_{it} + \epsilon_{it}, \tag{3.4}$$

where i denotes companies, and t denotes time (156 weeks spanning from W1–2019 to W52–2021 inclusive). D is a binary variable equal to one for R&D spenders in 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. My interest lies in estimating the parameter α, and it is identified if the two assumptions of parallel trends and Granger causality hold. I test both assumptions and provide appropriate test statistics and diagnostic graphs. [6]

Second, I estimate binary outcome (logit) regression models for panel data to test the relationship between being an R&D spender and my first measure of resilience, *impact resistance* (Cameron and Trivedi 2022, pp. 1139–1190):

$$\Pr(IR_{it} = 1 \mid RDS_i, \alpha_i) = \Lambda(\alpha_i + \beta RDS_i), \tag{3.5}$$

where IR_{it} is the crisis impact resistance of firm i at time t; RDS_i is its status in terms of R&D expense (spender or non–spender); and α_i is a random effect (RE).

The augmented specification with controls has the following form:

$$\Pr(IR_{it} = 1 \mid RDS_i, x_i, \alpha_i) = \Lambda(\alpha_i + \beta RDS_i + \boldsymbol{x}_i'\boldsymbol{\gamma}). \tag{3.6}$$

Third, I estimate count data (Poisson) regression models for panel data to examine the relationship between being an R&D spender and my second measure of resilience, *recovery speed*:

$$\mathrm{E}(RS_{it} \mid RDS_i, \alpha_i) = \exp(\alpha_i + \beta RDS_i), \tag{3.7}$$

where RS_i is the recovery speed of company i at time t; RDS_i is its status in terms of R&D expense (spender or non–spender); and α_i is a random effect.

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

$$\mathrm{E}(RS_{it} \mid RDS_i, x_i, \alpha_i) = \exp(\alpha_i + \beta RDS_i + \boldsymbol{x}_i'\boldsymbol{\gamma}). \tag{3.8}$$

6. All analyses were carried out with Stata 18 software and reproduced using Stata 19. Specifically, I utilised the `xtdidregress`, `estat ptrends`, `estat granger`, `estat trendplots`, and `estat grangerplot` commands. See StataCorp (2025) for further details.

Controls: The augmented specifications of RE logit and Poisson regression models include as controls several variables that simultaneously affect corporate innovation and resilience, such as *liquidity*, *profitability*, and *age*. The rationale for including these controls is that older and financially less constrained companies are both more likely to allocate resources to innovation (O'Sullivan 2006; Hall and Lerner 2010; Akcigit, Hanley, and Stantcheva 2022) and withstand and rebound from exogenous crises (Williams et al. 2017; Fahlenbrach, Rageth, and Stulz 2021; Smith et al. 2024). 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; and age is measured by years since incorporation. In addition, I control for industry, as there are differences in the allocation of resources to innovation across industries, with some industries being more R&D–intensive than others (Malerba 2006; Smith 2006), and also the impact of the COVID–19 pandemic was uneven across industries: those that enabled work from home to a greater extent were less affected by the pandemic than other industries (Davenport et al. 2020; Dingel and Neiman 2020; Bloom et al. 2025). Industry is identified by the SIC section in which a company operates, and my sample is representative of 15 sections (see Appendix Figure C2).

3.5 Results

3.5.1 TWFE DID Regression Results

Table 3.3 below provides estimation results of the TWFE DID regression model, as specified in Equation 3.4 above. It can be observed that the coefficient of the interaction term *R&D spender* × *Crisis* is positive and significant at the 5% level ($\alpha = 0.105, se = 0.045$), which suggests that the stock prices of companies allocating resources to innovation increased by 10%, on average, during the crisis period. In support of Hypothesis 1, the effect is stronger for the six regions that received above median (GBP 80 million) funding from the UKRI under the Innovate UK scheme in FY 2018–2019, i.e., the West Midlands, South East, London, South West, East Midlands, and East of England ($\alpha = 0.135, se = 0.054$); no significant effect is observed for the other six regions ($\alpha = 0.025, se = 0.077$).

Both the parallel trends and Granger causality assumptions necessary for the validity of TWFE DID regression estimates hold, as evidenced by F test statistics reported in Table 3.3 and the two panels of Figure 3.4 below. Specifically, Panel (a) of Figure 3.4 suggests that there were no appreciable differences between the two groups (*R&D spenders* vs. *non–spenders*) before the crisis, i.e., for the whole period from W1–2019 to W11–2020, and the differences appear during the crisis. In addition, Panel (b) of Figure 3.4 suggests that the positive and significant effect of being an R&D spender during the crisis persists for most of the observed period (up to W39–2021).

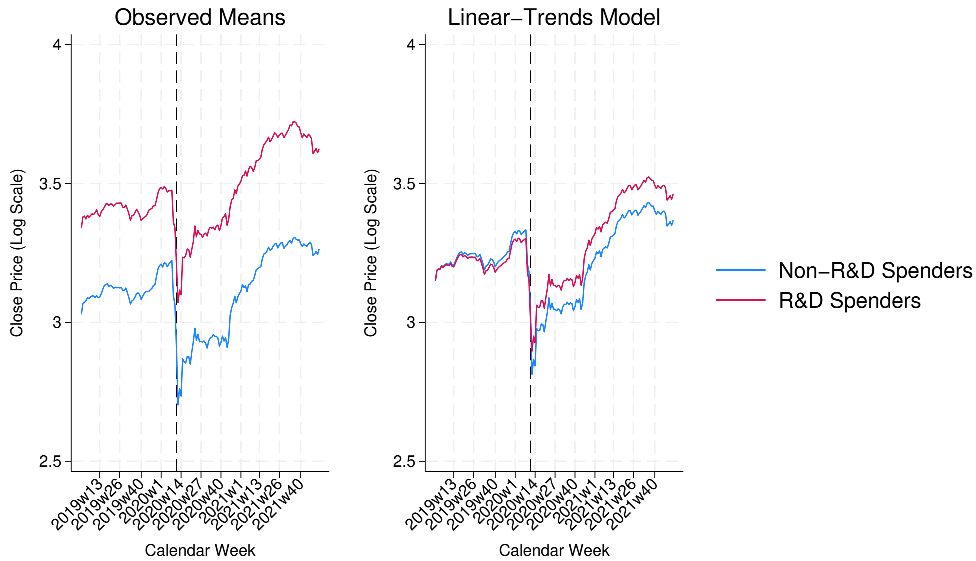
Table 3.3: TWFE DID Regression Results, United Kingdom

	All Regions	Funding above Median	Funding below Median
	(n = 12)	(n = 6)	(n = 6)
R&D spender × *Crisis*	0.105	0.135	0.025
	(0.045)	(0.054)	(0.077)
	[0.017; 0.193]	[0.029; 0.241]	[-0.128; 0.177]
Company FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
n (R&D spenders)	121	89	32
n (non–R&D spenders)	192	148	44
N (company–week obs.)	48,828	36,972	11,856
Parallel trends test	$F_{(1,312)} = 0.46$	$F_{(1,236)} = 0.00$	$F_{(1,75)} = 1.79$
Granger causality test	$F_{(62,312)} = 0.94$	$F_{(62,236)} = 1.20$	$F_{(62,75)} = 6.61$

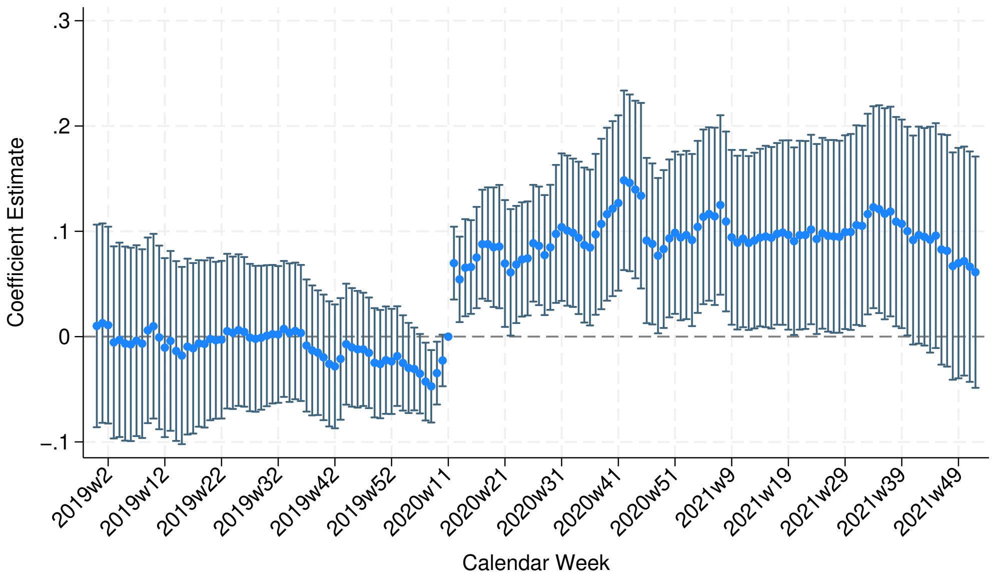
Notes: The classification of a company as an R&D spender is based on the Companies House accounts; 'post' indicates weeks after COVID–19 was declared an emergency, i.e., W12–2020 onward. Regions that received above median (GBP 80 million) funding from the UKRI under the Innovate UK scheme in FY 2018–2019 include the West Midlands, South East, London, South West, East Midlands, and East of England. 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 time period are parallel; the null hypothesis for the Granger causality test is that there is no effect in anticipation of treatment.

Figure 3.4: Graphical Diagnostics for Parallel Trends and Granger Causality, United Kingdom

(a) Parallel Trends



(b) Granger Causality



Note: The sample includes 313 publicly traded companies in the UK observed weekly from W1–2019 to W52–2021, of which 121 are R&D spenders based on the Companies House data classification.

3.5.2 Logit Regression Results

The baseline estimate of the effect of innovation on resilience as crisis impact resistance in all UK regions (see Table 3.4, column 1) is positive and significant ($\beta = 0.247, se = 0.130$), suggesting that R&D spenders were less likely to incur a loss due to the crisis. The coefficient increases in size and retains its significance at the 5% level as additional controls are added to the regression specification (see Table 3.4, columns 2–5): for instance, $\beta = 0.255$ ($se = 0.151$) when controlling for liquidity, profitability, age, and industry fixed effects. Disaggregation of the sample by funding amount across regions (see Table 3.5 below) suggests, as expected, that the effect of innovation on resilience as crisis impact resistance is stronger in regions that received greater funding for R&D. The baseline estimate is positive and significant ($\beta = 0.348, se = 0.157$), increasing in size as other factors are accounted for (e.g., $\beta = 0.350, se = 0.185$ in column 5).

3.5.3 Poisson Regression Results

The baseline estimate of the impact of innovation on resilience as crisis recovery speed in all regions (see Table 3.6, column 1) is negative but insignificant ($\beta = -0.085, se = 0.061$); it stays insignificant as additional controls are added to the regression specification (see columns 2–5). By contrast, the effect is negative and significant in regions that received greater funding for R&D (see Table 3.7 below): for instance, $\beta = -0.147$ ($se = 0.078$) when controlling for liquidity, profitability, and age. The inclusion of industry fixed effects in recovery regressions for the latter renders the coefficient estimate insignificant ($\beta = -0.110, se = 0.090$), suggesting that industry is a stronger determinant of faster recovery from the crisis (see Table 3.7, column 5).

Table 3.4: RE Logit Regression Results, All UK Regions

	Baseline	Extensions			
	(1)	(2)	(3)	(4)	(5)
R&D spender	0.247	0.256	0.255	0.418	0.255
	(0.130)	(0.130)	(0.133)	(0.147)	(0.151)
Log *Liquidity*		-0.009	-0.009	-0.003	-0.009
		(0.006)	(0.006)	(0.007)	(0.007)
Log *Profitability*			0.000	-0.001	0.001
			(0.008)	(0.009)	(0.009)
Age				-0.015	-0.014
				(0.003)	(0.003)
Constant	1.129	1.133	1.135	1.655	1.996
	(0.073)	(0.073)	(0.080)	(0.151)	(0.464)
Industry FE	No	No	No	No	Yes
Observations	48,828	48,828	48,828	48,828	48,828
Log pseudo–L	-26,254.343	-26,253.789	-26,253.787	-26,222.321	-26,209.370
Wald χ^2	3.63	5.63	6.03	29.15	77,203.54

Notes: Robust standard errors clustered at the company level (n = 313) in parentheses below coefficient estimates. See Appendix Figure C2 for the distribution of companies across industries.

Table 3.5: RE Logit Regression Results, UK Regions with Greater Funding

	Baseline	Extensions			
	(1)	(2)	(3)	(4)	(5)
R&D spender	0.348	0.361	0.352	0.495	0.350
	(0.157)	(0.158)	(0.161)	(0.178)	(0.185)
Log *Liquidity*		-0.010	-0.010	-0.006	-0.005
		(0.006)	(0.006)	(0.007)	(0.008)
Log *Profitability*			0.006	0.010	0.013
			(0.009)	(0.010)	(0.009)
Age				-0.015	-0.015
				(0.004)	(0.003)
Constant	1.157	1.163	1.182	1.726	2.050
	(0.084)	(0.085)	(0.094)	(0.186)	(0.507)
Industry FE	No	No	No	No	Yes
Observations	36,972	36,972	36,972	36,972	36,972
Log pseudo–L	-19,539.66	-19,539.255	-19,539.005	-19,516.652	-19,503.613
Wald χ^2	4.93	6.90	7.98	20.75	—

Notes: Robust standard errors clustered at the company level (n = 237) in parentheses below coefficient estimates. Regions with greater funding (Innovate UK, FY 2018–2019) are the West Midlands, South East, London, South West, East Midlands, and East of England. See Appendix Figure C2 for the distribution of companies across industries.

Table 3.6: RE Poisson Regression Results, All UK Regions

	Baseline	Extensions			
	(1)	(2)	(3)	(4)	(5)
R&D spender	-0.085	-0.088	-0.088	-0.114	-0.062
	(0.061)	(0.061)	(0.063)	(0.064)	(0.075)
Log *Liquidity*		0.004	0.004	0.004	0.006
		(0.003)	(0.003)	(0.003)	(0.003)
Log *Profitability*			0.000	0.001	-0.001
			(0.003)	(0.003)	(0.003)
Age				0.002	0.002
				(0.001)	(0.001)
Constant	3.684	3.680	3.681	3.620	3.270
	(0.034)	(0.035)	(0.038)	(0.046)	(0.394)
Industry FE	No	No	No	No	Yes
Observations	11,618	11,618	11,618	11,618	11,618
Log pseudo–L	-33,829.797	-33,829.366	-33,829.365	-33,827.682	-33,816.209
Wald χ^2	17,905.94	18,176.21	18,206.23	19,114.00	71,425.30

Notes: Robust standard errors clustered at the company level (n = 302) in parentheses below coefficient estimates. See Appendix Figure C2 for the distribution of companies across industries.

Table 3.7: RE Poisson Regression Results, UK Regions with Greater Funding

	Baseline	Extensions			
	(1)	(2)	(3)	(4)	(5)
R&D spender	-0.125	-0.130	-0.130	-0.147	-0.110
	(0.073)	(0.073)	(0.076)	(0.078)	(0.090)
Log *Liquidity*		0.004	0.004	0.004	0.004
		(0.004)	(0.004)	(0.004)	(0.004)
Log *Profitability*			0.000	0.000	-0.003
			(0.004)	(0.004)	(0.004)
Age				0.001	0.002
				(0.001)	(0.001)
Constant	3.665	3.662	3.662	3.613	3.294
	(0.040)	(0.041)	(0.044)	(0.054)	(0.418)
Industry FE	No	No	No	No	Yes
Observations	8,500	8,500	8,500	8,500	8,500
Log pseudo–L	-24,668.2	-24,667.982	-24,667.982	-24,667.26	-24,658.569
Wald χ^2	13,446.69	13,709.18	13,710.76	14,180.24	76,342.63

Notes: Robust standard errors clustered at the company level (n = 228) in parentheses below coefficient estimates. Regions with greater funding (Innovate UK, FY 2018–2019) are the West Midlands, South East, London, South West, East Midlands, and East of England. See Appendix Figure C2 for the distribution of companies across industries.

3.6 Discussion

As noted by McCann (2016), the problem of a place–based versus space–blind economic development policy has been perennial in the UK policy agenda. After enactment of the *Higher Education and Research Act 2017* and establishment of the UKRI in April 2018, the higher education and research funding system in the UK has been centralized, and decisions on which projects to fund are made without reference to the location of applicants, in accordance with the Haldane principle (UK Research and Innovation 2025g). The findings of this paper, based on the analysis of UKRI funding distribution data across 12 NUTS regions—combined with financial statements and stock price data of companies based in these regions—suggest that corporate innovation enhances resilience to a greater extent in regions that receive more funding for research and innovation. Therefore, there are interactions between regional innovation investment and resilience that should be taken into account in both current academic research on organizational resilience (Williams et al. 2017; Hillmann and Guenther 2021), as well as public policymaking.

The policy dimension of factors enhancing business resilience has received academic attention only recently. In a theoretical contribution, Grossman, Helpman, and Lhuillier (2023) examine policy responses to global supply chain disruptions, asking whether governments should contribute to resilience by subsidizing supply from multiple countries or promote sourcing from domestic suppliers. Their findings suggest that under certain conditions, subsidies for diversification may be socially optimal. Chapter 2 of this dissertation (Shakhmuradyan 2025) empirically examines corporate innovation and resilience in the euro area (EA) member states—countries that are in a monetary union but do not form a fiscal union—advancing the hypothesis that private expenditure on R&D enhances resilience to a greater extent in countries that provide fiscal incentives for innovation during crises. Shakhmuradyan (2025)'s findings, based on the analysis of data for over 1,200 companies in 19 EA member states, suggest that the impact of innovation on resilience is stronger in countries that had lower effective tax rates and extended tax incentives during the COVID–19 pandemic, such as Germany. The current paper contributes to this literature by emphasizing that due to public policy, the impact of innovation on resilience may also vary *within* a single country, such as the UK.

Several limitations affect the results reported in this paper. First, the procedure of matching corporate to regional data is based on the registered address of the headquarters of a company, which may not necessarily be the same as the location where R&D takes place (Cantwell and Iammarino 2000). For instance, Shell PLC, one of the companies in the matched panel, is registered in London (postcode: SE1 7NA), but its operations are spread across the UK and in over 70 countries. [7] This limitation—known as the 'headquartering effect'—has been acknowledged by the UKRI, in its annual *Geographical Distribution of Funding* reports (UK Research and Innovation 2025d), as well as by Innovate UK, in a separate publication (Innovate UK 2024). Therefore, future research may consider alternative ways of matching corporate locations to regional funding data.

Second, this paper focuses on *research expenditure*, and thus, measures innovation by R&D expenses reported in corporate financial statements. Patents are an alternative measure of innovation and have been widely used in the innovation, productivity, and growth literature generally (Griliches 1998; Smith 2006; Cohen 2010; Kogan et al. 2017; Acemoglu et al. 2018; Akcigit et al. 2022), as well as in studies on regional resilience specifically (Clark, Huang, and Walsh 2010; Rocchetta et al. 2022). The patent data provided by the UK Intellectual Property Office are quite detailed, containing applicant postcodes and regions; therefore, these may be matched to the Companies House and UKRI data used in this paper. [8] Nevertheless, it should be acknowledged that not all companies that report R&D would have patents due to the time lags between patent application and publication; thus, the share of companies identified as innovative may differ across samples.

Last but not least, due to the methodological changes associated with the UK exit from the EU, this paper did not test the impact of UKRI funding allocated *during* the COVID–19 pandemic on the relationship between corporate innovation and resilience. This is a fruitful direction for future research and may be carried out using project–level

7. See https://find-and-update.company-information.service.gov.uk/company/04366849.

8. Available at: https://www.gov.uk/government/publications/ipo-patent-data.

data available through the Gateway to Research system (UK Research and Innovation 2025c).

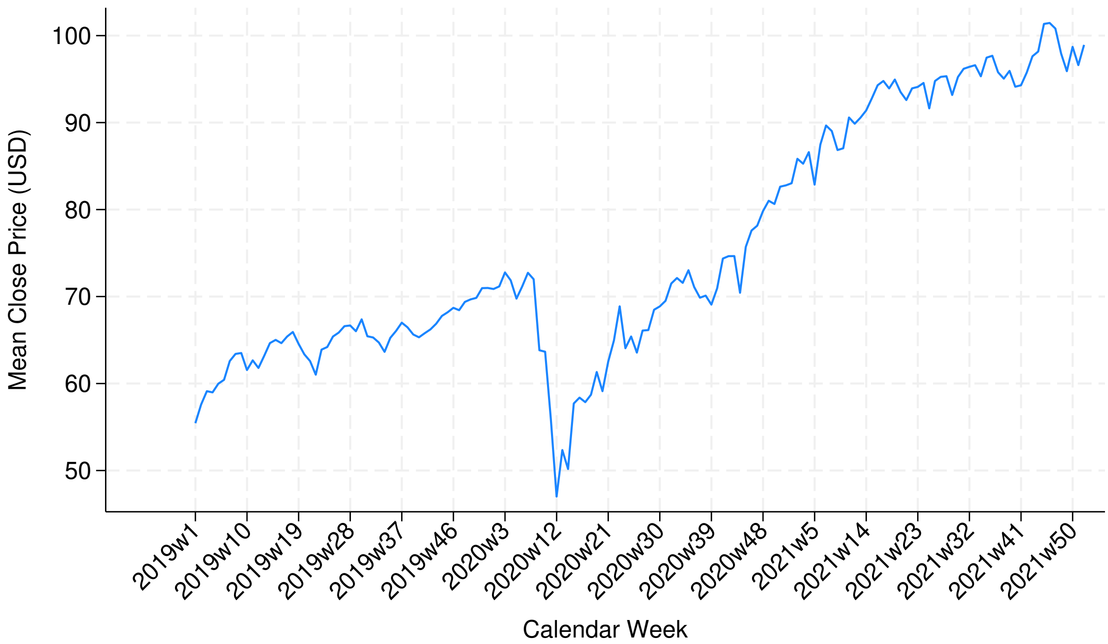
3.7 Conclusion

This paper studied corporate innovation and resilience by synthesizing the two streams of literature on organizational resilience and regional resilience. I advanced the hypothesis that private expenditure on innovation has a stronger impact on corporate resilience in regions that receive greater public funding for research and innovation, *ceteris paribus*. I found support for this hypothesis by using the financial statements and weekly stock price data of around 300 publicly traded companies in the UK during the COVID–19 pandemic, matched by location to data on the geographical distribution of UKRI funding before the pandemic. My findings are aligned with the literature on regional disparities in the UK and call for a greater emphasis on the interactions between public policies aimed at regional development, such as funding for research and innovation, and private–sector outcomes, such as business resilience to exogenous crises.

SUPPLEMENT

A1 Appendix 1

Figure A1: Time Series of Weekly Stock Prices, United States



Note: 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 of the US Sample

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. 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 of the US Sample

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 US 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 percent of total within the full sample and within the subsample of R&D spenders, respectively.

Table A4: Distribution of the US 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 percent of total within the full sample and within the subsample of R&D spenders, respectively.

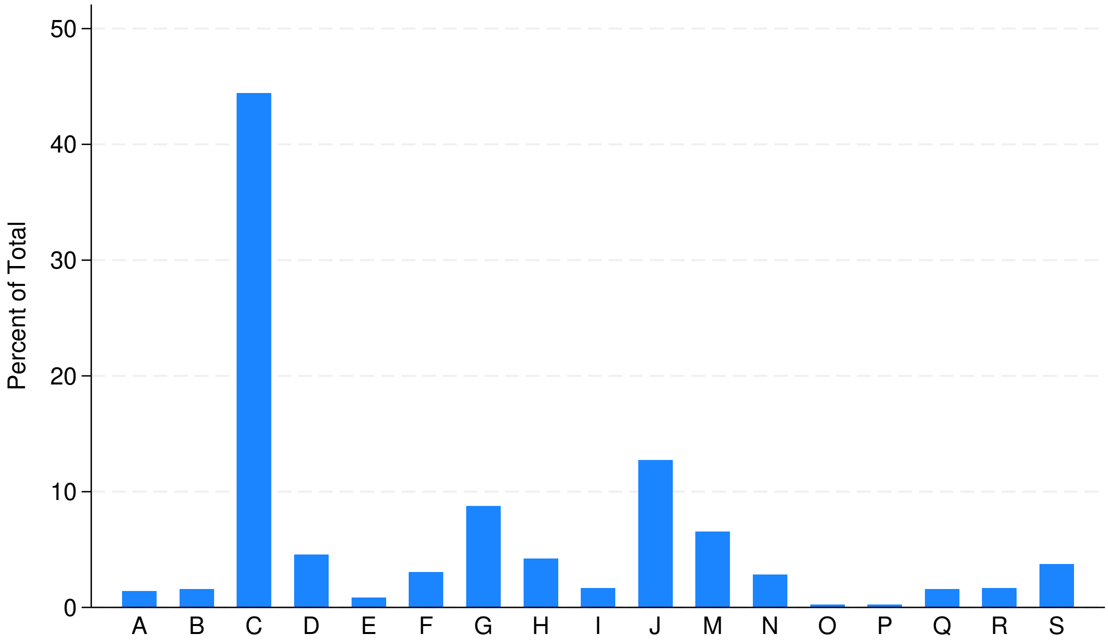
Table A5: Distribution of the US Sample by Locations

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 percent of total within the full sample and within the subsample of R&D spenders, respectively.

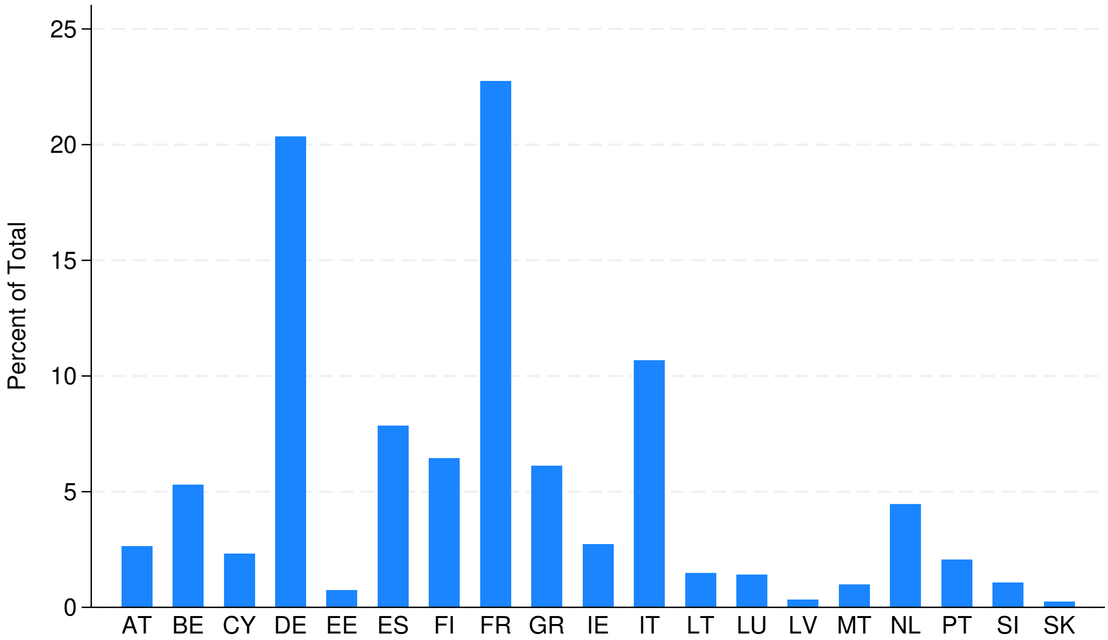
A2 Appendix 2

Figure B1: Distribution of the Sample by Industries, Euro Area



Notes: The sample includes 1,209 publicly traded companies in 19 EA member states as of 1 January 2019. NACE Rev.2 section codes are as follows: A (agriculture, forestry, and fishing), B (mining and quarrying), C (manufacturing), D (electricity, gas, steam, and air conditioning supply), E (water supply, sewerage, waste management, and remediation), F (construction), G (wholesale and retail trade; repair of motor vehicles and motorcycles), H (transportation and storage), I (accommodation and food services), J (information and communications), M (professional, scientific and technical services), N (administrative and support services), O (public administration and defense; compulsory social security), P (education), Q (human health and social work), R (arts, entertainment and recreation), and S (other services). Sections K (finance and insurance) and L (real estate) were excluded at the research design stage due to the incomparability of financial ratios of companies in those industries with companies in other industries (Fama and French 1992). See Eurostat (2008) for further details on the NACE Rev.2 classification.

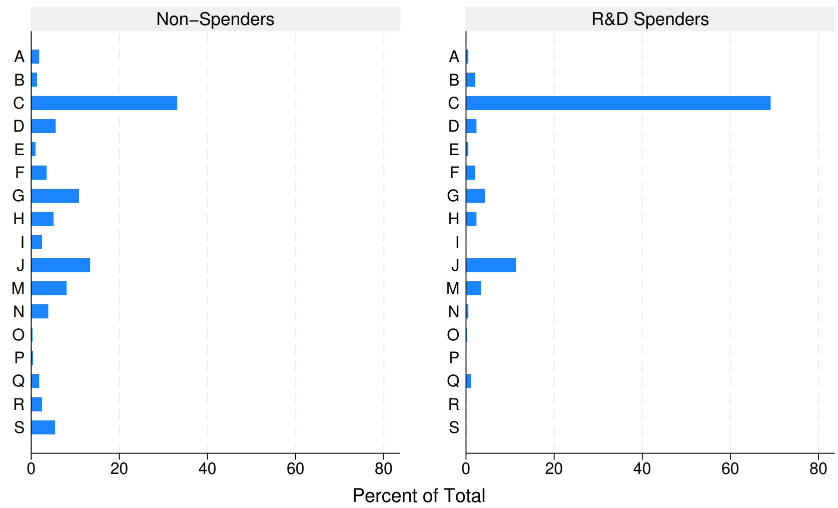
Figure B2: Distribution of the Sample by Locations, Euro Area



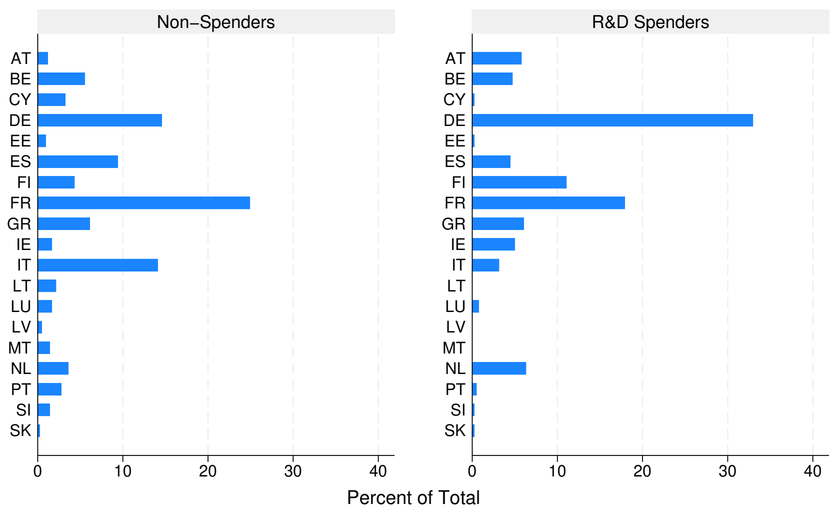
Notes: The sample includes 1,209 publicly traded companies in 19 EA member states as of 1 January 2019. Country codes are as follows: AT (Austria), BE (Belgium), CY (Cyprus), DE (Germany), EE (Estonia), ES (Spain), FI (Finland), FR (France), GR (Greece), IE (Ireland), IT (Italy), LT (Lithuania), LU (Luxembourg), LV (Latvia), MT (Malta), NL (Netherlands), PT (Portugal), SI (Slovenia), and SK (Slovakia).

Figure B3: Distribution of R&D Spenders and Non–Spenders by Industries and Locations, Euro Area

(a) Industries: NACE Rev.2 Sections



(b) Locations: EA Member States



Notes: The sample includes 1,209 publicly traded companies in 19 EA member states as of 1 January 2019, of which 379 are R&D spenders based on BvD Orbis data classification. NACE Rev.2 section and country codes as defined above.

Table B1: Distribution of the EA Sample by Industries: Manufacturing Divisions

NACE Rev.2 Division	All Companies	R&D Spenders
Division 10: Manufacture of Food Products	2.81	3.17
Division 11: Manufacture of Beverages	2.32	1.06
Division 12: Manufacture of Tobacco Products	0.08	0.00
Division 13: Manufacture of Textiles	1.49	0.79
Division 14: Manufacture of Wearing Apparel	1.32	1.06
Division 15: Manufacture of Leather and Related Products	0.50	1.06
Division 16: Manufacture of Wood and Wood and Cork Products, except Furniture	0.74	0.79
Division 17: Manufacture of Paper and Paper Products	1.24	1.58
Division 18: Printing and Reproduction of Recorded Media	0.91	0.53
Division 19: Manufacture of Coke and Refined Petroleum Products	0.33	0.79
Division 20: Manufacture of Chemicals and Chemical Products	3.64	7.12
Division 21: Manufacture of Basic Pharmaceutical Products and Pharmaceutical Preparations	2.81	7.39
Division 22: Manufacture of Rubber and Plastic Products	1.41	3.43
Division 23: Manufacture of Other Non–Metallic Mineral Products	1.90	1.85
Division 24: Manufacture of Basic Metals	1.32	2.11
Division 25: Manufacture of Fabricated Metal Products, except Machinery and Equipment	1.24	2.64
Division 26: Manufacture of Computer, Electronic, and Optical Products	6.62	11.87
Division 27: Manufacture of Electrical Equipment	2.07	6.98
Division 28: Manufacture of Machinery and Equipment (n.e.c.)	6.12	2.90
Division 29: Manufacture of Motor Vehicles, Trailers, and Semi–Trailers	2.15	3.96
Division 30: Manufacture of Other Transport Equipment	0.99	1.58
Division 31: Manufacture of Furniture	0.17	0.00
Division 32: Other Manufacturing	2.07	3.43
Division 33: Repair and Installation of Machinery and Equipment	0.17	0.26

Notes: The sample includes 1,209 publicly traded companies in 19 EA member states as of 1 January 2019, of which 379 are R&D spenders. Numbers denote percent of total within the full sample and within the subsample of R&D spenders, respectively. See Eurostat (2008) for further details on the NACE Rev.2 classification; n.e.c. stands for "not elsewhere classified."

Table B2: Distribution of the EA Sample by Industries: Non–Manufacturing Divisions 1

NACE Rev.2 Division	All Companies	R&D Spenders
Division 01: Crop and Animal Production, Hunting and Related Service Activities	0.24	0.53
Division 02: Forestry and Logging	0.08	0.00
Division 03: Fishing and Aquaculture	0.08	0.00
Division 06: Extraction of Crude Petroleum and Natural Gas	0.33	0.53
Division 07: Mining of Metal Ores	0.33	0.79
Division 08: Other Mining and Quarrying	0.25	0.26
Division 09: Mining Support Service Activities	0.66	0.53
Division 35: Electricity, Gas, Steam and Air Conditioning Supply	4.55	2.37
Division 36: Water Collection, Treatment and Supply	0.41	0.00
Division 37: Sewerage	0.08	0.26
Division 38: Waste Collection, Treatment and Disposal Activities	0.25	0.00
Division 39: Remediation Activities and Other Waste Management Services	0.08	0.26
Division 41: Construction of Buildings	1.41	0.79
Division 42: Civil Engineering	0.41	0.06
Division 43: Specialized Construction Activities	0.25	0.26
Division 45: Wholesale and Retail Trade and Repair of Motor Vehicles and Motorcycles	0.33	0.00
Division 46: Wholesale Trade, except Motor Vehicles and Motorcycles	5.29	3.43
Division 47: Retail Trade, except Motor Vehicles and Motorcycles	3.14	0.79
Division 49: Land Transport and Transport via Pipelines	0.58	0.53
Division 50: Water Transport	0.66	0.26
Division 51: Air Transport	0.33	0.26
Division 52: Warehousing and Support Activities for Transportation	2.23	1.32
Division 53: Postal and Courier Activities	0.41	0.00
Division 55: Accommodation	1.24	0.00
Division 56: Food and Beverage Service Activities	0.41	0.00

Notes: The sample includes 1,209 publicly traded companies in 19 EA member states as of 1 January 2019, of which 379 are R&D spenders. Numbers denote percent of total within the full sample and within the subsample of R&D spenders, respectively. See Eurostat (2008) for further details on the NACE Rev.2 classification.

Table B3: Distribution of the EA Sample by Industries: Non–Manufacturing Divisions 2

NACE Rev.2 Division	All Companies	R&D Spenders
Division 58: Publishing Activities	3.23	5.28
Division 59: Motion Picture, Video and Television Program Production, Sound Recording and Music Publishing Activities	0.66	0.26
Division 60: Programming and Broadcasting Activities	0.74	0.00
Division 61: Telecommunications	3.06	2.37
Division 62: Computer Programming, Consultancy and Related Activities	4.80	3.43
Division 63: Information Service Activities	0.25	0.00
Division 69: Legal and Accounting Activities	0.08	0.00
Division 70: Activities of Head Offices; Management Consultancy Activities	2.23	0.53
Division 71: Architectural and Engineering Activities; Technical Testing and Analysis	0.83	0.53
Division 72: Scientific Research and Development	0.33	0.26
Division 73: Advertising and Market Research	1.08	0.53
Division 74: Other Professional, Scientific and Technical Activities	1.99	1.58
Division 77: Rental and Leasing Activities	0.50	0.00
Division 78: Employment Activities	0.33	0.00
Division 79: Travel Agency, Tour Operator Reservation Service and Related Activities	0.83	0.26
Division 80: Security and Investigation Activities	0.41	0.00
Division 81: Services to Buildings and Landscape Activities	0.25	0.00
Division 82: Office Administrative, Office Support and Other Business Support Activities	0.50	0.26
Division 84: Public Administration and Defense; Compulsory Social Security	0.25	0.26
Division 85: Education	0.25	0.00
Division 86: Human Health Activities	1.57	1.06
Division 92: Gambling and Betting Activities	0.33	0.00
Division 93: Sports Activities and Amusement and Recreation Activities	1.32	0.00
Division 94: Activities of Membership Organizations	3.64	0.00
Division 96: Other Personal Service Activities	0.08	0.00

Notes: The sample includes 1,209 publicly traded companies in 19 EA member states as of 1 January 2019, of which 379 are R&D spenders. Numbers denote percent of total within the full sample and within the subsample of R&D spenders, respectively. See Eurostat (2008) for further details on the NACE Rev.2 classification.

Table B4: Distribution of the EA Sample by Regions: Germany and France

NUTS 1 Region	All Companies	R&D Spenders
DE1: Baden–Württemberg	2.98	6.07
DE2: Bayern	5.13	8.18
DE3: Berlin	1.08	2.11
DE5: Bremen	0.58	0.26
DE6: Hamburg	1.24	1.58
DE7: Hessen	1.82	2.90
DE9: Niedersachsen	0.91	1.58
DEA: Nordrhein–Westfalen	3.97	6.07
DEB: Rheinland–Pfalz	1.08	1.32
DEC: Saarland	0.17	0.26
DED: Sachsen	0.08	0.26
DEE: Sachsen–Anhalt	0.17	0.26
DEF: Schleswig–Holstein	0.58	1.06
DEG: Thüringen	0.58	1.06
FR1: Île–de–France	13.23	11.35
FRB: Centre–Val de Loire	0.17	0.36
FRC: Bourgogne–Franche–Comté	0.74	0.79
FRD: Normandie	0.17	0.00
FRE: Hauts–de–France	0.08	0.00
FRF: Grand Est	1.32	0.00
FRG: Pays de la Loire	0.50	0.53
FRH: Bretagne	0.41	0.53
FRI: Nouvelle–Aquitaine	0.83	0.53
FRJ: Occitanie	0.58	0.26
FRK: Auvergne–Rhône–Alpes	3.06	2.64
FRL: Provence–Alpes–Côte d'Azur	1.41	1.06

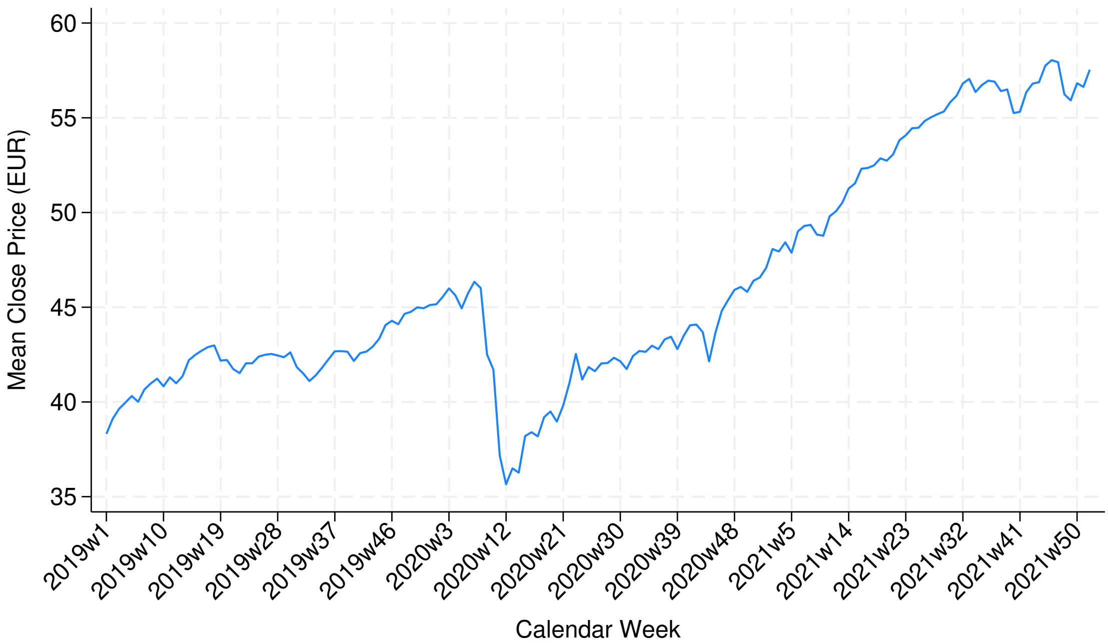
Notes: The sample includes 1,209 publicly traded companies in 19 EA member states as of 1 January 2019, of which 379 are R&D spenders. Numbers denote percent of total within the full sample and within the subsample of R&D spenders, respectively. See Eurostat (2025) for further details on the NUTS classification.

Table B5: Distribution of the EA Sample by Regions: Other Member States

NUTS 1 Region	All Companies	R&D Spenders
AT1: Ostösterreich	1.41	2.37
AT2: Südösterreich	0.33	1.06
AT3: Westösterreich	0.91	2.37
BE1: Région de Bruxelles–Capitale/Brussels Hoofdstedelijk Gewest	2.15	2.37
BE2: Vlaams Gewest	2.40	1.85
BE3: Région Wallonne	0.74	0.53
EL3: Attiki	4.47	3.96
EL4: Nisia Aigaiou, Kriti	0.17	0.26
EL5: Voreia Ellada	1.24	1.58
EL6: Kentriki Ellada	0.25	0.26
ES1: Noroeste	0.50	0.26
ES2: Noreste	1.24	0.79
ES3: Comunidad de Madrid	4.22	2.64
ES4: Centro (ES)	0.17	0.00
ES5: Este	0.49	0.79
ES6: Sur	0.08	0.00
ES7: Canarias	0.17	0.00
FI1: Manner–Suomi	6.37	11.8
FI2: Åland	0.08	0.00
ITC: Nord–Ovest	4.80	1.58
ITF: Sud	0.25	0.00
ITH: Nord–Est	2.73	0.26
ITI: Centro (IT)	2.89	1.32
NL2: Oost–Nederland	0.41	0.79
NL3: West–Nederland	3.47	4.49
NL4: Zuid–Nederland	0.58	1.06
PT1: Continente	2.07	0.53

Notes: The sample includes 1,209 publicly traded companies in 19 EA member states as of 1 January 2019, of which 379 are R&D spenders. Numbers denote percent of total within the full sample and within the subsample of R&D spenders, respectively. Nine member states (Cyprus, Estonia, Ireland, Latvia, Lithuania, Luxembourg, Malta, Slovakia, and Slovenia) do not have regional divisions due to their small size. See Eurostat (2025) for further details on the NUTS classification.

Figure B4: Time Series of Weekly Stock Prices, Euro Area



Notes: The sample includes 1,209 publicly traded companies in 19 EA member states observed for 156 weeks from W1–2019 to W52–2021.

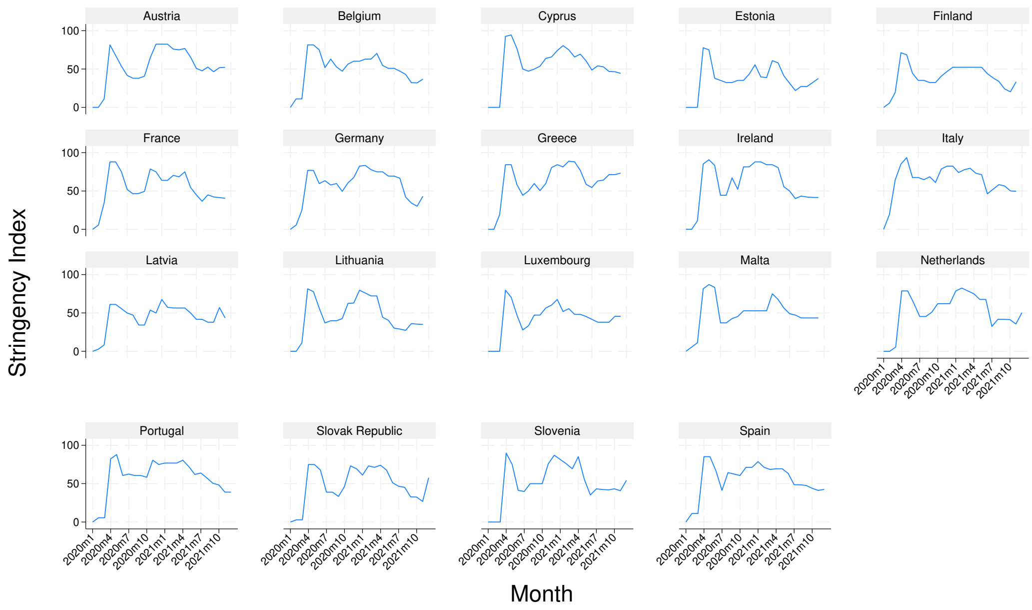
Table B6: t–test Statistics of the EA Sample

Variable	Sample	Obs.	Mean	SD	Difference	p–value
Impact resistance	All	188,604	0.735	0.441		
	Non–spenders	129,480	0.723	0.447	-0.038	0.000
	R&D spenders	59,124	0.761	0.426		
Recovery speed	All	43,551	49.631	17.664		
	Non–spenders	31,388	51.066	17.691	5.139	0.000
	R&D spenders	12,163	45.927	17.045		
Log *Liquidity*	All	186,108	0.438	0.708		
	Non–spenders	126,984	0.409	0.779	-0.091	0.000
	R&D spenders	59,124	0.500	0.519		
Age	All	188,604	46.203	39.042		
	Non–spenders	129,480	43.467	35.505	-8.728	0.000
	R&D spenders	59,124	52.195	45.272		

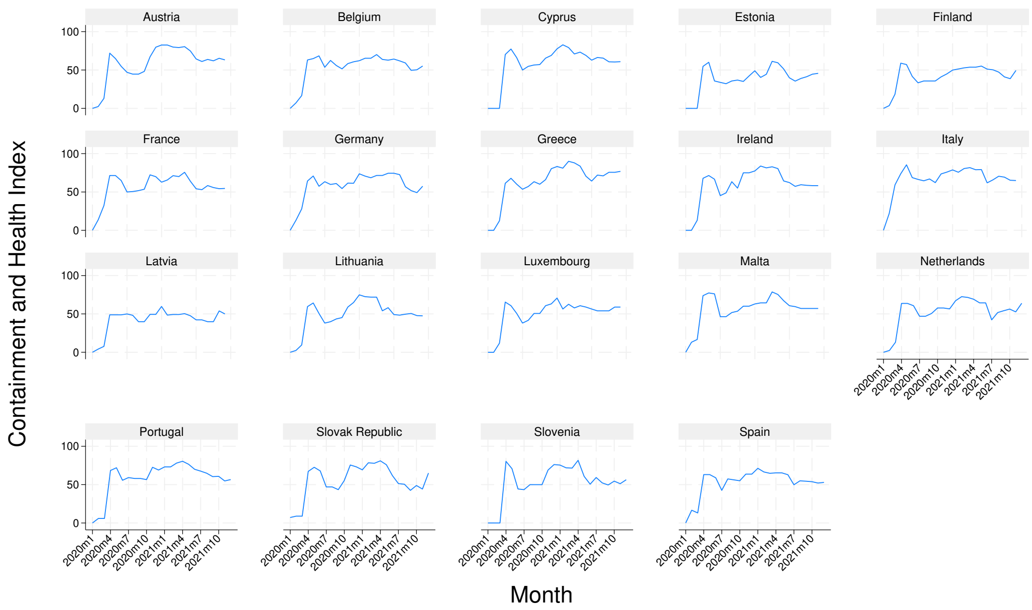
Notes: The sample includes 1,209 publicly traded companies in 19 EA member states observed weekly from W1–2019 to W52–2021, of which 379 are R&D spenders based on 2019 annual financial statements. Unequal variances are assumed.

Figure B5: Non–Fiscal Policy Responses to the Pandemic, Euro Area

(a) Stringency



(b) Containment and Health



Source: Hale et al. (2021) and own calculations.

Table B7: Corporate Tax and Subsidy Rates in EA–OECD Member States

Country	EATR			EMTR			ITSR (R&D)		
	2019	2020	2021	2019	2020	2021	2019	2020	2021
Austria	24.37	23.87	23.87	27.70	23.27	23.27	0.17	0.17	0.17
Belgium	26.73	23.29	23.39	15.03	18.14	19.05	0.15	0.15	0.16
Estonia	17.00	17.00	17.00	0.00	0.00	0.00	0.00	0.00	0.00
Finland	19.73	19.40	19.40	22.74	20.03	20.03	-0.01	0.00	0.00
France	31.75	29.53	26.02	25.24	22.64	17.50	0.43	0.39	0.37
Germany	28.32	28.03	26.41	27.67	24.92	9.18	-0.02	0.19	0.19
Greece	22.96	22.96	21.05	22.47	22.47	20.07	0.08	0.29	0.26
Ireland	12.36	12.36	12.36	13.21	13.21	13.21	0.29	0.27	0.27
Italy	19.37	20.24	14.44	-39.35	-31.39	-84.94	0.07	0.11	0.20
Latvia	17.00	17.00	17.00	0.00	0.00	0.00	0.00	0.00	0.00
Lithuania	13.67	13.67	13.67	7.25	7.25	7.25	0.31	0.31	0.31
Luxembourg	23.54	23.54	23.54	20.83	20.83	20.83	-0.01	-0.01	-0.01
Netherlands	23.71	23.71	23.71	21.89	21.89	21.89	0.15	0.15	0.15
Portugal	28.35	28.42	28.42	15.30	16.01	16.01	0.39	0.39	0.39
Slovakia	19.20	19.20	19.20	11.41	11.41	11.41	0.41	0.55	0.55
Slovenia	17.38	17.38	17.38	10.15	10.15	10.15	0.21	0.21	0.21
Spain	23.45	23.45	23.45	19.55	19.55	19.55	0.33	0.33	0.33

Source: Organization for Economic Cooperation and Development (2024b)
Notes: EATR stands for effective average tax rate, and EMTR stands for effective marginal tax rate; both are measured as a percent of taxable income. ITSR stands for implied tax subsidy rate, and it is measured as 1 minus the B–index, an indicator of how much before–tax income a representative firm needs to break even on a unit of R&D expense. See Organization for Economic Cooperation and Development (2024a) for further details.

Table B8: Corporate R&D Tax Incentives in EA–OECD Member States

Country	Policy	Year	Base	Rate (%)		
				2019	2020	2021
Austria	Research premium	2002	CIT	14	14	14
Belgium	R&D investment deduction	1992	CIT	13.5	13.5	13.5
Finland	R&D cooperation deduction	2021	CIT	–	–	150
France	R&D tax credit *(crédit d'impôt recherche, CIR)*	1983	CIT	30	30	30
Germany	R&D tax credit *(Forschungszulage)*	2020	CIT	–	25	25
Greece	R&D tax allowance	2004	CIT	100	100	100
Ireland	R&D corporation tax credit	2004	CIT	25	25	25
Italy	R&D tax credit	2020	CIT	–	10	10
Lithuania	R&D tax credit	2008	CIT	200	200	200
Netherlands	R&D tax credit	1994	SSC	32	32	32
Portugal	R&D tax credit	1997	CIT	32.5	32.5	32.5
Slovakia	R&D tax allowance	2015	CIT	100	100	100
Slovenia	R&D tax allowance	2005	CIT	100	100	100
Spain	R&D tax credit	2015	CIT	25	25	25

Source: Organization for Economic Cooperation and Development (2025c).
Notes: Year refers to the year in which the policy took effect, as opposed to the year when it was legislated, if the two differ. Base refers to the tax base for the policy (corporate income tax, CIT, or social security contribution, SSC). In case of multiple rates (e.g., small vs. large firms and capital vs. labor costs), only the base rate applicable to large firms is reported. In case of multiple policies (e.g., Belgium), the oldest policy applicable to most firms is reported. Three member states (Estonia, Latvia, and Luxembourg) did not provide R&D tax incentives during the observed period.

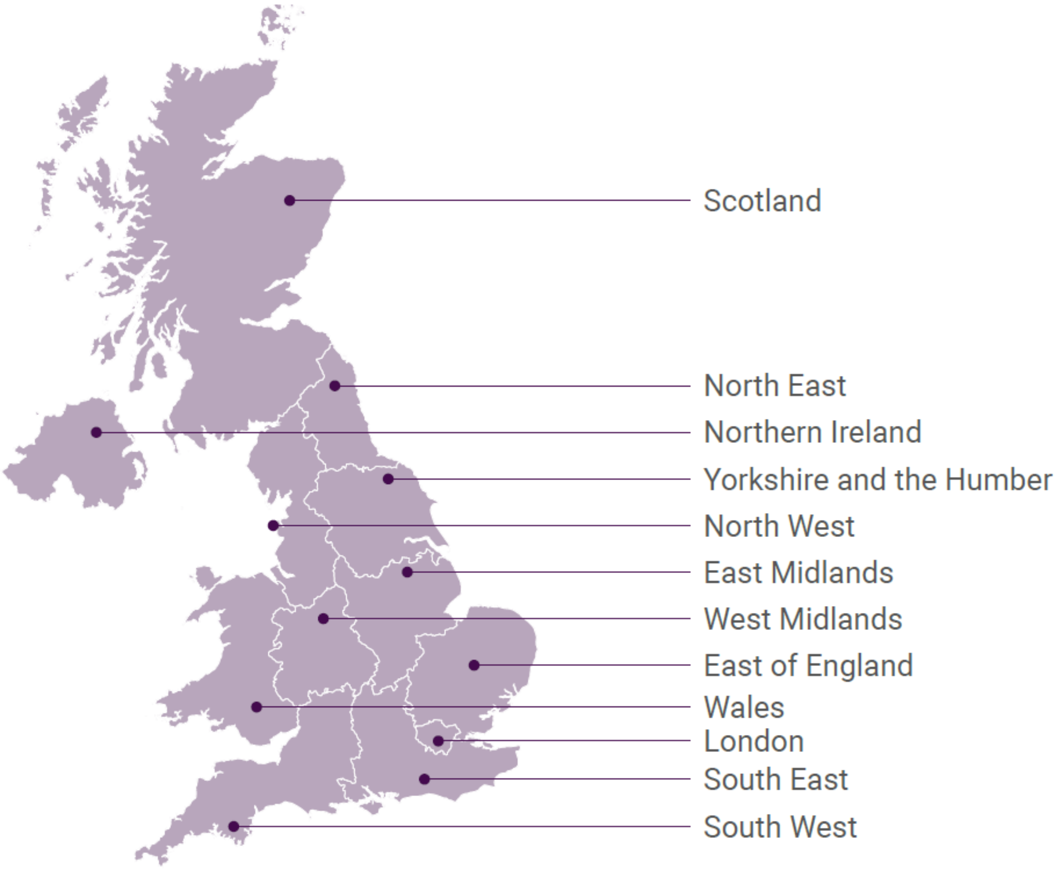
Table B9: Public Finances in EA Member States

Country	Debt (% GDP)	Budget Balance (% GDP)				
	2019	2019	2020	2021	Δ (2020–2019)	Δ (2021–2020)
Austria	71.0	2.0	-6.9	-4.6	-8.9	2.3
Belgium	97.6	0.0	-7.1	-3.7	-7.1	3.4
Cyprus	92.3	3.2	-3.5	0.1	-6.7	3.6
Estonia	9.0	-0.1	-5.4	-2.5	-5.3	2.9
Finland	65.3	-0.1	-4.9	-2.1	-4.8	2.8
France	98.2	-0.9	-7.7	-5.2	-6.8	2.5
Germany	58.7	2.1	-3.7	-2.6	-5.8	1.1
Greece	183.2	3.8	-6.6	-4.6	-10.4	2.0
Ireland	55.9	1.7	-3.9	-0.6	-5.6	3.3
Italy	133.9	1.9	-6.0	-5.5	-7.9	0.5
Latvia	37.9	0.6	-3.4	-6.7	-4.0	-3.3
Lithuania	35.6	1.3	-5.7	-0.7	-7.0	5.0
Luxembourg	22.3	3.0	-2.9	1.1	-0.1	-1.8
Malta	39.3	2.0	-7.5	-6.0	-9.5	1.5
Netherlands	47.7	2.6	-2.9	-1.7	-5.5	1.2
Portugal	116.1	3.0	-2.9	-0.5	-5.9	2.4
Slovakia	48.0	0.0	-4.1	-4.0	-4.1	0.1
Slovenia	66.0	2.3	-6.1	-3.4	-8.4	2.7
Spain	97.7	-0.8	-7.7	-4.5	-6.9	3.2
EA 19 average	72.4	1.5	-4.9	-3.0	-6.4	1.9

Source: European Central Bank (2025a, 2025b) and own calculations.
Notes: Debt refers to total government debt. Budget balance refers to the primary deficit/surplus.

A3 Appendix 3

Figure C1: UK Map with Regional Designations



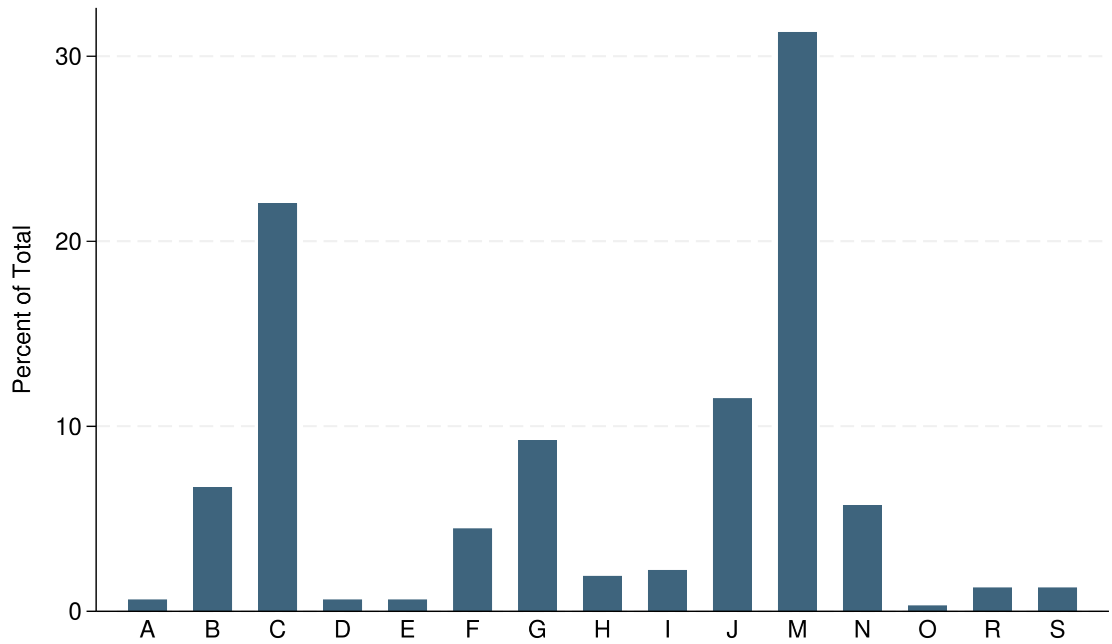
Source: UK Research and Innovation (2025d)

Table C1: UK NUTS 1 and 2 Regions

NUTS 1 Region	NUTS 2 Regions
UKC: North East	Tees Valley and Durham, Northumberland and Tyne and Wear
UKD: North West	Cumbria, Cheshire, Greater Manchester, Lancashire, Merseyside
UKE: Yorkshire and The Humber	East Yorkshire and Northern Lincolnshire, North Yorkshire, South Yorkshire, West Yorkshire
UKF: East Midlands	Derbyshire and Nottinghamshire, Leicestershire, Rutland and Northamptonshire, Lincolnshire
UKG: West Midlands	Herefordshire, Worcestershire and Warwickshire, Shropshire and Staffordshire, West Midlands
UKH: East of England	East Anglia, Bedfordshire and Hertfordshire, Essex
UKI: London	Inner London – East, Inner London – West, Outer London – East and North East, Outer London – South, Outer London – West and North West
UKJ: South East	Berkshire, Buckinghamshire and Oxfordshire, Surrey, East and West Sussex, Hampshire, and Isle of Wight, Kent
UKK: South West	Gloucestershire, Wiltshire and Bristol/Bath area, Dorset and Somerset, Cornwall and Isles of Scilly, Devon
UKL: Wales	East Wales, West Wales and The Valleys
UKM: Scotland	Eastern Scotland, Highlands and Islands, West Central Scotland, North Eastern Scotland, Southern Scotland
UKN: Northern Ireland	Northern Ireland

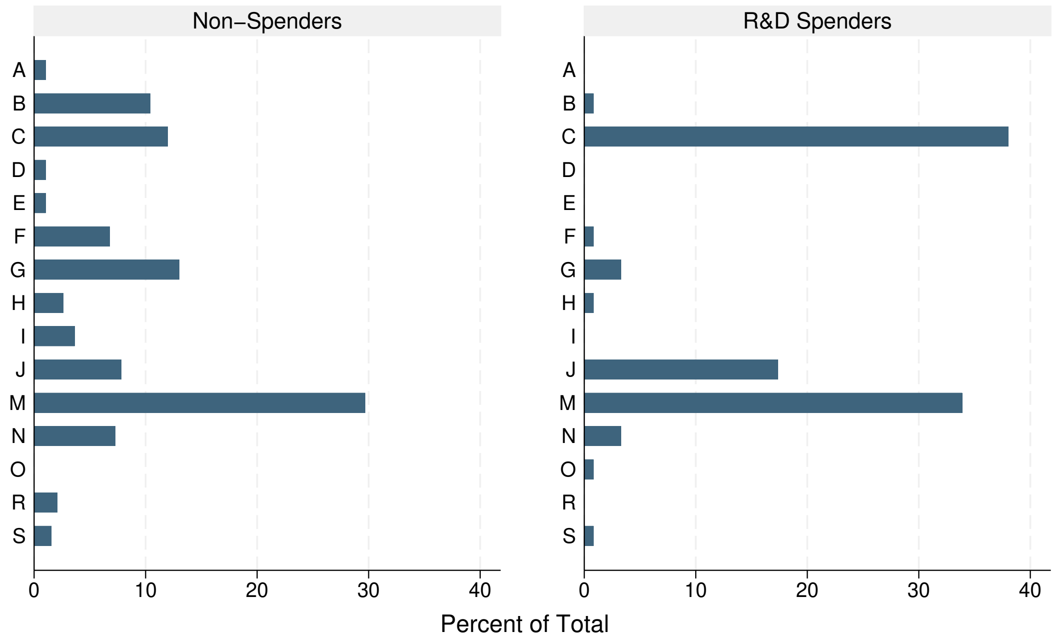
Source: Office for National Statistics (2019)

Figure C2: Distribution of the Sample by Industries, United Kingdom



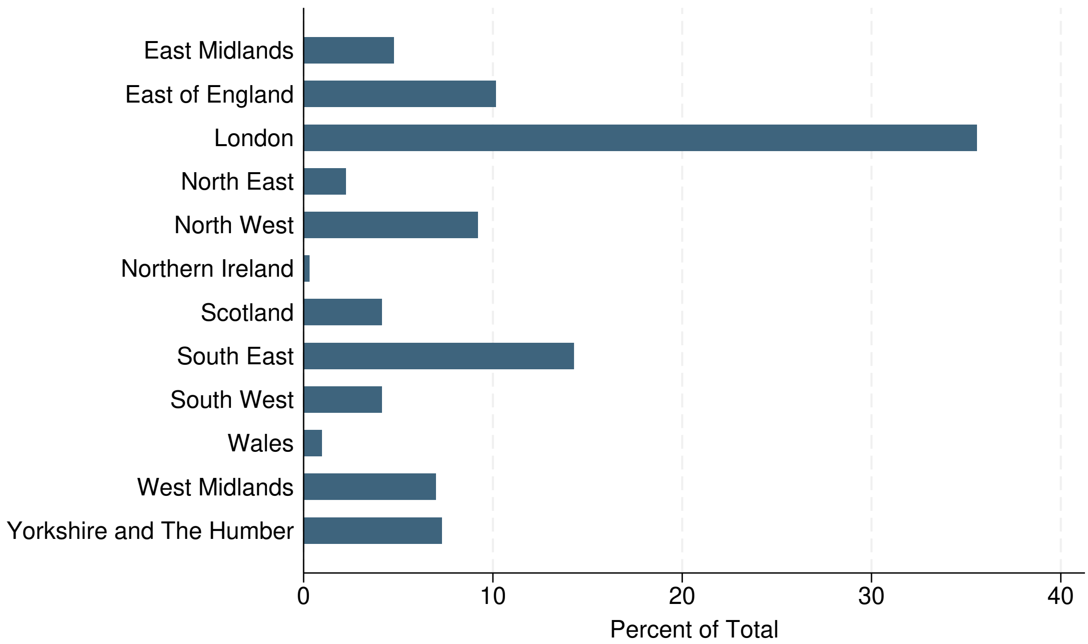
Notes: The sample includes 313 publicly traded companies in the UK observed from 2019 to 2021. Standard Industry Classification (SIC) section codes are as follows: A (agriculture, forestry, and fishing), B (mining and quarrying), C (manufacturing), D (electricity, gas, steam, and air conditioning supply), E (water supply, sewerage, waste management, and remediation), F (construction), G (wholesale and retail trade; repair of motor vehicles and motorcycles), H (transportation and storage), I (accommodation and food services), J (information and communications), M (professional, scientific, and technical services), N (administrative and support services), O (public administration and defense; compulsory social security), R (arts, entertainment and recreation), and S (other services). Sections K (finance and insurance) and L (real estate) were excluded at the research design stage due to the incomparability of financial ratios of companies in those industries with companies in other industries (Fama and French 1992). There are no companies in the sample operating under Sections P (education) and Q (human health and social work). See UK Companies House (2025b) for further details on the SIC classification.

Figure C3: Distribution of R&D Spenders and Non–Spenders by Industries, United Kingdom



Notes: The sample includes 313 publicly traded companies in the UK observed from 2019 to 2021, of which 121 are R&D spenders based on the Companies House data classification. SIC section codes as defined above.

Figure C4: Distribution of the Sample by Regions, United Kingdom

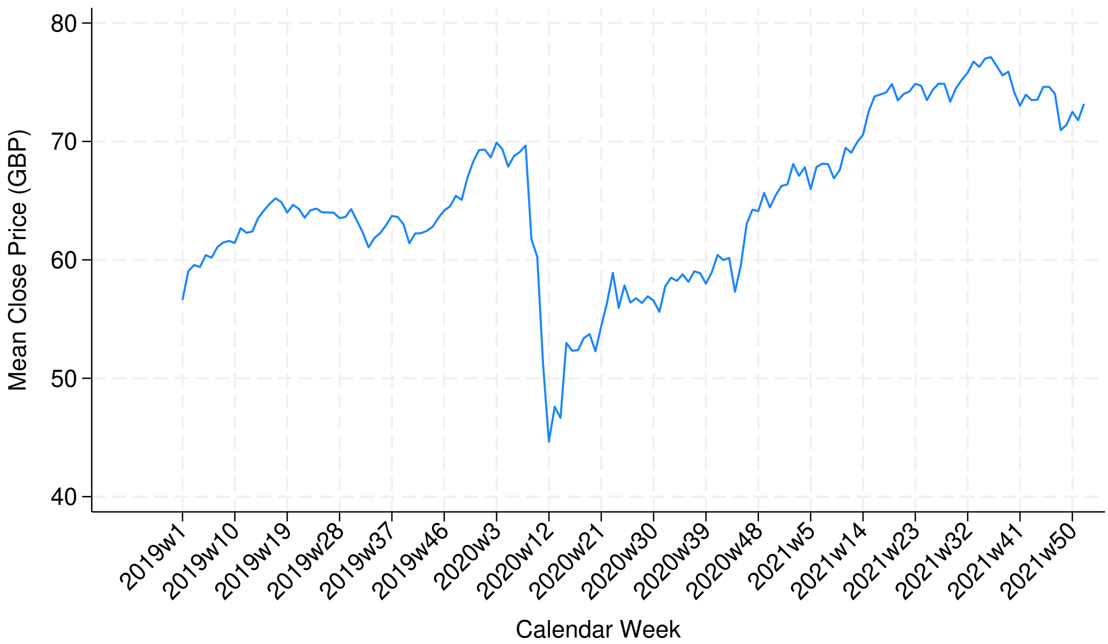


Notes: The sample includes 313 publicly traded companies in the UK observed from 2019 to 2021. NUTS 1 regions are reported. See Office for National Statistics (2019, 2025) for further details.

Figure C5: Distribution of R&D Spenders and Non–Spenders by Regions, United Kingdom

Notes: The sample includes 313 publicly traded companies in the UK observed from 2019 to 2021, of which 121 are R&D spenders based on the Companies House data classification. NUTS 1 regions are reported. See Office for National Statistics (2019, 2025) for further details.

Figure C6: Time Series of Weekly Stock Prices, United Kingdom



Note: The sample includes 313 publicly traded companies in the United Kingdom observed for 156 weeks from W1–2019 to W52–2021.

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