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Firm-level effects of the Portuguese R&D tax credit:

a microeconomic and sectoral analysis

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A thesis submitted in partial fulfilment of the requirements for the degree of
Doctor in Information Management

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FIRM-LEVEL EFFECTS OF THE PORTUGUESE R&D TAX CREDIT:

A MICROECONOMIC AND SECTORAL ANALYSIS

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Doctoral Thesis presented as partial requirement for obtaining the PhD in

Information Management

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledge the Rules of Conduct and Code of Honor from the NOVA Information Management School.

José Alexandre da Silva Paredes

Lisbon, 28th of February 2025

To Fernanda, Zé, Mafalda, João, Leonor, Zé Maria, and Francisco.

In memoriam of my parents.

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ABSTRACT

This Doctoral thesis investigates the impact of innovation policies, focusing on the Oslo Manual's role in shaping innovation research and the effects of R&D tax credits on firm behaviour and employment dynamics. Addressing gaps in the literature, it explores the Oslo Manual's academic influence, the allocation of highly qualified personnel in response to R&D tax credits, and the broader employment effects of these incentives.

The first study (Chapter 3), *"Accounting for the Oslo Manual: reflecting on the past and setting the stage for future research"*, applies bibliometric and textmetric analyses to over 1,300 research articles, assessing the Oslo Manual's adoption and relevance over three decades. The findings highlight its increasing importance, particularly after 2008, and its integration with fields such as entrepreneurship, performance, and knowledge management.

The second study (Chapter 4), *"Does R&D tax credit impact firm behaviour? Micro evidence for Portugal"*, investigates how R&D tax credits influence the allocation of PhD holders across firms with different R&D intensities. Using firm-level data (1995–2017) from Portugal, the study finds that tax credits significantly affect the distribution of PhD holders in medium-high and high R&D intensity firms after three years. This research shifts the focus from R&D expenditure to human capital effects.

The third study (Chapter 5), *"Do R&D tax credits really boost hiring? Insights into employment dynamics"*, employs a difference-in-differences approach with a staggered design to assess employment effects in Portugal (2014–2022). Results indicate a substantial increase in R&D staff, with sector-specific variations, such as an 18.4% rise in information and communication and 12.3% in manufacturing.

This thesis advances knowledge by bridging theoretical and empirical perspectives on science and technology policies. It provides insights into the Oslo Manual's influence, the human capital effects of R&D tax credits, and sectoral employment dynamics, offering evidence-based recommendations for policymakers and future research.

Keywords: R&D tax credits; Innovation; Policy; Employment; Firms; Oslo Manual.

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List of Abbreviations and Acronyms

A&HCI	Arts & Humanities Citation Index
API	Application Programming Interface
ATT	Average Treatment effect on the Treated
BERD	Business Enterprise Research and Development
BJS	Borusyak, Javarel and Spiess
BRICS	Brazil, Russia, India and China
CdH	Chaisemartin and D'Haultfoeuille
CIS	Community Innovation Survey
CPCI-S	Conference Proceedings Citation Index – Science
CPCI-SSH	Conference Proceedings Citation Index – Social Science & Humanities
CS	Callaway and Sant'Anna
DGEEC	Direção-Geral de Estatísticas da Educação e Ciência
DiD	Difference-in-Differences
ESCI	Emerging Sources Citation Index
EU	European Union
FCT	Fundação para a Ciência e Tecnologia
FTE	Full-Time Equivalent
GDP	Gross Domestic Product
GVA	Gross Value Added
INE	Instituto Nacional de Estatística
IRF	Impulse-Response Functions
ISIC	International Standard Industrial Classification
ISSN	International Standard Serial Number
JEI	Jeune Entreprise Innovante
MNE	Multinational Enterprise
MSME	Micro, Small, and Medium Enterprises
NACE	Nomenclature d'Activités Économiques dans la Communauté Européenne

NESTI	National Experts on Science and Technology Indicators
OECD	Organization for Economic Co-operation and Development
OLS	Ordinary Least Squares
PhD	Doctor of Philosophy
PT	Parallel Trends
R&D	Research and Development
R&D&I	Research and Development and Innovation
R&I	Research and Innovation
SA	Sun and Abraham
SCI-EXPANDED	Science Citation Index Expanded
SIFIDE	Sistema de Incentivos Fiscais à Investigação e Desenvolvimento Empresarial
SJR	Scimago Journal Rank
SME	Small and Medium-sized Enterprises
SPRU	Science Policy Research Unit
SSCI	Social Sciences Citation Index
TWFE	Two-Way Fixed Effects
ZEW	Zentrum für Europäische Wirtschaftsforschung
WoS	Web of Science

"It does not matter how slowly you go as long as you do not stop"

(Confucius)

1. Introduction

1.1 Research Context and Motivation

This dissertation explores the evolving landscape of innovation measurement and the impact of R&D tax credits on firm behaviour. The study is motivated by the need to understand how the Oslo Manual, which serves as a foundational framework for measuring innovation, has evolved over its different editions (Castellacci *et al*., 2005; OECD/Eurostat, 2018; Santos & Mendonça, 2022a), and how policy instruments, such as R&D tax credits, influence firm-level outcomes, including R&D investment and employment dynamics (Dimos & Pugh, 2016; Vanino *et al*., 2019; Wang *et al*., 2017). These objectives are closely aligned with the goals of the Horizon Europe Framework Programme, as established by Regulation (EU) 2021/695 of the European Parliament and of the Council of 28 April 2021 (European Parliament and Council of the European Union, 2021), particularly its emphasis on enhancing human capital in research and innovation (R&I) and creating more and better jobs, as outlined in its Key Impact Pathway Indicators (Annex V, Tables 1 and 3). By analysing the role of R&D tax credits in fostering employment growth and strengthening firms' absorptive capacity, this research contributes to the broader objectives of Horizon Europe, which aims to maximise the societal and economic impact of innovation policies.

The Oslo Manual, initially focused on technological innovations in manufacturing (1992), has evolved to encompass non-technological innovations, services, and collaborative innovation processes (OECD/Eurostat, 1997; OECD/Eurostat, 2005; OECD/Eurostat, 2018). This evolution reflects the growing recognition of innovation as a multifaceted phenomenon that extends beyond R&D expenditures and patents (Castellacci *et al*., 2005; Santos & Mendonça, 2022a). The Oslo Manual's development underscores the importance of standardised innovation metrics, which are crucial for policymakers and researchers aiming to assess the effectiveness of innovation policies and their impact on economic growth and competitiveness (OECD/Eurostat, 2018). These metrics are also essential for aligning national innovation policies with the strategic priorities of Horizon Europe, particularly in fostering open science and facilitating knowledge diffusion (Regulation (EU) 2021/695).

The motivation for this research is further driven by the increasing reliance on R&D tax credits as a policy tool to stimulate private-sector innovation. R&D tax credits are widely adopted across OECD countries, including Portugal, where the SIFIDE (Sistema de Incentivos Fiscais à I&D Empresarial) program has been a key instrument for promoting business R&D since 1997 (Appelt *et al.*, 2016; Carvalho, 2011; OECD, 2021). The dissertation explores whether these tax incentives achieve their intended outcomes, such as increased R&D investment, enhanced firm competitiveness, and job creation, particularly in high-skilled roles like R&D staff and PhD holders (Freitas *et al.*, 2017; Paredes *et al.*, 2022).

The dissertation is also motivated by the need to address gaps in the existing literature. While there is substantial evidence on the input additionality of R&D tax credits (i.e., increased R&D expenditure), there is limited research on their output additionality, particularly in terms of employment dynamics and sector-specific impacts. Understanding their output additionality is crucial as it provides insights into the tangible effects of policy interventions (Antonucci & Pianta, 2002; Bogliacino & Vivarelli, 2012; Evangelista & Savona, 2002). By examining the effects of R&D tax credits on firm behaviour and employment in Portugal, this research contributes to a deeper understanding of how innovation policies can be designed to maximise their economic and social benefits (Appelt *et al.*, 2016; Freitas *et al.*, 2017). This aligns with Horizon Europe's mission to address global challenges through R&I, particularly in fostering sustainable economic growth and job creation (Regulation (EU) 2021/695).

In summary, this dissertation is motivated by the dual objectives of enhancing the understanding of innovation measurement through the lens of the Oslo Manual (Castellacci *et al.*, 2005; OECD/Eurostat,

2018) and evaluating the effectiveness of R&D tax credits as a policy tool (Dimos & Pugh, 2016; Vanino *et al*., 2019; Wang *et al*., 2017). By bridging these two areas, the research aims to provide insights that can inform future science and technology policies and contribute to the broader discourse on the role of innovation in driving economic growth and competitiveness.

1.2 Theoretical Foundations, Research Focus, and Methodology: A Multidisciplinary Approach

1.2.1 Theoretical Framework

The theoretical framework of this dissertation is anchored in the evolution of innovation measurement and the role of R&D tax credits in shaping firm behaviour, particularly in the context of employment dynamics. Drawing on the historical development of the Oslo Manual, the dissertation situates its analysis within the broader context of innovation research, which has progressively expanded from a narrow focus on R&D and patents to encompass a more comprehensive understanding of innovation, including non-technological, organisational, and marketing dimensions (OECD/Eurostat, 1997; OECD/Eurostat, 2005; OECD/Eurostat, 2018). The Oslo Manual's evolution reflects the growing recognition of innovation as a multifaceted phenomenon, influenced by systemic factors such as collaboration, knowledge sharing, and the interplay between technological and non-technological advancements (Castellacci *et al*., 2005; Santos & Mendonça, 2022a). This framework provides a foundation for understanding how innovation is measured and how policies, such as R&D tax credits, are designed to stimulate R&D and innovation activities (Appelt *et al*., 2016; Carvalho, 2011).

The dissertation further integrates economic theories that underscore the importance of R&D as a driver of productivity, economic growth, and competitiveness. Schumpeterian (1949) theories of innovation and technical change highlight the role of R&D in fostering long-term economic development, while the concept of absorptive capacity (Cohen & Levinthal, 1990) emphasises the importance of firms' ability to leverage external knowledge for innovation (Castellacci *et al*., 2005; Cohen & Levinthal, 1990). These theoretical perspectives are critical for understanding the rationale behind R&D tax credits, which aim to address market failures, such as underinvestment in R&D due to information asymmetries and the public good nature of knowledge (Appelt *et al*., 2016; Freitas *et al*., 2017). The dissertation also engages with the literature on additionality, exploring how R&D tax credits influence firms' R&D expenditures and, subsequently, their employment practices, particularly in terms of hiring highly skilled personnel, such as PhD holders (Freitas *et al*., 2017; Paredes *et al*., 2022).

The theoretical framework is further enriched by the analysis of the design and implementation of R&D tax credit schemes, particularly in Portugal. The SIFIDE program serves as a case study to examine how hybrid tax credit systems, combining volume-based and incremental approaches, impact firm behaviour (Carvalho, 2011; OECD, 2021). The framework incorporates insights from the literature on the differential effects of R&D tax credits across industries, emphasising the varying impacts on high-tech versus low-tech sectors (Antonucci & Pianta, 2002; Bogliacino & Vivarelli, 2012; Evangelista & Savona, 2002). This aspect aligns with the broader theoretical discourse on the role of knowledge-intensive industries in driving innovation and employment growth (Freitas *et al*., 2017; Paredes *et al*., 2022).

1.2.2 Research Focus

The research focus of this dissertation is centred on understanding the impact of R&D tax credits on firm behaviour, with a particular emphasis on employment dynamics and the composition of R&D personnel. The dissertation is situated within the broader context of innovation measurement and policy, as articulated in the Oslo Manual, which has evolved over time to encompass a more comprehensive understanding of innovation, including non-technological, organisational, and marketing dimensions. The dissertation builds on this foundation to explore how R&D tax credits, as a policy instrument, influence firms' activities and their subsequent effects on employment, particularly in terms of hiring highly skilled personnel such as PhD holders.

A key aspect of this research is the analysis of the Oslo Manual's evolving thematic landscape, as outlined in Chapter 3. Through keyword processing and textmetric analysis, this study explores how core concepts such as "innovation," "performance," "knowledge," and "management" have developed over time, shaping both academic discourse and policy frameworks. This historical perspective provides a foundation for understanding the shifting priorities in innovation measurement and policy evaluation. Specifically, the study addresses the following research questions derived from the analysis of the Oslo Manual:

RQ1: How do economic and social changes impact the definitions of innovation over time?

RQ2: Are emerging economies increasingly engaged in using metrics for measuring innovation?

Building on this foundation, Chapters 4 and 5 focus on the empirical assessment of R&D tax incentives, with particular emphasis on the Portuguese context. Chapter 4 examines whether R&D tax credits effectively stimulate firm behaviour. Based on the estimation of impulse-response functions by local projections, the study assesses the impact of introducing the tax incentive scheme for corporate R&D in firms from different R&D intensity sectors. The research questions guiding this chapter are:

RQ3: Does an R&D tax credit impact the allocation of PhD holders at the firm level?

RQ4: Is this impact consistent across firms in low R&D intensity sectors compared to medium-high and high R&D intensity sectors?

Chapter 5 expands the scope to analyse employment dynamics, questioning whether R&D tax credits lead to increased hiring and shifts in workforce composition. The research leverages firm-level microdata to assess the additionality effects of tax incentives on employment, particularly the allocation of highly skilled personnel, including PhD holders. It further explores sectoral disparities, considering how different industries respond to R&D incentives and the implications for firms from the different activity economic sectors. The research addresses the following research question:

RQ5: Do R&D tax credits impact hiring employees, R&D staff, or PhD holders, depending on the economic activity sector?

By addressing these research questions, the dissertation provides a comprehensive and systematic analysis of the effects of R&D tax credits on firm behaviour, employment dynamics, and the allocation of highly skilled personnel. The findings contribute to the broader literature on innovation policy and offer valuable insights for policymakers and researchers interested in designing and evaluating R&D tax incentive schemes.

1.2.3 Research Methodology

The research methodology employed in this dissertation combines textmetric, quantitative methods, and econometric techniques to investigate the evolution of innovation research and assess the impact of R&D tax credits on employment dynamics. The methodology is structured around three main components: data collection and preprocessing, econometric modelling, and data analysis with robustness checks, ensuring a comprehensive and reliable analysis.

The first component of this research applies a scientometric framework to examine the review process of the Oslo Manual. This methodological approach relies on bibliometric and textmetric analysis to extract insights from a vast corpus of academic literature. Bibliometric analysis provides a quantitative assessment of research output, tracing the evolution of scientific contributions and identifying key trends, influential journals, and leading authors. Textmetric analysis complements this by enabling a deeper examination of the content within these publications.

A comprehensive dataset was compiled using the Web of Science (WoS) and Scopus databases, incorporating citation indexes such as Social Sciences Citation Index (SSCI), Emerging Sources Citation Index (ESCI), Science Citation Index Expanded (SCI-EXPANDED), Conference Proceedings Citation Index – Social Science and Humanities (CPCI-SSH), Conference Proceedings Citation Index – Science (CPCI-S), and Arts & Humanities Citation Index (A&HCI). The analysis leveraged specialised software, including R (Aria & Cuccurullo, 2017), to conduct network analysis and bibliometric mapping. Centrality measures such as degree, betweenness, and closeness were applied to evaluate the influence of key contributors in the field. Furthermore, supervised machine learning techniques were implemented for textmetric analysis, allowing an in-depth understanding of thematic structures and trends within the literature.

We employed the local projection method to assess the impact of R&D tax credits on firm behaviour, particularly in relation to R&D personnel (Jordà, 2005). This approach enables the estimation of impulse-response functions (IRFs) by tracking the effect of R&D tax credits (SIFIDE) on R&D personnel. The method was applied both at the aggregate level and across different economic activity sectors to analyse the heterogeneity of the effect. Local projections offer advantages such as robustness to model misspecification, ease of estimation, and the ability to capture dynamic effects rather than static impacts.

An econometric approach was employed to evaluate the impact of R&D tax credits on employment dynamics, utilising a staggered Difference-in-Differences (DiD) design. This methodology enables the assessment of causal relationships by comparing the employment trajectories of firms that were granted tax credits (treatment group) with those that did not receive such incentives (control group) over a specified time horizon.

Advanced DiD estimators for staggered treatment designs, including those proposed by Callaway and Sant'Anna (2021), Chaisemartin and D'Haultfoeuille (2020), Borusyak, Jaravel, and Spiess (2021), and Sun and Abraham (2021), were employed to mitigate potential bias from heterogeneous treatment timing.

We conducted robustness tests, such as parallel trends assumption, to ensure the validity of our findings. We initially estimated treatment effects without covariates to verify if pre-treatment trends were similar across groups. If deviations were detected, covariates such as R&D expenditure and labour costs were included.

By integrating scientometric and econometric methodologies, namely combining local projections and staggered DiD estimators, this research offers a comprehensive and robust methodological framework to evaluate innovation and the impact of R&D tax incentives on firm behaviour and employment. The data science and textmetric analyses provide a detailed examination of the evolution of innovation literature, while the econometric analysis offers rigorous empirical insights into the effects of R&D tax credits on employment. The combination of these methodologies enhances the robustness of the findings, contributing to both theoretical advancements and policy discussions in the field of science and technology studies.

1.3 Research Structure and Path of Research: A Coherent Journey from Theory to Policy

1.3.1 Research Structure

The research structure of this dissertation is designed to provide a comprehensive and systematic exploration of the impact of R&D tax credits on firm behaviour, with a particular focus on employment dynamics and the composition of R&D personnel. The thesis is organised into five chapters, each addressing distinct but interconnected aspects of the research problem. This structure ensures a logical flow from theoretical foundations to empirical analysis, culminating in policy implications and future research directions.

The introductory chapter sets the stage for the research by outlining the importance of innovation and R&D as drivers of economic growth and competitiveness. It highlights the role of policy instruments, such as R&D tax credits, in stimulating private-sector R&D activities. The chapter introduces the research questions, and the significance of the study, particularly in the context of Portugal's SIFIDE program. It also provides an overview of the methodological approach and the structure of the thesis.

Chapter 2 (“Literature Review”) establishes the theoretical foundations of the study by reviewing key concepts and frameworks related to innovation and R&D tax incentives. It draws on the Oslo and Frascati Manuals to define innovation and R&D, respectively, and discusses the evolution of innovation measurement over time. The chapter also reviews the economic theories underpinning R&D tax credits, including market failure theory, absorptive capacity, and Schumpeterian growth theory. A comprehensive literature review examines prior studies on the impact of R&D tax credits on firm behaviour, and employment, identifying gaps the thesis aims to address.

Chapter 3 (“Accounting for Oslo Manual: reflecting on the past and setting the stage for future research”) provides a historical and analytical perspective on the Oslo Manual, which serves as a foundational framework for innovation measurement. This chapter examines the evolution of the Oslo Manual across its editions, highlighting key thematic shifts and methodological advancements using bibliometric and textmetric analyses. The analysis reveals the growing importance of non-technological innovations, collaboration, and systemic approaches in innovation research. This chapter contextualises the study within the broader field of innovation studies.

Chapter 4 ("Does R&D tax credit impact firm behaviour? Micro evidence for Portugal") shifts the focus to the empirical analysis of R&D tax credits in Portugal. This chapter employs the local projection approach to estimate the impact of the SIFIDE program on R&D personnel, including PhD holders, using firm-level data from the official business R&D survey and administrative tax incentive records. The analysis is conducted across firms in low, medium-high, and high R&D intensity sectors, revealing significant variations in the impact of R&D tax credits on the allocation of highly skilled personnel. The chapter concludes with policy implications and recommendations for designing targeted R&D tax incentive schemes.

The final empirical chapter ("Do R&D tax credits really boost hiring? Insights into employment dynamics") examines the employment effects of R&D tax credits across different economic sectors in Portugal. Using a staggered difference-in-differences (DiD) approach, the study evaluates the impact of the SIFIDE program on total employment, R&D staff, and PhD holders. The analysis highlights sector-specific variations in the effectiveness of tax credits, with significant positive effects observed in the manufacturing and, information and communication sectors. The chapter concludes with a discussion of the policy implications and the need for sector-specific strategies to maximise the impact of R&D tax incentives.

The concluding chapter synthesises the findings from the empirical analyses and discusses their implications for innovation policy and firm behaviour. It highlights the importance of R&D tax credits in fostering employment growth, particularly in knowledge-intensive sectors, and underscores the need for tailored policy measures to address sector-specific challenges. The chapter also identifies the study's limitations and proposes avenues for future research, including regional analyses, and comparisons between R&D newcomers and established firms.

1.3.2 Path of Research

This dissertation represents a multifaceted exploration into the intersections of innovation, public policy, and firm behaviour, with s particular focus on the role of the Oslo Manual in shaping research on innovation metrics and the impact of R&D tax credits on firm dynamics, specifically in Portugal.

The research begins with a comprehensive analysis of the Oslo Manual, a cornerstone in innovation studies. This foundational text provides the methodological framework for measuring and interpreting innovation, influencing research across disciplines. Chapter 3 of this thesis traces the evolution of the Oslo Manual, from its inception to the last edition, employing advanced bibliometric and textmetric analyses to explore trends, gaps, and emergent areas within innovation research. By analysing over 1,300 publications referencing the Oslo Manual, this study charts its role in defining innovation and identifies how it has adapted to changing global economic and social landscapes. This section also sets the stage for future research by highlighting key stakeholders, potential collaborations, and emerging research networks reshaping innovation studies.

The subsequent chapters shift the focus to the microeconomic implications of R&D tax incentives. Chapter 4 presents an in-depth examination of the impact of R&D tax credits on firm behaviour in Portugal, addressing the scarcity of empirical studies on this topic. Utilising extensive firm-level data from Portugal over a 23-year period, the study reveals that R&D tax credits significantly influence the allocation of highly qualified personnel, such as PhD holders in medium-high and high R&D intensity sectors. By exploring sectoral differences in R&D intensity, this study uncovers the nuanced impact of tax credits on firms' human resource strategies, providing valuable insights for policymakers.

Chapter 5 extends the research trajectory into employment dynamics, analysing how R&D tax credits influence hiring practices. By employing a longitudinal methodology, including a staggered DiD approach, the research assesses the enduring impact of R&D tax credits on employment, focusing on roles critical to R&D, such as R&D staff and PhD holders. This research addresses gaps in the existing literature by offering a sector-specific analysis of how tax incentives shape employment outcomes within firms engaged in R&D activities.

Collectively, these chapters delineate a coherent path of research that progresses from understanding the foundational frameworks of innovation measurement to exploring the microeconomic and employment impacts of R&D tax incentives. The thesis not only contributes to the academic discourse by addressing critical gaps in the literature but also offers practical implications for policymakers aiming to foster innovation and economic growth through targeted R&D incentives. As suggested by the findings, future research avenues could further explore the long-term impacts of R&D tax incentives, cross-country comparisons, and the interplay between innovation policies and labour market dynamics.

2. Literature review

2.1 The Importance of R&D for Economic Growth and the Impact of Public Policies

R&D is a key driver in economic growth, driving not only innovation but also productivity and competitiveness, both in more developed and emerging economies. Economic theory emphasises that knowledge creation and technological advancement, based on R&D investments, are key determinants of long-term productivity growth (European Commission, 2020; Guellec & van Pottelsberghe de la Potterie, 2001; Henrekson & Johansson, 2025; Lehmann *et al*., 2022; Schumpeter, 1949; Zhang *et al*., 2025).

Due to the high costs inherent in R&D activities, as well as the uncertainty of returns, companies tend to invest less in R&D than is socially desirable. To mitigate this market failure, such as underinvestment in R&D, governments adopt fiscal policies, including tax incentives and subsidies, to stimulate private investment. Public policies, particularly tax incentives, emerge as effective tools to encourage private investment in R&D, reducing costs and mitigating risks, making R&D more accessible and attractive to businesses (Appelt *et al*., 2016; Dechezleprêtre *et al*., 2016; Hall & van Reenen, 2000; Nasirov & Castaldi, 2025).

Tax incentives, in particular, offer a neutral and flexible approach, allowing firms across industries and regions to benefit from government support (Lhuillery, 2005; Mardones & Natalia, 2020). These incentives are widely adopted in OECD countries, including Portugal, where programmes such as SIFIDE have proven successful in increasing R&D expenditure and employment in knowledge-intensive sectors (Ferreira *et al*., 2019). Unlike direct funding, which involves administrative costs and risks of misallocation, tax incentives integrate seamlessly into existing tax systems, offering firms greater autonomy in resource allocation (OECD, 2014). Empirical studies suggest these incentives are particularly effective in R&D-intensive industries (Freitas *et al*., 2017). However, the effectiveness of these policies varies across countries and sectors, highlighting the need for tailored approaches to specific market and technological contexts (Thomson, 2017). In Portugal, for example, SIFIDE has not only increased R&D investments but also improved employability and the creation of skilled jobs, particularly in high-tech industries (Ferreira *et al*., 2019; Piva & Vivarelli, 2018).

Despite the widespread adoption of business R&D tax incentive systems, their impact on hiring specialised personnel, such as researchers, PhD holders and R&D personnel, remains underexplored. Further research at the firm-level is essential to understand how these policies influence R&D employment dynamics across different economic sectors (Bogliacino & Vivarelli, 2012; David *et al*., 2000). As economies become more reliant on intangible assets and knowledge-based sectors, maintaining and refining public policies that support R&D are crucial in ensuring sustained long-term economic growth (European Commission, 2020).

2.2 The Role of the Oslo Manual in Defining and Measuring Innovation

The Oslo Manual, first published in 1992 by the OECD and Eurostat, has played a pivotal role in shaping the conceptualisation and measurement of innovation. The Manual has provided standard guidelines for conducting innovation surveys, offering policymakers, researchers, and businesses a comprehensive tool to assess innovation. The Community Innovation Survey (CIS), developed in accordance with the Manual's guidelines, has become a primary data source for assessing innovation at the firm level across Europe and beyond (Hall *et al*., 2010). Its development reflects the evolving understanding of innovation, moving from narrow, technology-centric definitions to a broader, more inclusive framework that captures the multifaceted nature of innovation across industries and sectors. This section reviews the literature on the Oslo Manual's contributions to defining and measuring innovation, highlighting its methodological advancements and its influence on innovation research and policy.

It is important to first understand how innovation was traditionally measured before its introduction in order to fully grasp the significance of the Oslo Manual. Before the Oslo Manual, innovation measurement relied heavily on proxies such as patents and R&D expenditures (Freeman, 1987; Schmookler, 1950, 1954). While these indicators were relatively easy to collect, they provided a limited view of innovation, failing to capture non-technological aspects and the broader innovation process (Godin, 2005; OECD, 1976). The 1980s saw increased interest in direct innovation measurement, spurred by OECD workshops and national surveys, but these efforts lacked standardisation (Freeman, 1971; Pavitt, 1983; Rothwell *et al*., 1974). The Oslo Manual emerged as a response to this gap, providing a unified framework for innovation surveys and indicators (Godin, 2005; OECD, 1992).

The first edition of the Oslo Manual (1992) established a foundational definition of innovation, focusing primarily on technological innovations within manufacturing industries. It emphasised the importance of measuring innovation outputs, such as new products and processes, and their economic impacts (OECD, 1992). The need for a more inclusive framework became evident as the understanding of innovation broadened beyond technology-driven advancements. This shift led to the publication of the second edition in 1997, which expanded the Manual's scope to encompass non-technological innovations, such as organisational and marketing changes (OECD/Eurostat, 1997).

The second edition (OECD/Eurostat, 1997) expanded the scope to include non-technological innovations, such as organisational and marketing innovations, reflecting the growing recognition that innovation occurs across diverse economic activities (Arundel *et al*., 2008). The second edition introduced guidelines for measuring innovation inputs (e.g., R&D expenditures, human resources) and outputs (e.g., market success), as well as a new chapter on institutional classifications (OECD/Eurostat, 1997). Subsequent editions further refined these definitions, incorporating service sector innovations and acknowledging the heterogeneity of innovation types across different industries (OECD/Eurostat, 2005, 2018).

The third edition (2005) further advanced these efforts by providing explicit guidance on capturing non-technological innovations and introducing the concept of "innovation cooperation," which emphasised the role of partnerships and networks in innovation processes (OECD/Eurostat, 2005). This edition also highlighted the importance of intangible assets, such as intellectual property and human capital, reflecting the growing complexity of innovation ecosystems (OECD/Eurostat, 2005).

Scholars have examined the implications of the Oslo Manual's evolving definitions. Edquist (2005) highlights that the expansion of innovation categories aligns with broader innovation system perspectives, emphasising the interactive and systemic nature of innovation. Additionally, Godin (2010) argues that the Manual has contributed to shifting innovation studies from a linear model (science-push or demand-pull) to a more complex framework that acknowledges multiple actors and feedback loops in the innovation process (Godin, 2010).

The fourth edition (2018) represents the most comprehensive iteration of the Manual, incorporating advances in data collection methods, such as web-based surveys and big data analytics, and introducing the concept of "open innovation" and the role of digitalisation in innovation measurement, reflecting contemporary shifts in innovation dynamics (Bogers *et al*., 2018; Chesbrough, 2006). It also dedicates significant attention to measuring innovation impacts and outcomes, with six out of eleven chapters focusing on measurement-related topics. This expansion underscores the Manual's commitment to staying relevant in a rapidly changing innovation landscape (OECD/Eurostat, 2018).

The Oslo Manual's influence extends beyond academic research to innovation policy and firm strategy. Policymakers have used its guidelines to design national innovation surveys, shaping evidence-based innovation policies (Fagerberg *et al*., 2005). Additionally, the Manual has been instrumental in shaping international comparisons of innovation performance, as seen in the European Innovation Scoreboard and OECD's Science, Technology, and Industry Scoreboard (Archibugi & Pianta, 1996; Fagerberg *et al*., 2005).

The Manual's role in guiding firm-level innovation strategies is also well documented. Firms utilise the standardised innovation metrics to benchmark their innovation performance, identify key innovation drivers, and assess their competitive positioning (Hall & Mairesse, 2006). Moreover, innovation measurement frameworks have informed business models emphasising knowledge-sharing and collaboration (Hall & Mairesse, 2006; Teece, 2010).

The Oslo Manual has been a cornerstone in defining and measuring innovation, influencing academic research, policy frameworks, and firm-level strategies. Its evolution over successive editions reflects a shift from a narrow focus on technological innovation to a broader understanding encompassing organisational, marketing, and service innovations. By standardising innovation measurement methodologies, the Manual has enhanced the comparability of innovation data across countries and industries, enabling more informed decision-making. As innovation processes continue to evolve in response to digital transformation and globalisation, the Oslo Manual will remain an essential reference for future innovation studies and policies (OECD/Eurostat, 2018).

2.3 Comparing Tax Incentives with Other Forms of Direct Support for R&D

Governments use multiple policy instruments to stimulate private investment in R&D, namely tax incentives, direct subsidies, and public funding. While direct support measures, such as subsidies and state-funded projects, provide direct financial assistance, they often entail high administrative costs and risks of inefficiency in project selection (Dechezleprêtre *et al*., 2016; Curado *et al*., 2021; Hall & van

Reenen, 2000). In contrast, tax incentives, which include tax credits and deductions, offer a more market-driven approach by reducing the tax burden on firms that invest in R&D. Any firm investing in R&D can benefit, regardless of the economic sector or geographical location. This aspect minimises the administrative burden on the government and mitigates the risk of 'picking losers' (Mardones & Natalia, 2020; Moon, 2025), ensuring that resources are allocated according to the actual investment decisions of firms, rather than bureaucratic criteria (OECD, 2014).

R&D tax incentives are classified as either incremental or volume-based schemes. The former rewards firms that exceed a baseline level of previous R&D activities, while the latter offers benefits for total R&D expenditure, regardless of historical performance (Thomson, 2017). Hybrid approaches, such as those used in Canada and Spain, combine both schemes to maximise their impact on R&D intensity (OECD, 2020). These highly flexible and adaptable incentives allow governments to tailor policies to specific economic contexts without imposing significant administrative costs (Guceri, 2018; Lhuillery, 2005).

Investment in R&D plays a crucial role in technological change, which is one of the main drivers of productivity growth and economic development (Guellec & van Pottelsberghe de la Potterie, 2001). However, the effectiveness of R&D investments heavily depends on the absorptive capacity of firms — the ability to recognise, assimilate, and apply new knowledge (Cohen & Levinthal, 1990). Tax incentives enhance this capacity by reducing financial barriers to R&D, enabling firms to invest in skilled personnel, infrastructure, and intangible assets (Freitas *et al*., 2017). In Portugal, for example, the SIFIDE programme not only increased R&D expenditure but also improved employability and job quality in knowledge-intensive sectors (Cohen & Levinthal, 1990; Ferreira *et al*., 2019).

Despite their advantages, the impact of tax incentives on hiring specialised R&D personnel, such as researchers and PhD holders, remains underexplored. Further research at the firm-level is needed to understand how these policies influence employment dynamics across different economic sectors (Bogliacino & Vivarelli, 2012; David *et al*., 2000). As economies increasingly rely on knowledge and intangible assets, the strategic design of R&D tax incentives will continue to play a critical role in driving innovation and long-term economic growth (European Commission, 2020).

2.4 Effectiveness of R&D Tax Incentives: Variations between SMEs and Large Firms

Tax incentives have proven to be an effective tool in stimulating private investment in R&D, with varying impacts on SMEs and large firms. While in some countries, SMEs often face greater financial constraints and, consequently, benefit more substantially from these incentives, large firms can better leverage economies of scale and allocate more resources to research activities (Barros *et al*., 2013; Bronzini & Piselli, 2016; Castellacci & Lie, 2015; Damásio *et al*., 2018). However, the opposite trend is observed in other countries, with a greater impact on large firms, particularly in high-tech intensive industries, which tend to have higher R&D expenditures and greater absorptive capacity (Straathof *et al*., 2014). Among OECD countries, Spain and Portugal prevail as the most generous in offering R&D tax incentives. For instance, large high-tech firms in Spain have significantly benefited from this type of incentive (Busom *et al*., 2017). Similarly, the SIFIDE programme in Portugal has effectively promoted R&D investments, particularly in intangible assets and skilled labour within knowledge-intensive sectors (Bronzini & Piselli, 2016; Ferreira *et al*., 2019).

The effectiveness of R&D tax incentives is most evident in R&D-intensive sectors, where the additional impact of subsidies and tax credits is higher (Jose *et al*., 2019). The literature also suggests that tax incentives should be tailored to the specific realities of each economic sector, thereby maximising their impact on productivity and competitiveness. Chinese high-tech firms have shown better research outcomes when they have benefited more frequently from tax incentives, highlighting the importance of sustained support for such policies (Dai *et al*., 2020; Guceri, 2018).

It is essential to conduct microeconomic-level studies to better understand the heterogeneous effects of tax incentives. Firm-level analysis allows for assessing how different sectors and types of firms respond to incentive policies, generating more robust evidence of their effectiveness. Aggregate data often mask the nuances of how these incentives influence individual firms, particularly in terms of hiring specialised personnel, such as researchers and R&D personnel (Bogliacino & Vivarelli, 2012; David *et al*., 2000).

Microeconomic analyses can provide deeper insights into the mechanisms through which tax incentives drive R&D investments, helping policymakers design more effective measures. For example, while macroeconomic studies show a positive correlation between tax incentives and R&D expenditure, firm-level research can reveal how these incentives affect specific outcomes, such as the hiring of PhD holders or the development of new technologies (David *et al*., 2000; Guellec & van Pottelsberghe, 2003).

Although tax incentives for R&D activities have demonstrated their importance in stimulating investment, their impact is not uniform across firms or sectors. Countries such as Spain and Portugal exemplify how generous and well-designed policies can drive significant R&D investments in the private sector, particularly in high-tech industries. However, to fully harness the potential of these incentives, it is essential to advance firm-level research to uncover the various ways tax incentives influence different dynamics, particularly in employment, and to inform more targeted policy approaches (Carvalho, 2011).

2.5 The Evolution of SIFIDE and its Impact on R&D Investments and the Competitiveness of Portuguese Firms

SIFIDE has played a fundamental role in promoting R&D activities in Portugal. Since its creation in 1997, changes have been introduced to enhance its attractiveness and effectiveness. The introduction of SIFIDE II brought significant improvements, broadening the eligibility criteria and allowing firms to apply for multiple projects, which expanded the programme's scope across different sectors of the economy. Studies, such as those by Ferreira *et al*. (2019), highlight that companies benefiting from SIFIDE exhibit distinct behaviours compared to non-beneficiaries, particularly regarding their reliance on public and private funding and the quality of jobs created, further contributing to the growth of R&D-intensive sectors (Ferreira *et al*., 2019).

Although studies such as those by Dai *et al*. (2020) and Jose *et al*. (2019) emphasise the positive correlation between R&D tax incentives and increased R&D expenditure, particularly in high-tech industries, further research is needed to understand the programme's impact at the sectoral level and its role in addressing market failures (Guceri, 2018).

2.6 Challenges and Limitations in Assessing R&D Tax Incentives

Assessing the effectiveness of R&D tax incentives faces significant challenges due to the complexity of isolating their impact from other variables that influence investment decisions. Macroeconomic conditions, industry-specific trends, and individual firm characteristics can interact with tax incentives, making it difficult to establish a clear causal relationship and justify changes based on fiscal policies (Guellec & van Pottelsberghe, 2003). Moreover, when other forms of public support, such as subsidies or direct funding, are present, evaluation becomes even more challenging, as these interventions often overlap with tax incentives, creating potential biases in empirical studies (Dai & Zou, 2025; David *et al*., 2000).

Another critical challenge lies in the heterogeneity of firms and sectors. The impact of R&D tax incentives varies across industries, firm size, and levels of technological intensity. For example, high-tech industries and large firms tend to benefit more from tax credits due to their high initial expenditure on R&D activities and their greater absorptive capacity (Freitas *et al*., 2017). In contrast, SMEs or firms in low-tech sectors may not respond as positively to these incentives, as they often face different types of constraints, such as limited access to capital or expertise (Bronzini & Piselli, 2016). This factor highlights the need for more granular, firm-level analyses to better understand how different contexts influence the effectiveness of tax incentives (Guceri, 2018).

The long-term effects of R&D tax incentives remain understudied, particularly in terms of their ability to generate sustainable economic growth and impact employability. While short-term increases in R&D expenditure are frequently observed, the extent to which these translate into tangible outcomes, such as productivity gains, job creation, or competitiveness, is less clear (Conte & Vivarelli, 2005; Mairesse & Sassenou, 1991; Ortega-Argilés *et al*., 2010; Parisi *et al*., 2006).

Furthermore, the design of tax incentive schemes, such as incremental versus volume-based approaches, can influence their effectiveness. The issue of additionality — whether incentives lead to new investments or merely subsidise existing efforts — remains central to public policy debates. There is limited consensus on which model is most suitable depending on the economic context (Thomson, 2017). More robust methodologies are needed to overcome these limitations, including longitudinal studies and counterfactual analyses, to isolate the true impact of tax incentives on R&D investments and their broader economic implications (Guceri, 2018).

2.7 Key Findings from the Literature and Future Directions for Research on R&D Tax Incentives

The literature highlights the widespread adoption of R&D tax incentives in OECD and EU member countries, driven by their flexibility, neutrality, and ability to stimulate innovation in the private sector and promote long-term economic growth. Tax incentives, such as tax credits, are preferred over direct funding due to their lower administrative costs and more market-driven nature, benefiting any firm that invests in R&D, regardless of the economic sector, size, or location (Lhuillery, 2005; Mardones & Natalia, 2020).

Studies indicate that these incentives are particularly effective in increasing R&D investment and strengthening existing R&D activities, although their impact varies across firms of different sizes, industries, and technological levels (Bronzini & Piselli, 2016; Castellacci & Lie, 2015). For example, in Portugal, SIFIDE has proven effective in promoting investments in intangible assets and hiring highly skilled labour, especially in R&D-intensive sectors (Ferreira *et al*., 2019).

Despite the widespread adoption of R&D tax credits, their effectiveness in job creation remains an open question, particularly for highly skilled professionals such as PhD holders and specialised technicians. While they have shown positive effects on R&D expenditure and employment in high-tech industries, their impact on job creation in traditional sectors is less evident (Barbieri *et al*., 2019; Piva & Vivarelli, 2018). Moreover, research remains limited on how these incentives influence hiring specialised personnel, such as PhD holders and R&D personnel, who are essential to performing R&D activities. This gap underscores the need for firm-level analyses to better understand the sectoral and macroeconomic dynamics of R&D tax incentives (Barros *et al*., 2014; David *et al*., 2000; Guellec & van Pottelsberghe, 2003).

Future research should explore the differentiated impacts of R&D tax incentives at the industry level. Additionally, new methodological approaches are needed to assess the effectiveness of these incentives in promoting innovation and employment, such as longitudinal studies and micro-level data analyses. Investigating the role of tax incentives in attracting and retaining highly skilled talent, as well as their long-term effects on productivity and competitiveness, could provide valuable insights for designing more targeted and effective public policies to support R&D activities (Carvalho, 2011; Metzger *et al*., 2023).

3. Accounting for the Oslo Manual: reflecting on the past and setting the stage for future research

The Oslo Manual is the internationally recognized reference for guiding the collection and interpretation of evidence on innovation. This research explores its three-decade-long implementation and influence, emphasizing its role within the research community. We assess the content's quantity and quality through an advanced bibliometric and textmetric analysis of over 1300 research papers published in internationally indexed journals. Our study offers an evidence-based understanding of the Oslo Manual's adoption and impact, elucidating disciplinary integration, geographical interest, and reception phases. Notably, the findings unveil the increasing significance of innovation-related topics since its inaugural edition in 1992, with a pronounced surge gaining momentum after 2008. Furthermore, the consistently cited references underscore the researchers' focus, highlighting the rising importance of innovation and interconnected domains like entrepreneurship, performance, knowledge, and management. This study enhances our insight into the Oslo Manual's utilization and influence, revealing its enduring relevance and the broader impact on shaping innovation research.

3.1 Introduction

Innovation is a practical topic that holds significant importance for individuals, institutions, productive sectors, and countries, as it enhances living standards and economic growth (OECD/Eurostat, 2018). Nevertheless, it is also an object of research in itself. Indeed, the study of innovation has recently developed into a vibrant field in its own right (Castellaci *et al*., 2005; Santos & Mendonça, 2022a). A valuable resource bridges these two worlds: the tool known as the Oslo Manual. The Oslo Manual is an internationally recognized reference that provides guidelines for collecting and interpreting evidence on innovation (Smith, 1992).

In innovation research, researchers dell into key topics from existing literature or uncover their dynamics (Rossetto *et al*., 2018; Sun & Zhai, 2018). Some works, like those by Nelson and Winter (1977) and Abernathy and Clark (1985), provide comprehensive literature reviews on innovation. Additionally, Merigó *et al*. (2016) and Cancino *et al*. (2017a) conducted literature reviews on innovation. Other researches utilise bibliometric and textmetric analyses to examine innovation literature (Rakas & Hain, 2019; Santos & Mendonça, 2022a), scientific journals (Kajikawa *et al*., 2022), and authors (Mendonça, 2017) in the field of science, technology, and innovation[1]. This paper employs advanced analytical techniques, including text mining, to evaluate the review process of a technical report called the Oslo Manual.

This paper aims to compare changes in different editions of the Oslo Manual over the years and present a comprehensive and evidence-based analysis of its development. Using text mining techniques, we examine a collection of internationally peer-reviewed publications, conducting a content analysis of research articles that assess the evolution of the Oslo Manual's structure and content (primary areas of analysis).

In this study, we apply a comprehensive approach, combining bibliometric and textmetric analytical dimensions, to evaluate 1,388 scientific papers that cite the Oslo Manual. These papers are authored by individuals affiliated with various entities from every country, spanning 30 years from 1992 to 2021. The methodological shifts (do economic and social changes impact innovation definitions?) and the increasing interest in the Oslo Manual (are emergent economies more engaged to use metrics for measuring innovation?) are discussed. This study can provide helpful evidence for those interested in

[1] Fagerberg *et al*. (2012) analysed the development of innovation research and used an empirical approach based on the analysis of chapters in authoritative innovation research handbooks to determine which original publications had the most significant influence (Fagerberg & Verspagen, 2009).

innovation studies. Policymakers can gain insights into key stakeholders and potential partners for collaboration in innovation-related initiatives. On the other hand, researchers can understand the trends, gaps, and emerging areas related to innovation. They can identify potential research collaborations and knowledge-sharing opportunities, as well as gauge the visibility and influence of their work in the context of innovation.

The paper is organized as follows: Section 3.2 presents the institutional history of the Oslo Manual, what it tried to fix in each edition, and what it represented as innovation in each edition. Section 3.3 presents the source and methodology for assessing the Oslo Manual review. Section 3.4 presents and debates the significant patterns and key salient found in the data. Section 3.5 offers conclusions and looks ahead.

3.2 The Oslo Manual

3.2.1 Genealogy of the Oslo Manual

Before the 1970s, innovation was primarily measured using proxies such as patents and industrial expenditures on R&D (Freeman, 1987). The extensive use of patents as an indicator of innovation was pioneered by Jacob Schmookler in the 1950s (Schmookler 1950, 1954). Industrial R&D data was relatively easier to collect and measure than other innovation aspects (Godin, 2005). However, these early measures were limited in providing a comprehensive view of innovation (OECD, 1976).

OECD members' interest in direct measures of innovation dates back to the late 1970s, when its work on direct or proxy output indicators led to seminars at the end of the 1970s (OECD, 1992). However, systematic innovation surveys were only widely conducted in the 1980s. There had been some sporadic data collection by government departments (US Department of Commerce), statistical institutes (Statistics Canada), and research units (SPRU, University of Sussex, UK) before then, but rarely in any standardized way (Freeman, 1971; Rothwell *et al*., 1974; Pavitt, 1983).

In 1980, the OECD arranged a conference to explore output indicators and discuss national innovation surveys and indicators. Subsequently, workshops dedicated to innovation took place in 1982 and 1986 since patents were recognized as a poor indicator of a country's technological position (see OECD, 1980, 1982, 1986).

The OECD's involvement in innovation surveys began with the Nordic Fund for Industrial Development's initiative to collect data on innovation activities in Scandinavian countries (Nordic Industrial Fund, 1991). In 1988, a workshop was organized by the Nordic Fund, inviting the OECD and its member countries to participate (OECD, 1988). The workshop introduced a conceptual framework for developing innovation indicators written by Keith Smith (1989). The framework underwent revisions in a subsequent workshop and was presented to the OECD Group of National Experts on Science and Technology Indicators (NESTI) in 1989, which recommended that the Nordic Fund prepare a draft Manual (OECD, 1990).

The draft Manual, prepared by Keith Smith and Mikael Akerblom, underwent discussions and amendments by OECD member countries between 1990 and 1991 (OECD, 1991a). The first edition of the Manual, named after the city of Oslo, was officially adopted in 1992 (OECD, 1991b).

In 1993, a significant milestone was achieved when delegates from twelve European countries collaborated to carry out the first-ever coordinated survey of innovation activities based on the Oslo Manual (Godin, 2005). After completing the initial round of surveys in member countries, the Manual was subjected to review and further development based on the valuable experience gained during the process (OECD, 1992). As a result, the Oslo Manual underwent its first review in 1996 and was subsequently published in collaboration with the European Commission (Eurostat) in 1997 as the second edition.

While the Oslo Manual's initial focus was primarily on technological innovations within manufacturing industries (OECD, 1992), the concept of innovation and the need for comprehensive measurements started to evolve. Recognizing these shifts, the Manual expanded its scope to include additional dimensions of innovation beyond technology. This expansion encompassed non-technological innovations and services, acknowledging their growing significance in the innovation landscape (OECD/Eurostat, 1997). The second edition's publication in the same year marked a crucial shift in perspective, reflecting a broader conceptual framework that embraced the evolving nature of innovation measurement and its applications.

The subsequent editions of the Oslo Manual continued to adapt and respond to changing perspectives and demands in the field of innovation. There was a noticeable increase in emphasis on services, reflecting the growing recognition of their role in fostering innovation. With each new edition, the Manual's genealogy mirrored the dynamic evolution of innovation measurement. It illustrates the ongoing efforts to refine and update the framework, ensuring its relevance in capturing the multifaceted nature of innovation in an ever-changing global landscape. The Oslo Manual's journey exemplify the commitment to staying abreast of emerging trends and methodologies, ultimately contributing to a more comprehensive understanding of innovation and its impact.

3.2.2 Oslo Manual comes of age

Between the first and fourth editions, the Oslo Manual experienced an increase of 50% or more in the number of pages, starting with 62 pages and reaching 258 in the fourth edition. Figure 3.1 displays the evolution of the Oslo Manual concerning its contents. Notably, the first three editions shared four common topics: “Objectives and scope of the Manual”, “Basic definitions”, “Innovation process”, and “Survey procedures”. Furthermore, upon comparing only the first two editions, we observed another shared chapter: measuring the cost/expenditure on innovation.

Figure 3.1 Table of contents of the four Oslo Manual editions

Note: In green are the four common topics in the first three editions; in orange is another shared chapter in the first two editions; in red are the chapters focused on "measurement" in the 4th edition.

The first edition of the Oslo Manual, published in 1992, laid the foundation for measuring and analysing innovation. This first edition had two primary objectives: to establish a framework that enables existing surveys to evolve towards comparability and to assist researchers in innovation. According to the OECD (1992, p. 35), "From the policy viewpoint, indicators of the outcomes of the innovation process are perhaps the most important results of innovation surveys".

Regarding the methodological change from the first to second editions, the second edition of the Oslo Manual expanded the scope of innovation measurement beyond R&D to include non-technological areas such as marketing, organizational changes, and design (OECD/Eurostat, 1997). The second edition emphasized capturing the innovation process's inputs, activities, and outputs. It highlighted the need to measure innovation inputs (e.g., R&D expenditures, human resources dedicated to innovation) and outputs (e.g., new products, improved processes, market success). The guidelines covered various aspects, including measuring expenditures on innovation, identifying innovation sources, assessing innovation's impact on firm performance, and introducing a new chapter related to “Institutional classifications” (Chapter 4), as shown in Figure 3.1.

The Manual has progressively expanded its coverage and definitions to accommodate a broader range of industries and capture the complexity and heterogeneity of innovation, reflecting the maturation and growing significance of innovation research as a multidisciplinary field (Castellaci *et al.*, 2005).

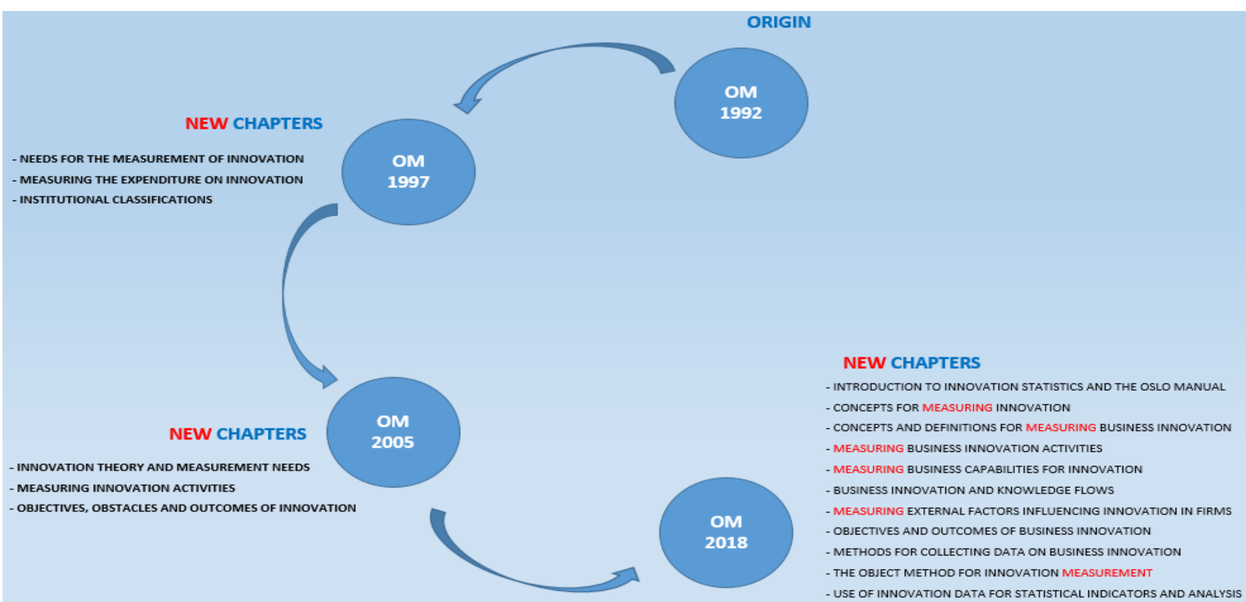
Regarding the methodological change from the second to third editions, the third edition of the Oslo Manual provided more explicit guidelines on capturing and measuring non-technological innovations, such as organizational and marketing innovations (OECD/Eurostat, 2005). It recognized that innovation is not limited to technological advances and that firms can innovate in various dimensions.

The Manual expanded the discussion on measuring intangible assets, such as intellectual property and human capital. Moreover, the third edition introduced the concept of "innovation cooperation". It recognized that innovation often involves partnerships, alliances, and networks among different actors and provided guidance on measuring and assessing these collaborative efforts. It emphasized the role of innovation systems in fostering organizational innovation. In addition to the four chapters common with the first edition, the third edition retained the new chapter introduced in the second edition, the “Institutional Classifications”, and included a new chapter dedicated to “objectives, obstacles and outcomes of innovation” (OECD/Eurostat 2005, Chapter 7).

The fourth edition of the Oslo Manual incorporates methodological changes from the third edition, including advances in data collection methods, such as new data sources and techniques for measuring innovation (OECD/Eurostat, 2018). It guides the use of new data collection tools, such as web-based surveys and big data analytics. The fourth edition introduces the concept of "open innovation", emphasising the importance of collaboration and knowledge sharing between organizations.

Comparing the fourth edition with the previous editions, in addition to the increase in the number of pages and chapters, we can also observe a new chapter (Chapter 11) dedicated to the "Use of innovation data for statistical indicators and analysis". Moreover, more than half of the chapters (six out of eleven) focus on "measurement" (see Figure 3.2): "measuring innovation", "measuring business innovation", "measuring business innovation activities", "measuring business capabilities for innovation", "measuring external factors influencing innovation in firms", and "the object method for innovation measurement".

Figure 3.2 Oslo Manual timeline



Note: For each new edition, the new chapters are identified. Regarding the 4th edition, the chapters related to the "measurement" are highlighted in red.

The Oslo Manual evolved over the four editions to capture a more comprehensive understanding of innovation. It expanded from a focus on R&D-related activities to encompass various dimensions of innovation, including non-technological, organizational, marketing, and business innovation. The different editions also incorporated advances in data collection methods and highlighted the importance of measuring innovation impacts and outcomes. Open innovation, innovation cooperation, and systemic innovation were introduced to reflect innovation processes' collaborative and interconnected nature.

3.3 Materials and methods

3.3.1 Article subject matching system

The field of innovation embraces diverse methodologies and approaches, drawing upon disciplines such as economics, management, and sociology. Researchers have utilized a range of quantitative and qualitative research methods to explore innovation processes, employing surveys, case studies, interviews, and various data analysis techniques. For instance, Nelson (1959) pioneered the application of economic theories to the study of innovation, while Burns and Stalker (1961) introduced organizational and management perspectives. Furthermore, Rogers (1962) made significant contributions by examining how innovation diffuses through social networks. As time passed, the field of innovation developed into a global research community, promoting collaboration and knowledge exchange among researchers worldwide (Martin, 2012).

The exponential growth in the number of scientific platforms and their online journals, coupled with the massive increase in research outputs, has made it challenging for researchers to select the appropriate journal to publish their work, as these platforms represent the privileged channel for disseminating their research (Bornmann & Mutz, 2015; Confraria & Godinho, 2015; Gu & Blackmore, 2016; Ioannidis *et al*., 2018; Santos & Mendonça, 2022a; Shifrin *et al*., 2018; Ware & Mabe, 2015).

The first attempt to describe authors' motivations for submitting an article to a particular journal dates back to the 1950s and 1960s, when de Solla Price (1965) treated science as a measurable entity, developed some quantitative techniques and introduced the concept of scientometrics (see also Rousseau, 2021). Later, Kochen and Tagliacozzo (1974) identified five fundamental factors influencing journal selection: relevance, acceptance rate, circulation, prestige and publication lag.

Until now, we can observe bibliometric and textmetric materials on innovation literature (Klarin, 2019; Santos & Mendonça, 2022b), scientific journals (Singh *et al*., 2020) and authors (Meyer *et al*., 2004) with contributions to the study of science, technology and innovation. This paper assesses the review process of a technical report – The Oslo Manual. For this purpose, we assemble a set of observations to compose a meaningful understanding of the Oslo Manual review.

The raw observations for the analysis are scientometric data, that is, the publication (bibliometric) and content (textmetric) materials on scientific-level types of knowledge. The scientometric toolbox is usually deployed to understand the scientific enterprise (Mendonça *et al.*, 2022). We extracted and tabulated all the relevant academic publications that focus on or refer to the Oslo Manual. A supervised machine learning algorithm was developed to enable textmetric analysis.

However, despite its complex nature, this methodology offers a high level of granularity, comparability, and adaptability to effectively address the changing demands of analytical and policy requirements (Glänzel *et al.*, 2019)[2]. What sets our integrated approach, combining bibliometric and textmetric analyses, apart is its ability to reveal the underlying processes that drive the review of the Oslo Manual.

[2] Other indicators could have been used, from the most conventional like patents (e.g. Mendonça *et al*., 2019) to less conventional ones, like trademarks (Castaldi, 2020; Mendonça *et al*., 2004, 2012, 2014) and standards (Foucart & Li, 2021; Laer *et al*., 2021; Teubner *et al*., 2021).

This paper extends our analysis to incorporate social network analysis techniques, specifically focusing on centrality measures such as degree, betweenness, and closeness. We investigate the network's most influential journals and authors, exploring their pivotal role.

3.3.2 Analysing the Oslo Manual review: a comprehensive scientometric approach

Scientific publication data have been used in many econometric analyses[3]. Three fields - bibliometrics, technometrics and econometrics – converged as publication statistics started to be used in economic and policy analysis (Meyer *et al*., 2004). By conducting bibliometric analysis, the evolution of a topic can be analysed. The bibliometric analysis employs a quantitative approach to describe, evaluate, and monitor published research (Dzikowski, 2018; Small, 1973). This study employs quantitative bibliometric analysis in reviewing a technical report – The Oslo Manual.

Bibliometric methods are effective approaches to support a comprehensive understanding of the journal because they use tools and statistical methods for publications, including research articles (Thelwall, 2008). They facilitate the comprehension of large amounts of data and enable the discovery of hidden patterns. Bibliometrics is applied to studying academic disciplines, topics, or journals (Mejia *et al*., 2021).

Bibliographic items are appealing because they span time, space, and institutional and thematic categories. They can be examined individually, aggregated or put into a relational perspective. As indicators of creative enterprise, formal publications in scientific peer-reviewed journals provide a robust data pool (Mendonça *et al*., 2022).

[3] See, for example, Griliches (1990), Hall *et al*. (2001), and Jaffe and Trajtenberg (2002).

To process the substantial amount of data, specialized software like R, VOSviewer, and Gephi (Manoj Kumar *et al*., 2022) was employed. A comprehensive computer-assisted literature exploration was conducted on the Web of Science (WoS) database to capitalize on this potential.[4] The following citation indexes were queried: SSCI, ESCI, SCI-EXPANDED, CPCI-SSH, CPCI-S, and A&HCI. The Scopus database supplies authors' identification since retrieval could be automated through an Application Programming Interface (API). Bibliometrix (R package) was used since it automatically adds affiliation dates to authors' identifications. Descriptors regarding the standing and prestige of periodicals were gleaned from Scimago Journal Rank (SJR), the public repository of journal metrics. Finally, a search for academic journal articles only was performed for the complete database with no date restrictions to ensure completeness.

Research findings can be represented in different formats, such as tables, charts, citation maps and network displays. Many indicators can be identified from bibliometric analysis, offering valuable insights into the research landscape. These include the top journals and articles, the most active authors, institutions and countries, the most popular research subjects or keywords, and patterns of collaboration and citation among researchers, institutions and countries. It can also facilitate the identification of research gaps and contribute to formulating research objectives or policies in a specific subject (Cancino *et al*., 2017b; Ellegaard & Wallin, 2015). The bibliometric indicators also measure the quantity and quality of publications, where quantity is measured in terms of the number of publications, whereas the impact of received total number of citations by a publication measures quality.

In this study, the final sample includes 1388 articles that cited the Oslo Manual in the above citation indexes. Each article can be classified in more than one index. Items were published in 403 journals

[4] This source is well-known and has extended coverage, and its findings are highly correlated with other databases (Archambault *et al*., 2009).

(unique ISSNs) and classified into 94 different categories, where five (Management, Business, Economics, Environmental Studies/Sciences, and Regional & Urban Planning/Geography) out of 94 different categories aggregate two-thirds of the articles, and containing 56,600 references to other documents.

The publication records and their characteristics were processed from a descriptive perspective. In addition, summary statistics were computed (namely, the conventional concentration index), and network analysis was carried out (graph representations and the usual network metrics). Finally, we incorporated WoS's subject and disciplinary framework without any limitations. However, it is widely acknowledged that it may not always offer an optimized bibliometric classification for every research endeavor. The identification of individuals is challenging, and their identities are retrieved via Scopus (“rscopus” package)[5].

3.4 A bibliometric account of Oslo Manual-related research

3.4.1 An overview of the studies published about the Oslo Manual until 2021

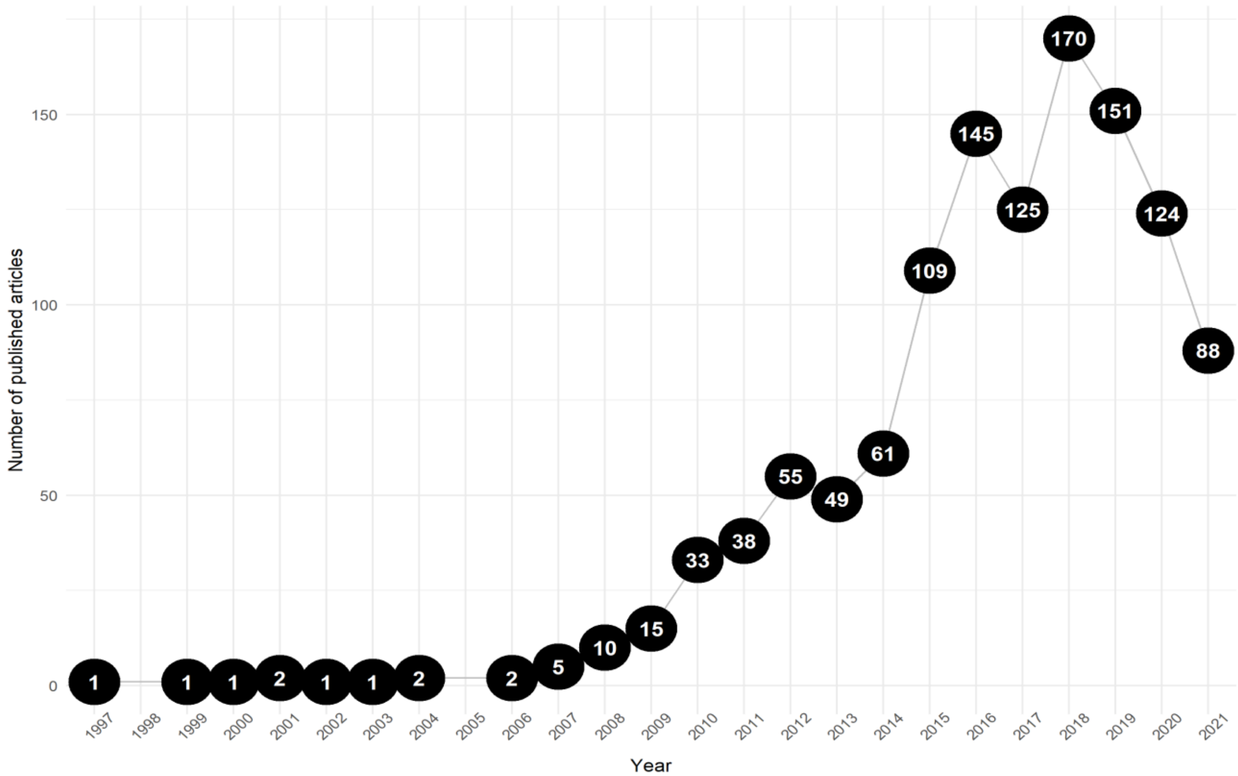
Trends in Oslo Manual citations

The total entries related to the Oslo Manual are shown in Figure 3.3. The 1388 articles that cited the Oslo Manual were authored by 1735 individuals (estimated) from 87 countries between 1997 and 2021. The first publication was in 1997, the same year as the second edition. From 2006 onwards, after the publication of the third edition, we can observe a persistent and rising production ensues until 2018. The peak in the number of published articles coincides with the year of the publication of the fourth edition, 2018. We can also observe an identical number of publications in the three years before and three years

[5] Authors may have changed affiliations throughout their careers. This implies making decisions: papers were counted for the affiliation at the year of the publication, and where the change happened, all those papers were assigned to the institution and country of the authors’ last paper in the database.

after the publication of the fourth edition. Between 2015 and 2021, this period concentrates on two-thirds of all publications.

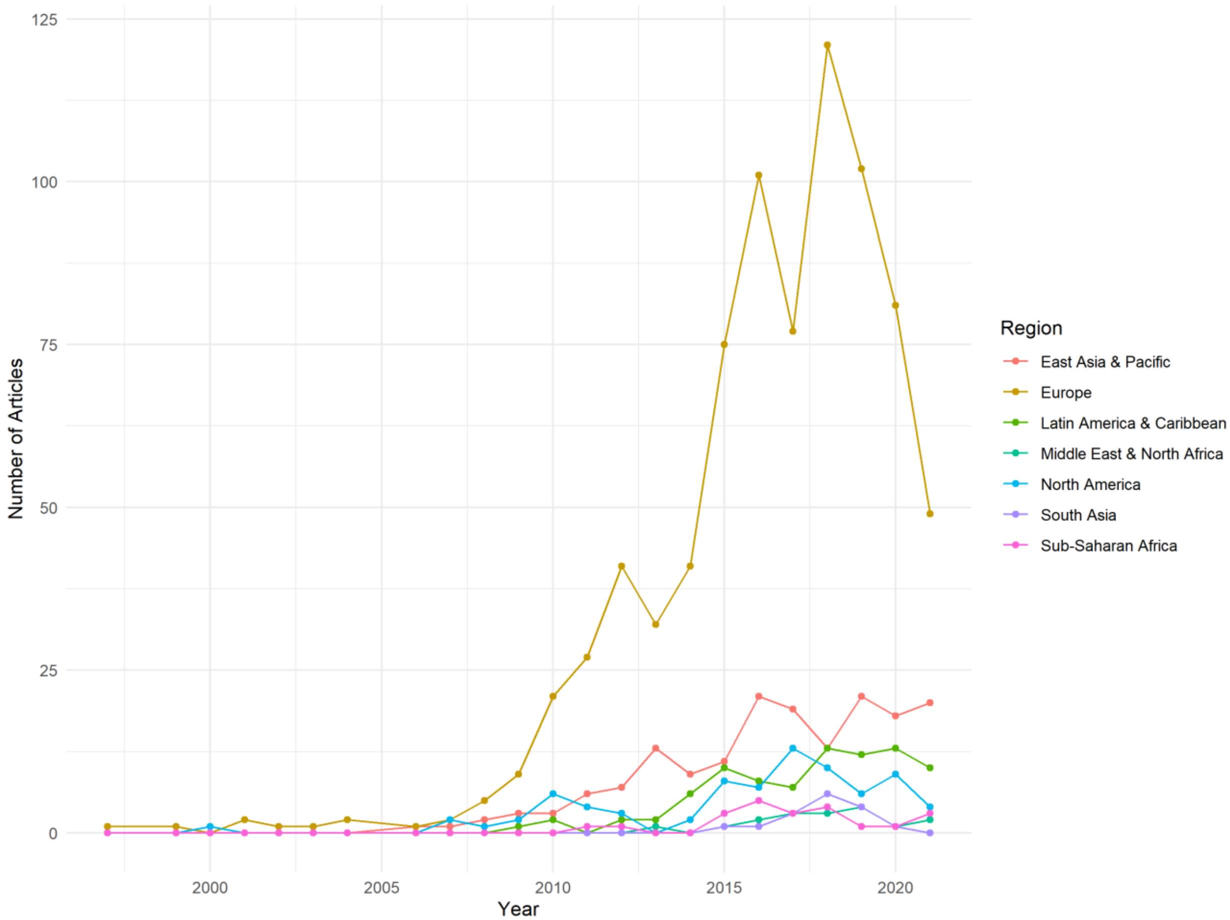
Figure 1.3 Number of published articles, by year



The geography of authorship

It is possible to picture the international distribution of knowledge production by processing authorship information. Figure 3.4 presents the number of articles by region published in the time series per year. We can observe that most of the authors are established in Europe, East Asia & Pacific, and Latin America & Caribbean. The distribution of the publications in Europe can explain the distribution observed in Figure 3.3. As can be observed in Europe, the peak of the number of publications coincides with the year of the publication of the fourth edition, and the distribution of the number of publications in the three years before and three years after the publication of the fourth edition is very similar, representing almost half of the total of publications.

Figure 3.4 Number of articles per region, by year



In analyzing the geography of authorship, we focused on the peak of the distribution, which aligns with the year of publication of the fourth edition of the Oslo Manual, along with the three years preceding and following it. This period accounts for approximately two-thirds of the total publications we examined. To gain a comprehensive understanding, we further explored the trends before and after the publication of the last edition, 2018. The figures below (Figure 3.5 for the period before 2018 and Figure 3.6 for the period after 2018) depict the distribution of knowledge production during these distinct timeframes.

Figure 3.5 Number of published articles before 2018, by region and country

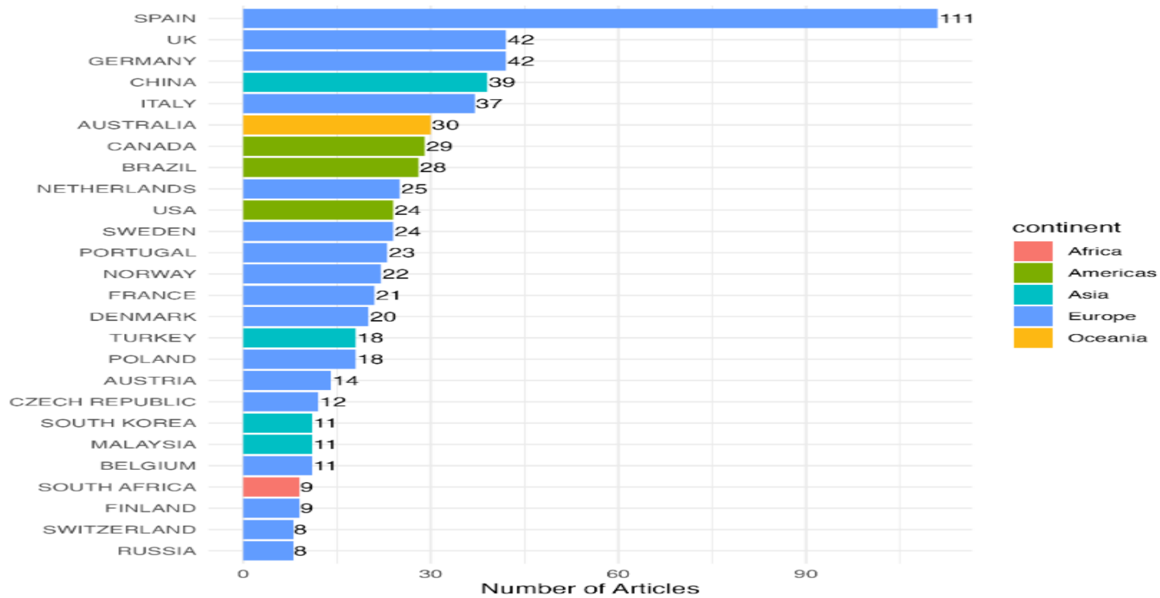
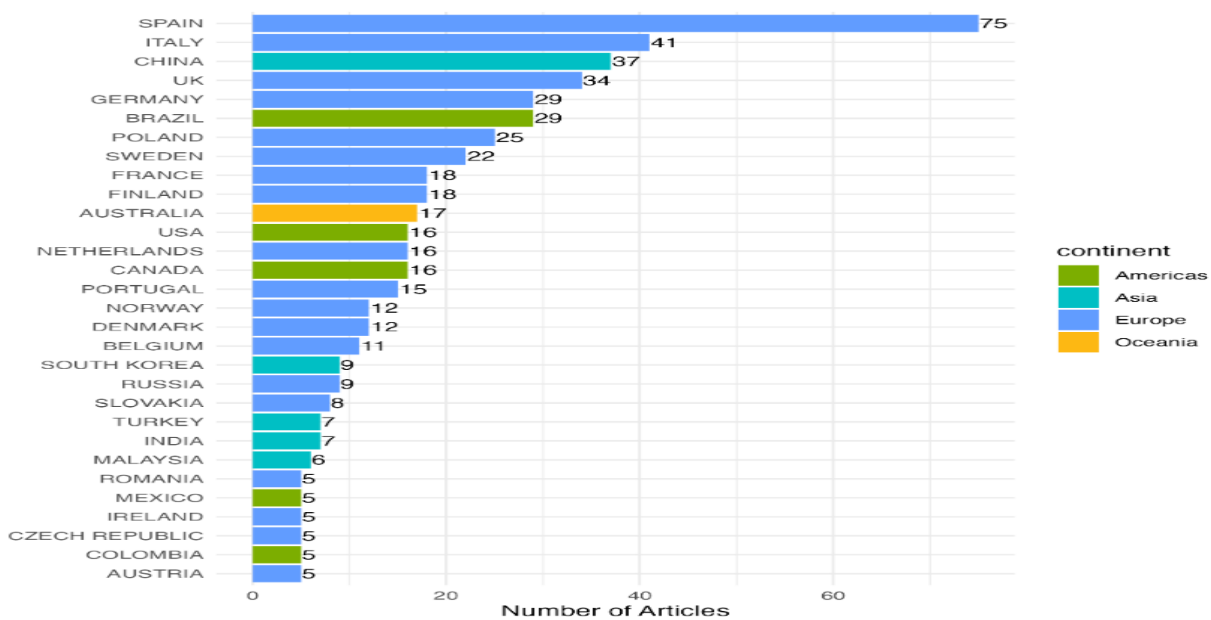


Figure 3.2 Number of published articles after the publication of the 4th edition of the Oslo Manual



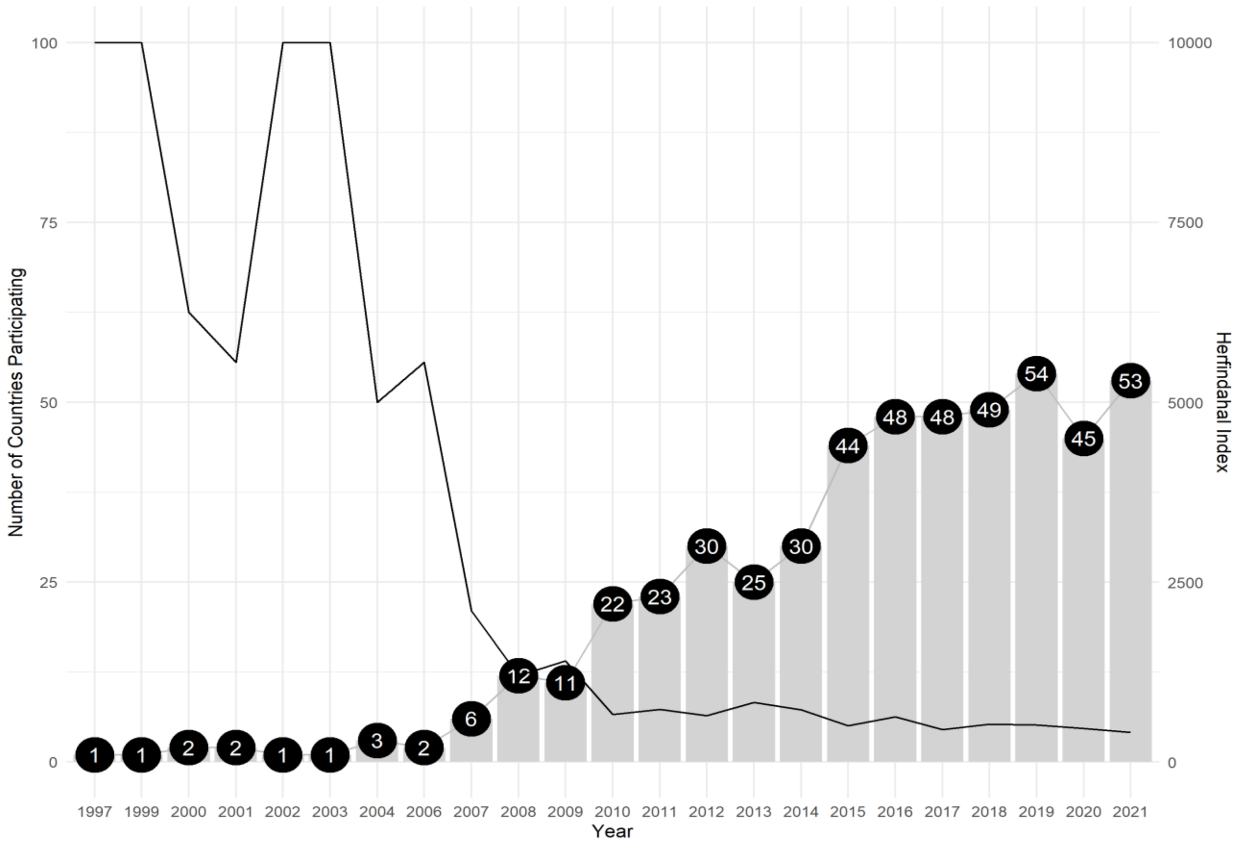
Despite the evidence that the number of published articles is spread among different countries across all regions (mainly Europe, East Asia & Pacific, and Latin America & Caribbean) after the publication of the fourth edition of the Oslo Manual, the share of the publications among the non-OECD countries, in the total of the publications increased from 11% to 18% of total publications. This fact is even more significant since 24 out of the top 25 scientific journals (see Figure 3.10) from the different indexes of the Web of Science are from the OECD countries.

International diffusion of Oslo Manual-related research

Figure 3.7 accounts for the spread of research around the Oslo Manual over time. The period in which the Oslo Manual comes alive as the research topic is after the publication of the third edition of the Oslo Manual. Before the third edition, only a few countries were engaged in the topics related to the Oslo Manual. However, during the last decade, before (as a result of the increasing interest that the review of the Manual implied) and after (as a result of the new structure of the Manual) the publication of the fourth edition in 2018, there was a significant increase in the number of countries active in the Oslo Manual agenda, particularly the BRICs. Compared with the third edition's dissemination period, by the fourth, approximately ten times more countries participated in research activities related to the Oslo Manual.

A consequence was the steady decline in the country's concentration of research in publication shares, as can be gleaned from the Hirschman-Herfindahl index in Figure 3.7. That is to say, over the years, but mainly after the second edition's publication, the interest in the Oslo Manual has become increasingly distributed, opened up, and more participated.

Figure 3.3 Increasing participation in Oslo Manual – related publications per year



3.4.2 Institutions, journal platforms and thematic profile

Major research actors

Regarding research volume (number of articles), in Figure 3.8, we can observe that the top places are occupied by European Institutions, namely the ZEW (Zentrum für Europäische Wirtschaftsforschung), the United Nations University Maastricht and the Universidad Complutense de Madrid. Of the top 10 institutions more active, only one is from outside Europe: Universidade de São Paulo.

Figure 3.8 Most active institutions

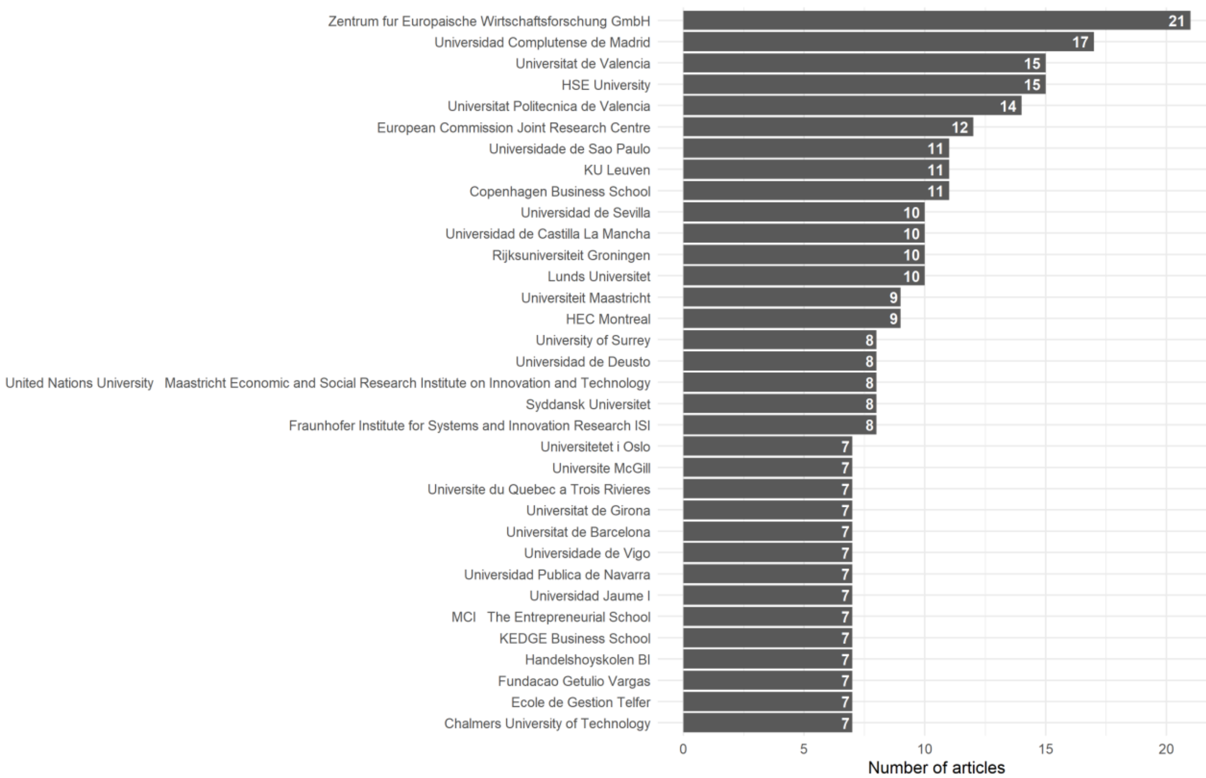
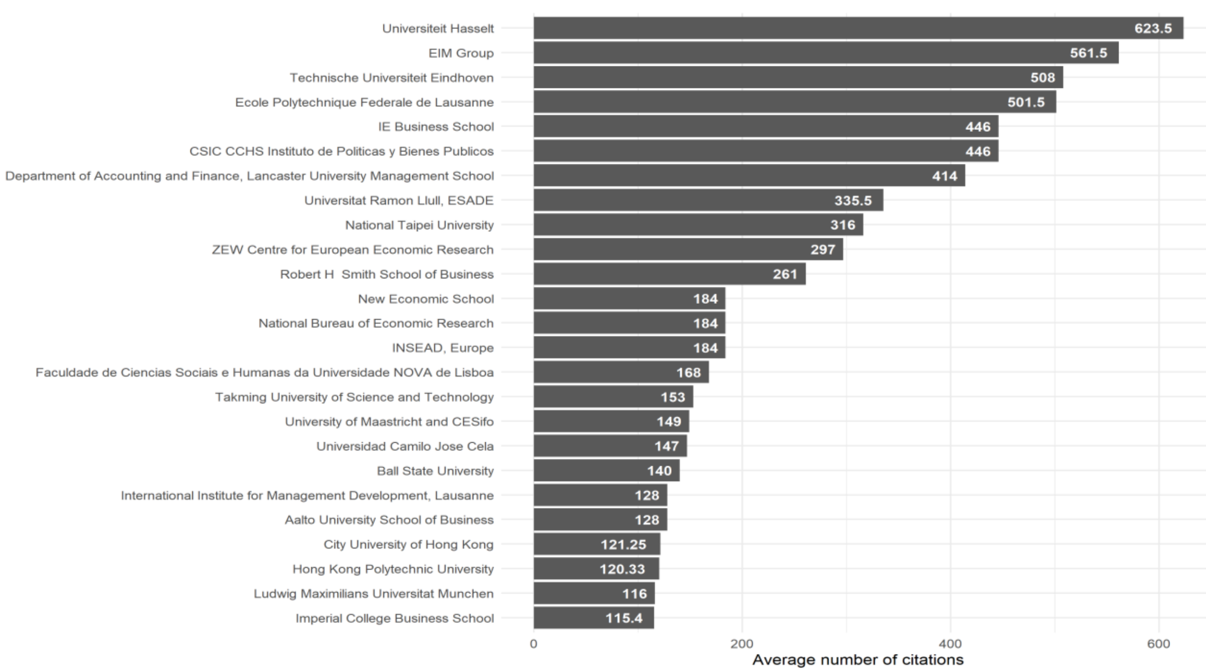


Figure 3.4 Average number of citations, per institution



However, regarding the average number of citations, Figure 3.9 shows that the top higher scores were observed in the Universiteit Hasselt, the EIM Group, the Technische Universiteit Eindhoven, and the Ecole Polytechnique Federale de Lausanne. The European institutions are the most active and present a relevant average number of citations. Figure 3.9, presenting the top 25 institutions with the higher average number of citations, also allows us to see the discrepancies between institutions – the first institution has more than five times more citations than the 25th, on average.

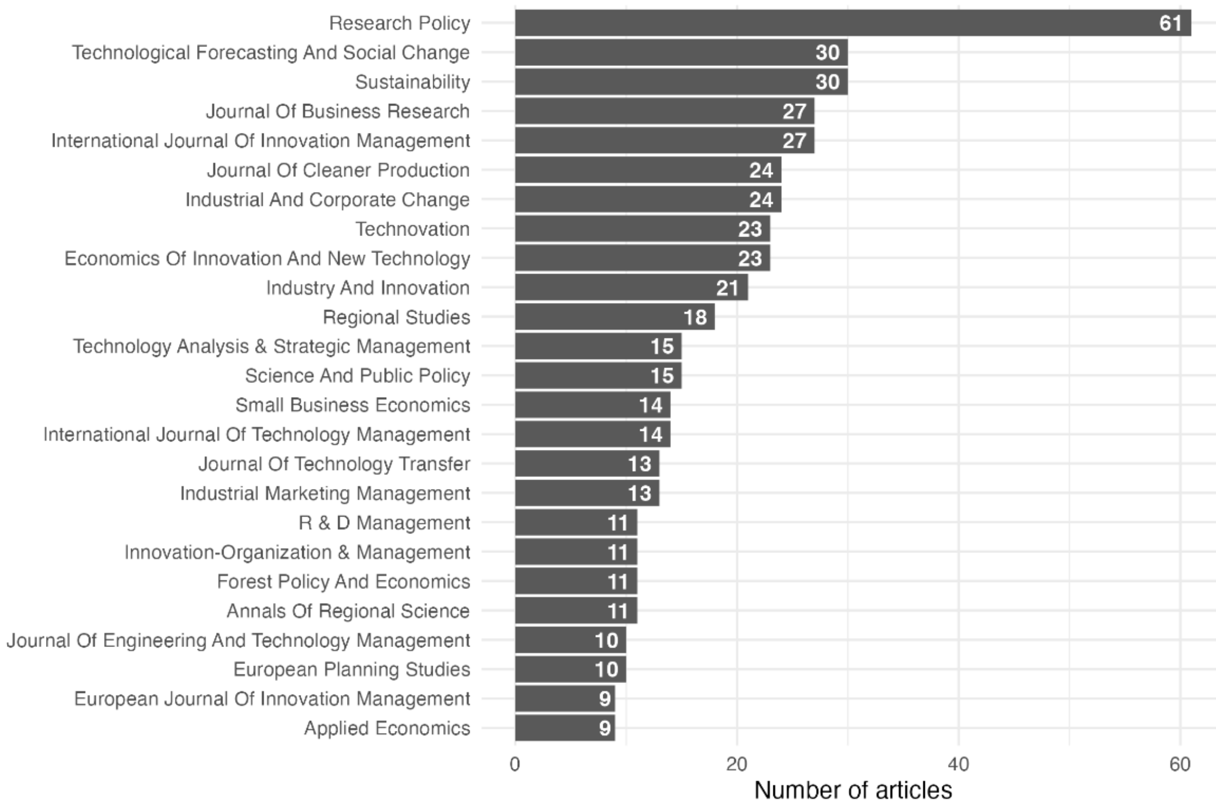
Main publishing outlets

Figure 3.10 shows the major journals in which the research appears. *Research Policy* is dominant among the top venues for Oslo Manual–related research. We can see that the first journal (*Research Policy*) has more than twice as many publications as the second journal (*Technological Forecasting and Social Change*). These results confirm previous research (Chesbrough, 2003; Dahlander, 2010; Rossetto *et al*., 2018). Regarding the major journals in which the research appears, 9[6] out of 25 were among the 20 most influential journals in Innovation Studies identified by Fagerberg *et al*. (2012).

During the second half of the last decade, there was a significant shift in the number of scientific journals publishing articles related to the Oslo Manual, with an increase from just a few journals prior to the publication of the third edition to dozens of diverse scientific journals coinciding with the release of the latest edition of the Manual. This statistic is not just about growth in the distribution capacity of research; it should also be understood as indicating the increase in the branching out of thematic strands. Different journals position themselves differently, tackling other topics and angles of analysis and addressing distinct audiences.

[6] *Research Policy, Technological Forecasting and Social Change, Technovation, Industrial and Corporate Change, Regional Studies, Technology Analysis & Strategic Management, Small Business Economics, R&D Management, International Journal of Technology Management.*

Figure 3.5 Top 25 journals, number of total articles published



According to the Scimago Journal Rank, the journals are classified in a specific subject and within each subject in a specific category. Table 3.1 shows how each journal out of the top 25 from Figure 10 is classified in subject and category terms. Table 3.1 shows that 17 out of 25 journals are classified as "Business, Management and Accounting". On the top 25 journals, the other subjects more representative are "Social science" (#7), "Environmental science" (#6), and "Engineering" (#6). Regarding the categories, within the "Business, Management and Accounting", the most representative is the "Management of Technology and Innovation" (8 out of 17).

Table 3.1 Top 25 journals by subject and category

Rank	Journal	Subject	Category
1	Research Policy	Business, Management and Accounting; Decision Sciences; Engineering	Management of Technology and Innovation; Strategy and Management; Management Science and Operations Research; Engineering (miscellaneous)
2	Technological Forecasting & Social Change	Business, Management and Accounting; Psychology	Business and International Management; Management of Technology and Innovation; Applied Psychology
3	Sustainability	Computer Science; Energy; Environmental Science; Social Sciences	Computer Networks and Communications; Hardware and Architecture; Energy Eng. And Power Tech.; Renewable Energy, Sustainability and the Environment; Environ. Science; Management, Monitoring, Policy and Law; Geography, Planning and Development
4	Journal of Business Research	Business, Management and Accounting	Marketing
5	International Journal of Innovation Management	Business, Management and Accounting	Business and International Management; Management of Technology and Innovation; Strategy and Management
6	Journal of Cleaner Production	Business, Management and Accounting; Energy; Engineering; Environmental Science	Strategy and Management; Renewable Energy, Sustainability and the Environment; Industrial and Manufacturing Engineering; Environmental Science
7	Industrial and Corporate Change	Economics, Econometrics and Finance	Economics and Econometrics
8	Technovation	Business, Management and Accounting; Engineering	Management of Technology and Innovation; ; Engineering (miscellaneous)
9	Economics of Innovation and New Technology	Business, Management and Accounting; Economics, Econometrics and Finance	Management of Technology and Innovation; Economics, Econometrics and Finance
10	Industry and Innovation	Business, Management and Accounting;	Business, Management and Accounting; Management of Technology and Innovation
11	Regional Studies	Environmental Science; Social Sciences	Environmental Science; Social Sciences
12	Technology Analysis & Strategic Management	Business, Management and Accounting; Decision Sciences	Strategy and Management; Management Science and Operations Research
13	Science and Public Policy	Environmental Science; Social Sciences	Management, Monitoring, Policy and Law; Geography, Planning and Development; Public Administration
14	Small Business Economics	Business, Management and Accounting; Economics, Econometrics and Finance	Business, Management and Accounting; Economics and Econometrics
15	International Journal of Technology Management	Business, Management and Accounting; Computer Science; Engineering ; Social Sciences	Industrial Relations; Strategy and Management; Computer Science Applications; Engineering; Law
16	Journal of Technology Transfer	Business, Management and Accounting; Engineering	Accounting; Business and International Management; Engineering
17	Industrial Marketing Management	Business, Management and Accounting	Marketing
18	R&D Management	Business, Management and Accounting	Business and International Management; Business, Management and Accounting; Management of Technology and Innovation; Strategy and Management
19	Innovation-Organization & Management	N/A	N/A
20	Forest Policy and Economics	Agricultural and Biological Sciences; Economics, Econometrics and Finance; Environmental Science; Social Sciences	Forestry; Economics and Econometrics; Management, Monitoring, Policy and Law; Sociology and Political Science
21	Annals of Regional Science	Environmental Science; Social Sciences	Environmental Science; Social Sciences
22	Journal of Engineering and Technology Management	Business, Management and Accounting; Decision Sciences; Engineering	Industrial Relations; Strategy and Management; Information Systems and Management; Management Science and Operations Research; Engineering (miscellaneous)
23	European Planning Studies	Social Sciences	Geography, Planning and Development
24	European Journal of Innovation Management	Business, Management and Accounting	Management of Technology and Innovation
25	Applied Economics	Economics, Econometrics and Finance	Economics and Econometrics

In Figure 3.11, some well-known domains related to innovation are singled out: the rising trends highlight their differential dynamics. In particular, we confirm how relevant and linked to innovation are or have become domains like Management, Business and Economics.

Figure 3.11 Number of published articles by scientific domain, 2000-2021

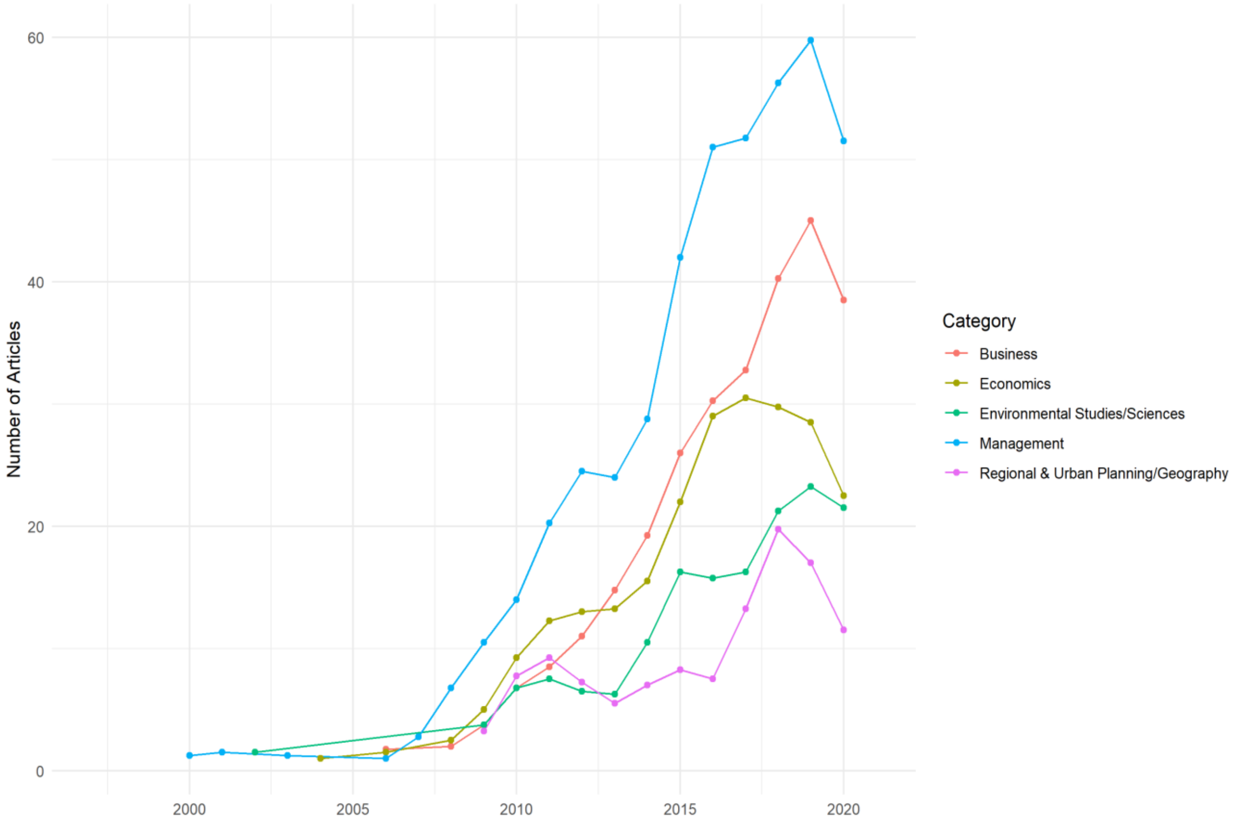


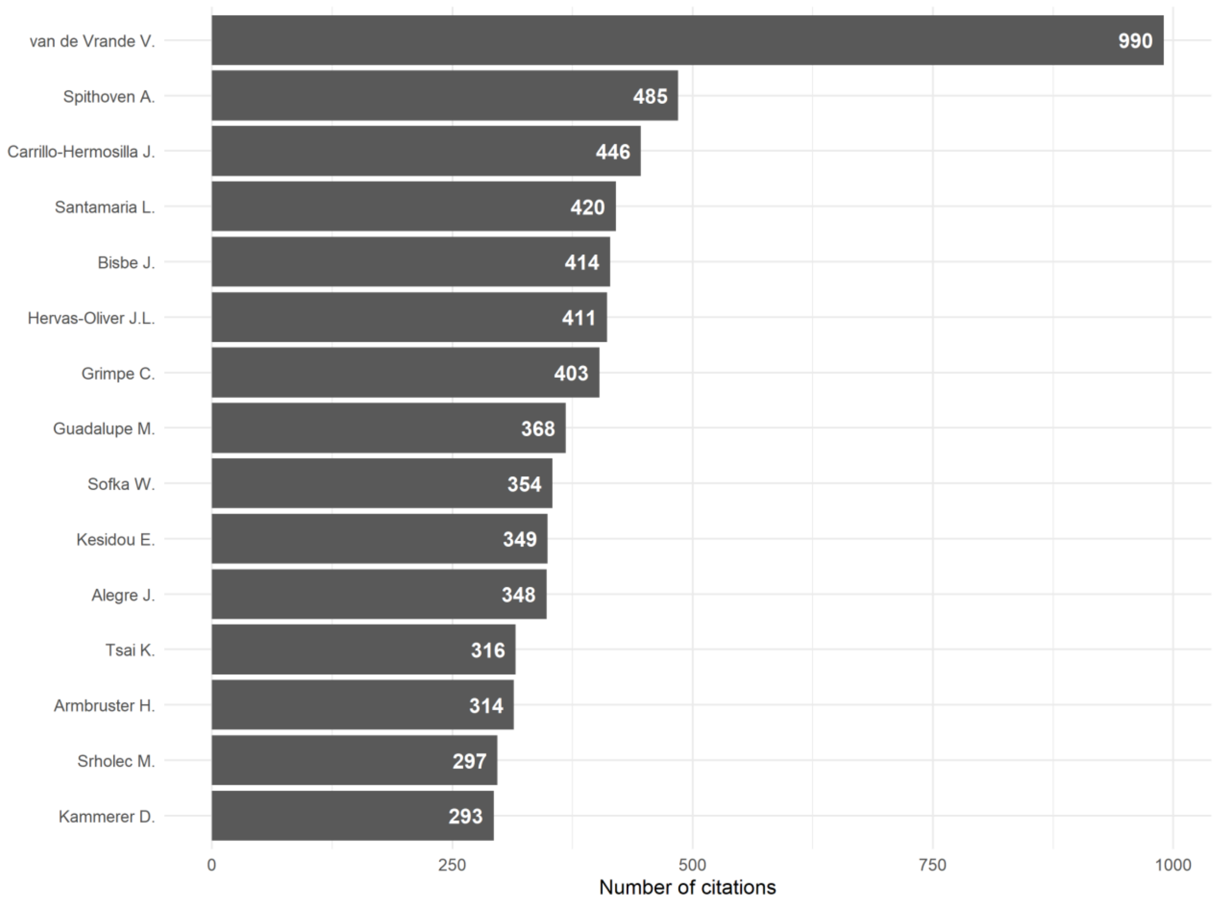
Figure 3.11 also shows that the persistent and rising production that ensues from 2006 and 2007 is mainly explained by three main domains: Management, Business and Economics. More recently, a significant increase was observed in Environment Studies/Sciences and Regional & Urban Planning/Geography domains in the last five years.

3.4.3 Evidence on performance and impact

Impact

Influence can be unpacked by investigating leadership in terms of authorship but also in terms of consequences. Here we look at outputs (publications) and outcomes (number of citations). In Figure 3.12, we can observe the top 15 influential authors based on the number of citations and that the author with more citations has more than twice the second author with more citations.

Figure 3.12 Impactful contributors, top 15, in number of citations



3.4.4 Research networks

International collaboration

Figure 3.13 expands the analysis by offering a representation of the authorship network – a graph with 74 nodes (countries). The representation highlights the connections and clusters between countries. The distance between each pair of nodes on the map indicates their similarity and connection. The proximity of two nodes on the map reflects the similarity and correlation of their bibliometric attributes (McAllister *et al*., 2022). Different colours on the map represent distinct clusters, which are groups of countries more strongly connected than others on the map. The map shows unexpected connections due to the geographical distances of some countries in the same cluster. Nevertheless, these unexpected connections are also opportunities for further collaboration regarding those countries. The network has a density of 0.11, the proportion of existing links relative to the possible number.

Furthermore, the diameter is 5, the shortest distance between the two farthest nodes, and the average path length is 7.2. These metrics jointly underscore a significant level of interaction, indicating that there is diversity and a role for positive effects from the periphery to the centre that cannot be ignored (Gilsing *et al*., 2008). Additionally, the network is not homogeneous, and six clusters of countries can be identified. Cluster 1 gathers countries that share as their mother tongue Spanish (e.g. Mexico, Spain, Peru and Ecuador), Portuguese (e.g. Brazil and Portugal), and Russian (e.g. Russia and Belarus). Cluster 3 gathers countries with English as their mother tongue (e.g. USA, New Zealand and South Africa). Cluster 4 gathers mainly European countries (e.g. UK, Germany, France and Italy). Clusters 2, 5 and 6 gathers countries close geographically, respectively, from Central Europe, Africa and the Middle East.

Figure 3.13 Country collaboration

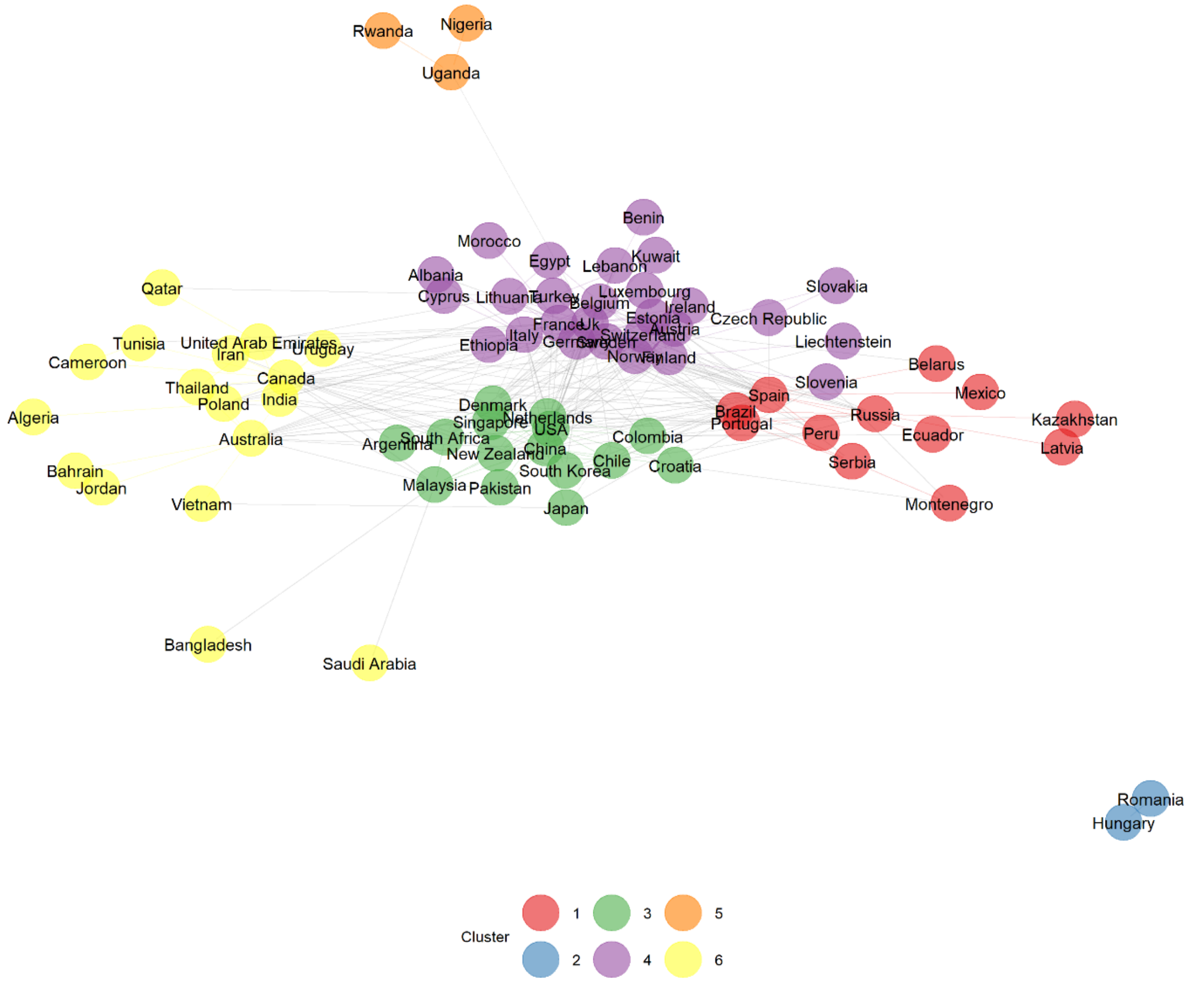


Table 3.2 presents measures of the influence and position of countries in the network. The UK has the highest "pagerank" and "betweenness" centrality. In a statistical sense, it is the country with the most direct and indirect connections to other countries. It is also the most central by the shortest paths that flow through it, making it an information intermediary (Wasserman & Faust, 1994).

Table 3.2 Country network statistics, ranked

Country rank	Cluster	Pagerank Centrality	Country rank	Betweenness Centrality	Country rank	Closeness Centrality
UK	4	0.0455	UK	790.92	Romania	0.10000000
USA	3	0.0333	Spain	664.57	Hungary	0.10000000
China	3	0.0328	The Netherlands	316.97	Spain	0.00336700
France	4	0.0305	Australia	267.56	UK	0.00335570
Spain	1	0.0305	Canada	263.98	The Netherlands	0.00321543
Canada	6	0.0305	France	242.19	USA	0.00320513
Germany	4	0.0293	USA	215.31	China	0.00313480
Sweden	4	0.0286	Russia	215.08	Denmark	0.00313480
Italy	4	0.0269	Malaysia	152.79	Germany	0.00311526
Austria	4	0.0265	Italy	146.27	France	0.00309598
Belgium	4	0.0260	Uganda	143.00	Australia	0.00309598
Australia	6	0.0240	Croatia	142.00	Canada	0.00309598
Norway	4	0.0237	Austria	129.40	Russia	0.00306748
The Netherlands	3	0.0223	Germany	112.26	Italy	0.00304878
Finland	4	0.0219	Belgium	95.46	Brazil	0.00303951
Russia	1	0.0201	Denmark	89.13	Portugal	0.00303951
Malaysia	3	0.0190	China	88.09	Colombia	0.00298507
Estonia	4	0.0187	Poland	86.60	New Zealand	0.00297619
Brazil	1	0.0185	South Africa	85.53	South Korea	0.00295858
Poland	6	0.0182	Brazil	82.29	Finland	0.00295858

3.4.5 Research directions

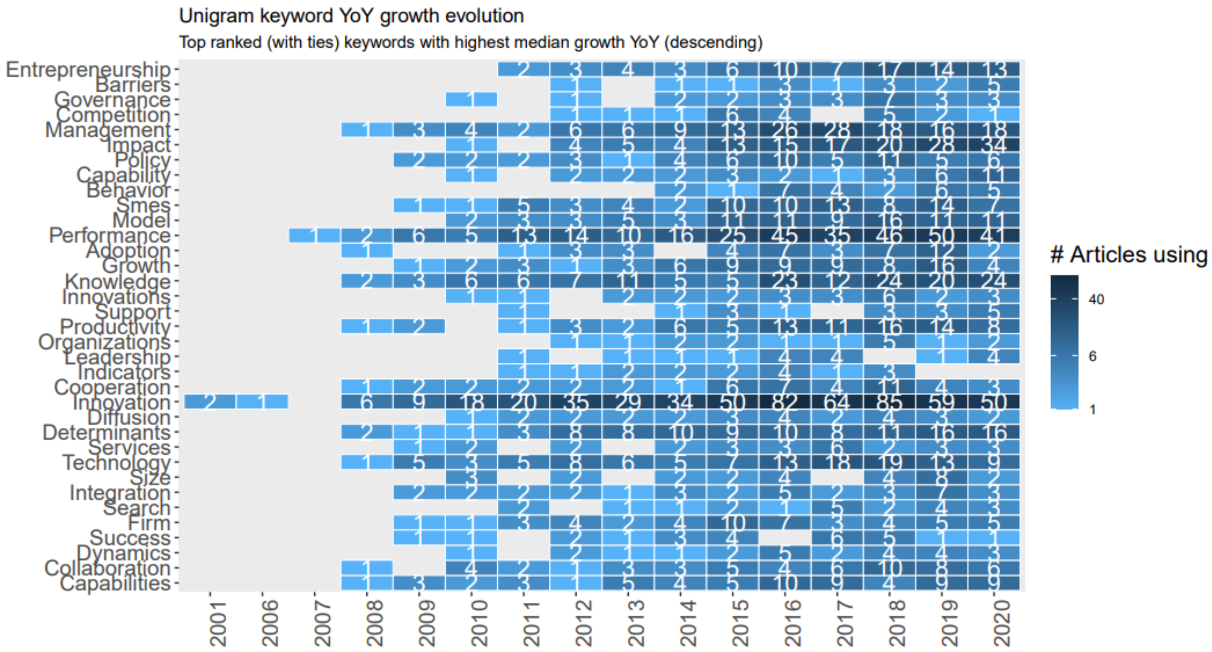
Content dynamics

In order to understand the dynamics of content over time, we employed keyword processing, mainly focusing on term extraction and textmetric analysis related to Oslo Manual publications. Our approach is based on analysing single words or unigrams.

Figure 3.14 visually represents the presence and growth of specific themes. Dark colours indicate a heavy relative presence, while the numbers in the tiles represent the frequencies of these themes in abstracts for each year. The Y-axis displays the terms with the highest growth rates (year-on-year) in descending order. Notably, we observe a rapid rise in mentions of "Entrepreneurship." Furthermore, this analysis highlights the distinctive importance of key features of the Oslo Manual, including "Innovation," "Performance," "Knowledge," and "Management."

These straightforward observations demonstrate textmetric approaches' effectiveness in capturing the Oslo Manual's underlying characteristics and developments. Additionally, the content analysis provides insights into central thematic and sub-thematic categories directly associated with the manual and potential future developments.

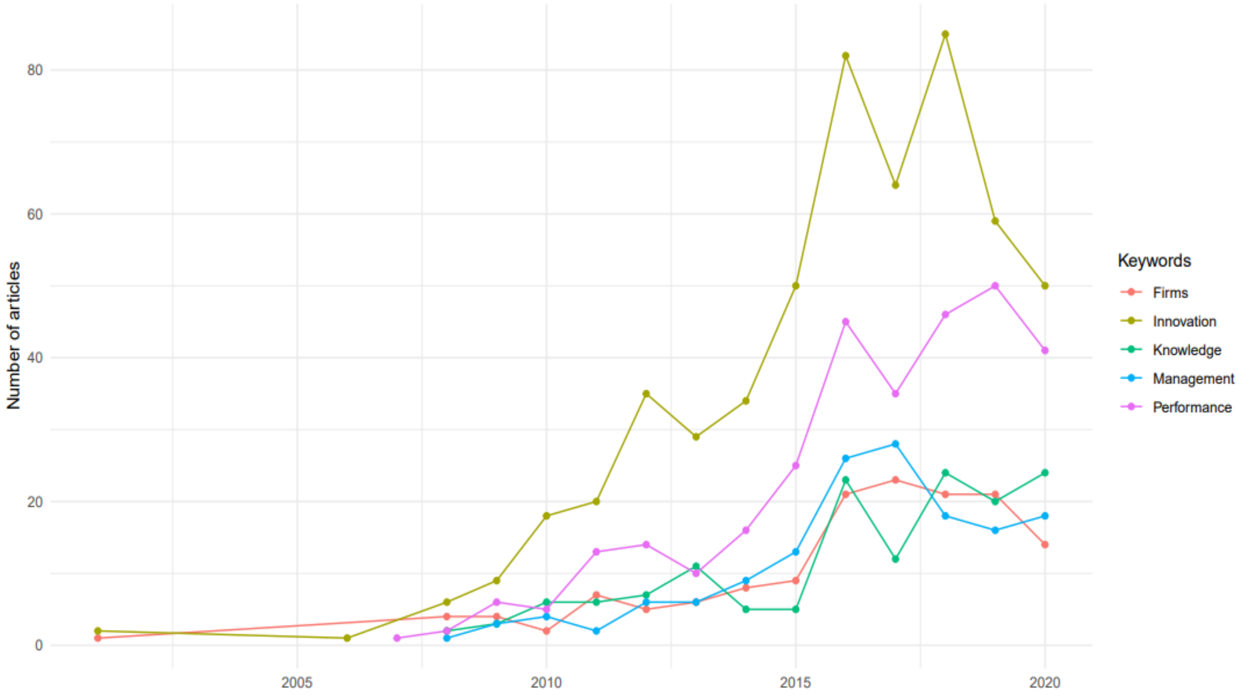
Figure 3.14 Thematic keywords (unigrams)



3.4.6 Framing factors and rising themes around Oslo Manual

In Figure 3.15, distinct domains associated with the Oslo Manual have been identified through the identification and assessment of specific keywords. These domains are recognized for their unique dynamics, reflected in emerging trends. Notably, trends observed in Figure 3.15 confirm the significance of dimensions such as innovation and performance in the context of the Oslo Manual. Furthermore, other aspects such as knowledge, management, and firms are also evident, although they appear less frequently.

Figure 3.15 Main categories (keywords) related to the Oslo Manual



3.5 Conclusions

Innovation is vital in enhancing living standards and has far-reaching impacts on individuals, institutions, economic sectors, and countries. As a guide for collecting and interpreting evidence of innovation, the Oslo Manual has evolved through three revisions, reflecting the need to adapt to the changing landscape of innovation and accommodate new practices. This research article employs an enhanced bibliometric and text-mining approach, analysing a comprehensive dataset from 1992 to 2021 to gain insights into the quantitative and qualitative aspects of the Oslo Manual's review. The findings offer valuable contributions to innovation research and serve as an orientation for future theoretical developments.

The longitudinal analysis revealed significant streams of thought underpinning current innovation research. By studying a substantial database comprising 1,388 research articles, this study demonstrates an increased interest among researchers and policymakers in innovation-related topics, including entrepreneurship, performance, knowledge, and management. This growing interest aligns with previous studies (Chesbrough, 2003; Dahlander, 2010; Rossetto *et al*., 2018), affirming the integration of innovation with established management and economic theories (Van de Vrande, 2010).

This research stands out by focusing on the interpretation of innovation within the context of the Oslo Manual, utilizing network analysis methodology. It complements previous works (e.g. Rossetto *et al*. 2018; Cancino *et al*. 2017a; Merigó *et al*. 2016; Shafique 2013), offering a more comprehensive understanding of the theoretical basis of innovation research and providing valuable insights for future theoretical developments in the field.

By examining the references cited in the analysed papers, the study provided insights into how this literature connects with broader management and innovation studies, further contributing to understanding innovation research's theoretical foundation.

However, challenges such as changes in definitions and methodologies across different editions of the Oslo Manual and comparability issues across countries need careful consideration when interpreting trends. Future research can explore specific themes, authors, and relationships and employ innovative methodologies to illuminate emerging areas within innovation research (Sharma & Lenka, 2022; Silva *et al*., 2023; Wulff *et al*., 2023). This study offers valuable insights into the evolution and practical implications of the Oslo Manual, highlighting its critical adaptability to capture the dynamic innovation landscape and foster global cooperation.

4. Does R&D tax credit impact firm behaviour? Micro evidence for Portugal

In this study, we use panel data to analyse the impact of an R&D tax credit on R&D personnel, particularly the impact on PhD holders allocation, comparing low R&D intensity firms with medium-high and high R&D intensity firms. The results show that, in medium-high and high R&D intensity firms, the R&D tax credit had a significant impact on allocating PhD holders in firms after three years of participation in the tax incentive scheme. We use a database covering 7710 firms that performed R&D at least once in Portugal over the twenty-three-year period 1995 to 2017, provided by the official business R&D survey data and a database of firms that applied for tax credit incentives at least once in the same period. Based on the estimation of impulse-response functions by local projections, we assess the impact of introducing the tax incentive scheme for corporate R&D in firms from different R&D intensity sectors.

4.1 Introduction

As noted in recent studies, there is so far very little theoretical guidance or definite empirical evidence on the stimulating effect of public funding on private R&D (Dimos & Pugh, 2016, Wang *et al*., 2017, Vanino *et al*., 2019). Incentivising and providing the conditions for R&D investment by businesses ranks high on the innovation policy agenda of countries. In addition to providing direct funding for R&D through instruments such as grants and public procurement, many countries also provide indirect support through the tax system (OECD, 2019). Literature has shown the impact of a tax credit on firms' R&D activities (Billings, B. *et al*., 2001), mainly at the aggregate or sectoral level (Bogliacino & Vivarelli, 2012; Antonucci & Pianta, 2002; Evangelista & Savona, 2002). Some relevant research has also started exploring increased technological collaborations or access to external financial and human resources as a result of subsidies (Ahn *et al*., 2020; Söderblom *et al*., 2015; Meuleman & De Maeseneire, 2012; Bianchi *et al*., 2019).

There is relevant research comparing direct funding to perform R&D activities versus tax incentives as political instruments (Mansfield & Switzer, 1985). There is also work that assesses and compares the impact of public support, whether in the form of grants or tax credits, between SMEs and large firms (Wang & Tsai, 1998), and other authors focus on the impact of tax credits for business R&D on productivity (Ortega-Argilés *et al*., 2010; Parisi *et al*., 2006; Conte & Vivarelli, 2005; Mairesse & Sassenou, 1991). Finally, some research evaluate the impact of adoption of fiscal incentives instruments for R&D due to the conviction that R&D contributes to economic growth or assures competitiveness, to assist exporting companies in gaining market power in international markets (Ho *et al*., 2021). However, little is known about the impact of an R&D tax credit on R&D personnel, particularly the impact on highly qualified human resources who hold a PhD Thus, an important novelty of this study is that its focus of interest shifted from the detection of possible effects of an R&D tax credit on R&D expenditure and consequently on productivity and economic growth for the detection of possible effects of an R&D tax credit on R&D personnel and in particular the effect on PhD holders allocation.

Countries have used different policy instruments to promote and increase engagement in R&D activities, including R&D tax incentives. In the EU and OECD, several countries use this type of instrument (Appelt *et al*., 2016). This paper aims at evaluating the impact of R&D tax credits on the R&D activities of firms in Portugal. We make use of two databases containing R&D firm-level microdata from a twenty-three-year period 1995 to 2017, based on an R&D survey and administrative R&D tax relief microdata. We use a database covering 7710 firms that performed R&D at least once in Portugal, provided by the official business R&D survey data and a database of firms that applied for tax credit incentives at least once in the same period.

Our research gives a valuable contribution to the literature as it uses extensive data for a considerable period, allowing the evaluation of the effects of a concrete political instrument aimed at firms that performed R&D activities, not at an aggregate or sectoral level, but the firm level. A key advantage of studying the impact of R&D tax credits at a firm level is that it allows capturing much more variation in R&D tax subsidy rates than is possible at a more aggregate level of data (Bogliacino & Vivarelli, 2012), like evaluating and comparing the impact of R&D tax credits in different sectors of R&D intensity (Ortega *et al*., 2011).

In this context, we address the following research questions: Does a tax credit impact the allocation of PhD holders at the firm level? Will this impact be identical both in firms that have performed R&D activities in low R&D intensity and medium-high and high R&D intensity sectors?

In this study, having access to a multitude of variables for the characterization of firms that performed R&D activities, namely types of expenditure, nature of human resources, whether they used internal funds or had access to public funds, and economic activity sector, we intend, considering the local projection approach (Jordà, 2005) to estimate the impulse-response functions (IRF) of SIFIDE[7] on the number of PhD holders allocated at firm level from different R&D intensity sectors.

We find that R&D tax credits have significant implications after three years in the allocation of PhD holders in medium-high and high R&D intensity sectors, those that by their nature necessarily require more highly qualified R&D personnel.

The remaining sections of this paper are organized as follows: we present a literature review on the R&D tax incentives and their impacts in section 4.2. In section 4.3, we present the data source and methodology used to assess the impact of R&D tax incentives

[7] Tax incentive scheme for corporate R&D

on R&D personnel. We present and discuss the main findings in section 4.4 and conclude in section 4.5, suggesting the relevance of the findings for policies and potential avenues for future research in this area.

4.2 Background

4.2.1 The policy perspective and the effectiveness of R&D tax credits

R&D expenditures have long been an important concern for innovation analysts, who have used them as proxies for innovation inputs and have considered them a determinant of growth, productivity, and competitiveness (Mowery & Rosenberg, 1989; Coccia, 2008). For this reason, R&D intensity targets are one of the main objectives of the European Union's research and innovation policy agenda, namely the Lisbon Strategy, devised in 2000, and the related Barcelona Target, set in 2003, which targets EU R&D expenditure to 3% of gross domestic product (GDP) on R&D, of which two-thirds should come from the private sector.

More recently, the importance of the Barcelona Target has been reiterated and reinforced in the Europe 2020 strategy, part of the EU flagship initiative (European Commission, 2010), which supports an increase in private research and innovation investment and places emphasis on the importance of policies positively affecting the demographics (creation and growth) of firms operating in new/knowledge-intensive industries.

The growing knowledge orientation of the economy and society, together with changes in the labour market, makes investment in skills and their lifelong upgrading increasingly important. Skilled human capital for research, innovation, and economic development is crucial in sustaining the needs of a knowledge economy (European Commission, 2020).

Economic theory indicates that knowledge development (Schumpeter, 1949) and technical change are the major sources of productivity growth in the long term. R&D is a major source of technical change (Guellec & van Pottelsberghe de la Potterie, 2001), and this is recognized as a key element for increasing the knowledge base and, with it, the growth, productivity, and competitiveness of an economy (Mowery & Rosenberg, 1989; Coccia, 2008). In fact, most of the arguments in favour of policies targeted at raising the level and efficiency of R&D rely on the assumption that there are close links between R&D investment and micro-and macro-economic performance (Mitchell, 1999; Bilbao-Osorio & Rodríguez-Pose, 2004; Griffith *et al*., 2004; Kafouros, 2008). The effects of 'micro-macro convergence' of private and public drivers in the implementation and promotion of business R&D are not only visible in the potential returns in productivity but also in employment growth (Morbey & Reithner, 1990; Cincera *et al*., 2009; Hall *et al*., 2010).

An increasing number of countries adopted goals-based R&D policies to stimulate innovation and R&D based on two principles: business R&D is the main driver of innovation and economic growth; and current R&D expenditures are insufficient to reach the desired levels of innovativeness and competitiveness (Carvalho, 2011). Governments can stimulate private R&D in different way, namely through direct funding, which include grants, loans, subsidies and incentives, such as tax credits. Many countries whether adopted fiscal incentive instruments for R&D, due to the conviction that R&D contributes to economic growth or assures competitiveness, or alternatively granting of subsidies, to assist exporting companies in gaining market share in international markets (Ho *et al*., 2021). However, direct government funding for private research has several disadvantages vis-à-vis R&D tax incentives. First, it results in substantially larger administrative costs. Furthermore, government do not have an information advantage as to which projects will succeed or potentially bring highest social returns (CPB *et al*., 2014). Governments increasingly rely on R&D tax incentives to promote business R&D

investment, expecting this to result in at least additional R&D performance - often described as input additionality (Appelt *et al*., 2016). Both theoretical and empirical evidence shows that tax incentives effectively help firms reduce R&D costs and achieve market efficiency (Hall & van Reenen, 2000). Between tax incentives and direct funding, literature shows that tax incentives have a lower administrative burden and mitigate the risk of "picking losers" more than direct funding (Dechezleprêtre *et al*., 2016). Therefore, tax incentives are more market-friendly and have become more prevalent in facilitating R&D activities (OECD, 2014).

Firms' R&D efforts in response to policy changes may vary depending on whether policy changes are perceived to be permanent or transitory. Thus, the magnitude of public support may vary over time and be affected by firms' R&D investment behaviour and its persistency. The additionality of R&D tax incentives may also vary with their design and with the use of direct funding or other forms of government support (Appelt *et al*., 2016). R&D fiscal incentives lead to stronger additionality effects in R&D intensive sectors being stronger for companies in more R&D oriented industries than for firms in sectors with lower R&D orientation (Freitas, *et al*., 2017). Different tax treatments of different expenditure categories imply that tax policies vary in their relative generosity across industries, being crucial to find exogenous measures and tax policy instruments that exhibit sufficient variation to identify their impact robustly (Thomson, 2017).

4.2.2 The different dimensions of analysis of an R&D tax credit

The reasons behind the growing preference for the tax incentives go beyond any possible advantage of any tax incentive scheme over direct support measures (Carvalho, 2011). Despite many scholars believe that the production and dissemination of knowledge exhibit a range or market failures and these failures are likely to undermine incentives to invest in R&D and introduce new innovations (Geroski 1995), the market failure is no longer the sole economic rationale for the public support of private R&D. Others factors reveals being more important, namely the *absorptive capacity* and in particular the competition for R&D investment and human resources highly qualified, namely researchers to perform R&D activities. R&D is essential to a firm's *absorptive capacity* – “the ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends is critical to its innovative capabilities” (Cohen & Levinthal, 1990, p2).

Studies carried out to date assessed and compared the impact of public support for R&D activities, whether in direct funding (grants) or tax credits, but little is known about the impact that these instruments have on R&D personnel, in particular. Those studies were developed at the sectoral level where (micro)data of firms arises aggregated by economic activity sector. However, at the sectoral level, the impact of public support for R&D activities can be affected by biases and negative (Antonucci & Pianta, 2002) or positive effects (Evangelista & Savona, 2002) on employment, depending on the activity sector. Bogliacino and Vivarelli (2012) took a sectoral approach and showed the positive and highly significant impact that R&D expenditure has on employment. This study suggests, however, that further investigation at the firm level is needed.

Aggregate micro-level statistics can be particularly useful for understanding industry and macro-level dynamics and are thus extremely valuable for policy design, monitoring, and evaluation. Moreover, micro-level statistics allow the evaluation of an economic system's characteristics at the most accurate scale (unitary/firm) and industry and macro-level when such data can be aggregated. The majority of studies at a macroeconomic level show a positive effect of public funding and tax incentives on private R&D expenditure (David *et al*., 2000).

The problem of a study at the macroeconomic level is that both types of funding (public and private) may be influenced by common factors (Guellec & van Pottelsberghe, 2003), with consequent bias in the estimated relationships.

The existing literature allows identifying the positive impact that R&D expenditure has on productivity (Mairesse & Sassenou, 1991; Ortega-Argilés *et al*., 2010), however little is known about the impact that R&D expenditure has on employment. The French *Jeune Entreprise Innovante* (JEI) scheme supports firms who have been in business for less than eight years and whose R&D expenditure represents at least 15% of tax-deductible expenditure. Small technology firms are the primary beneficiaries of this scheme (fewer than 20 employees). Firms that benefited from the JEI scheme in 2004 or 2005 experienced higher annual employment growth, with an estimated growth differential of 8.4 percentage points compared with similar firms that did not receive the JEI scheme support (Mitchell, J. *et al*., 2020).

The majority of studies focused on the impact of innovation activities on productivity, competitiveness, economic growth, and employment dynamics (Conte & Vivarelli, 2005; Parisi *et al*., 2006). However, innovation is a much broader concept than R&D, and not all firms that are successful at developing or implementing innovation are necessarily R&D performers, as noted by the OECD Innovation Strategy (OECD, 2010) and its update (OECD, 2015a).

As economies become more knowledge-based and dependent on intangible assets, economies and firms achieve large returns on R&D investments, creating new and better jobs (European Commission, 2020). Incorporating and performing R&D activities, require personnel with high levels of knowledge and specialization together with scientific and technical expertise. The terms of incorporating R&D are different from sector to sector, particularly when comparing high-tech and low-tech sectors (Pavitt, 1984). The larger the weight of knowledge-intensive sectors, the higher the capacity to invest in R&D. Among knowledge-intensive activities, high and medium-high-tech manufacturing are key engines for R&D investments in the business sector (Coad & Vezzani, 2017; Hernández *et al*., 2018).

In studies carried out to date, firms in the high-tech sector, requiring more highly skilled human resources, not only have higher R&D expenditure but also the efficiencies and higher productivity compared with companies in the low-tech sector (Ortega *et al*., 2011). In recent studies (Piva & Vivarelli, 2018; Barbieri *et al*., 2019), a positive effect of R&D expenditures totally due to firms operating in high-tech industries and large companies was found while no job creation due to technical change was detectable in traditional sectors. For these reasons, the present research focuses on the impact of an R&D tax credit and its implications on the educational composition of R&D personnel in firms, particularly in the allocation of Ph.D. holders, whether in low R&D intensity firms or medium-high and high R&D intensity firms.

4.2.3 The design of R&D tax relief provisions in Portugal

Government support for business R&D seeks to encourage firms to invest in knowledge that can result in innovations that transform markets and industries and result in benefits to society. For this purpose, beyond providing grants and buying R&D services ("direct" support), many governments provide fiscal incentives. These fiscal incentives can take the form of advantageous tax treatment of innovation inputs (R&D expenditures), as well as preferential treatment of R&D outputs (incomes from licensing or asset disposal attributable to R&D or patents).

The will to foster a knowledge-based economy has led several countries, including Portugal, to a greater compromise with public policies to stimulate business R&D. Since the introduction of SIFIDE in 1997, with a temporary suspension of the R&D tax credit in 2004-05, there has been a sustained growth of total government support to business R&D as a percentage of GDP, considering ‘the policy mix’: direct government funding of business R&D and tax incentives for R&D (Carvalho, 2013; OECD, 2021).

Public support is provided to firms with the intention of correcting or alleviating difficulties to appropriate the returns to their investment in new knowledge and shortcomings in the market for the financing of risky projects, especially for small start-up firms without collateral. Public support for business R&D is typically justified as a means of overcoming these market failures. In addition, countries may use tax incentives to attract the R&D activities of multinational corporations (MNEs) which typically account for a substantial share of R&D expenditure (Appelt *et al.*, 2016).

In its scientific and technological system, Portugal provides a tax relief through a hybrid R&D tax credit. Start-ups enjoy an enhanced credit rate on R&D volumes as long as they have not yet made use of the incremental tax offset. The mains features of the R&D tax incentives in Portugal are: in the case of insufficient tax liability, unused credits can be carried-forward for 8 years; the base amount above which R&D expenditures qualify for the incremental tax credit is defined as average amount of qualifying R&D expenditures in the two previous fiscal years; there is no ceiling and incremental R&D expenses are capped at EUR 1.5 million (OECD, 2021).

4.3 Data and methodology

4.3.1 Data source

To develop this analysis, we used data from the official business R&D survey[8] data over the twenty-three-year period 1995 to 2017. The R&D Survey is a compulsory survey delivered to all firms that potentially performed R&D activities in Portugal. The information collected focuses on resources related to R&D activities, financing, and

[8] Follows the Eurostat and OECD methodological guidelines and the definitions of the Frascati Manual

performing R&D activities. In Portugal, the landscape of R&D expenditure structure changed significantly in this period, with the Business Sector representing 21% of the total weight in 1995 while in 2017 representing more than 50% (DGEEC 2021 and DGEEC 2014. available at: (https://www.dgeec.mec.pt/np4/206/).

The R&D survey is a census survey of all firms that potentially performed R&D activities between 1995 and 2017. The survey was only conducted in the odd years (every two years) between 1995 and 2007 and became annual after 2008. In this period, 7710 firms carried out R&D at least once but not in all the years. Therefore, we faced an unbalanced panel of firms.

Data on R&D tax incentives were gathered through administrative data. The R&D tax incentive database is also an unbalanced panel of firms since 1997 to 2015, the tax incentive system was disrupted in 2004 and 2005, and the fact that 2875 firms resorted to tax incentives in at least one year, but not in all the years.

In the scope of the European Statistical System, there are a few databases with microdata available for scientific research purpose, for instance the microdata from the CIS (Community Innovation Survey) with microdata from firms from European Countries that provided those microdata to Eurostat. However, microdata regarding expenditures and human resources on R&D activities are not available. The microdata from the official business R&D survey, as well the administrative R&D tax relief microdata from the fiscal incentives programs, used in this study, were made available by the Direcção-Geral de Estatísticas da Educação e Ciência, in the scope of a Protocol with the National Statistical Institute and the National Science Foundation that allows researchers having access to microdata for scientific research purpose.

For this analysis, we merged both databases using firms' fiscal numbers as the primary key. Although the periods of the two databases are not precisely coincident - the database created from the surveys has data for 1995 to 2017, while the database created from tax incentives has data for 1997 to 2015 - it was decided to maintain these two periods with the following objectives: (i) having data on R&D activities from 1995 onwards, assess the impact of the introduction of the tax incentive system (1997); and ii) with available data on the tax credit granted up to 2015, assess the impact of this measure on expenditure on R&D activities up to two years (2017) after the tax credit was granted.

After merging the two databases, some outliers were identified. For instance, in the twenty-three-year period, some firms could be in the database in a single year with high R&D expenditure. Since it is unlikely that a firm would invest a massive amount in R&D in a single year, we investigated this situation and realized that, in fact, this could happen as a result of a change in the status of the firm or as a result of mergers, acquisitions and the reorganization of a group of firms. In these cases, there was a change in the fiscal number and, as a consequence, a change in the ID number in the database.

Outliers were removed from the database when a firm invested a large amount in R&D in only a single year. For the sake of data quality in the time series, in cases of mergers, acquisitions, and reorganizations of a group of firms, firms within the group were grouped according to the same area of economic activity (NACE at 2-digit level). The primary purpose of this aggregation was to create subgroups of firms performing R&D in the same NACE allowing to treat them coherently in the time series and avoid treating them as outliers and simply to delete those records.

For this analysis and from the official business R&D survey database, we used the following set of variables at the firm level: at the human resources level, the number of R&D personnel, the total full-time equivalent (FTE) staff, and the number of doctorates. In terms of R&D expenditure, the following variables were used: current R&D expenditure (labour costs of R&D personnel and other current R&D costs), capital R&D

expenditure (land and buildings; machinery and equipment), internal funds, expenditure according to the sector of activity (NACE Rev. 2). Despite the existence of other sources of funds data, their share in the whole were negligible. In fact, firms have limited access to external finance and to rely on their internal funds to undertake R&D projects (Sterlacchini & Venturini, 2019). A dummy variable was created for firms that resorted to tax credits (1 if a firm resorted to tax incentives and 0 if not).

We used the OECD taxonomy of economic activities based on R&D intensity based on International Standard Industrial Classification, ISIC Revision 4 (OECD, 2016) since this taxonomy focuses solely and explicitly on a measure of R&D intensity[9]. This taxonomy is an alternative to the taxonomy proposed by Eurostat and OECD to classify the manufacturing industry according to technological intensity and knowledge-intensive services based on NACE Rev. 2.

In the present study, we adopt the concept of R&D from the Frascati Manual, where R&D comprises creative and systematic work undertaken in order to increase the stock of knowledge - including knowledge of humankind, culture, and society - and to devise new applications of available knowledge (OECD, 2015b).

Table 4.1 presents the summary statistics of the data used. It is worth mentioning that 7710 firms performed R&D at least once but not in all the years and the fact that 2875 firms resorted to tax incentives in at least one year, but not in all the years.

[9] R&D intensity is calculated as the industry's business R&D expenditure divided by gross value added

Table 4.1 Summary statistics and description of the variables

Variable	Mean	SD	Min	Max	Description
Employee	121.59	785.85	0	37,437	Number of employees
R&D employee	6.99	27.52	0	1,172.80	Employees in R&D activities
PhD	0.39	1.69	0	83	PhD holders
Current expenditure	386.41	1,959.46	0	71,535.37	Current R&D expenditure (€ 000's)
Labor costs	236.20	1,133.55	0	49,794.78	Labor costs of R&D personnel (€ 000's)
Other current costs	150.20	1,143.54	0	51,326.75	Other current R&D costs (€ 000's)
Capital expenditure	123.13	2,209.12	0	176,491.85	Capital R&D expenditure (€ 000's)
Internal funds	442.82	3,169.75	0	191,719.01	Internal funds for R&D (€ 000's)
SIFIDE	0.23	0.42	0	1	Dummy, 1 if a firm resorted to tax incentive and 0 if not

Firms have limited access to external finance and have to rely on their internal resources to undertake R&D projects. Credit constraints to R&D are mainly due to information asymmetries between firms and lenders, which make monitoring costs very high, as well as to the intangible nature of R&D that makes these investments hard to collateralised (Brown *et al*. 2012). This might also explain the fact that the weight of public funds in total of funds for R&D in the set of 7710 firms that performed R&D at least once our database is negligible, and for this reason in our research we used only the internal funds variable.

4.3.2 Methodology

As regards the firm size class, the theoretical framework of determinants of corporate R&D intensity of a given country depends on both the sector (structural) composition effect and intrinsic effect (Pakes & Schankerman, 1984; Erken, 2008; Mathieu & van Pottelsberghe de la Potterie, 2010; Becker & Hall, 2013; Sterlacchini & Venturini, 2019). The structural factors affecting an economy can be exogenous or endogenous. Endogenous factors are characteristics typical of a given industry sector(s), while exogenous factors are usually external to the sector(s) and the country's macroeconomic system. Intrinsic factors determine the characteristics of the firm(s) and its behaviour, for example, the firm's knowledge, financial capacity or strategy, and its R&D investment (Moncada-Paternò-Castello & Smith, 2009). Firm location is also an important factor as a firm's R&D investment increases with its proximity to universities and a skilled labour force (Vivarelli, 2013; Capello, 2014; Amoroso *et al*., 2015), namely, PhD holders.

The variation of R&D tax incentives support can be used to compare the R&D performance of firms that receive support and those that do not. The fundamental estimation challenge is that it is not possible to observe the "counterfactual" – how much R&D the firms receiving R&D tax relief would have performed if they had not received this support. Given the inability to observe the "counterfactual" directly, the best alternative is to compare the firms that receive tax relief with those that do not receive it but are as similar as possible.

In the present study, we consider the local projection approach (Jordà, 2005) to estimate the impulse-response functions (IRF) of SIFIDE on R&D personnel. Considering the IRF, we assessed the impact of – introduction of SIFIDE – on the different R&D personnel categories: persons employed, R&D personnel in FTE, and PhD holders. First, this assessment was made considering all firms regardless of the economic activity sector, and then by organizing firms by economic activity sector using the NACE Rev.2 classification, particularly according to R&D intensity criteria, from low to high R&D intensity.

Furthermore, we track the h-period ahead impact of SIFIDE event (participation in the tax incentive scheme) occurring in firm i and year t on the cumulative growth of the number of R&D personnel, by way of the estimation of the following successive equations:

$$y_{i,t+h} - y_{i,t-1} = \boldsymbol{x}'_{it}\boldsymbol{\beta}^h + \delta^h D_{it} + \varepsilon_{i,t+h}, \text{where } \varepsilon_{i,t+h} = \lambda_{t+h} + \mu_i + v_{i,t+h}$$

Where: $y_{i,t}$ denotes the number of R&D personnel in the i-th firm and period t (therefore $y_{i,t+h} - y_{i,t-1}$ is the growth from $t-1$ to $t+h$); $\boldsymbol{x}'_{it}$ is a vector of covariates (in our case labour costs of R&D personnel and capital R&D expenditures); D_{it} is a binary variable that takes value one if the i-th firm participated in the SIFIDE program in period t and zero otherwise. It is worth noting that our main interest comprises the coefficients δ^h as these quantities underpin the structure of the IRF, as we shall see later on. It should also be pointed out that, to ensure the appropriate identification of the causal effect of R&D expenditure on R&D employment, that is, to avoid endogeneity issues, both time and firm fixed effects were considered and denoted by, respectively, λ_{t+h} and μ_i. $v_{i,t+h}$ is an idiosyncratic random disturbance i.i.d. robust clustered standard errors are considered.

The advantages of local projections are numerous: i) they can be estimated by simple regression techniques with standard regression packages; ii) they are more robust to misspecification; iii) joint or point-wise analytic inference is simple; and iv) they easily accommodate experimentation with highly nonlinear and flexible specifications (Jordà, 2005). Since local projections can be estimated by univariate equation methods, they can be easily calculated with available standard regression packages. Moreover, local projections are easy to implement, the shocks are estimated in a robust way, the inference is simple and more important allow to capture the dynamic effect of shock and not only the static effect of shock like in a propensity score matching design.

4.4 Results and discussion

The results from the model adopted show that the fiscal shock – the introduction of SIFIDE, had no significant impact in the two first categories of R&D personnel (persons employed and R&D personnel in FTE), but a positive impact in the case of PhD holders. Fig. 4.1 shows the positive impact of introducing the tax incentive scheme for R&D (SIFIDE), regardless of the R&D intensity sector, in PhD holders allocation.

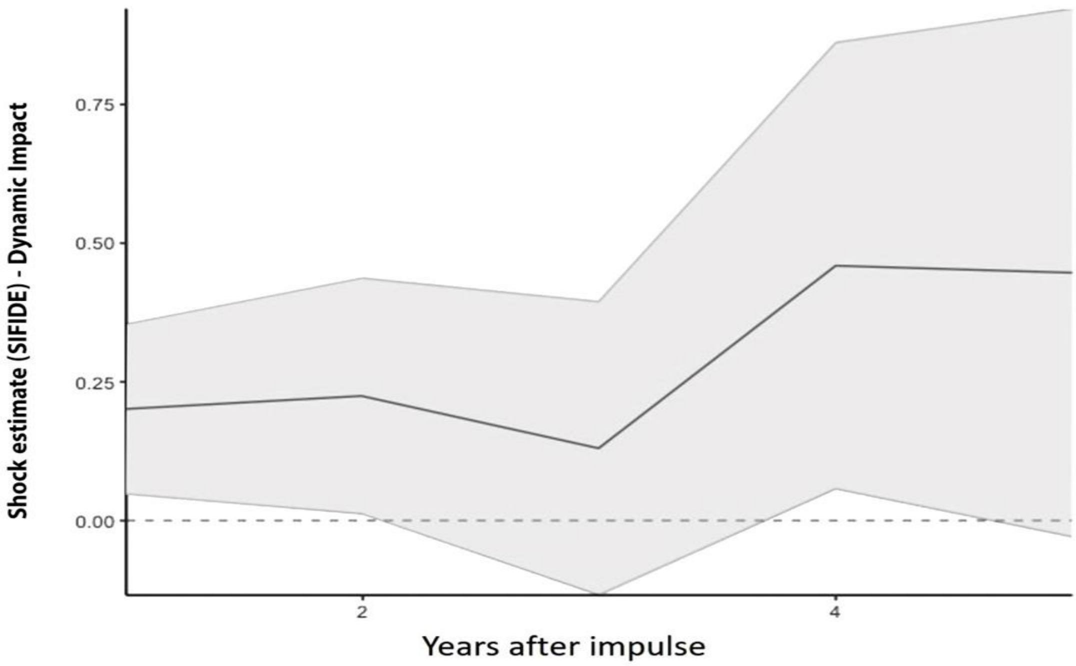


Figure 4.1 Impulse responses to a shock in the introduction of tax incentive scheme (SIFIDE): all firms, regardless of the technological intensity

Notes: The solid central dark line is the response corresponding to estimates based on the model adopted for the set of firms that performed R&D; the shaded grey area is the conventional 95-percent confidence level error of the linear projection response.

In Fig. 4.1, we can observe the impact of the introduction of SIFIDE in a defined period, where the solid central dark line represents the IRF, whereas the shaded grey area is the 95% confidence interval. Based on the model adopted, the solid central dark line show predicted values h-period after the impact of SIFIDE event. Considering the whole set of firms, regardless the R&D intensity sector, in the short-run (one year after the impulse) there is a positive impact in the cumulative addition of PhD holders (0.20) and three years later the cumulative addition of PhD holders is much more significant – more than double: in the beginning of the period was 0.20 and in the end 0.45 (see table 4.2). These findings are in line with the results from Martinez-Ros (2019), where the results showed a positive impact of R&D&I tax credit and environmental investment on employment for Spanish

MSMEs (micro firms), and SMEs. In the same fashion, these findings are in line with the results observed in France in 2004 and 2005, where firms that benefited from the *Jeune Entreprise Innovante* scheme experienced higher annual employment growth, with an estimated growth differential of 8.4 percentage points compared with similar firms that did not receive the JEI scheme support (Mitchell, J. *et al*., 2020).

The multitude of variables for the characterization of firms that performed R&D activities in Portugal, as already described, namely the nature of human resources, led us to evaluate the impact of SIFIDE in the PhD holders allocation and not only the R&D personnel overall.

Table 4.2 shows the impact of introducing the tax incentive scheme for R&D (SIFIDE), where all firms were included regardless of the R&D intensity sector. We can observe that the tax credit had a slight impact in PhD holders' allocation, whether in the short-run (0.20) or three years ahead (0.46), but remaining stable in the subsequent years (0.45).

Table 4.2 Impulse responses to a shock in the introduction of a tax incentive scheme in all firms

Years after the impulse	h=1	h=2	h=3	h=4	h=5
Estimate	0.20	0.23	0.13	0.46	0.45
Std. Error	0.09	0.13	0.16	0.25	0.29
t-statistic	2.16	1.74	0.81	1.88	1.54
p-value	0.031	0.082	0.418	0.060	0.123
Number of observations included	5,829	5,476	5,078	4,020	3,133
Number of events included	3,042	2,890	2,694	2,163	1,686

Notes: The table reports the Estimates of the impulse response function, where dependent variable $y_{i,t}$ denotes the number of PhD holders and Estimates the predicted values h-period after the impact of SIFIDE event.

Considering the set of firms, regardless the R&D intensity sector, a firm that having performed R&D and resorted to tax incentives had a positive impact of 0.20 in the cumulative addition of PhD holders one year later and 0.45 five years later.

To better understand the impulse responses to a shock in the introduction of SIFIDE, we assessed this impact in firms classified in different R&D intensity sectors, namely comparing low R&D intensity with high R&D intensity.

All firms were classified according to the NACE rev.2, which allows us to classify them according to the R&D intensity. After assessing the impact of the introduction of the tax incentive scheme in overall firms, we assessed the same impact by one hand in the firms classified as low R&D intensity and by the other hand the firms classified as medium-high and high R&D intensity[10].

When compare low R&D intensity firms with medium-high and high R&D intensity firms, we can observe (Fig. 4.2) that in the low R&D intensity firms, the impulse responses to a shock (introduction of SIFIDE) remain stable after a second year, and the grey area of the confidence region falls into a negative area (under zero).

[10] Since the number of firms classified as high R&D intensity was relatively low we considered both categories together: medium-high and high R&D intensity

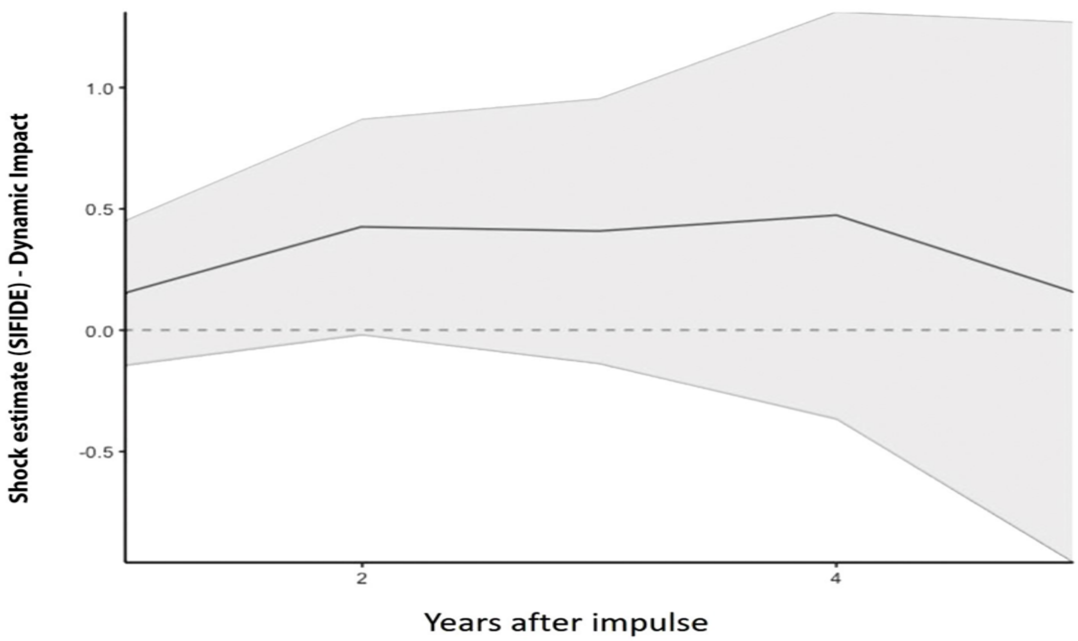


Figure 4.2 Impulse responses to a shock in the introduction of tax incentive scheme in the Low R&D intensity firms

Notes: The solid central dark line is the response corresponding to estimates based on the model adopted for the set of firms that performed R&D; the shaded grey area is the conventional 95-percent confidence level error of the linear projection response.

We can observe a very different situation in the medium-high and high R&D intensity firms (Fig. 4.3), sectors that by their nature require highly qualified human resources (PhD holders). Here the effect is very clear and permanent, where a significant impact in the PhD holders allocation exists after three years, and the grey area (95% confidence interval) is clearly above zero. Regardless the type of R&D performed, basic research, applied research or experimental development, PhD holders play a determinant role within firms as researchers. R&D contributes to a firm's *absorptive capacity*, where PhD holders are determinant in influencing the *absorptive capacity* within firms. Firms need to develop *absorptive capacity* by interacting with academia (Rafols, I. *et al*., 2013).

In Fig. 4.3, we can observe that in the short-run (one year after the impulse) there is a positive impact in the cumulative addition of PhD holders (0.46) and four years later this cumulative addition of PhD holders is much more significant (1.18). The estimates gathering from the model adopted shows that in the case of the medium-high and high R&D intensity firms, beyond the significant increase of the cumulative addition of PhD holders these firms turned to be more prone to increase their *absorptive capacity* with natural implications in their innovative capabilities.

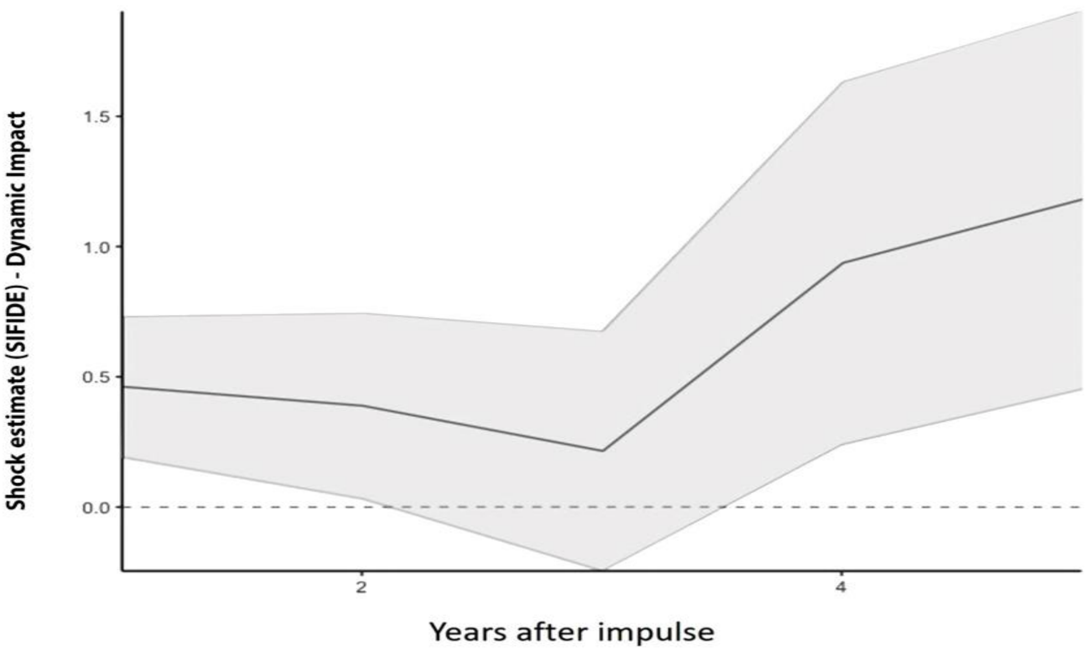


Figure 4.3 Impulse responses to a shock in the introduction of a tax incentive scheme in the Medium-high and High R&D intensity firms

Notes: The solid central dark line is the response corresponding to estimates based on the model adopted for the set of firms that performed R&D; the shaded grey area is the conventional 95-percent confidence level error of the linear projection response.

These findings are in line with the results from Evangelista and Savona (2002), where the results show that public support for R&D activities can positively affect employment, depending on the activity sector. In the same fashion, these findings are in line with the results from Bogliacino and Vivarelli (2012). Despite taking a sectoral approach (having suggested further investigation at the firm level), it shows a positive and highly significant impact that R&D expenditure has on employment.

Finally, Table 4.3 shows the difference observed when comparing the estimations of the impact of the tax incentive scheme in low R&D intensity firms with medium-high and high R&D intensity firms. Here we can observe distinct estimates when comparing the impact in the PhD holders allocation after three years and subsequent years in low R&D intensity (0.41 and 0.16) with the medium-high and high R&D intensity firms (0.93 and 1.18). Comparing the two R&D intensity sectors, we can observe that in the short-run (one year after the impulse) the cumulative addition of PhD holders in the medium-high and high R&D intensity firms (0.46) is more than three times higher than in low R&D intensity firms (0.15). Four years later there was a stagnation in the addition of PhD holders in low R&D intensity firms (0.16), while in the medium-high and high R&D intensity firms there was a significant increase (1.18).

Table 4.3 Impulse responses to a shock in the introduction of tax incentive scheme: Low R&D intensity firms versus Medium-high and High R&D intensity firms

	Low R&D intensity firms					Medium-high and High R&D intensity firms				
Years after the impulse	h=1	h=2	h=3	h=4	h=5	h=1	h=2	h=3	h=4	h=5
Estimate	0.15	0.43	0.41	0.41	0.16	0.46	0.39	0.21	0.93	1.18
Std. Error	0.18	0.27	0.33	0.33	0.68	0.16	0.22	0.28	0.42	0.44
tstat	0.84	1.57	1.23	1.23	0.23	2.80	1.79	0.77	2.21	2.67
p-value	0.403	0.116	0.219	0.219	0.818	0.005	0.074	0.444	0.027	0.008
Number of observations included	5,829	5,476	5,078	4,020	3,133	5,829	5,476	5,078	4,020	3,133
Number of events included	813	750	679	521	388	2,229	2,140	2,015	1,642	1,298

Notes: The table reports the Estimates of the impulse response function, where dependent variable $y_{i,t}$ denotes the number of Ph.D. holders and Estimates the predicted values h-period after the impact of SIFIDE event. Estimates were calculated separately for the low R&D intensity firms and medium-high and high R&D intensity firms.

This means that, while for the low R&D intensity firms, at the end of the period, there is no cumulative addition of PhD holders (the addition of PhD holders is residual in the last year: 0.16), the other way around, in the medium-high and high R&D intensity firms there is a significant incremental number of PhD holders (cumulative addition of 1.18 on average per firm in the last year).

4.5 Conclusions

The limited number of studies on the impact of fiscal schemes makes it difficult to draw any major policy conclusions or distinguish between the merits of these policy instruments' various designs. Nevertheless, despite the noted limitations, we can conclude that R&D tax credit is important since it positively impacts PhD holders' allocation. We conclude that there is sufficient evidence to suggest that the tax credit implemented in Portugal offers an attractive source of support for firms in the allocation of PhD holders, in particular in the medium-high and high R&D intensity sectors.

The paper analyses the impact of tax incentive scheme for corporate R&D on R&D personnel on an unbalanced panel of 7710 firms that performed R&D at least once in Portugal over the twenty-three-year period 1995 to 2017. The results from the model adopted suggest that the tax credit impacts the allocation of PhD holders at firm level and this impact is different depending on the R&D intensity sector. The results suggest that the tax credit impact, on the cumulative addition of PhD holders on average per firm, is much more significant in firms from medium-high and high R&D intensity sectors than in firms from low R&D intensity, after three years, in particular in the last year.

A tax credit scheme must be designed and implemented to induce a positive socio-economic impact, whether temporary or more permanent. The reported results contribute to the literature since they suggest that, from the science and technology policy perspective, firms from medium-high and high R&D intensity sectors that applied for tax credit incentives at least once are more prone to allocating PhD holders, in particular after three years.

Policymakers need to consider the context firms face and many characteristics of firms, namely the economic activity sector and, in particular, the R&D intensity sector. The design of policy incentives should also be specific, rather than generic, focusing on targeting and identifying firms that are more proactive in performing R&D activities. We contribute to the literature by analysing the impacts of a public instrument on R&D personnel for firms of different R&D intensity sectors. Additionally, policymakers must invest in human capital to face potential skill shortages. More importantly, such policies must be designed and implemented in a way such that they produce assets and net positive social returns.

The findings of this paper are essential for both top managers and policymakers. From the management point of view, our research points to the possibility that top managers in firms can adjust their R&D activities, namely the composition of R&D personnel. Knowing the impact in the allocation of PhD holders, year after year, would help in the development of the program of work and budget of R&D projects. Regardless the type of R&D performed, basic research, applied research or experimental development, PhD holders play a determinant role within firms as researchers. R&D contributes to a firm's *absorptive capacity*, where PhD holders are determinant in influencing the *absorptive capacity* within firms. Firms need to develop their *absorptive capacity* by interacting with academia (Rafols, I. *et al*., 2013). From the policy perspective and regarding the firms with lowest ability to make the most of external, state-driven support, we would sensitize those firms, in particular firms from low R&D intensity sector, highlighting the role of the PhD holders in the *absorptive capacity*, since it is essential for firms to recognize the value of new, external information, assimilate it, and apply it to commercial ends which is critical to its innovative capabilities. As well from the policy perspective, our research highlights the impact of a policy instrument in the composition of R&D personnel from the business enterprise sector. Therefore, policy instruments can be improved and better designed to boost R&D activities and particularly the allocation of PhD holders.

A further promising avenue for future evaluation research could be to explain the choice of the type of instrument (e.g., grants versus tax credits) based on the characteristics of firms (e.g., size, year of registration), since for instance, SME are the dominant structure of the Portuguese economy. Future research should explore the impact of a tax incentive scheme for corporate R&D in productivity, at the firm level, particularly in medium-high and high R&D intensity sectors, where the reported results in this study suggest that firms in these sectors of R&D intensity are more prone to allocating PhD holders. Future research should also explore the impact of a tax incentive scheme for corporate R&D in the allocation of R&D personnel, namely researchers, regarding the academic background and, in particular, the allocation of PhD holders regarding their research area.

5. Do R&D tax credits really boost hiring? Insights into employment dynamics

The present study probes the impact of Research and Development (R&D) tax credits on employment growth in Portugal from 2014 to 2022, particularly on the total employees, R&D staff, and PhD (Doctor of Philosophy) holders across economic activity sectors. Objectives: We aim to assess whether R&D tax credits lead to employment growth, particularly in industries reliant on highly skilled R&D personnel. Methods/Analysis: Using firm-level data from Portugal's R&D survey, we apply a difference-in-differences (DiD) approach with an event study and staggered design for temporal analysis. This methodology, enhanced by a staggered design, allows us to isolate the effects across periods, comparing treated firms with controls within sectors classified by the NACE Rev. 2 system. Findings: Results reveal that R&D tax credits significantly enhance employment for R&D staff, with the information and communication sector having an 18.4% increase and the manufacturing sector rising 12.3%. Novelty/Improvement: Using firm-level data and a staggered DiD design, this study offers granular insights into sectoral variations, underscoring the importance of sector-specific policies. Findings provide valuable guidance for policymakers optimising and enhancing the R&D tax credits framework to support employment at different levels of expertise and across different economic activity spheres.

5.1 Introduction

Theoretical and empirical research examining the effects of public financing on private R&D activities is still somewhat limited, particularly regarding its implications for employment (Dimos & Pugh, 2016; Wang *et al*., 2017; Vanino *et al*., 2019). Public financing can be direct or indirect (tax credits), and some studies compare direct R&D funding with tax incentives as policy tools (Mansfield & Switzer, 1985; Yang *et al*., 2024; Zhu & Yang, 2024). Studies comparing direct support with tax incentives suggest that tax incentives successfully lower R&D costs for firms and enhance market effectiveness (Hall & Van Reenen, 2000; Yang *et al*., 2024). However, the limited literature on this topic leaves room for further exploration into how public financing might stimulate private R&D (Xu *et al*., 2024).

This study analyses the impact of R&D tax credits granted to companies that performed R&D activities and applied for these credits, particularly the effect on the number of employees, R&D staff, and PhD holders. This impact is evaluated by economic activity sectors. The data were collected via the business R&D survey.

Human resources with high qualifications are required to perform R&D activities, usually at levels six to eight from the ISCED[11] classification (Paredes *et al*., 2022). Since the capacity to perform and incorporate R&D activities differs from sector to sector (Pavitt, 1984), the study focused on a comparative analysis of the tax credits across economic activity sectors. The economic activity sectors used were classified according to the NACE Rev. 2[12] classification, and the sectors were selected according to the percentage of Portuguese gross value added (GVA) by industry. Findings from recent research emphasised the effects of R&D tax credits on the employment of PhD holders in companies depending on the company's levels of R&D intensity[13] (Paredes *et al*., 2022).

[11] ISCED – International Standard Classification of Education
[12] Statistical Classification of Economic Activities in the European Community, Rev. 2
[13] R&D intensity is measured by dividing the industry's research and development expenditure by its total gross value added (Zhu & Yang, 2024).

Prior research has evaluated the implications of R&D tax incentives at aggregate or sectoral levels (Billings *et al*., 2001; Laredo *et al*., 2015), overlooking sector-specific features that may shape the efficiency of R&D tax incentives in fostering hiring employees within R&D roles (Bogliacino & Vivarelli, 2012; Antonucci & Pianta, 2002; Evangelista & Savona, 2002). This study addresses this gap by analysing the impact of R&D tax credits on hiring employees by categories (total employees, R&D staff and PhD holders), providing insights into how specific economic sectors respond to this tax incentive scheme.

In addition, there is sparse empirical research evaluating the effects of tax incentives on employment based on R&D roles within specific economic activity sectors. Prior studies have shown that R&D tax credits attract the highly skilled human resources necessary for firms' R&D activities (Appelt *et al*., 2016). This study provides a closer look at how a tax incentive scheme influences hiring highly qualified employees like R&D staff or PhD holders. Analysing R&D tax credits at the firm level rather than at a more aggregated level captures more significant variability in R&D tax credit rates and reflects the employment dynamics within sectors more accurately (Bogliacino & Vivarelli, 2012). This detailed analysis enables us to determine which roles and industries are most affected by this tax incentive scheme.

The literature on the employment implications of R&D tax incentives over time across economic activity sectors is limited (Castellacci & Lie, 2015; Freitas *et al*., 2017). This study addresses this gap by using a longitudinal method, such as a staggered DiD approach, to assess whether the employment effects of tax credits endure across multiple years and sector contexts. This approach allows us to capture the effects of R&D-related employment within companies in response to tax incentives.

This study addresses the following research question: Does the R&D tax credit impact hiring employees, R&D staff, or PhD holders, depending on the economic activity sector? Data collected via an R&D survey from companies involved in Research and Development activities in Portugal from 2014 to 2022 and fiscal data from firms that applied for R&D tax credit were used to address this question.

A DiD approach integrated with an event study, utilising a staggered design, is used to evaluate the impact of the Fiscal Incentive System for Business R&D (SIFIDE). By evaluating both short-term and longitudinal impacts, this approach provides a more detailed insight into how tax credits influence R&D employment over time. The results indicate a beneficial effect of the tax credit, with the average impact depending on the firm's duration of exposure. These findings align with those of Evangelista and Savona (2002), who demonstrated that public funding for R&D can have beneficial implications on employment, varying by industry sector.

The following chapters of this study present, in the first moment, the literature review on the R&D tax credits to support companies engaged in R&D activities. The subsequent chapters present the data source, methodology, and discussion of the results. Finally, the last chapter presents concluding remarks and recommendations for future investigations in this area of study.

5.2 Literature review

5.2.1 Overview of R&D tax credits

Government assistance for private R&D generally occurs as direct subsidies or tax incentives (Appelt *et al*., 2016). Due to their neutral nature, tax incentives are often preferred to subsidies as they support any firm that performs R&D activities, regardless of its economic sector, location, or size (Mardones & Natalia, 2020). These incentives give firms more flexibility in allocating their R&D spending (Yang *et al.*, 2024; Yang *et al*., 2023). Tax incentives are easier to manage than direct funding and reduce the risk of governments backing unsuccessful projects (Dechezleprêtre, *et al*., 2016). They also tend to boost ongoing R&D activity in industries (Tassey, 1996).

A newer rationale for public support is "market-based," aiming to encourage business R&D, retain human talent, and attract foreign direct investment and skilled researchers (Carvalho, 2011). Many countries compete by offering attractive fiscal R&D incentives to draw relocatable R&D expenditures (Clark & Arnold, 2005; OECD, 2008). As economies increasingly rely on knowledge and intangible assets, both economies and companies see significant returns on R&D expenditures, generating new and improved job opportunities (European Commission, 2020). By 2020, 32 of the 38 OECD nations had implemented favourable tax regimes for business R&D expenditures[14].

Tax credits are popular because they can be implemented within the existing tax system, requiring minimal additional administrative costs for the government and firms (Laredo *et*

[14] The information is available at: https://www.oecd.org/en/topics/sub-issues/rd-tax-incentives.html

al., 2015). Despite this popularity, no clear evidence exists of their impact, particularly on hiring technical staff, R&D staff, or PhD holders essential to perform R&D activities. Their widespread adoption can be attributed to their neutrality, as they provide tax benefits for any qualifying R&D expenditures without the selective nature of direct subsidies (Lokshin & Mohnen, 2013). However, despite some disadvantages, such as uncertainty in the budget and difficulties in the tax system, tax credits have better support due to their neutrality and integration into existing tax systems (Guceri, 2018).

Laredo *et al*. (2015) examine how tax incentives influence private R&D expenditure, while other studies focus on other metrics such as patent registration (Karkinsky & Riedel, 2012), R&D staff levels and salaries (Lokshin & Mohnen, 2013) and the launch of new or improved products in the market (Czarnitzki, *et al*., 2011). This study aims to assess the effects of tax credits on hiring employees, R&D staff, or PhD holders by economic activity sectors.

R&D tax credits are generally classified as incremental or volume-based. Incremental schemes reward firms for exceeding a baseline level of past R&D activities, while volume-based schemes benefit total R&D expenditures, irrespective of past performance (Guceri, 2018). One key area that requires further investigation is how different R&D tax credits across countries affect R&D additionality. Volume-based schemes cover all eligible R&D expenditures and benefit large firms, boosting the country’s overall R&D intensity. Some countries, such as Canada and Spain, use a hybrid approach integrating volume-based and incremental schemes (Castellacci & Lie, 2015).

As governments increasingly turn to R&D tax credits to promote business expenditure on R&D, policymakers expect this to lead to raised R&D output, often called input additionality (OECD, 2019). Studies suggest that direct funding programs, like those from Innovation Norway and the Research Council of Norway, generate less additionality for each funding unit relative to tax credits (Nilsen *et al*., 2020).

5.2.2 Implications of R&D tax credits on firms

Often, companies underinvest in innovation due to issues in financial markets, information imbalances, and the beneficial spillovers related to R&D (Walter, *et al*., 2022; Mao, 2024). These obstacles hinder firms from capitalising on their R&D activities. To address these inefficiencies and motivate firms to undertake R&D activities, governments worldwide have introduced R&D tax credits (Walter, *et al*., 2022), which can serve as practical tools for guiding innovation in high-cost or heavily regulated environments, as observed in China's green technology transformation policy for resource-based cities (Liu, *et al*., 2024).

Although direct funding and tax credits aim to mitigate the effects of market failures, they are not perfect substitutes, as they target different difficulties firms face (Busom, 2014). For instance, Bérubé and Mohnen (2009) emphasise that these incentives are designed to reduce the negative impacts of market failures, thereby promoting higher investment in innovation. Acknowledging the relevance of R&D for economic growth, governments have adopted fiscal policies such as tax credits to mitigate market failures and make R&D expenditures more attractive (Appelt *et al*., 2016). Huang *et al*. (2020) suggest these incentives spur the development of innovative products with a positive impact on job creation.

Empirical studies often examine the effectiveness of R&D tax incentives through the incremental increase in inputs, which denotes the rise in R&D expenditure as a direct result of these fiscal programs (Freitas *et al*., 2017). Research from the Netherlands revealed that R&D tax credits partially contributed to increased salaries for R&D personnel (Lokshin & Mohnen, 2013). Output additionality, which encompasses broader economic impacts such as employment, has been less explored in the literature (Freitas *et al*., 2017). However, the available evidence indicates positive effects (Paredes *et al*., 2022; Mitchell *et al*., 2020). For example, Austrian tax credits have been associated with growth in innovation, sales, and employment (Falk *et al*., 2009a; Falk *et al*., 2009b).

Increases in R&D tax credits often impact positively on R&D staff within firms (Guceri, 2018). Analysis using the Business Enterprise Research and Development (BERD) dataset indicates that this growth in expenditure is driven more by higher employment in R&D roles than by wage increases for R&D staff (Guceri, 2018). Firms in sectors with a strong focus on R&D activities tend to gain greater advantages from R&D tax credits, showing more significant effects in both input and output additionality (Freitas *et al*., 2017). There is a need for further research into how these effects vary across industries, considering their different technological and market contexts (Freitas *et al*., 2017).

5.2.3 R&D tax credits in Portugal

The SIFIDE was implemented in Portugal in 1997 to increase private sector participation in R&D on a global scale. SIFIDE encourages firms to become more competitive by allowing them to offset R&D expenditures from their firms' tax liabilities. Throughout the years, the scheme has experienced some adjustments to enhance its attractiveness to firms performing R&D activities.

In 2011, SIFIDE II was introduced (State Budget Law for 2011 (Law No. 55-A/2010, later amended by Law 83-C/2013)), replacing the original SIFIDE. Its primary aim was to improve firms' competitiveness by assisting their R&D activities. Eligible expenditures within this scheme include R&D activities. Research costs involve acquiring new scientific or technical knowledge, while Development costs focus on using that knowledge to make substantial advancements in materials, products, services, or manufacturing processes.

Additional eligible expenditures increase the attractiveness of the SIFIDE scheme (OECD, 2023). These include costs associated with outsourcing R&D to public entities or recognised R&D organizations. Moreover, spending related to acquiring patents for R&D (especially for small and medium-sized enterprises (SMEs)) and labour costs with hiring PhD holders is considered eligible at 120% of their value.

Changes in SIFIDE II have played a crucial role in its attractiveness. For example, the upper bound on the incremental rate increased from 750,000 euros to 1.5 million euros (OECD, 2021). Companies can apply multiple times for different projects if other financial support programs do not cover the expenditures. Since its relaunch in 2006, SIFIDE has grown significantly. The overall value of tax credits granted rose from 92 million euros in

2006 to 624 million euros in 2022. Likewise, the number of companies benefiting from SIFIDE grew from 442 in 2006 to 4,457 in 2022 and 5,598 in 2023[15].

Research shows that tax credits in Portugal directly affect employment, particularly in the increase of staff (Lelarge, 2008; Hallépée & Garcia, 2012; Ferreira *et al*., 2019). This outcome is tied to the reality that 55% of R&D labour costs in Portugal qualify for tax credits (Carvalho, 2013). These incentives provide resources for new projects and support investments in infrastructure, hiring, and sales growth, creating beneficial spillovers for firms and society (Walter, *et al*., 2022).

This study analyses the mixed scheme of R&D tax credits adopted in Portugal that integrates aspects of volume-based and incremental designs (OECD, 2021; Carvalho, 2013). The country stands out for its generous fiscal incentive program promoting R&D activities in firms. Ferreira *et al*. (2019) noted that Portuguese firms receiving support from SIFIDE show different behaviour than non-beneficiaries, particularly regarding job quality.

Moreover, SIFIDE has been successful in promoting R&D investments in Portugal. Its effectiveness is recognised internationally, making it among the best R&D tax credit programs globally (Gonzales-Cabral, 2017). The growth in R&D employment attributable to tax credits is a key result of the program (Guceri, 2018). This research examines the impact of these incentives on employment across economic sectors.

[15] The information is available at: https://www.ani.pt/pt/financiamento/incentivos-fiscais/sifide/

5.3 Empirical strategy

5.3.1 The data

This investigation utilised data from 8,136 entities that conducted R&D activities from 2014 to 2022. These data were collected in the scope of the official business R&D survey, which is mandatory for all companies potentially executing R&D activities. This survey allows for the collection of all financial and human resources data related to R&D activities. The data on R&D tax credits were obtained via the online platform of the Portuguese Tax and Customs Authority (SIFIDE)[16].

The two datasets were combined using companies' fiscal numbers as the primary key, having been selected from the first dataset (business R&D survey): the number of employees, R&D staff in FTE, PhD holders, current R&D expenditure, capital R&D expenditure, and internal funds. A dummy variable was created from the second dataset to identify firms that utilised tax credits, with a value of 1 assigned if a company benefited from tax credits and 0 if it did not. The goal of the merging process was to combine the two datasets into a unified and comprehensive dataset ready for further examination and analysis.

Regarding the data on sources of funds available from the R&D survey, despite the availability of data on alternative sources of funds, their overall proportion was negligible. Due to restricted access to external financing, firms depend mainly on internal funds for R&D projects (Sterlacchini & Venturini, 2019).

[16] The information is available at: https://info.portaldasfinancas.gov.pt/pt/dgci/divulgacao/Area_Beneficios_Fiscais/Paginas/default.aspx

The data utilised in this study obtained from the official business R&D survey were supplied by the Direção-Geral de Estatísticas da Educação e Ciência under an agreement with the INE (Instituto Nacional de Estatística) and the FCT (Fundação para a Ciência e Tecnologia), which allows researchers to access the data for research purposes (Paredes *et al*., 2022).

This study adopts the definition of R&D as outlined in the Frascati Manual, which states that R&D involves both creative and systematic work aimed at expanding the body of knowledge which encompasses the understanding of humanity, culture, and society - and creating new uses for existing knowledge (OECD, 2015b).

Firms often face restricted access to external financing and depend upon their internal assets for R&D projects. Financial limitations for R&D primarily arise from information asymmetries between firms and financial institutions, leading to high monitoring costs. The abstract quality of R&D investments renders them challenging to use as a guarantee (Brown *et al*., 2012). This aspect could also account for why the share of public funding within the overall financing for R&D is negligible. Therefore, our study focused solely on the internal funds' variable.

Although SIFIDE data is available for years before 2014, the starting year of 2014 was chosen because 2011-2013 could bias the results with the phase of the economic cycle (reduction of hiring). These were years of more significant uncertainty in which firms were less likely to invest. According to Hud and Hussinger (2014), firms are more reluctant to invest during crises. Therefore, homogeneous behaviour within the units before the treatment is required, making it more reasonable to consider a shorter time frame. Table 5.1 provides a summary of the statistics for the 8,136 companies involved in R&D activities during the reference period.

Table 5.1 Summary statistics and description of the variables

Variable	Mean	SD	Min	Max	Description
Employee	14.74	64.65	1	7,555	Number of employees
R&D employee	7.32	24.00	0.05	1,172.80	Employees in R&D activities
PhD	0,52	2.07	0	72	PhD holders
Current expenditure	389.12	1,786.52	0	76,287.80	Current R&D expenditure (€ 000's)
Labor costs	250.44	1,028.07	0	50,243.49	Labor costs of R&D personnel (€ 000's)
Other current costs	138.68	1,089.31	0	61,209.33	Other current R&D costs (€ 000's)
Capital expenditure	57.76	828.29	0	57,730.27	Capital R&D expenditure (€ 000's)
Internal funds	389.00	2,081.39	0	78,184.75	Internal funds for R&D (€ 000's)

The primary goal of the investigation is to evaluate the implications of the R&D tax credit on employment, comparing the economic activity sectors. The economic activity sectors were selected and organised following the NACE Rev. 2 classification and the Portuguese gross value added (GVA) contribution by industry. Table 5.2 illustrates the distribution of Portugal's gross value added by industry in 2022.

Table 5.2 GVA and income, by industry, as a percentage of GDP

Description [NACE Rev. 2]	% of GDP
Agriculture, forestry and fishing [A]	2,0
Industry (except construction) [B, D and E]	14,3
Manufacturing [C]	11,9
Construction [F]	3,7
Wholesale and retail trade, transport, accommodation and food service activities [G, H and I]	21,3
Information and communication [J]	4,0
Financial and insurance activities [K]	5,5
Real estate activities [L]	9,6
Professional, scientific and technical activities; administrative and support service activities [M and N]	8,0
Public administration, defence, education, human health and social work activities [O, P and Q]	16,1
Arts, entertainment and recreation; other service activities; activities of household [R, S, T and U]	2,4

Source: Eurostat - Dataset: Gross value added and income by A*10 industry breakdowns [nama_10_a10]

Table 5.3 presents the distribution of BERD by industry in 2022 and the number of companies conducting R&D activities during the reference period.

Table 5.3 Share of BERD and number of firms that performed R&D activities

Description [NACE Rev. 2 - Section and Division]	% of BERD	# Firms
Manufacturing [C: 10-33]	35,1	11662
Energy [NACE D: 35]	2,4	175
Construction & Real estate activities [F & L: 41-43; 68]	1,9	664
Wholesale and retail trade [G, H and I: 45-47; 49-53; 55-56]	5,8	3112
Information and communication [J: 58-63]	20,8	5638
Financial and insurance activities [K: 64-66]	7,0	443
Professional, scientific and technical activities [M: 69-75]	19,8	5762
Human health and social work activities [Q: 86-88]	0,8	527
Total	93,6	

Source: DGEEC [https://www.dgeec.medu.pt/p/ciencia-e-tecnologia/estatisticas/investigacao-e-desenvolvimento-(ipctn)]

5.3.2 Methodology

In this study, a DiD approach was used to evaluate the implications of the SIFIDE on firms engaged in R&D activities. The DiD method is widely regarded as the primary method for public policy evaluation (Roth *et al*., 2023; Angrist & Pischke, 2010).

The DiD estimation requires two different types of groups: a treatment group and a group not exposed to the treatment (control group) (Cunningham, 2021). The canonic DiD approach relies on stringent assumptions, notably that both groups would exhibit similar patterns over time in the absence of treatment (Paredes & Damásio, 2023). In Abadie (2005), a semiparametric DiD estimator was proposed that allowed for deviation from the parallel trends' assumption in cases where differences in observed characteristics result in divergent outcome dynamics in the treatment group and comparison group. In summary, the work proposed the conditional parallel trends (PT) hypothesis, suggesting that the PT assumption is valid when accounting for covariates. Despite the popularity of this method, the classical DiD method is not appropriate for the assessment of most public policy programs since it assumes that all the units are subject to the treatment at the same time. In this study, we will consider the DiD estimators for staggered treatment, where the units are exposed to treatment at varying times. Extrapolating the PT assumption to staggered settings has as conditions that PT would be applicable to all combinations of periods and groups submitted to treatment at different moments in time.

These estimators can combine treatment impacts in staggered treatment scenarios, allowing for cases with multiple treated periods and cohorts and enabling weighted averages of treatment effects (Roth *et al*., 2023; Callaway & Sant'Anna, 2021). The primary aim of the research is to assess the effects of the SIFIDE on employment across different economic activity sectors. The outcome variables evaluated include the natural logarithm of total employment (log(Total)), R&D staff (log(R&D staff)), and PhD holders (log(PhD)). The methodological approach followed key steps. First, we examined the rollout of the treatment, documenting the number of units within each cohort to ensure that sample sizes were sufficient for reliable estimates. Next, we analysed the summary statistics and tracked the evolution of average outcomes across the different cohorts.

In defining the comparison group, we included untreated units and units not yet exposed to treatment within the control group. An event study was then conducted using staggered design estimators. Initially, the analysis was performed without covariates to determine whether the unconditional PT assumption was valid. If this assumption did not hold, we repeated the event study estimation while incorporating covariates to assess if the conditional PT assumption holds. The covariates included in this analysis were current R&D expenditure, labour costs, other current expenditures, capital expenditure, and internal funds.

To address differences in treatment timing, estimators such as those by Callaway and Sant'Anna (CS), Chaisemartin and D'Haultfoeuille (CdH), Borusyak, Javarel and Spiess (BJS), and Sun and Abraham (SA) were chosen for staggered settings. These estimators represent the latest advances in difference-in-differences techniques for staggered designs (Roth *et al*., 2023).

To provide clarity, consider the following specification:

$$\log(Y)_{i,t} = \alpha_i + \phi_t + \sum_{r \neq 0} 1[R_{i,t} = r]\beta_r + \epsilon_{i,t} \,, \qquad (1)$$

where, $Y_{i,t}$ represents the outcome variable for firm i at time t, α_i is the firm fixed effect accounting for time-invariant differences across firms, Φ_t the time fixed effect, capturing time-specific shocks affecting all firms, $R_{i,t} = t - G_i + 1$ is the time since treatment began (e.g. $R_{i,t} = 1$ in the first treated period for unit i), and the summation encompasses all potential values of $R_{i,t}$ except for 0, β_r represent the effect for a specific time r relative to the treatment, except for r = 0, and $\epsilon_{i,t}$ the idiosyncratic random disturbance.

Regarding the CS estimator to obtain the average treatment effect on treated (ATT) in the staggered design setting, this estimator yields as many average treatment effects as treated groups. Specifically, the proposed estimator applies a DiD estimator to obtain the ATT for a given treated group g at a given period t (Callaway & Sant'Anna, 2021). Specifically, it estimates:

$$ATT(g,t) = E\left[Y_{1it} | G_g = 1\right] - E\left[Y_{0it} | G_g = 1\right]$$

The CdH estimator considers each consecutive period pair $t-1$ and t. It compares the outcome between the groups that switched treatment status during that consecutive period pair and the control group (De Chaisemartin & d'Haultfoeuille, 2020). Essentially, it considers the same approach as CS but weights the effects according to observations that switch treatment status.

The estimator proposed by BJS considers an imputation approach (Borusyak *et al*., 2021). We estimate an OLS (Ordinary Least Squares) model for the non-treated observations to obtain the time and unit fixed effects. These estimated fixed effects are plugged into a regression for the treated group, from which we subtract the outcome of the untreated group.

The SA estimator considers a Two-Way Fixed Effects (TWFE) estimator, accounting for time and unit fixed effects (Sun & Abraham, 2021). However, it comprises a dummy variable for each cohort (each treated group), interacting with a dummy indicating the relative period until treatment.

The main distinction among these estimators lies in their choice of control group. CS and CdH use the last pre-treated group as control, while BJS take the average of all pre-treatment periods. SA use either the previously treated group or a never-treated group. In practical terms, the BJS estimator is stricter than CS, CdH and SA since it relies on the average across all pre-treatment periods. If we are considering a sizeable pre-treatment period, with differences throughout time, this comparison could introduce bias in the results.

Overall, these estimators offer alternatives to overcome the bias from standard DiD estimators in staggered designs. Understanding the differences between these estimators, along with comparing the results between them, can enhance the plausibility of the results.

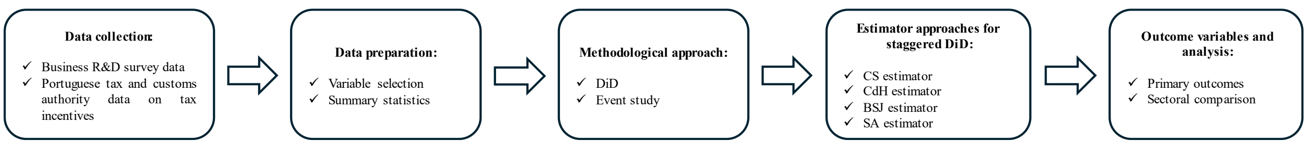


Figure 5.1 Flowchart of the research methodology

5.4 Results and discussion

The paper analyses the implications of SIFIDE on the number of employees, R&D staff in FTE, and PhD holders across all firms, irrespective of their industry sector. Subsequently, it examines the impact of SIFIDE on the same dependent variables by industry.

5.4.1 Overall effect of the SIFIDE

Figure 5.2 shows the yearly distribution of the companies receiving treatment (treated group) and firms not receiving treatment (control group) by industry. Table 5.4 shows the units available for each relative period to the treatment date.

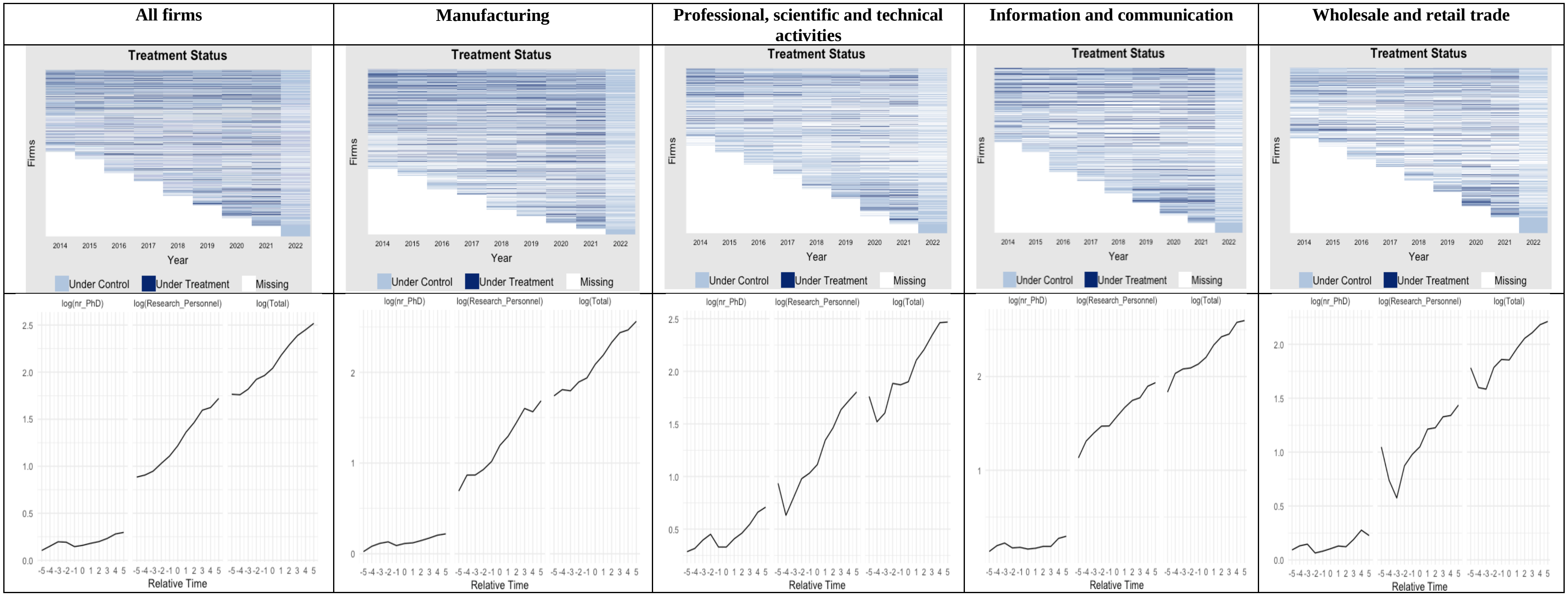


Figure 5.2 Firms under treatment and under control and average outcomes across cohorts by industry

Note: The figure shows an increase in all average outcomes across cohorts.

Table 5.4 Number of units available in each cohort

Number of units	lead5	lead4	lead3	lead2	lead1	lag0	lag1	lag2	lag3	lag4	lag5
All firms	170	252	372	561	1105	2242	1943	1557	1230	1016	866
Manufacturing	66	99	158	234	459	936	819	687	562	486	421
Professional, scientific and technical activities	31	48	63	91	164	352	305	233	177	133	108
Information and communication	34	43	75	107	211	414	360	297	242	186	159
Wholesale and retail trade	15	19	28	45	112	238	192	133	92	77	58

Figure 5.2 shows an increase in all average outcomes across cohorts. We conducted an event study to determine whether this increase is attributable to the incentive since this could be due to an economic boost, which is characterised by the period considered in the sample (2014-2022).

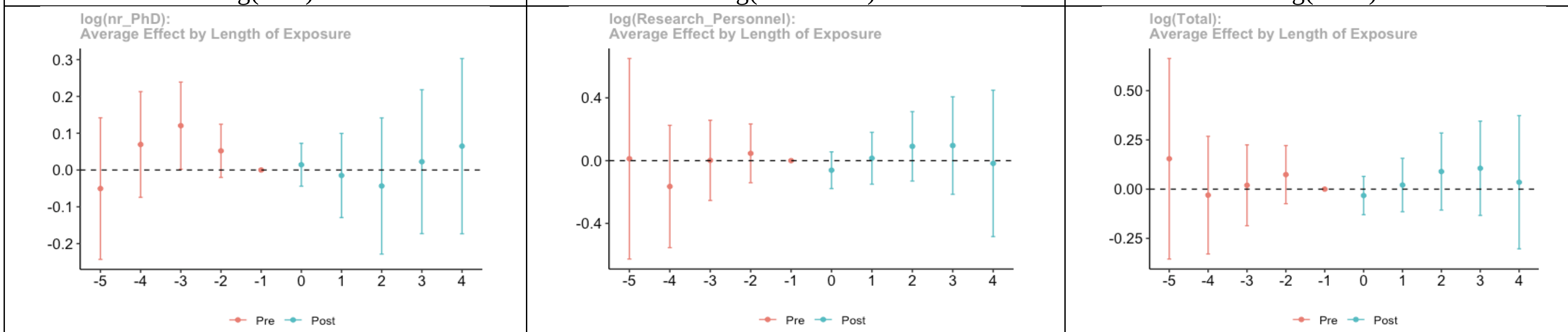
The treatment rollout visualised the distribution of treated and control units over time. Darker shades indicate sectors with a higher concentration of treated observations, while lighter shades represent more observations in the control group. For instance, manufacturing companies exhibit a higher proportion of treated units compared to sectors like wholesale and trade. Table 5.4 complements this, showing the available treated or yet-to-be-treated units for each cohort.

By applying the CS estimator, we evaluate the validity of the PT assumption without including covariates. The estimation method employed is the doubly robust estimator. The results of the PT tests suggest that the null hypothesis of PT for log(R&D staff) ($p = 0.5461$) and log(Total) ($p = 0.7394$) cannot be rejected, indicating that the PT assumption holds for these variables. However, for log(PhD), we reject the null hypothesis ($p = 0.0032$), suggesting a potential violation of the PT assumption for this variable.

Next, we examine whether the conditional PT assumption is satisfied by adding labour costs, total and current expenditures, and the total number of employees as covariates. Based on the results ($p = 0.1124$), we do not reject the null hypothesis for log(PhD), indicating that the conditional PT assumption holds when these additional factors are considered.

Figure 5.3 illustrates the event study plot and estimates for PhD holders, R&D staff, and the total employee number. The event study results align with the PT test, showing no significant treatment effect in the post-periods.

log(PhD)	log(R&D staff)	log(Total)



log(PhD)

Event Time	Estimate	Std. Error	[95% Simult.	Conf. Band]
-5	-0.0505	0.0774	-0.2428	0.1419
-4	0.0694	0.0578	-0.0742	0.2130
-3	0.1205	0.0477	0.0020	0.2390
-2	0.0521	0.0291	-0.0201	0.1244
-1	0.0000	NA	NA	NA
0	0.0143	0.0234	-0.0440	0.0726
1	-0.0149	0.0460	-0.1293	0.0995
2	-0.0434	0.0744	-0.2284	0.1416
3	0.0226	0.0786	-0.1729	0.2181
4	0.0648	0.0958	-0.1732	0.3029

log(R&D staff)

Event Time	Estimate	Std. Error	[95% Simult.	Conf. Band]
-5	0.0120	0.2386	-0.6266	0.6507
-4	-0.1645	0.1456	-0.5540	0.2251
-3	0.0018	0.0954	-0.2536	0.2572
-2	0.0464	0.0699	-0.1407	0.2335
-1	0.0000	NA	NA	NA
0	-0.0611	0.0437	-0.1781	0.0559
1	0.0153	0.0617	-0.1500	0.1805
2	0.0911	0.0826	-0.1300	0.3122
3	0.0962	0.1160	-0.2144	0.4067
4	-0.0175	0.1742	-0.4838	0.4487

log(Total)

Event Time	Estimate	Std. Error	[95% Simult.	Conf. Band]
-5	0.1544	0.1856	-0.3546	0.6633
-4	-0.0303	0.1089	-0.3290	0.2683
-3	0.0196	0.0748	-0.1856	0.2248
-2	0.0738	0.0538	-0.0737	0.2213
-1	0.0000	NA	NA	NA
0	-0.0324	0.0355	-0.1298	0.0649
1	0.0210	0.0494	-0.1146	0.1567
2	0.0895	0.0713	-0.1061	0.2850
3	0.1060	0.0872	-0.1332	0.3452
4	0.0352	0.1233	-0.3029	0.3733

Figure 5.3 Event study plot and estimates for log(PhD), log(R&D staff) and log(Total)

Note: The figure presents the event study findings from **Callaway and Sant'Anna**. This plot enables us to evaluate the validity of the PT assumption and identify any outcome disruptions following the treatment. The presence of zero within the **red bars** (prior to period zero) supports the validity of the PT assumption. The following periods – indicated by the **green bars** (after period zero) illustrate the annual increase expressed as a percentage. The bars indicate the upper and lower limits of 95% confidence intervals. Overall, there is no evidence of an effect after the treatment.

Next, we use the CdH estimator to evaluate the validity of the PT assumption without incorporating any covariates. The results indicate that the assumption holds across most variables. Specifically, the p-values for the PT test are 0.7772 for log(PhD), 0.0893 for log(R&D staff), and 0.2624 for log(Total). We do not reject the null hypothesis since these p-values exceed the 5% significance level. Consequently, there is no evidence to suggest an impact that supports the validity of the PT assumption in this context.

Figure 5.4 displays the event study plot and results for log(PhD), log(R&D staff), and log(Total). For R&D staff, a statistically significant impact was observed up to four periods after the treatment, with the overall ATT showing a significant average effect of 11.4%. Likewise, a statistically significant effect was found for the total number of employees up to three periods after the treatment, with an average impact of 7.4%. These findings are outlined in Table 5.5 and align with Martinez-Ros' research showing a positive employment impact of R&D tax credits for Spanish micro, small and medium-sized enterprises (MSMEs) and SMEs (Martinez-Ros & Kunapatarawong, 2019), which are similar to the study on France's *Jeune Entreprise Innovante* (JEI) scheme, where firms benefiting from R&D incentives showed more significant employment growth (Lelarge, 2008).

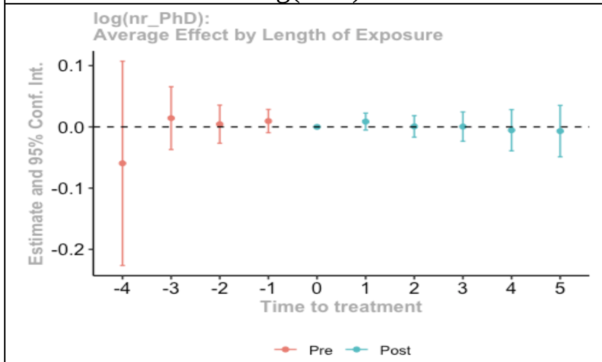
Table 5.5 Average treatment effect for R&D staff and total number of employees

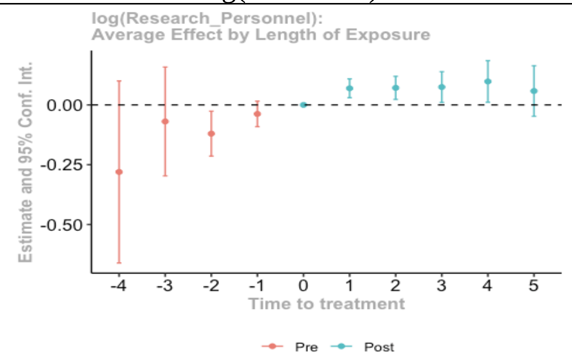
Outcome	Estimate	SE	LB CI	UB CI	N
R&D staff	0.11384	0.03689	0.04154	0.18614	20019
Total number of employees	0.07354	0.02923	0.01624	0.13084	20019

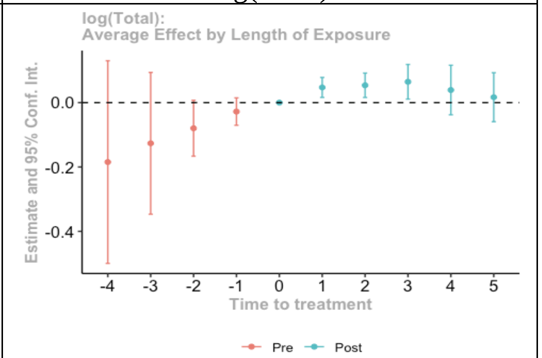
Note: SE: Standard Error; LB CI: Lower Bound Conf. Interval; UB CI: Upper Bound Conf. Interval

While SIFIDE significantly influenced total employment and R&D staff, and not extended to PhD hires, it may reflect sectoral and structural factors within the tax credit design. Some sectors, namely manufacturing, and information and communication, show substantial growth in R&D staff, suggesting that SIFIDE more effectively supports these categories than PhD-level expertise. The incentive structure offering increased eligibility to hire PhD holders may not cover the high costs associated with these roles. This could lead firms to favour hiring patterns aligned with short-term projects and not requiring PhD holders.

log(PhD)	log(R&D staff)	log(Total)







log(PhD)

Event Time	Estimate	SE	LB CI	UB CI	N
-4	-0.05948	0.08510	-0.22626	0.10730	463
-3	0.01431	0.02616	-0.03696	0.06559	2153
-2	0.00441	0.01589	-0.02673	0.03556	5205
-1	0.00954	0.00969	-0.00945	0.02853	9129
1	0.00865	0.00706	-0.00519	0.02248	14165
2	0.00078	0.00896	-0.01679	0.01835	11543
3	0.00049	0.01221	-0.02344	0.02443	8084
4	-0.00542	0.01718	-0.03909	0.02826	5611
5	-0.00687	0.02143	-0.04887	0.03513	3778

log(R&D staff)

Event Time	Estimate	SE	LB CI	UB CI	N
-4	-0.28041	0.19420	-0.66103	0.10021	463
-3	-0.06930	0.11602	-0.29669	0.15809	2153
-2	-0.12030	0.04791	-0.21420	-0.02640	5205
-1	-0.03766	0.02720	-0.09097	0.01564	9129
1	0.06936	0.02013	0.02990	0.10883	14165
2	0.07124	0.02462	0.02298	0.11950	11543
3	0.07457	0.03274	0.01041	0.13874	8084
4	0.09803	0.04437	0.01107	0.18499	5611
5	0.05807	0.05382	-0.04741	0.16355	3778

log(Total)

Event Time	Estimate	SE	LB CI	UB CI	N
-4	-0.18465	0.16063	-0.49948	0.13018	463
-3	-0.12643	0.11241	-0.34675	0.09388	2153
-2	-0.07962	0.04426	-0.16637	0.00713	5205
-1	-0.02778	0.02171	-0.07033	0.01477	9129
1	0.04725	0.01581	0.01626	0.07824	14165
2	0.05394	0.01931	0.01610	0.09179	11543
3	0.06480	0.02744	0.01103	0.11857	8084
4	0.03919	0.03925	-0.03774	0.11613	5611
5	0.01686	0.03882	-0.05922	0.09294	3778

Figure 5.4 Event study plot and estimates for log(PhD), log(R&D staff) and log(Total)

Note: The figure presents the event study findings from **Chaisemartin and D'Haultfoielle**. This plot allows us to assess the validity of the PT assumption and identify any outcome disruptions following the treatment. The presence of zero within the **red bars** (prior to period zero) supports the validity of the PT assumption. The following periods – indicated by the **green bars** (after period zero) illustrate the annual increase expressed as a percentage. The bars indicate the upper and lower limits of 95% confidence intervals. Overall, there is a positive effect for research personnel and the total number of employees up to four and three periods after the treatment, respectively. The positive effect on the total number of employees is less transitory than in the number of research staff, as it remains significant for up to three periods post-treatment. In contrast, the impact on research staff numbers lasts only two periods. Both effects are ultimately transitory, as neither shows a lasting, permanent impact for the time periods available.

Using the BJS estimator, we checked the plausibility of the PT without using any covariates. The R package does not include the variance and covariance matrix, preventing us from computing the Wald test on the pre-periods to verify the PT hypothesis. Nevertheless, considering the plots below (Figure 5.5), we have evidence supporting the PT hypothesis, as all the confidence intervals for event time before zero include zero. For the periods post-treatment, the confidence intervals include zero, thus indicating that there is no statistical evidence of a significant impact on the outcome variables.

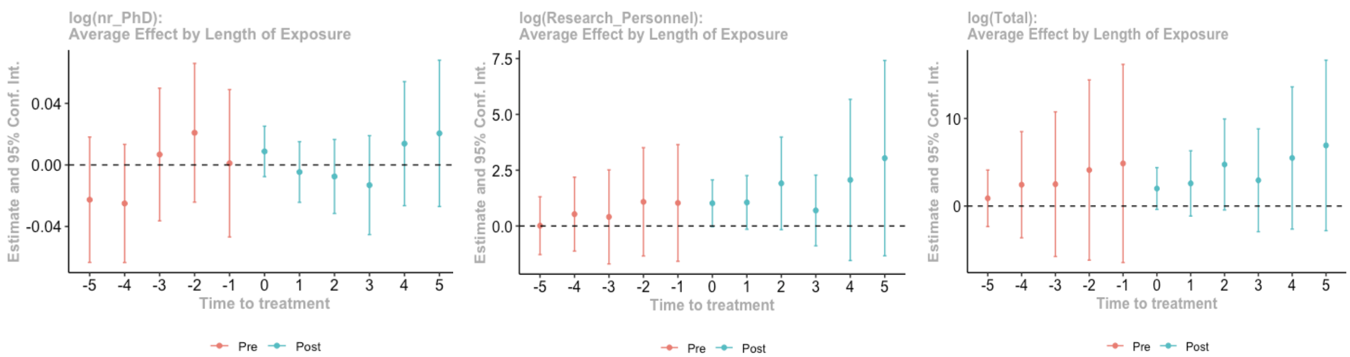


Figure 5.5 Event study plots: log(PhD); log(R&D staff); log(Total)

Note: The figure presents the findings of the event study from **Borusyak, Javarell, and Spiess**. This plot allows us to assess the validity of the PT assumption and identify any outcome disruptions following the treatment. The presence of zero within the **red bars** (prior to period zero) supports the validity of the PT assumption. The following periods – indicated by the **green bars** (after period zero) illustrate the annual increase expressed as a percentage. The bars indicate the upper and lower limits of 95% confidence intervals. Overall, there is no evidence of an effect after the treatment.

The SA approach employs a TWFE (Two-Way Fixed Effects) estimator, controlling for both time and unit fixed effects. This estimator includes a dummy variable for each cohort, interacting with a dummy indicating the relative period until treatment. We assessed the plausibility of PT without incorporating any covariates. The findings suggest that the null hypothesis of PT is not supported for both log(R&D staff) and log(Total) (p-values = 0.000), suggesting a deviation from the PT assumption.

However, for log(PhD), the p-value is 0.3313, meaning we do not reject the null hypothesis for this variable. Adding covariates did not change these results, indicating robustness in the findings.

Figure 5.6 presents the event study plot for log(PhD), log(R&D staff) and log(Total). Considering the log(PhD) event study plot, we have the visual confirmation of the PT hypothesis, given that every confidence interval in the periods before treatment includes zero. Moreover, we have statistical evidence of a negative impact following the treatment. This impact is not aligned with the previous results and the summary statistics. Regarding the R&D staff and the total employee number, the PT assumption does not hold. The SA estimator only considers the untreated units as the control group, while the previous estimators include the units that have not yet been treated in addition to the untreated group. Additionally, the SA estimator does not permit the estimation of the conditional PT. Thus, this estimator can be seen as a less flexible version of CS (Baker, *et al*., 2022).

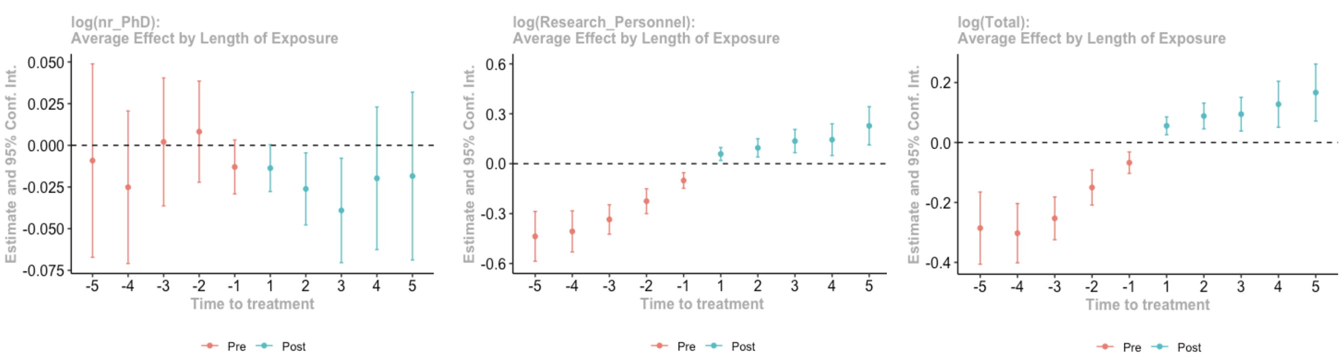


Figure 5.6 Event study plots: log(PhD) log(R&D staff) and log(Total)

Note: The figure presents the findings of the event study from **Sun and Abraham**. This plot allows us to evaluate the validity of the PT assumption and identify any outcome disruptions following the treatment. The presence of zero within the **red bars** (prior to period zero) supports the validity of the PT assumption. The following periods – indicated by the **green bars** (after period zero) illustrate the annual increase expressed as a percentage. The bars indicate the upper and lower limits of 95% confidence intervals. Overall, there is no evidence of an effect after the treatment.

The PT assumption was valid for the CS, CdH and BJS estimators. However, only the CdH showed significant results. Specifically, this estimator showed a statistically meaningful effect on R&D staff for four periods after the treatment, resulting in an average increase of 11%. For the Total number of employees, the treatment has a statistically significant impact up to three periods following the treatment, resulting in an average increase of 7.4%. These results correspond with the findings from Martinez-Ros (2019), which demonstrated a positive effect of the R&D and technological innovation (R&D&I) tax credit on employment for Spanish MSMEs and SMEs. Similarly, these findings are consistent with observations in France during 2004 and 2005, in which companies that benefited from the JEI scheme experienced significantly higher annual employment growth, with an estimated growth differential of 8.4 percentage points comparable to similar companies that did not receive the JEI scheme support (Lelarge, 2008). Thus, considering the CdH estimator, we will proceed to capture heterogeneous effects per sector.

To ensure the robustness of the PT assumption across sectors, we employed staggered DiD estimators, such as CS or BJS, which mitigate biases associated with staggered treatment adoption. Additionally, pre-treatment trends for treated and control groups were assessed, confirming similar trajectories across most sectors prior to treatment. For robustness, we conducted sector-specific analyses and used both logged and non-logged estimations, with consistent results across transformations, which stabilized sample variability and narrowed confidence intervals. Outlier influence was minimized by using log transformations.

5.4.2 Impact of the SIFIDE by industry[17]

The impact of the SIFIDE varies across different sectors, highlighting the nuanced consequences of policy interventions on industry-specific R&D dynamics. In the manufacturing sector, to evaluate the

[17] In some industries (Financial and insurance services, Construction & Property Development, Healthcare and social services, and Energy), the low number of observations per year makes computing the estimates impossible.

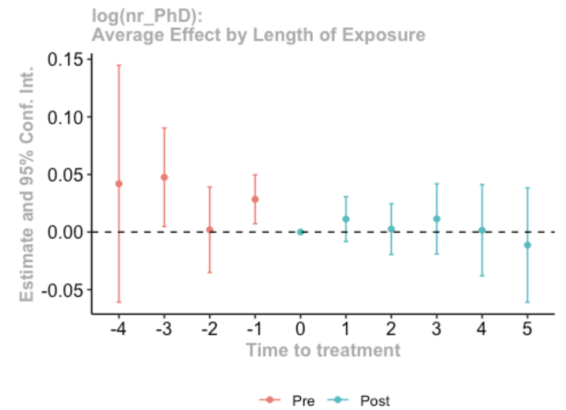
validity of the PT assumption, we applied the CdH estimator without including any covariates. The results suggest that the PT assumption is valid for log(R&D staff) ($p = 0.1323$) and log(Total) ($p = 0.253$), as the p-values exceed the 5% significance level. However, for log(PhD), the PT assumption is not supported ($p = 0.0114$). Notably, adding covariates did not alter this result for log(PhD), confirming the robustness of the finding.

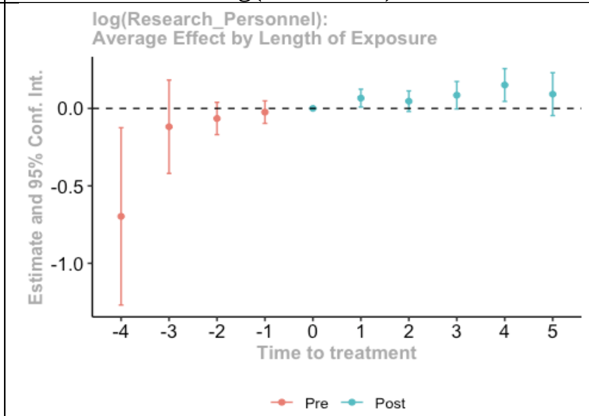
In the manufacturing sector, we observed a statistically significant rise in the R&D staff up to four periods post-treatment, with an overall ATT of 12.3% (Table 5.6). Despite this positive impact on R&D staff, no significant influence was observed on the total employee number (Figure 5.7). These findings align with those of Evangelista and Savona (2002), who demonstrated that public funding for R&D can have beneficial implications on employment, varying by industry sector.

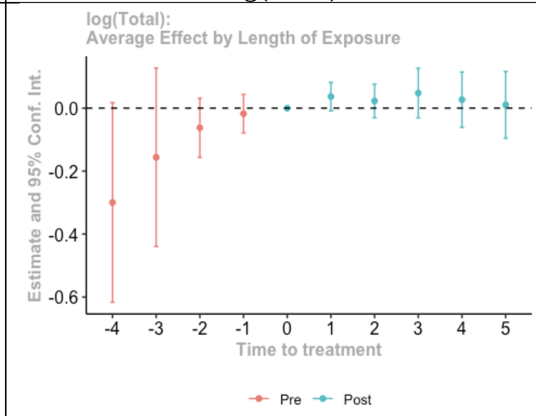
Table 5.6 Average treatment effect for R&D staff

Outcome	Estimate	SE	LB CI	UB CI	N
R&D staff	0.12279	0.0501	0.02459	0.221	7550

log(PhD)	log(R&D staff)	log(Total)







log(PhD)

Event Time	Estimate	SE	LB CI	UB CI	N
-4	0.04195	0.05247	-0.06090	0.14480	195
-3	0.04754	0.02185	0.00472	0.09037	848
-2	0.00197	0.01894	-0.03516	0.03909	1981
-1	0.02842	0.01081	0.00724	0.04960	3358
1	0.01124	0.00992	-0.00821	0.03069	5127
2	0.00254	0.01125	-0.01952	0.02459	4234
3	0.01142	0.01554	-0.01905	0.04188	3033
4	0.00157	0.02020	-0.03802	0.04117	2153
5	-0.01133	0.02533	-0.06098	0.03831	1484

log(R&D staff)

Event Time	Estimate	SE	LB CI	UB CI	N
-4	-0.69700	0.29208	-1.26947	-0.12453	195
-3	-0.11832	0.15378	-0.41973	0.18308	848
-2	-0.06499	0.05322	-0.16929	0.03931	1981
-1	-0.02393	0.03706	-0.09656	0.04871	3358
1	0.06643	0.02942	0.00877	0.12410	5127
2	0.04670	0.03384	-0.01964	0.11303	4234
3	0.08529	0.04522	-0.00335	0.17392	3033
4	0.15114	0.05402	0.04525	0.25702	2153
5	0.09203	0.07063	-0.04641	0.23047	1484

log(Total)

Event Time	Estimate	SE	LB CI	UB CI	N
-4	-0.29965	0.16165	-0.61647	0.01717	195
-3	-0.15602	0.14461	-0.43946	0.12742	848
-2	-0.06239	0.04790	-0.15627	0.03149	1981
-1	-0.01762	0.03126	-0.07889	0.04366	3358
1	0.03664	0.02307	-0.00858	0.08186	5127
2	0.02263	0.02721	-0.03069	0.07596	4234
3	0.04785	0.04019	-0.03092	0.12661	3033
4	0.02675	0.04478	-0.06102	0.11452	2153
5	0.01031	0.05408	-0.09568	0.11630	1484

Figure 5.7 Event study plot and estimates for log(PhD), log(R&D staff) and log(Total)

Note: The figure presents the event study findings from **Chaisemartin and D'Haultfoielle**. This plot allows us to assess the validity of the PT assumption and identify any outcome disruptions following the treatment. The presence of zero within the **red bars** (prior to period zero) supports the validity of the PT assumption. The following periods – indicated by the **green bars** (after period zero) illustrate the annual increase expressed as a percentage. The bars indicate the upper and lower limits of 95% confidence intervals. Overall, there is a positive effect for research personnel up to four periods after the treatment. In spite of its positive impact, this estimate is minimal, further indicating that the treatment did not lead to a notable long-term change in research personnel. The small confidence intervals indicate the high precision of these estimates.

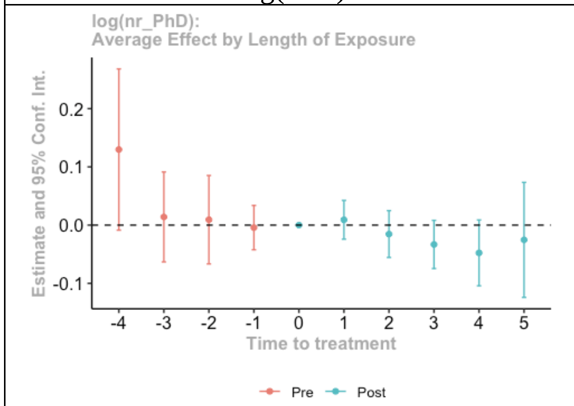
The information and communication sector exhibited a different pattern. To evaluate the validity of PT, we applied the CdH estimator without including any covariates. The results indicate that the PT assumption is valid for all three variables, with p-values of 0.4575 for log(PhD), 0.675 for log(R&D staff), and 0.5515 for log(Total). These p-values suggest no statistically significant deviation from the parallel trend assumption across these variables.

The information and communication sector did not significantly impact on PhD holders (Figure 5.8). However, for R&D staff, we observed a statistically significant impact up to two periods after the treatment, with the overall ATT indicating an average impact of 18.4%. Similarly, for the total number of employees, we found evidence of a statistically significant impact up to three periods after the treatment, with an average impact of 18.8%. These results are presented in Table 5.7 and align with prior research (Paredes *et al*., 2022), where the implementation of the SIFIDE tax incentive scheme in Portugal also demonstrated a favourable influence on the employment of highly skilled R&D personnel, specifically PhD holders, particularly in companies with medium-high and high R&D intensity. This finding suggests a consistent positive impact of SIFIDE across various R&D employment indicators, emphasising the efficacy of targeted policy support for R&D-focused human capital.

Table 5.7 Average treatment effect for R&D staff and total number of employees

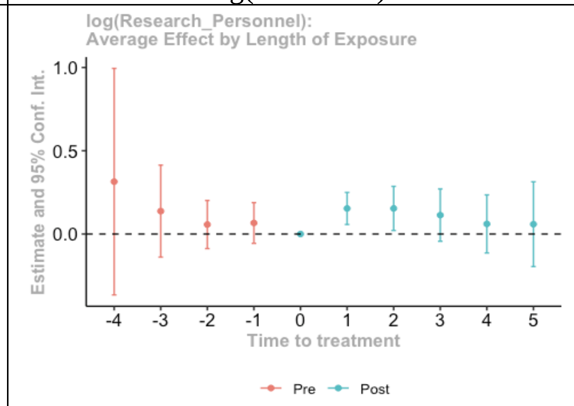
Outcome	Estimate	SE	LB CI	UB CI	N
R&D staff	0.18359	0.09051	0.0062	0.36099	3544
Total number of employees	0.18765	0.06523	0.0598	0.3155	3544

log(PhD)



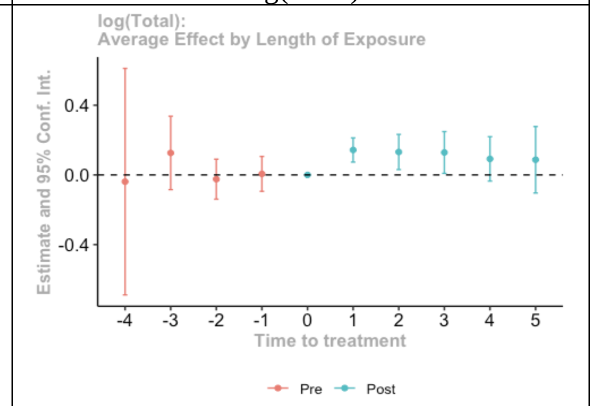
Event Time	Estimate	SE	LB CI	UB CI	N
-4	0.12977	0.07064	-0.00868	0.26823	59
-3	0.01402	0.03942	-0.06324	0.09128	288
-2	0.00928	0.03875	-0.06667	0.08523	788
-1	-0.00428	0.01942	-0.04233	0.03378	1504
1	0.00914	0.01698	-0.02415	0.04242	2446
2	-0.01538	0.02051	-0.05558	0.02483	1933
3	-0.03323	0.02112	-0.07462	0.00816	1312
4	-0.04770	0.02885	-0.10425	0.00884	875
5	-0.02536	0.05039	-0.12413	0.07341	546

log(R&D staff)



Event Time	Estimate	SE	LB CI	UB CI	N
-4	0.31447	0.34704	-0.36573	0.99466	59
-3	0.13757	0.14091	-0.13861	0.41376	288
-2	0.05700	0.07373	-0.08751	0.20150	788
-1	0.06622	0.06237	-0.05603	0.18847	1504
1	0.15347	0.04911	0.05722	0.24972	2446
2	0.15375	0.06763	0.02120	0.28629	1933
3	0.11361	0.08018	-0.04354	0.27075	1312
4	0.06058	0.08896	-0.11378	0.23494	875
5	0.05909	0.12987	-0.19545	0.31363	546

log(Total)



Event Time	Estimate	SE	LB CI	UB CI	N
-4	-0.03863	0.33175	-0.68885	0.61160	59
-3	0.12631	0.10753	-0.08445	0.33707	288
-2	-0.02437	0.05859	-0.13920	0.09045	788
-1	0.00600	0.05111	-0.09417	0.10616	1504
1	0.14307	0.03542	0.07365	0.21248	2446
2	0.13168	0.05150	0.03075	0.23261	1933
3	0.12887	0.06118	0.00895	0.24879	1312
4	0.09206	0.06497	-0.03528	0.21939	875
5	0.08705	0.09737	-0.10380	0.27789	546

Figure 5.8 Event study plot and estimates for log(PhD), log(R&D staff) and log(Total)

Note: The figure presents the event study findings from **Chaisemartin and D'Haultfoielle**. This plot allows us to assess the validity of the PT assumption and identify any outcome disruptions following the treatment. The presence of zero within the **red bars** (prior to period zero) supports the validity of the PT assumption. The following periods – indicated by the **green bars** (after period zero) illustrate the annual increase expressed as a percentage. The bars indicate the upper and lower limits of 95% confidence intervals. Overall, there is a positive effect for research personnel and the total employee number up to two and three periods after the treatment, respectively. This effect is also transitory, given that after two and three periods, the effect is no longer significant.

These findings align with those of Bogliacino and Vivarelli (2012) and underscore the differential effect of the R&D tax credit across industries. While the manufacturing sector's response is primarily evident in the rise of R&D staff, the information and communication sector shows broader growth, encompassing both R&D staff and overall employment. The appendix provides additional insights, including detailed event study plots and estimates for the professional, scientific, and technical services sectors (Figure 5.9) and wholesale and retail trade sectors (Figure 5.10).

In the professional, scientific, and technical activities sector, the PT assumption holds for all outcome variables, with p-values of 0.8702 for PhD holders, 0.2186 for R&D staff, and 0.4497 for total employees. Despite the assumption holding, no significant impact was observed for these variables (Figure 5.9). Conversely, in the wholesale and retail trade sector, the PT assumption is valid solely for the total number of employees ($p = 0.1523$), while it does not hold for PhD holders ($p = 0.0078$) or R&D staff ($p = 0.0006$). Additionally, no influence was found regarding the overall number of employees (Figure 5.10). These sector-specific analyses further emphasize the importance of tailored evaluations to fully understand the varying effects of the R&D tax credit within different sectors.

The restricted impact of the SIFIDE in the professional, scientific, and technical sectors might suggest that this tax credit may not fully address the sector's specific R&D needs, such as the focus on research-related services and consulting. This observation aligns with findings from other sectors in this study and highlights the potential for sector-specific refinements to enhance policy inclusivity and impact. The adjustment of the SIFIDE to recognize these unique sectoral dynamics could potentially increase the efficacy of the R&D credits across diverse sectors.

5.5 Conclusions

This study aimed to evaluate the effects of the SIFIDE on employment growth across various economic sectors in Portugal, focusing on the total number of employees, R&D staff, and PhD holders. Using a robust DiD methodology extended for staggered treatment adoption, we analysed a comprehensive dataset of 8,136 firms from 2014 to 2022. Although it has varying effects across different sectors, findings reveal that the SIFIDE significantly impacts the number of R&D staff and total employees.

The SIFIDE significantly increased the number of R&D staff and total employees, aligning with similar findings in other research. Martinez-Ros (2019) reported a favourable effect of R&D&I tax credits on employment among Spanish MSMEs and SMEs. Lelarge (2008), and Hallépée and Garcia (2012) observed higher employment growth in French firms benefiting from the JEI scheme. Specifically, our results show an 11.4% average increase in the R&D staff and a 7.4% average increase in the total employees up to four and three periods after treatment, respectively. However, the tax credit did not significantly impact the number of PhD holders.

In the manufacturing sector, the SIFIDE positively impacts 12,3% of the R&D staff up to four post-treatment periods. However, no meaningful effect was observed on the total number of employees or PhD holders. For the professional, scientific, and technical services sectors, despite the positive trends observed, the tax credit did not significantly impact the total number of employees, R&D staff, or PhD holders. The information and communication sector experienced an 18.4% increase in the R&D staff and an 18.8% increase in the total employees up to two and three periods after treatment, respectively, highlighting the substantial impact of the SIFIDE in fostering employment growth. In the wholesale and retail trade sector, the tax credit significantly increased the total number of employees. However, the impact on R&D staff and PhD holders was not statistically significant. For sectors like financial and insurance services, construction and property development, healthcare and social services, and energy, the low number of observations per year prevented meaningful estimation of the tax credit's impact.

It is important to note that, despite an overall positive effect, the event plots indicate that this effect is temporary, showing only slight significance for one to three periods after treatment.

The validity of our findings is reinforced by multiple robustness checks using various DiD estimators, including those by CS, CdH, BJS, and SA. The PT assumption was valid in most cases, ensuring the reliability of our results. Specifically, the CdH estimators were instrumental in capturing heterogeneous effects across sectors.

Our results align with previous research suggesting that R&D tax credits positively impact employment growth. For instance, Martinez-Ros (2019) also found significant employment growth in firms benefiting from R&D tax credits. However, the degree of impact varies by sector, underscoring the need for tailored policy measures to maximize the effectiveness of such incentives.

The findings underscore the significant potential of R&D tax credits to drive employment growth, particularly in knowledge-intensive sectors such as information and communication and manufacturing. However, the varying impact across industries suggests that a uniform strategy may prove inadequate to maximize the effectiveness of these incentives. Policymakers should consider adopting a more ambitious, sector-specific strategy that tailors R&D tax incentives to each industry's unique needs and dynamics.

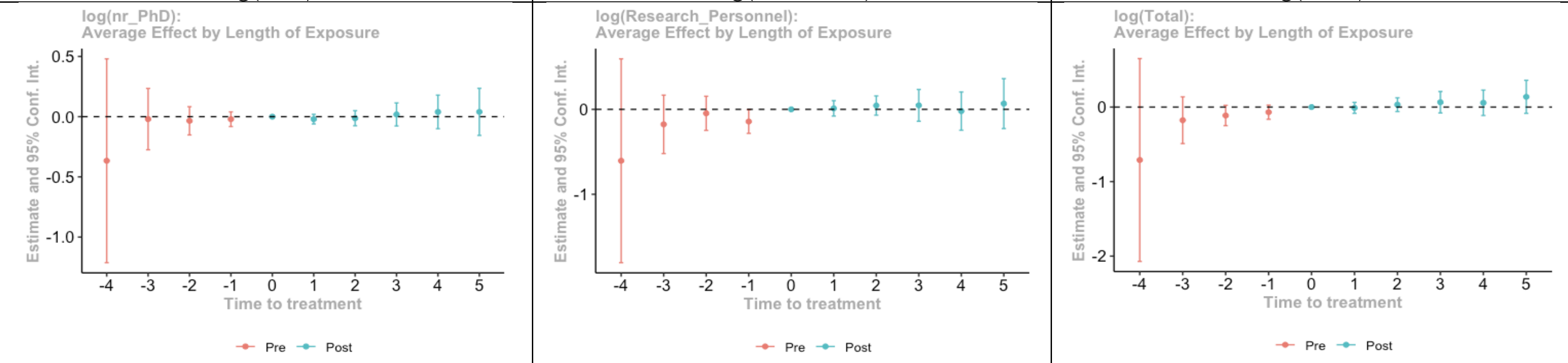
For example, increasing support for sectors like professional, scientific, and technical activities, where the impact of tax credits was less pronounced, could help unlock further potential in these fields. Additionally, expanding the scope of incentives to encourage hiring high-skilled workers, such as PhD holders, could strengthen the innovation ecosystem and drive long-term economic growth. Moreover, policymakers might consider regional variations in the application of these credits to ensure that all geographic areas benefit equally from these incentives, thus promoting balanced economic development across the country.

By refining and expanding R&D tax credit programs, Portugal can further enhance its competitive edge in the global market, ensuring that the benefits of R&D translate into sustained economic prosperity and job creation across all sectors.

In conclusion, within firms engaged in R&D activities, tax credits have proven to be a powerful tool in promoting employment growth. These incentives contribute to the Portuguese economy's overall economic development and competitiveness by fostering an environment conducive to innovation and research. Future policies should build on these findings to enhance the effectiveness of R&D assistance initiatives, ensuring sustained growth and advancement in various economic sectors.

While our study provides valuable insights, it is essential to acknowledge potential research limitations that warrant further investigation. A promising direction for future research is to explore whether the effect of R&D tax credits on employment differs among different regions, as certain geographic areas may show a stronger or weaker impact. Another promising investigation is to compare the effect of R&D tax credits on employment between R&D newcomers (firms with no prior R&D activity) and R&D established firms (firms already involved in R&D before obtaining assistance). Furthermore, in sectors such as finance, insurance, and construction, where smaller sample sizes limit statistical power, it would be beneficial to explore strategies to enhance the representativeness and reliability of findings. For instance, applying bootstrapping techniques or using similar-sector firms as control groups could provide more robust confidence intervals, allowing for a more detailed sectoral analysis even in low-sample contexts. Lastly, our analysis does not distinguish between firms engaged in basic research and those involved in more applied research or experimental development projects. This distinction could offer a greater understanding of the specific types of R&D activities that benefit most from fiscal incentives, thereby enabling more targeted and effective policy measures.

Appendix



log(PhD)

Event Time	Estimate	SE	LB CI	UB CI	N
-4	-0.36612	0.43190	-1.21263	0.48039	81
-3	-0.02013	0.12984	-0.27461	0.23436	377
-2	-0.03453	0.05980	-0.15173	0.08267	952
-1	-0.02093	0.03097	-0.08163	0.03976	1749
1	-0.02036	0.02037	-0.06028	0.01956	2737
2	-0.01279	0.03189	-0.07530	0.04972	2165
3	0.01850	0.04881	-0.07716	0.11415	1466
4	0.03950	0.07112	-0.09989	0.17890	998
5	0.03992	0.09972	-0.15553	0.23537	647

log(R&D staff)

Event Time	Estimate	SE	LB CI	UB CI	N
-4	-0.60533	0.61236	-1.80554	0.59489	81
-3	-0.17660	0.17547	-0.52051	0.16731	377
-2	-0.04666	0.10245	-0.24745	0.15414	952
-1	-0.14342	0.07105	-0.28267	-0.00417	1749
1	0.01163	0.04623	-0.07898	0.10224	2737
2	0.04479	0.05785	-0.06859	0.15818	2165
3	0.04685	0.09544	-0.14021	0.23391	1466
4	-0.02065	0.11484	-0.24572	0.20443	998
5	0.06764	0.14994	-0.22623	0.36152	647

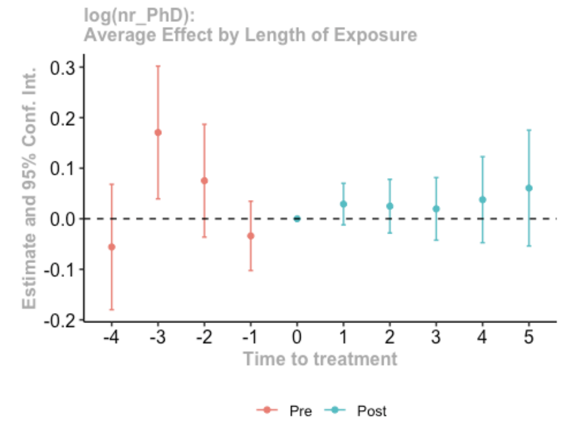
log(Total)

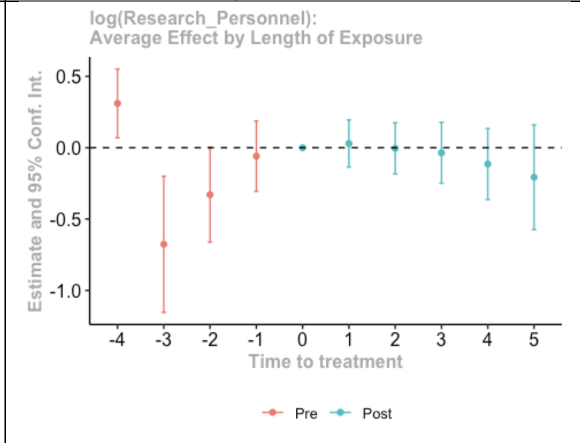
Event Time	Estimate	SE	LB CI	UB CI	N
-4	-0.70987	0.69437	-2.07082	0.65107	81
-3	-0.17618	0.15991	-0.48960	0.13724	377
-2	-0.11308	0.06960	-0.24950	0.02335	952
-1	-0.06866	0.04844	-0.16361	0.02629	1749
1	-0.01044	0.03731	-0.08358	0.06269	2737
2	0.03230	0.04697	-0.05976	0.12436	2165
3	0.06527	0.07339	-0.07857	0.20912	1466
4	0.05761	0.08692	-0.11275	0.22796	998
5	0.13761	0.11301	-0.08390	0.35911	647

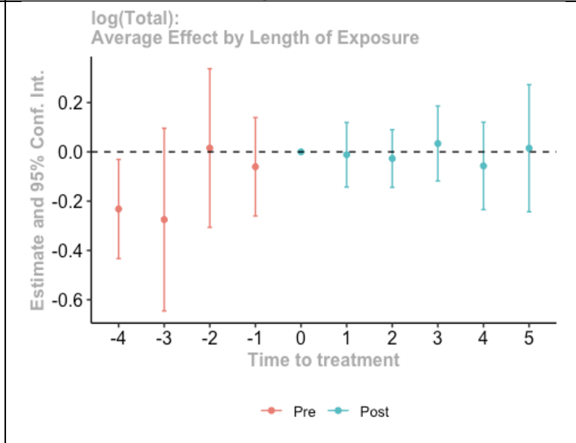
Figure 5.9 Event study plot and estimates for log(PhD), log(R&D staff) and log(Total)

Note: The figure presents the event study findings from **Chaisemartin and D'Haultfoielle**. This plot allows us to assess the validity of the PT assumption and identify any outcome disruptions following the treatment. The presence of zero within the **red bars** (prior to period zero) supports the validity of the PT assumption. The following periods – indicated by the **green bars** (after period zero) illustrate the annual increase expressed as a percentage. The bars indicate the upper and lower limits of 95% confidence intervals. Overall, there is no evidence of an effect after the treatment.

log(PhD)	log(R&D staff)	log(Total)







log(PhD)

Event Time	Estimate	SE	LB CI	UB CI	N
-4	-0.05588	0.06329	-0.17993	0.06816	38
-3	0.17066	0.06701	0.03932	0.30200	185
-2	0.07526	0.05694	-0.03634	0.18686	466
-1	-0.03388	0.03497	-0.10243	0.03467	855
1	0.02904	0.02098	-0.01207	0.07015	1366
2	0.02488	0.02707	-0.02819	0.07794	1086
3	0.01955	0.03159	-0.04237	0.08147	747
4	0.03769	0.04342	-0.04741	0.12278	499
5	0.06068	0.05848	-0.05394	0.17531	332

log(R&D staff)

Event Time	Estimate	SE	LB CI	UB CI	N
-4	0.31029	0.12295	0.06932	0.55126	38
-3	-0.67665	0.24339	-1.15369	-0.19961	185
-2	-0.32899	0.16953	-0.66127	0.00328	466
-1	-0.05953	0.12556	-0.30562	0.18656	855
1	0.02952	0.08437	-0.13584	0.19488	1366
2	-0.00479	0.09136	-0.18386	0.17428	1086
3	-0.03542	0.10903	-0.24912	0.17828	747
4	-0.11431	0.12700	-0.36323	0.13461	499
5	-0.20709	0.18741	-0.57441	0.16023	332

log(Total)

Event Time	Estimate	SE	LB CI	UB CI	N
-4	-0.23182	0.10267	-0.43304	-0.03060	38
-3	-0.27487	0.18912	-0.64553	0.09579	185
-2	0.01550	0.16422	-0.30636	0.33737	466
-1	-0.06051	0.10187	-0.26017	0.13914	855
1	-0.01171	0.06680	-0.14264	0.11922	1366
2	-0.02704	0.05970	-0.14406	0.08997	1086
3	0.03383	0.07758	-0.11822	0.18588	747
4	-0.05704	0.09048	-0.23437	0.12029	499
5	0.01478	0.13160	-0.24316	0.27272	332

Figure 5.10 Event study plot and estimates for log(PhD), log(R&D staff) and log(Total)

Note: The figure presents the event study findings from **Chaisemartin and D'Haultfoielle**. This plot allows us to assess the validity of the PT assumption and identify any outcome disruptions following the treatment. The presence of zero within the **red bars** (prior to period zero) supports the validity of the PT assumption. The following periods – indicated by the **green bars** (after period zero) illustrate the annual increase expressed as a percentage. The bars indicate the upper and lower limits of 95% confidence intervals. Overall, there is no evidence of an effect after the treatment.

6. Conclusions

6.1. Summary of Findings

The findings of this dissertation underscore the critical role of R&D tax credits in shaping firm-level behaviour and employment dynamics within the Portuguese economy, while also highlighting the evolving theoretical landscape of innovation research through the bibliometric analysis of the Oslo Manual. These findings are particularly relevant within the framework of Horizon Europe's objectives, as outlined in its Key Impact Pathway Indicators (Annex V, Tables 1 and 3 of Regulation (EU) 2021/695), which emphasise the importance of enhancing human capital in R&I and creating more and better jobs through innovation-driven policies.

The data science-driven assessment of the Oslo Manual illustrates its adaptability over time and its influence in structuring innovation research, revealing a growing scholarly interest in topics such as entrepreneurship, knowledge management, and performance. This evolution reflects broader economic and managerial theories, reinforcing the Manual's role in guiding innovation measurement and policy. The findings are consistent with Horizon Europe's strategic emphasis on promoting open science and knowledge diffusion, as well as its commitment to addressing global challenges through R&I.

The analysis of firm-level effects of R&D tax credits reveals that the nature of these incentives has a significant impact on firms' allocation of PhD holders, particularly in medium-high and high R&D intensity sectors, where a cumulative effect emerges after three years. This fact suggests that firms engaging with tax incentives are more likely to enhance their absorptive capacity by integrating highly skilled personnel into their workforce. These results align with Horizon Europe's strategic focus on maximising investments in R&I to drive innovation-led growth and create sustainable employment opportunities.

The findings reveal that R&D tax credits not only enhance firms' absorptive capacity but also foster employment growth — most notably in knowledge-intensive sectors such as information and communication, and manufacturing — their impact varies by sector, demonstrating the need for a more tailored policy approach. The sectoral heterogeneity of the policy's effectiveness indicates that a one-size-fits-all approach may be suboptimal, reinforcing the importance of sector-specific policy adjustments. Additionally, the temporary nature of the tax credit's effects on employment suggests that long-term sustainability in employment growth may require complementary measures beyond tax credits, such as direct grants or sector-targeted support mechanisms.

Overall, these findings contribute to the broader literature on innovation policy by demonstrating the differentiated impact of R&D tax credits on firm dynamics, and innovation capabilities, offering valuable insights for policymakers aiming to enhance the efficiency and targeting of fiscal incentives in fostering research and innovation-driven economic growth.

6.2. Contributions

This dissertation contributes to the literature by providing a comprehensive microeconomic and sectoral analysis of the firm-level effects of Portugal's R&D tax credit, addressing gaps in both policy evaluation and innovation measurement frameworks. This research advances the understanding of how tax incentives shape firm behaviour across different R&D intensity sectors. The findings are particularly relevant to Horizon Europe's objectives, as they underscore the importance of driving innovation-led growth and fostering sustainable employment opportunities through targeted policy interventions.

The bibliometric analysis provides a comprehensive longitudinal review of the Oslo Manual, offering valuable insights into its evolution and its role in shaping innovation research. By employing advanced network analysis and text-mining methodologies, this study identifies key trends and theoretical foundations in innovation research, such as the growing integration of innovation with management and economic theories. Furthermore, it highlights the Manual's adaptability to emerging practices. This aspect contributes to the literature by offering a deeper understanding of the Oslo Manual's theoretical and practical implications, while also identifying challenges in cross-country comparability and methodological consistency, thereby setting the stage for future research in innovation measurement. These contributions align with Horizon Europe's emphasis on fostering open science and knowledge diffusion, as well as its commitment to addressing global challenges through R&I.

The findings highlight that while R&D tax credits positively influence employment growth and the allocation of PhD holders, their effects are uneven across industries, with knowledge-intensive sectors experiencing greater benefits. This factor underscores the need for policymakers to refine the design of tax incentives to enhance their effectiveness, ensuring they are sector-specific and aligned with firms' absorptive capacity. By shedding light on the policy instruments, this dissertation provides a foundation for future research on optimising R&D tax credits to foster long-term economic and technological development. These insights are essential for aligning national innovation policies with Horizon Europe's strategic priorities, particularly in fostering a resilient and inclusive innovation ecosystem.

By employing robust methodologies, including staggered difference-in-differences estimators, this research provides reliable evidence on the heterogeneous impacts of fiscal incentives across sectors, contributing to the literature on the effectiveness of R&D tax credits. Collectively, this dissertation advances the understanding of how innovation policies, such as R&D tax credits, influence firm behaviour and sectoral performance, offering theoretical, methodological, and practical contributions that can inform future research, refine policy design, and enhance Portugal's innovation ecosystem.

6.3. Limitations and Future Research

While providing significant insights into the firm-level effects of the Portuguese R&D tax credit and the evolution of innovation measurement through the Oslo Manual, this dissertation is not without limitations, which pave the way for future research. First, the evolving nature of the Oslo Manual and its methodological revisions pose challenges in ensuring comparability across different editions and international contexts. Future research should explore the implications of changes in definitions and methods of measuring innovation activities and assess the extent to which harmonised frameworks can improve cross-country comparability.

Second, while this dissertation contributes to understanding the firm-level impact of R&D tax credits, its scope remains constrained by data availability and methodological limitations. The reliance on historical firm-level data limits the ability to capture real-time policy effects and behavioural responses. Future research could employ dynamic methodologies, such as real-time monitoring or experimental approaches, to assess fiscal incentives' immediate and long-term effects on firm behaviour.

Moreover, the findings indicate sectoral heterogeneity in the impact of R&D tax credits, suggesting that a one-size-fits-all approach may be suboptimal. While medium-high and high R&D-intensity sectors benefit significantly from these incentives, firms in low R&D-intensity sectors exhibit lower responsiveness. Future studies should investigate the underlying factors influencing this divergence, including firm size, absorptive capacity, and industry-specific constraints. Additionally, comparative analyses between tax credits and alternative policy instruments, such as direct grants, could yield valuable insights into the relative effectiveness of different support mechanisms, particularly for SMEs that dominate the Portuguese economy.

Another key limitation concerns the composition of R&D personnel. Although the research highlights the role of PhD holders in strengthening firms' absorptive capacity and innovation potential, the differential impact of tax credits on various categories of R&D personnel remains underexplored. Future research should assess the allocation patterns of researchers based on academic background and research area, examining how fiscal incentives shape the employment of highly skilled workers across different sectors.

Furthermore, while this study provides evidence of the positive effect of tax credits on employment growth, it also suggests that these effects may be temporary. The duration and sustainability of employment gains warrant further investigation, particularly regarding the retention of skilled workers beyond the incentivised period. Future research should explore the long-term career trajectories of employees hired through tax credit schemes and evaluate the extent to which these policies contribute to sustained human capital development.

Lastly, geographic disparities in the effectiveness of R&D tax incentives remain an underexamined area. Regional variations in firm characteristics, innovation ecosystems, and policy implementation may influence the extent to which firms benefit from fiscal incentives. Future studies should undertake a spatial analysis of the impact of R&D tax credits, assessing whether location-based policies could enhance the equitable distribution of innovation-driven economic growth.

By addressing these limitations and expanding the research agenda, future studies can contribute to a more nuanced understanding of how fiscal incentives shape firm behaviour, innovation capacity, and economic performance. Such insights are crucial for designing more effective and inclusive policy measures that maximise the socio-economic benefits of R&D tax credits.

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