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Examining the Impact of R&D Tax Credits on Employment Growth Across Economic Sectors

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Abstract

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 optimizing and enhancing the R&D tax credits framework to support employment at different levels of expertise and across different economic activity spheres.

Keywords:

R&D Tax Credits;

Difference-in-Differences;

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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 [1-3]. Public financing can be direct or indirect (tax credits), and some studies compare direct R&D funding with tax incentives as policy tools [4-6]. Studies comparing direct support with tax incentives suggest that tax incentives successfully lower R&D costs for firms and enhance market effectiveness [7, 8]. However, the limited literature on this topic leaves room for further exploration into how public financing might stimulate private R&D [9]. This study analyzes 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[†] classification [10]. Since the capacity to perform and incorporate R&D activities differs from sector to sector [11], the study focused on a comparative analysis of the tax credits across economic activity sectors. The economic

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[†] ISCED – International Standard Classification of Education

activity sectors used were classified according to the NACE Rev. 2[*] classification, and the sectors were selected according to the percentage of Portuguese gross value added (GVA) by industry. Findings from recent research emphasized 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[†] [10].

Prior research has evaluated the implications of R&D tax incentives at aggregate or sectoral levels [12, 13], overlooking sector-specific features that may shape the efficiency of R&D tax incentives in fostering hiring employees within R&D roles [14-16]. This study addresses this gap by analyzing 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 [17]. This study provides a closer look at how a tax incentive scheme influences hiring highly qualified employees like R&D staff or PhD holders. Analyzing 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 [14]. 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 [18, 19]. 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 credits were used to address this question. A DiD approach integrated with an event study, utilizing 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 [16], 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.

2- Literature Review

2-1- Overview of R&D Tax Credits

Government assistance for private R&D generally occurs as direct subsidies or tax incentives [17]. 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 [20]. These incentives give firms more flexibility in allocating their R&D spending [8, 21]. Tax incentives are easier to manage than direct funding and reduce the risk of governments backing unsuccessful projects [22]. They also tend to boost ongoing R&D activity in industries [23]. 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 [24]. Many countries compete by offering attractive fiscal R&D incentives to draw relocatable R&D expenditures [25, 26]. 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 [27]. By 2020, 32 of the 38 OECD nations had implemented favorable tax regimes for business R&D expenditures[‡].

Tax credits are popular because they can be implemented within the existing tax system, requiring minimal additional administrative costs for the government and firms [13]. Despite this popularity, no clear evidence exists of their impact, particularly on hiring technical staff, R&D staff, or PhD holders essential to performing 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 [28]. 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 [29]. Laredo et al. [13] examine how tax incentives influence private R&D

[*] Statistical Classification of Economic Activities in the European Community, Rev. 2

[†] R&D intensity is measured by dividing the industry's research and development expenditure by its total gross value added [6].

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

expenditure, while other studies focus on other metrics such as patent registration [30], R&D staff levels and salaries [28], and the launch of new or improved products in the market [31]. 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 [29]. 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 [18].

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 [32]. 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 [33].

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 [34, 35]. These obstacles hinder firms from capitalizing 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 [34], 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 [36].

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 [37]. For instance, Bérubé & Mohnen [38] emphasized 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 [17]. Huang et al. [39] suggested 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 [19]. Research from the Netherlands revealed that R&D tax credits partially contributed to increased salaries for R&D personnel [28]. Output additionality, which encompasses broader economic impacts such as employment, has been less explored in the literature [19]. However, the available evidence indicates positive effects [10, 40]. For example, Austrian tax credits have been associated with growth in innovation, sales, and employment [41, 42].

Increases in R&D tax credits often impact positively on R&D staff within firms [29]. 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 [29]. 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 [19]. There is a need for further research into how these effects vary across industries, considering their different technological and market contexts [19].

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 [43]. These include costs associated with outsourcing R&D to public entities or recognized R&D organizations. Moreover, spending related to acquiring patents for R&D (especially for small and medium-sized enterprises (SMEs)) and labor 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 [44]. 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[*].

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

Research shows that tax credits in Portugal directly affect employment, particularly in the increase of staff [45-47]. This outcome is tied to the reality that 55% of R&D labour costs in Portugal qualify for tax credits [48]. These incentives provide resources for new projects and support investments in infrastructure, hiring, and sales growth, creating beneficial spillovers for firms and society [34]. This study analyzes the mixed scheme of R&D tax credits adopted in Portugal that integrates aspects of volume-based and incremental designs [44, 48]. The country stands out for its generous fiscal incentive program promoting R&D activities in firms. Ferreira et al. [47] noted that Portuguese firms receiving support from SIFIDE show different behavior than non-beneficiaries, particularly regarding job quality.

Moreover, SIFIDE has been successful in promoting R&D investments in Portugal. Its effectiveness is recognized internationally, making it among the best R&D tax credit programs globally [49]. The growth in R&D employment attributable to tax credits is a key result of the program [29]. This research examines the impact of these incentives on employment across economic sectors.

3- Empirical Strategy

3-1- The Data

This investigation utilized 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) [*].

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 utilized 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 [50]. The data utilized 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 [10]. 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 that encompasses the understanding of humanity, culture, and society - and creating new uses for existing knowledge [51].

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 [52]. 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 & Hussinger [53], firms are more reluctant to invest during crises. Therefore, homogeneous behavior within the units before the treatment is required, making it more reasonable to consider a shorter time frame. Table 1 provides a summary of the statistics for the 8,136 companies involved in R&D activities during the reference period.

Table 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 information is available at: https://info.portaldasfinancas.gov.pt/pt/dgci/divulgacao/Area_Beneficios_Fiscais/Paginas/default.aspx

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 2 illustrates the distribution of Portugal's gross value added by industry in 2022.

Table 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 3 presents the distribution of BERD by industry in 2022 and the number of companies conducting R&D activities during the reference period.

Table 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)]

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 [54, 55].

The DiD estimation requires two different types of groups: a treatment group and a group not exposed to the treatment (control group) [56]. The canonic DiD approach relies on stringent assumptions, notably that both groups would exhibit similar patterns over time in the absence of treatment [57]. In Abadie [58], 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 [54, 59]. 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 analyzed 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, labor 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 [54].

To provide clarity, consider the following specification:

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

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 [59]. Specifically, it estimates:

$$ATT(g,t) = E\left[Y_{1it}|G_g = 1\right] - E\left[Y_{0it}|G_g = 1\right] \tag{2}$$

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 [60]. 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 [61]. 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 [62]. 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 takes the average of all pre-treatment periods. SA uses 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 1 shows the flowchart of the research methodology through which the objectives of this study were achieved.

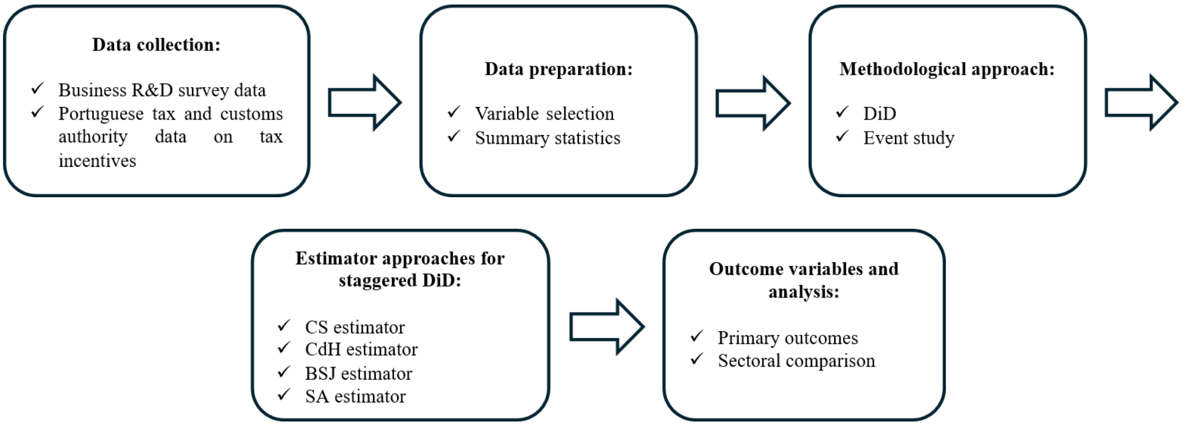


Figure 1. Flowchart of the research methodology

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.

4-1- Overall Effect of the SIFIDE

Figure 2 shows the yearly distribution of the companies receiving treatment (treated group) and firms not receiving treatment (control group) by industry. Table 4 shows the units available for each relative period to the treatment date.

Figure 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 characterized by the period considered in the sample (2014-2022).

The treatment rollout visualized 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 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 labor 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 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.

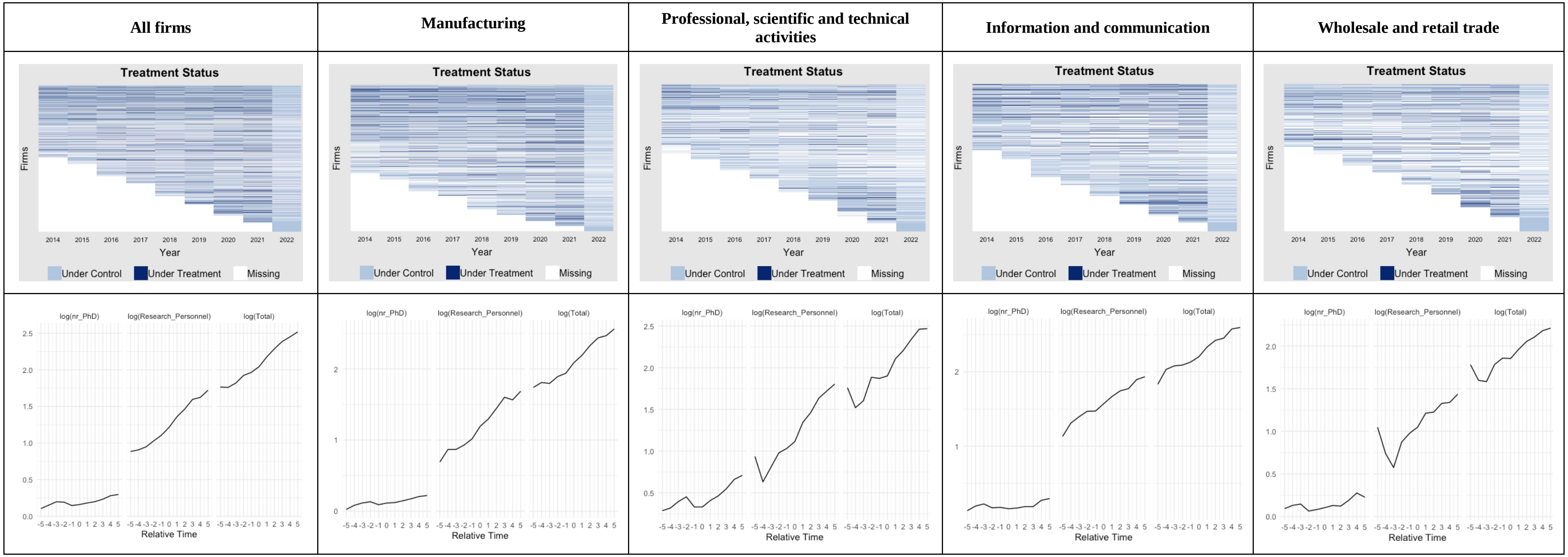
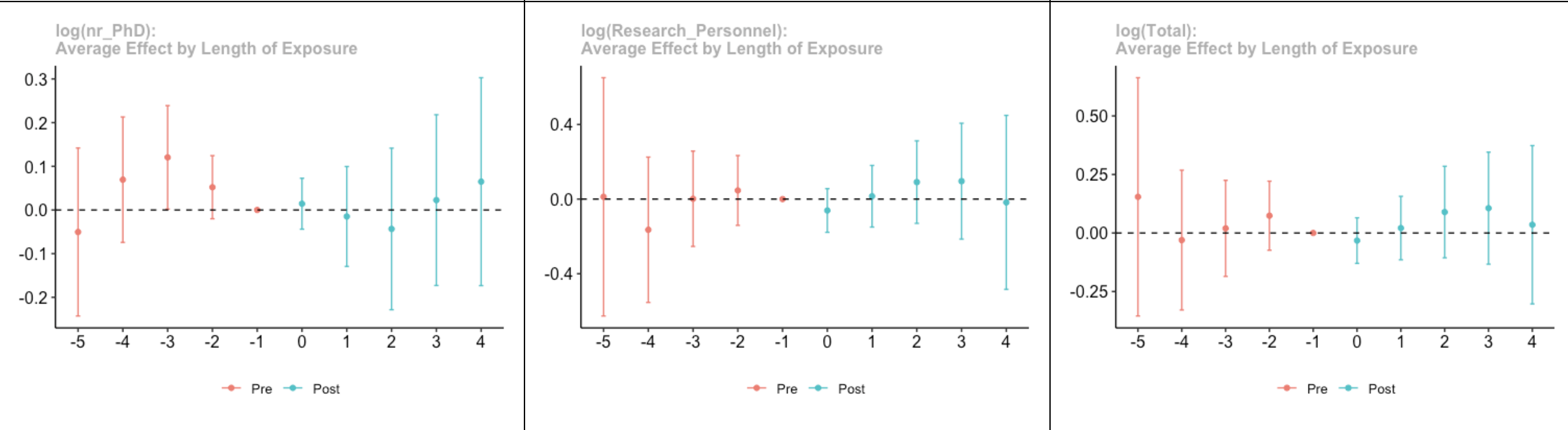


Figure 2. **Firms under treatment and under control and average outcomes across cohorts by industry (*Note*: The figure shows an increase in all average outcomes across cohorts)**

Table 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

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 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 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 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 [63], 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 [45].

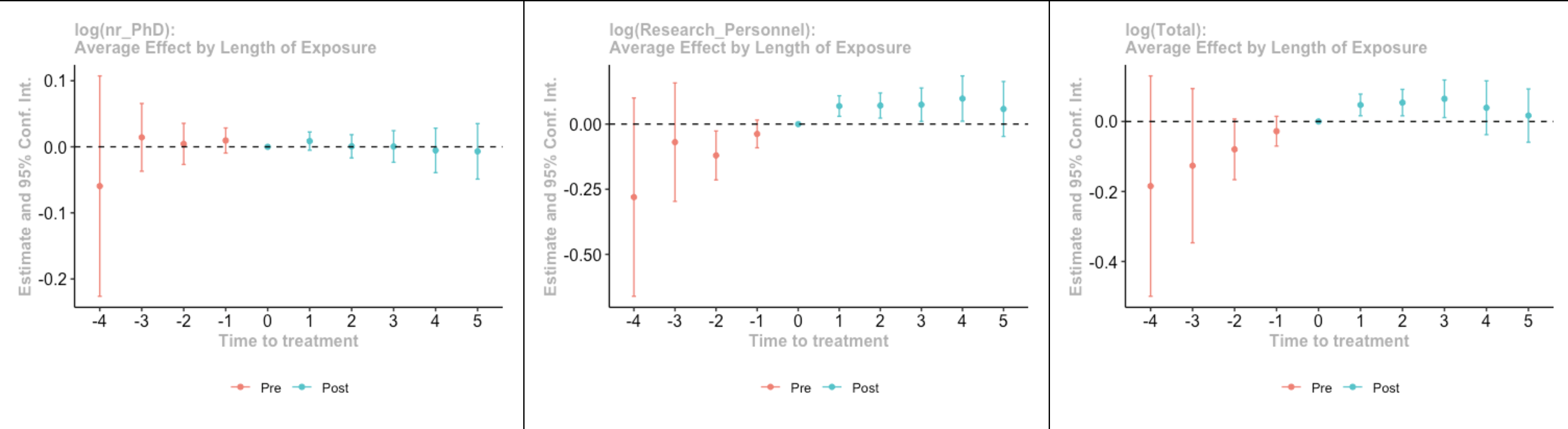
Table 5. Average treatment effect for R&D staff and total number of employees

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 favor 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 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), 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.

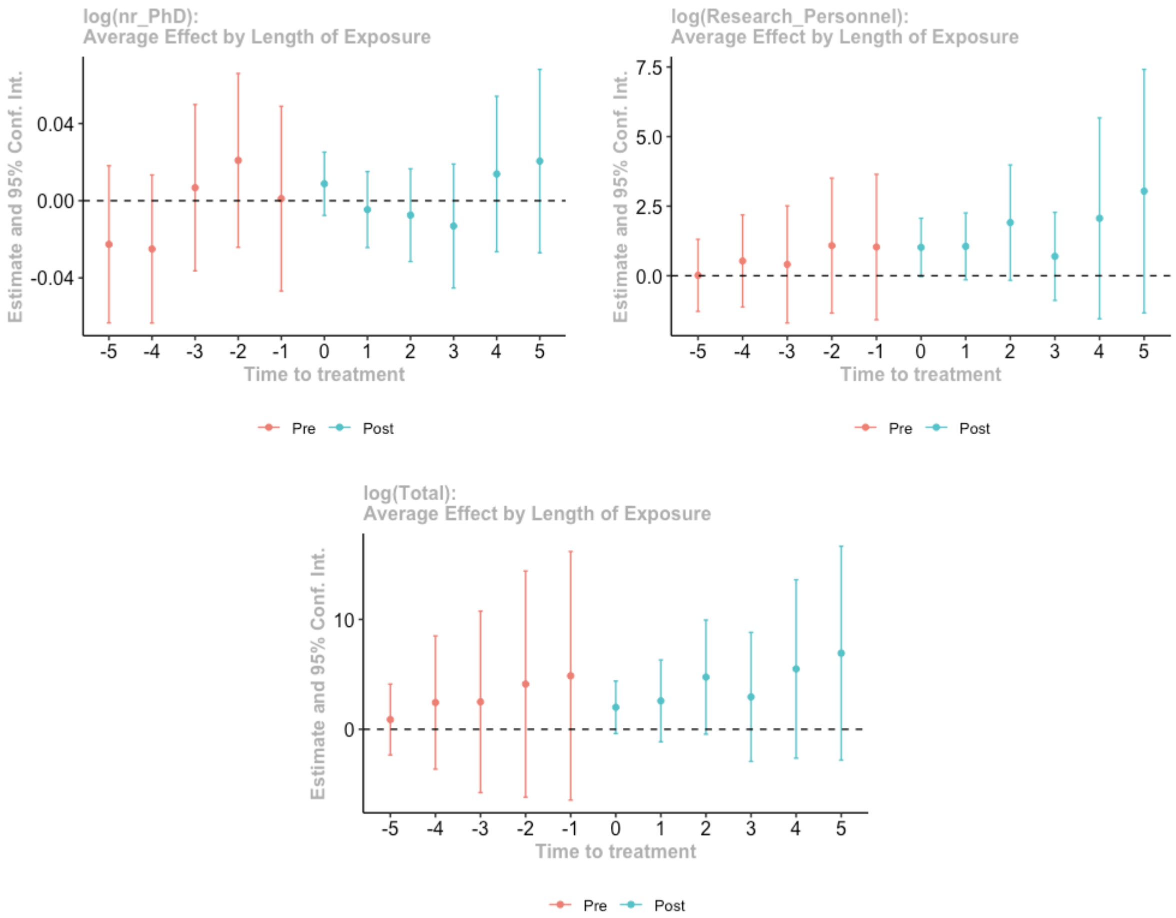


Figure 5. Event study plots: log(PhD); log(R&D staff); log(Total)

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 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 [64].

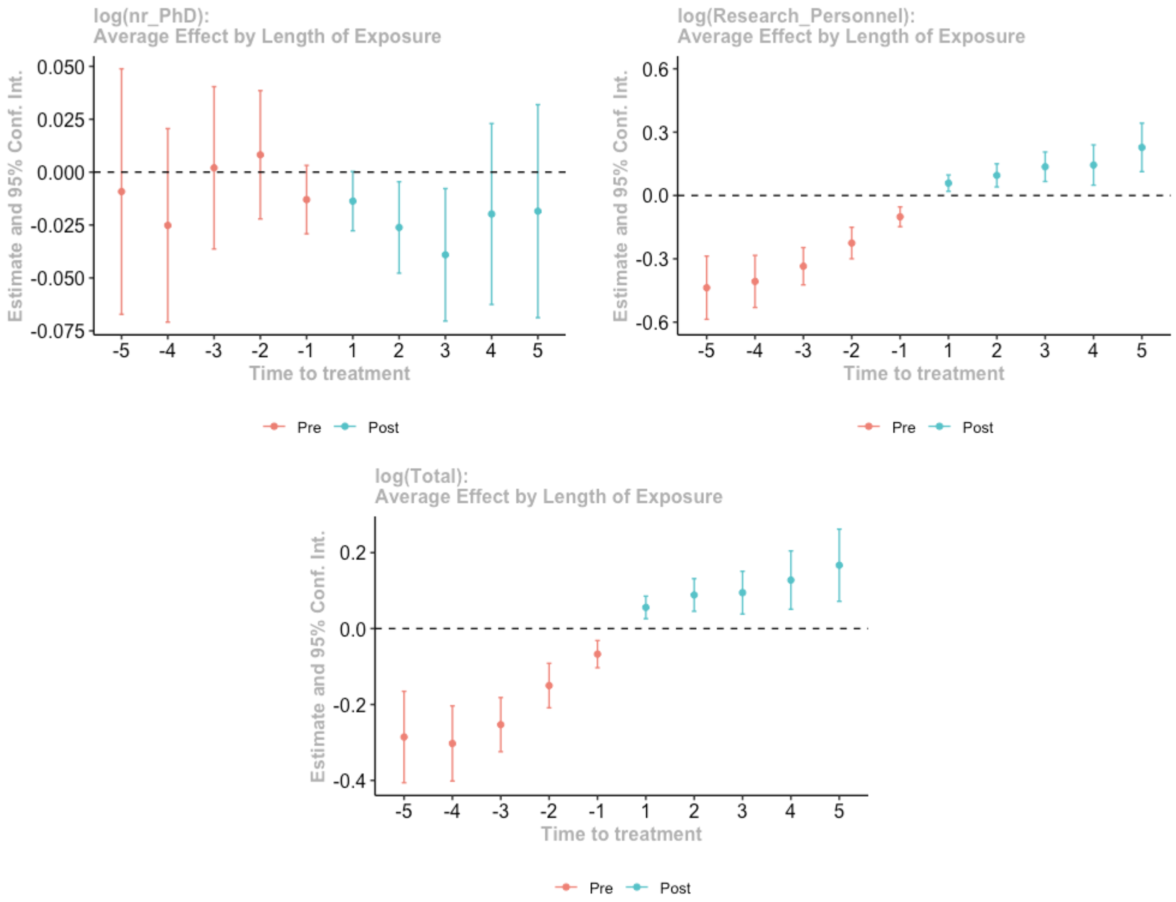


Figure 6. Event study plots: log(PhD) log(R&D staff) and log(Total)

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 & Kunapatarawong [63], 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 [45]. 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.

4-2- Impact of the SIFIDE by Industry

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 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 6). Despite this positive impact on R&D staff, no significant influence was observed on the total employee number (Figure 7). These findings align with those of Evangelista & Savona [16], who demonstrated that public funding for R&D can have beneficial implications on employment, varying by industry sector.

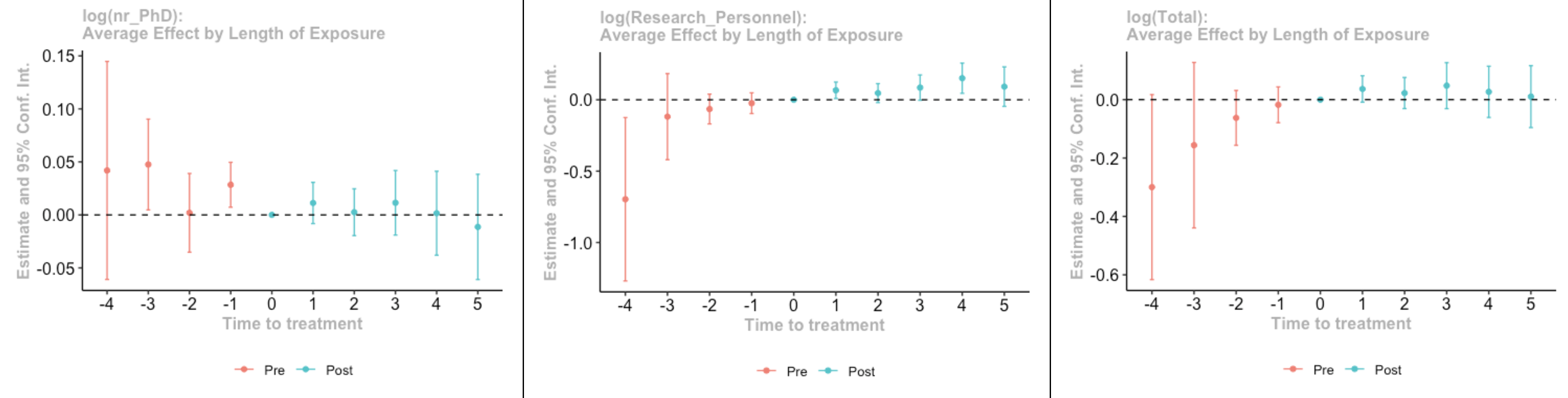
Table 6. Average treatment effect for R&D staff

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

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 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 7 and align with prior research [10], where the implementation of the SIFIDE tax incentive scheme in Portugal also demonstrated a favorable 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.

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

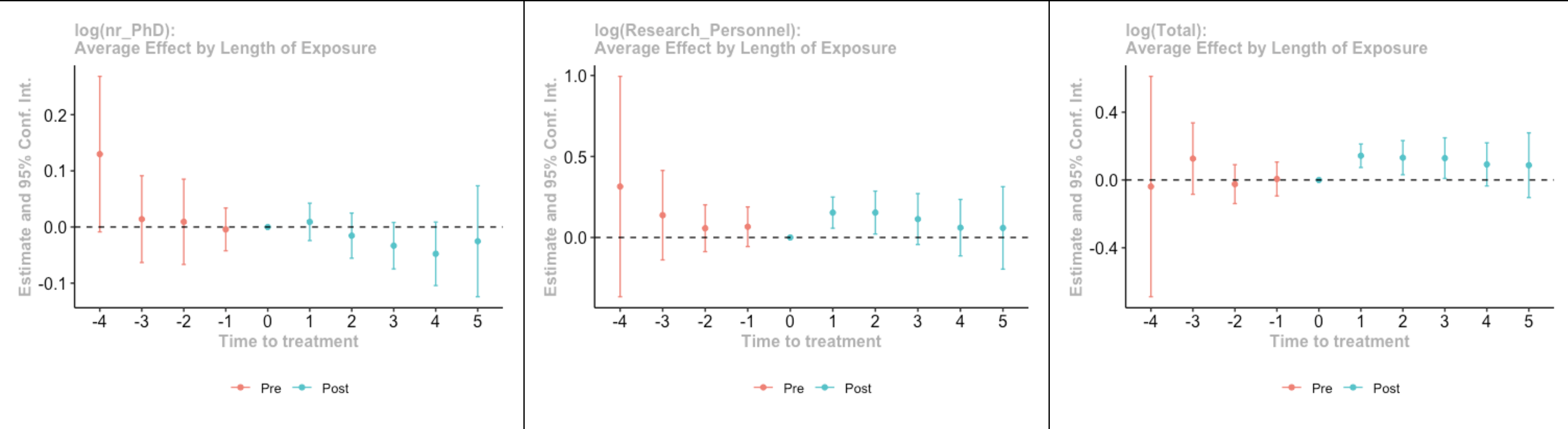
Figure 7. **Event study plot and estimates for log(PhD), log(R&D staff) and log(Total)**

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.

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



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)

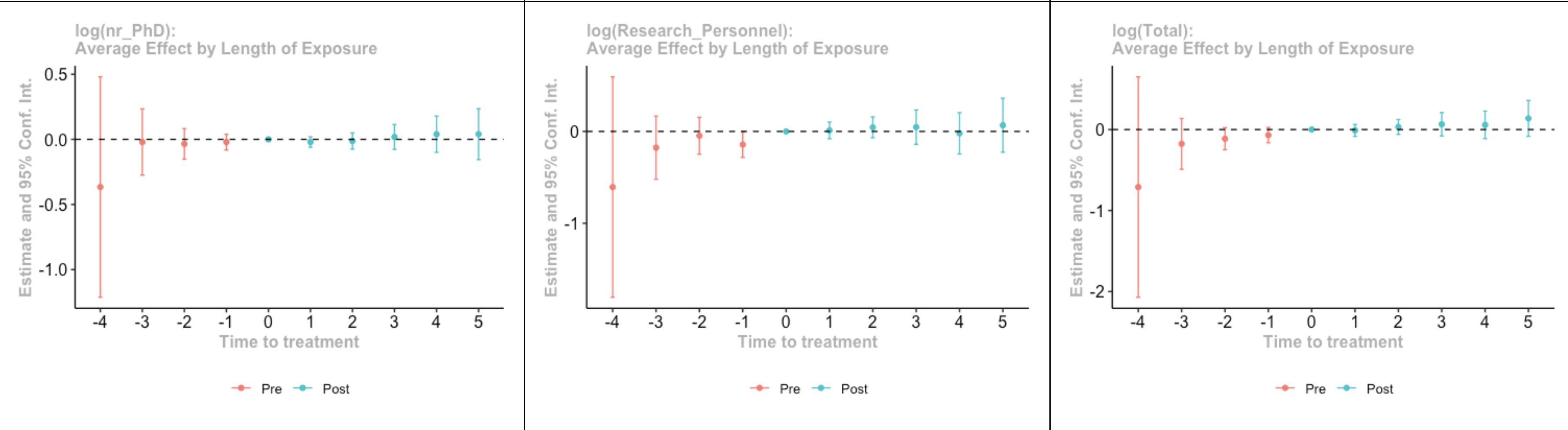
Event Time	Estimate	SE	LB CI	UB CI	N
-4	-0.03863	0.33175	-0.68885	0.61160	59
-3	0.12631	0.10753	-0.08445	0.33707	288
-2	-0.02437	0.05859	-0.13920	0.09045	788
-1	0.00600	0.05111	-0.09417	0.10616	1504
1	0.14307	0.03542	0.07365	0.21248	2446
2	0.13168	0.05150	0.03075	0.23261	1933
3	0.12887	0.06118	0.00895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

Figure 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 & Vivarelli [14] 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 9) and wholesale and retail trade sectors (Figure 10).

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



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

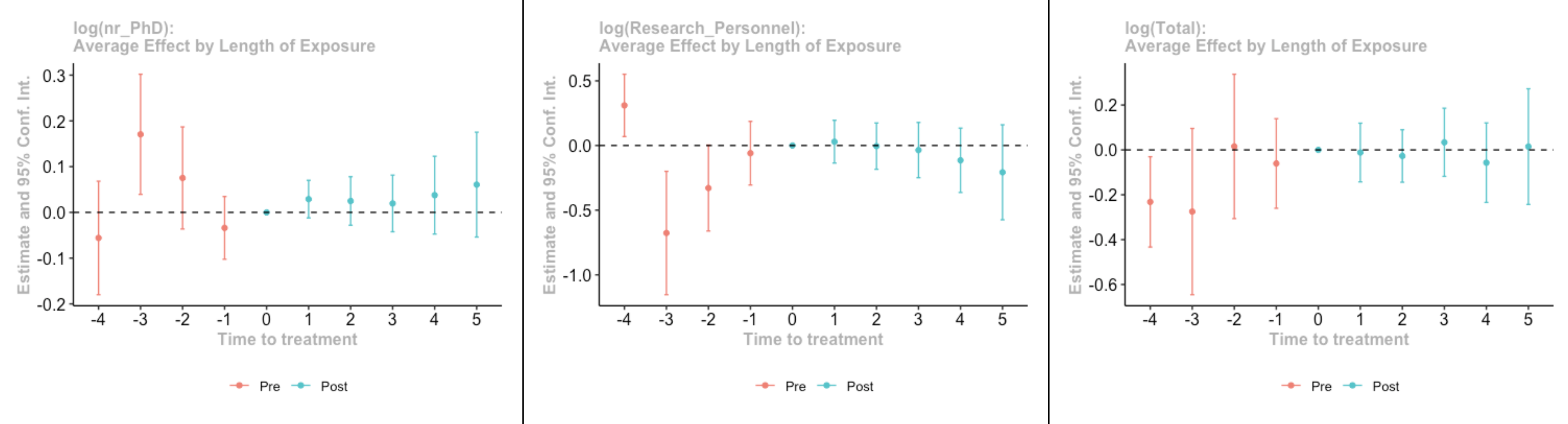
log(Total)

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 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 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.

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 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 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- 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 analyzed 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 & Kunapatarawong [63] reported a favorable effect of R&D&I tax credits on employment among Spanish MSMEs and SMEs. Lelarge [45] and Hallépée & Garcia [46] 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 & Kunapatarawong [63] 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.

6- Declarations

6-1- Author Contributions

Conceptualization, A.P. and B.D.; methodology, A.P., B.D., and C.V.; software, C.V.; validation, A.P. and B.D.; formal analysis, A.P. and B.D.; data curation, A.P.; writing—original draft preparation, A.P.; writing—review and editing, A.P., B.D., and C.V.; visualization, C.V.; supervision, A.P. and B.D.; project administration, A.P. and B.D.; funding acquisition, A.P., B.D., and C.V. All authors have read and agreed to the published version of the manuscript.

6-2- Data Availability Statement

The data used in this research are not publicly available due to confidentiality agreements and legal restrictions. Access to the data is governed by the Protocol established between the Direção-Geral de Estatísticas da Educação e Ciência (DGEEC), the Instituto Nacional de Estatística (INE), and the Fundação para a Ciência e Tecnologia (FCT). This Protocol provides a framework for researchers to access the data exclusively for scientific research purposes, in accordance with applicable regulations on data protection and statistical confidentiality. Researchers interested in accessing the data must obtain authorization and comply with the specific conditions outlined in the Protocol. For further information on how to request data access, please contact the relevant authorities.

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6-4- Acknowledgements

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6-5- Institutional Review Board Statement

Not applicable.

6-6- Informed Consent Statement

Not applicable.

6-7- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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