

Employment versus Efficiency: Which Firms should R&D Tax Credits Target?*

PROSPER

Universidade Católica Portuguesa

October 30, 2022

Abstract

R&D tax credits, by stimulating private sector innovation, can play a key role in promoting employment and firm performance. This paper examines the program impact on the trajectory of firms in terms of technology adoption, firm performance and workforce composition, and the extent to which it depends on the size of the targeted firms. It uses rich longitudinal micro-data on innovation, firms and their workers. Combining matching with a staggered adoption differences-in-differences, we show that tax credits increase investment in R&D-related activities while funds are being received, but not thereafter. Productivity and efficiency (but not employment) increase in large firms. These effects are driven by structural changes, both in terms of the increased share of skilled individuals within the firm (keeping the overall employment level constant), and enhanced technological adoption. In contrast, small firms mostly respond by increasing employment and production scale. Our results suggest that an important trade-off: R&D tax credit programs that target large firms are likely to lead to efficiency and productivity gains, but limited effects on employment of supported firms. In contrast, R&D tax credit programs that mostly benefit small firms may lead to employment gains in supported firms, but limited effects on structural changes in productivity and efficiency.

Keywords: Research and Development, Product Innovation, Process Innovation, Portugal

*anna.bernard@ucp.pt. We thank the Portuguese Institute of Statistics (INE) for data access. We remain responsible for any errors. We thank POAT for financial support.

Contents

1	Introduction	4
2	Institutional details and data	7
2.1	SIFIDE	7
2.2	Data	7
2.3	Descriptive statistics	8
3	Empirical strategy	10
3.1	Matching Firms	10
3.2	Empirical model	11
4	Main results	12
4.1	Effects on R&D: new innovators or more innovation?	12
4.2	Impact on firms' performance	17
4.3	Heterogeneous Effects by Firms Size	20
4.4	Robustness checks	22
4.5	Placebo test	23
5	Mechanisms	23
5.1	Adjusting the skill use towards skilled workers	23
5.2	Adjusting the production function	25
6	Conclusion	26
A	Appendix	30

List of Tables

1	Descriptive Statistics, 2004-2019	9
2	Effect of the R&D Tax Credits on R&D Activity	13
3	Effect of the Tax Credits Program on R&D Activity at the Extensive Margin	15
4	Dynamic Effects of R&D Tax Credits on R&D Activity	16
5	Impact of R&D Tax Credits on Product Variety and Scale	18
6	Effect of R&D Tax Credits on Productivity and Cost Efficiency	19
7	Impact of R&D Tax Credits by Firm Size	21
8	Impact of R&D of Tax Credits on Unskilled Workers, by Firm Size	22
9	Impact of R&D Tax Credits on Skill Use	24
10	Skill Bias and Technological Change	26
A1	Balance	30

A2	Logit Estimation for Propensity Score Estimation	31
A3	Effect of R&D Tax Credit Program on Selected Variables, using PSM 1-5	31
A4	Placebo on R&D Investment One Year Prior to Participation	32

List of Figures

1	SMD for the matched and unmatched sample	10
---	--	----

1 Introduction

Private sector innovation is a key engine of economic growth. As such, governments have allocated funds to incentivize such investments through various programs and plans. Although there is a vast literature on the relationship between incentive programs and R&D¹, there is still a dearth of evidence on how these incentives impact employment, firm performance and whether they lead to persistent structural changes among beneficiary firms (Köhler et al., 2012; Mitchell et al., 2020). Yet, such knowledge is crucial for understanding the medium to long-run effects of the policy and to obtain a clearer picture of the benefits and costs of R&D programs for policymakers. Do R&D incentives really push firms to engage in innovation? Do supported firms outperform their peers? Do such programs lead to structural changes in terms of the skill composition of the workforce and enhanced technological adoption? Which firms should these programs target for maximum impact on employment?

This paper estimates the effect of R&D incentives in the form of tax credits on the trajectory of firms, not only in terms of R&D, but also in terms of scale, productivity, workforce composition and technological adoption. We leverage Portuguese data on the SIFIDE tax credits scheme, combined with rich longitudinal data on innovation, employment, and performance at the firm-level. The SIFIDE program is an R&D tax credits program enacted by the Portuguese government that allows firms to recover a share of their R&D investment in the form of tax credits. The scheme allows firms to receive an initial 32.5% of their R&D spending as tax credits, with an additional rate for R&D spending above the prior two years average (Basto et al., 2021). We estimate the causal effects of the R&D tax credits scheme by leveraging matching techniques coupled with a staggered adoption differences-in-differences setting.

We assess the causal effects of the SIFIDE R&D tax credits scheme on firms strategies. First, we examine whether firms respond by increasing R&D investments. Leveraging data on investments in R&D-related activities at the firm level, we show that R&D tax credits have significant effects on the R&D activity of supported firms. Yet, this effect is mostly driven by the extensive margin, with firms that were not previously investing in R&D starting to do so. As such, the program pushes firms to overcome the initial barriers to engage in R&D. Yet, using an event study specification, we show that the effects, although strong, tend to be mostly concentrated while the firms are being supported by the funds and not thereafter. Such finding has implications on the fiscal sustainability of the program and raises questions on the ability of the R&D tax credits scheme to generate long-run incentives to innovate.

We then assess whether the use of R&D tax credits concretely translates into better firm performance and innovation. Evidence on the effects of these incentives on outcomes

¹See, for instance, Mitchell et al. (2020); Gaillard-Ladinska et al. (2019), for a meta-analysis.

such as scale and efficiency is sparse ([Köhler et al., 2012](#); [Mitchell et al., 2020](#)). This lack of evidence is mostly driven by the difficulty of finding linked microdata which would allow to follow firms for a variety of different performance metrics. We bridge this gap by linking five longitudinal datasets on a variety of performance outcomes. We show that firms that received the tax credits benefited in terms of increased product variety, scale and efficiency. However, these results are heterogeneous depending on firm size: large firms tend to see relatively stronger efficiency gains, keeping the overall employment levels, while small firms tend to witness relatively stronger scale and employment effects.

Finally, we examine whether firms that received the R&D tax credits exhibit structural changes in terms of the skill composition of the workforce and technological adoption. It has been argued that the knowledge generated through R&D is associated with an increase in the relative demand for qualified workers ([Toner, 2011](#)). Several papers provide theoretical micro-foundations for such trend ([Acemoglu, 2003](#)), and some studies leverage macro data to examine patterns of skill demand ([Card and DiNardo, 2002](#)). By contrast to these studies, we explore the effect of R&D tax credits on skill use using micro-level employer-employee data. We document an increase in the share of individuals with at least a bachelor’s degree in the firms that received the R&D tax credits. In addition, we document an increase in the probability of firms having a Master’s and/or PhD in the workforce. Although there are many reasons that may explain such results, it can be argued that the adoption of new technologies provides an important explanation for the increased expertise and human capital in the firm. Leveraging the Inquérito à Utilização de Tecnologias da Informação e da Comunicação dataset, an exclusive Portuguese dataset which contains detailed information on firm-level technological adoption, we report increased adoption of new, automated technologies by firms supported by the R&D program, which reinforces the hypothesis of complementarity between skill and technology ([Toner, 2011](#)). Such results also showcase the fact that R&D tax credits may lead to more structural, persistent changes within the firms supported by the program.

This paper relates to various strands in the literature. First, it relates to the large body of literature on impact assessments of R&D tax credits. Given the vast amount of literature on the topic, several meta-analyses show a positive effect of R&D tax credits on R&D investments ([Blandinieres and Steinbrenner, 2021](#); [Gaillard-Ladinska et al., 2019](#); [Köhler et al., 2012](#)). Although the exact effectiveness of R&D incentives depends on the structure and rules governing each program, recent papers provide quasi-experimental evidence to extract the causal effect of tax credits on R&D ([Blandinieres and Steinbrenner, 2021](#)). For example, [Guceri and Liu \(2019\)](#) exploit reforms in the UK in order to pin down the response of R&D investments to changes in tax credits, through a differences-in-differences setting. The authors find evidence that the R&D investments

undertaken by firms more than offset the revenue loss generated by tax credits for the government. Although our study also confirms the strong relationship between incentives and R&D, we distinguish ourselves by bridging the gap between direct, short-run and structural, persistent effects of the policy. This is only possible given the availability, in Portugal, of several, mergeable datasets which allow us to assess the effects of tax credits on a wide array of performance outcomes. To our knowledge, given this limitation, most studies are still heavily focused on the direct relationship between tax credits and R&D.

Second, this paper contributes to the growing body of research that relates R&D to skill-biased technological change (SBTC). We follow and verify closely recent studies that leveraged panel data to examine SBTC at the firm level. For instance, [Aghion et al. \(2017\)](#) leverages UK employer-employee matched data to establish the relationship between R&D intensity, wage premia and the skill level of employees. [Bøler et al. \(2015\)](#), on the other hand, leverages an R&D program in Norway to establish changes in the relative composition of the workforce while [Lindner et al. \(2021\)](#) use Hungarian data on innovation and workers to pin down the effect of different types of innovation on wage premia and skill use at the firm level. Our work is perhaps most closely related to [Bøler et al. \(2015\)](#), as we also leverage an R&D tax credits scheme in order to estimate the effects of such policy on the skill composition of the workforce. Yet, we distinguish itself by leveraging a unique Portuguese dataset on firm-level technology. This paper, therefore, provides additional evidence on the relationship between skill use and technological change by assessing technological adoption as a channel through which firms become more skill intensive. To our knowledge, the availability of such data is relatively rare.

Finally, this paper contributes to the literature on policy evaluation of long-term effects of tax credits on firm performance and its drivers. Previous evaluations of the SIFIDE and similar programs have focused on short-run effects on R&D investments. [Simões \(2019\)](#) and [Basto et al. \(2021\)](#) show that it generates strong effects on R&D investments in the short-run. Yet, they do not exploit the effects of the program beyond R&D investments. In this study, we emphasize the effects of the program beyond the traditional interplay between incentives and R&D, exploring scale and productivity effects on supported firms. In addition, in contrast to these two studies, this paper explores the possibility of the program generating persistent and structural effects within the treated firms, stressing the role of skill and technology, rather than putting emphasis on the impact effects of the tax credits.

The remainder of the paper is organized as follows. Section 2 describes the institutional details, the data sources and the descriptive statistics of the sample considered. Section 3 provides details on the matching methods and the empirical strategy. Section 4 presents the main results on the effect of the SIFIDE program on R&D investments, firms' performance and displays the differential effects by firm size. Section 5 discusses the

mechanisms at play in terms of workers composition and adoption of technology. Section 6 concludes.

2 Institutional details and data

2.1 SIFIDE

In Portugal, the Sistema de Incentivos Fiscais à I&D Empresarial (SIFIDE), initiated in 1997, is one of the most generous tax credit systems among OECD countries. It was first available from 1997 to 2004, being subsequently interrupted until 2006. A new program was implemented in 2006, providing more generous tax credit by raising the base rates (from 8% to currently 32.5% of the firms R&D eligible expenses) and broadening the spectrum of eligible expenses. This paper focuses on the effect of the new program, using data from 2006.

2.2 Data

The analysis in this paper draws on five main datasets.

A. SIFIDE The SIFIDE dataset contains information on the firms that participated in the program from 2006 up to 2019. Given that SIFIDE was initiated in 2006, the dataset covers the entire lifespan of the program. For every year, the dataset contains information on the firms that participated and received support through the R&D tax credits. It also includes information on firms that were denied such support. This dataset is at the core of our analysis, as it allows us to identify firms that participated to the program (as part of our “treatment” group) and therefore, allows us to identify firms that never participated to the program (which will act as possible candidates in the control group as we will detail later).

B. Sistema de Contas Integradas das Empresas (SCIE) SCIE is a dataset that contains yearly information on firm-level accounting, such as sales, profits, number of employees, value added, etc. from 2004 to 2019. This dataset contains information on R&D-related activities undertaken by firms through the investment in immaterial assets made by the firms each year. We follow [Basto et al. \(2021\)](#) and employ this variable as a proxy for R&D activity. The investment in immaterial assets consists of different components, including spending made in development projects, investment in IT and investment in intellectual property, such as patents, to protect the knowledge generated by the R&D process (INE, 2012). This variable tracks very closely firms’ R&D efforts, as any change in R&D would have a significant effect on the three components listed above.

Therefore, we use this variable as a proxy for the R&D activity and for simplicity, we label this variable, henceforth, as “Investment in R&D-Related Activities” or simply “R&D”. In addition, we leverage the data available in SCIE to compute different productivity metrics. Information on how these metrics were built is available in the Appendix.

C. Quadro de Pessoal (QP) Quadro de Pessoal is an employer-employee matched dataset that provides longitudinal information regarding all employees of each firm in Portugal with more than one employee, every year. It provides information on the qualifications of each employee, their tenure and experience, their educational attainment as well as data on the hours worked and wages paid to each employee. We use QP data from 2004 to 2019. This dataset will be especially important in order to understand the effect of the R&D program on the workforce composition of the firm, distinguishing skilled and unskilled workers.

D. Comércio Internacional Comércio Internacional is a dataset that contains information on export transactions undertaken by Portuguese exporting firms. In addition to providing information on firms’ exporting status and destinations, the dataset contains information on the number of product varieties that are exported by Portuguese firms abroad. This variable, as we will see later, will be important in order to cater information on the effect of R&D tax credits on firm product lines. The dataset contains firm-level data from 2004 to 2018.

E. Inquérito à Utilização de Tecnologias da Informação e da Comunicação (IUTICE) IUTICE dataset is a firm-level panel dataset which provides detailed information on the adoption of technologies by Portuguese firms. By contrast to the datasets above, this dataset is a survey and therefore only contains information on a sample of firms. Nevertheless, this dataset will be used in the analysis in order to examine the effect of the R&D tax credits on new technological adoption. The dataset is mergeable with all the previous ones and spans from 2004 to 2019.

2.3 Descriptive statistics

Table 1 presents some descriptive statistics on the observations in the estimation sample. We provide the descriptive statistics for (1) firms that received the tax credits and for (2) firms that never benefited from R&D tax credits. The most striking aspect, when comparing both groups, is the significant amount of heterogeneity in terms of observable covariates. As highlighted in Table 1, firms that benefited from the R&D incentives scheme exhibit larger scale, as shown by the significant differences in the (log) sales and employment. In addition, these firms tend to be much more productive (as shown by

total factor productivity (TFP), valued added per worker and sales per worker). Finally, we also witness large differences in terms of investment in innovation, as represented by the important gap in R&D between both groups. The length of exposure to the R&D program is relatively long: firms, on average, participated for a duration of 5 years in the program. Overall, the significant heterogeneity between both groups of firms illustrates the fact that both groups are very likely to have different trajectories in terms of the selected covariates shown in Table 1.

Table 1: Descriptive Statistics, 2004-2019

	Received the R&D Tax Credits (1)	Did Not Receive the R&D Tax Credits (2)	T-Statistic (2)-(1) [P-Value] (3)
Sales (log)	15.644 (2.117)	12.242 (2.010)	-271.790 [0.000]
Employment (log)	4.012 (1.466)	1.619 (1.014)	-376.979 [0.000]
R&D (log)	5.171 (5.387)	0.872 (2.333)	-289.657 [0.000]
TFP (log)	8.337 (2.121)	7.477 (2.278)	-60.570 [0.000]
Value Added per Worker (log)	10.320 (1.480)	9.058 (2.305)	-88.239 [0.000]
Sales per Worker (log)	11.639 (1.197)	10.631 (1.558)	-104.086 [0.000]
Sales Growth	0.069 (0.698)	0.012 (1.020)	-8.573 [0.000]
Firm Age	23.820 (18.809)	15.073 (13.248)	-105.504 [0.000]
Share of Firms in the Manufacturing Sector	0.605	0.154	-199.669 [0.000]
Average Length of Exposure to the Program (Years)	5.031 (3.710)	-	
Observations	26,073	2,511,570	

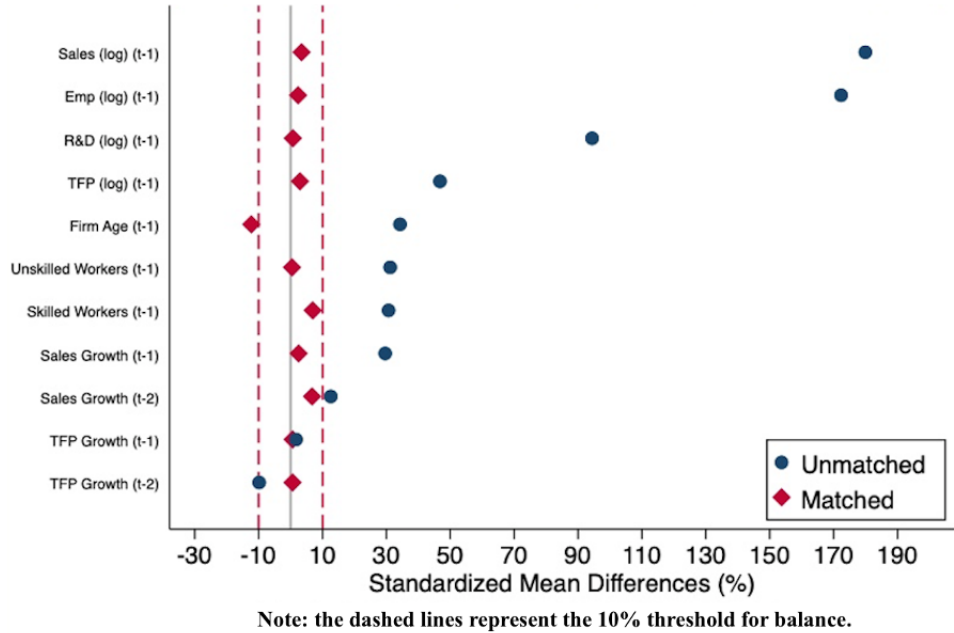
This table compares descriptive statistics. Columns (1) and (2) report the mean and standard deviation (in parenthesis) for firms that participated in the program between 2006 and 2019 and firms that did not participated in the program at all. Columns (3) shows the t-statistic and the p-value for the difference in means between columns (1) and (2).

3 Empirical strategy

3.1 Matching Firms

Firms that participate in the SIFIDE program show substantial differences in observable characteristics compared with firms that do not, as illustrated in Table 1. Observed differences between the two groups of firms are thus partly explained by these differences. To bypass this endogeneity issue, we follow Bastos et al. (2018) and use matching techniques to create a control group that would act as a suitable counterfactual to firms that received the tax credits. We use one-to-one distance matching² with replacement and match one year prior to participation on sales, employment, factor productivity, investment in R&D-related activities (log). Firms are also matched on the growth of sales and productivity, to ensure that the firms were on the same growth trajectory prior to support. Finally, the matching is conducted by year and industry. More than 1455 beneficiary firms and 1230 control firms were chosen as part of the matched sample. To illustrate covariate balance, Figure 1 shows the standardized mean differences (SMD) for a variety of observables.³ The SMD is the most important metric to evaluate matching quality (Ho et al., 2007).

Figure 1: SMD for the matched and unmatched sample



As shown above, the matching managed to reduce a significant amount of observable

²The choice of the matching technique, whether mahalanobis (MDM), propensity score (PSM) or exact matching depends on two factors: first, the sample size obtained and second, the bias reduction achieved. We opted for MDM matching as it provided us with a very similar sample size to PSM, but with better balance. However, the results are robust to the use of other forms of matching.

³Details about the balance can be found in the Appendix.

heterogeneity in the matched sample. The bias reduction is especially substantial for the log of sales, employment, factor productivity and R&D, where the standardized mean differences are very close to 0 for the matched sample. In addition, the SMD of the growth variables are below the threshold of 0.10. This not only ensures that our control group is very similar to the treatment group in terms of the main observable characteristics, but that the trajectory of the control group and treatment group prior to participation are very similar, reinforcing the likelihood of the parallel trend assumption.

3.2 Empirical model

Following [Bastos et al. \(2018\)](#), we use the matched groups and estimate the following two-way fixed effects model:

$$y_{it} = \alpha_i + \delta_t + \beta_1 D_{it} + \epsilon_{it} \quad (1)$$

Where y_{it} is the outcome of interest, α_i are firm fixed effects, δ_t are year effects, D_{it} is a dummy equal to 1 from the moment the firms receive the tax credits onward and 0 otherwise and ϵ_{it} is an error term; α_i captures observed and unobserved heterogeneity at the firm-level that is time invariant while δ_t captures the effect of shocks common to both the treatment and control groups across time. Equation (1) is a differences-in-differences that traces the evolution of the trajectory of the firms that benefited from the tax credits scheme from the moment the firms first collect the R&D tax credits onward, using the evolution of the control group as a counterfactual. If the parallel trend assumption holds (which is much more likely due to matching), the coefficient β_1 provides the causal effect of the incentives scheme on the outcome of interest.

Although specification (1) is our main model, it is important to note that not all firms participate equally in the program: some firms have longer exposure to the program than others. We exploit these differences in length of exposure (in years) as a measure of treatment effect heterogeneity. Hence, we also estimate equation (2):

$$y_{it} = \alpha_i + \delta_t + \beta_1 D_{it} \times Length_i + \epsilon_{it} \quad (2)$$

where $Length_i$ is a measure of the length of time the firm was exposed to the program (in years). This specification assumes that firms with lengthier exposure to the program may see more intense effects on the trajectory of the outcome of interest. The coefficient β_2 provides us the effect of an additional year of exposure to the incentives scheme on the outcome of interest. In a sense, specification (1) provides us with the average causal effect of the program on firms for an average participation length while specification (2) normalizes the effect to the length of exposure. We test the robustness of the results from specifications (1) and (2) by adding sector dummies as well as sector linear trends

to the specifications. Sector dummies capture additional heterogeneity at the sector level, while sector time trends control for different trajectories of the sectors on the outcomes of interest. In our estimation, standard errors are clustered at the firm level.

4 Main results

4.1 Effects on R&D: new innovators or more innovation?

More innovation? The Effect on Intensive margins Are firms benefiting from the R&D tax credits investing more in R&D related activities? We first examine the effect of the R&D incentives scheme on the research and development activity of the firms supported by the program (the intensive margins). We estimate equations (1) and (2) using the log investments in R&D-related activities as the outcome variable (the intensive margin). Results are shown in Table 2.

As illustrated in panel A, the R&D tax credits program has statistically significant and material effects on the R&D investments for participating firms (columns 1 and 2): we estimate that firms that participate in the scheme saw an increase in their internal R&D activity of more than 94%. In addition, we observe that the effect is increasing in the length of exposure to the program (columns 3 and 4): we estimate that for every additional year of participation, the incremental effect of the program on R&D investments is around 16%. This confirms the hypothesis that firms that are participating for lengthier periods tend to witness stronger effects, on average. As the tax credits reduce the marginal cost of investing in R&D, it incentivizes firms to engage in more R&D.

Note that the coefficients obtained in panel A are obtained from the estimation of the pooled sample, regardless of firms' innovative activity prior to participation. Therefore, the coefficients obtained tend to conflate both an extensive margin effect, that is, firms that never invested in R&D prior to participation and that, because of the program, decided to do so, as well as an intensive margin effect, that is, firms that already invested in R&D prior to participation and that, because of the program, decided to invest even more. Since we are using the log of the dependant variable, a strong effect at the extensive margin would lead to inflated coefficients, as a firm that never invested in R&D beforehand that starts to invest in R&D would see a very strong increase in relative terms. This may be why the coefficients in panel A are very large. To verify this hypothesis, we follow Bøler et al. (2015) and extract the extensive margin by removing, from the treated group, firms with a null average of R&D investment prior to participation. We re-estimate equations (1) and (2) using the adjusted sample. As illustrated in panel C, once we remove the extensive effect margin, the effect of the program on R&D investment drops to around 32%. This tells us that a significant share of the effect is driven by treated firms with no prior investment in R&D that decided to opt in the program.

Table 2: Effect of the R&D Tax Credits on R&D Activity

Dependent Variable	Investment in R&D-Related Activities (log)			
	(1)	(2)	(3)	(4)
Panel A: Pooled Estimate from Matched Sample				
Treatment	0.944*** (0.132)	0.949*** (0.132)		
Treatment \times length			0.158*** (0.022)	0.159*** (0.022)
Observations	35,772	35,772	35,772	35,772
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES
Panel B: Firms that never engaged in R&D prior to participation				
Treatment	2.586*** (0.207)	2.608*** (0.204)		
Treatment \times length			0.523*** (0.038)	0.520*** (0.038)
Observations	21,214	21,214	21,214	21,214
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES
Panel C: Firms that engaged in R&D prior to participation				
Treatment	0.323** (0.151)	0.312** (0.151)		
Treatment \times length			0.066*** (0.023)	0.065*** (0.024)
Observations	30,337	30,337	30,337	30,337
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

This table reports the effect of R&D tax credits on investments in R&D related activities. Column (1) reports the unconditional impact of enrolling in the program, column (2) includes sector fixed effects and trend; column (3) reports the unconditional impact of the length of exposure to the program and column (4) includes sector fixed effects and trend. Clustered standard errors are reported in parenthesis. .

More innovators? The Effect on Extensive Margins As shown by the magnitude of the coefficients in panel B of Table 2, we witness a very strong effect at the extensive margin, where firms that previously never invested in R&D started to do so after the program. Yet, the coefficients in panel B of the previous table cannot be interpreted in any straightforward way, as we cannot realistically compute a relative percentage change in R&D investments from firms that never invested in R&D prior to participation. In order to obtain a more intuitive interpretation of the effect of the program at the extensive

margin, we estimate a linear probability model (LPM) where the dependant variable is:

$$Innovation_{it} = \begin{cases} 0 & \text{if } R\&D_{it} = 0 \\ 1 & \text{if } R\&D_{it} > 0 \end{cases}$$

Results of the estimation of this model are shown in Table 3. As illustrated in panel B, the effect of the tax credits program on the probability of investing in R&D is statistically significant and very strong for firms that never undertook R&D prior to the program: it is estimated that, on average and *ceteris paribus*, the program yields an increase in the probability of investing in R&D of 26.9 percentage points. For firms that already invested in R&D prior to the program (columns 1 and 2 of panel C), the effect at the extensive margin is null. This is consistent with the idea that firms that already invested in R&D prior to participation to the program changed the intensity of their investment at the intensive margin, as shown in panel C of the previous Table 2.

Overall, R&D tax credits have strong effects on the investment decision in R&D of firms, both at the intensive margin as illustrated previously, but most importantly, at the extensive margin: the program leads to the creation of “new innovators”, that is, firms that because of the program first started to engage in R&D and in innovation. This is a positive aspect of the program, as it does not only cater to firms that already were acquainted with R&D.

Dynamic Effects of the Program Is the effect of the program on R&D continuous over time? Or is the effect only strong while the firms are supported? These questions are crucial to examine the long-term effects of the program: is the program able to generate long-term independent innovators that do not depend on financial support to engage in R&D? To answer these questions, we only consider, in our treatment group, firms with a length of exposure to the program of two years or less. The reason behind this choice is that in order to trace the dynamic paths of firms across periods and examine the persistence of the program on R&D, we need firms that have sufficient periods without direct support from tax credits in order to follow their behavior over time. In addition, we employ a dynamic two-way fixed effects model in order to trace the path of R&D investment from the moment the firm receives the tax credits up to seven years later. This is different from the previous section where we employed a static differences-in-differences that simply averages out the effect of tax credits from the moment the firm successfully participates onward. Using the sample of supported firms with 2 years of exposure and less, alongside with the control group, we run the following event-study design (following [Borusyak and Jaravel \(2017\)](#)):

Table 3: Effect of the Tax Credits Program on R&D Activity at the Extensive Margin

Dependent Variable	Investment Choice in R&D-Related Activities (0/1)			
	(1)	(2)	(3)	(4)
Panel A: Pooled Estimate from Matched Sample				
Treatment	0.082*** (0.013)	0.084*** (0.013)		
Treatment \times length			0.016*** (0.002)	0.016*** (0.002)
Observations	35,772	35,772	35,772	35,772
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES
Panel B: Firms that never engaged in R&D prior to participation				
Treatment	0.269*** (0.021)	0.272*** (0.021)		
Treatment \times length			0.055*** (0.004)	0.055*** (0.004)
Observations	21,214	21,214	21,214	21,214
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES
Panel C: Firms that engaged in R&D prior to participation				
Treatment	0.01 (0.015)	0.009 (0.015)		
Treatment \times length			0.006*** (0.002)	0.006** (0.002)
Observations	30,337	30,337	30,337	30,337
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

This table reports the effect of R&D tax credits on the decision to invest in R&D related activities. Column (1) reports the unconditional impact of enrolling in the program, column (2) includes sector fixed effects and trend; column (3) reports the unconditional impact of the length of exposure to the program and column (4) includes sector fixed effects and trend. Clustered standard errors are reported in parenthesis.

$$y_{it} = \alpha_i + \delta_t + \sum_{k=0}^7 \beta_k \mathbb{1}\{K_{it} = k\} \times T_{it} + \varepsilon_{it} \quad (3)$$

where α_i are firm fixed effects, δ_t are year effects, K_{it} is a variable defining the relative time-to-treatment, T_{it} is a dummy equal to 1 if the firm is part of the treatment group and 0 otherwise, ε_{it} is an error term and k takes the values from 0 to 7. The coefficients β_k therefore trace the dynamic paths of the firms that benefited from the tax credits from the moment they participate up to seven years later. If the program generates long-term innovators, then the effect on R&D should be continuous over time. On the other hand, if the program only yields short-run results, the effects should rapidly decay. The results of this regression are reported in Table 4.

Table 4: Dynamic Effects of R&D Tax Credits on R&D Activity

Dependant variable	Investments in R&D-related activities	
	(1)	(2)
Initial Support	0.876*** (0.226)	0.862*** (0.226)
1 Year After	0.650*** (0.239)	0.657*** (0.24)
2 Years After	0.492* (0.253)	0.498** (0.253)
3 Years After	-0.007 (0.264)	-0.009 (0.264)
4 Years After	-0.065 (0.299)	-0.066 (0.299)
5 Years After	-0.182 (0.325)	-0.174 (0.324)
6 Years After	-0.243 (0.368)	-0.229 (0.365)
7 Years After	-0.353 (0.399)	-0.350 (0.398)
Observations	20,279	20,279
Sector FE	NO	YES
Sector Trend	NO	YES

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

This table reports the effect of R&D tax credits on the investment in R&D related activities up to 7 years after enrolling in the program. The sample includes firms with two years exposure or less. Columns (1) reports the unconditional impact, column (2) includes sector fixed effects and trend. Clustered standard errors are reported in parenthesis.

As shown in columns (1) and (2), the effect is very strong on impact, yet decays and becomes non-significant from the third year onward. This shows that the program

effects on R&D exhibit little persistency: the program does not push firms in a different trajectory in terms of their R&D activity in the long-run. Once firms are no longer participating in the program, they have no incentive to continue to invest in R&D as the program does not require them to continue to invest. If the goal of the program is to foster firms that are by nature more R&D intensive, then the program is not able to reach this objective as firms depend on the tax credits received to engage in R&D. A possible way to induce longer-term effects is to re-structure the program by requiring firms to invest in R&D post-participation for a minimum number of years: for instance, the firms applying to the program will be able to benefit from more generous tax credits for a duration of three years and then onwards, the firms are required to invest a minimum amount in R&D for another three years. Such rule would push firms to innovate even in the absence of direct support from the scheme. Yet, this is not without costs: such rule may disincentive firms to participate in the program early on while reducing flexibility.

4.2 Impact on firms' performance

Firm scale The expansion of the product line of supported firms, illustrated above, may be closely tied to the effect of the R&D incentives scheme on firm scale, such as sales and employment. Indeed, the development of new products would allow firms to scale-up their operations, which would have a direct effect on sales and employment. Therefore, we ask if the program led to an increase in the scale of operations of supported firms? In order to answer this question, we estimate equations (1) and (2) using (log) sales and employment as dependent variables. Results are presented in Table 5.

As shown in column (1), recipients of the tax credits exhibit a statistically significant increase in scale, as illustrated by the effect on sales and employment: we estimate that firms that were supported by the tax credits experienced a 26.1% increase in sales and a 19.5% increase in employment compared to the control group. In addition, the results are robust to the presence of sector fixed effects and time trends, as illustrated in column (2). Finally, the effect on scale seems to be increasing with additional length of exposure to the program (columns 3 and 4). It is also important to note that if the regression were run using the entire pool of firms that never benefited from R&D tax credits as the control group rather than the matched sample, the effect on sales and employment would have been 52.7% and 35.2% respectively. This shows that the matching effectively managed to remove substantial amount of heterogeneity, which would have significantly biased the results.

Productivity and Cost Efficiency Is the scale increase in firms that were supported by the program accompanied with productivity gains? Or did firms increase scale at the detriment of efficiency? To verify, we estimate equations (1) and (2) using three main

Table 5: Impact of R&D Tax Credits on Product Variety and Scale

Dependent Variable	Number of Different Products Exported			
	(1)	(2)	(3)	(4)
Treatment	3.402*** (0.886)	3.129*** (0.861)		
Treatment \times length			0.651*** (0.175)	0.675*** (0.176)
Observations	26,526	26,526	26,526	26,526
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES

Dependent variable	Sales (log)			
	(1)	(2)	(3)	(4)
Treatment	0.261*** (0.024)	0.252*** (0.022)		
Treatment \times length			0.04*** (0.004)	0.038*** (0.003)
Observations	35,772	35,772	35,772	35,772
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES

Dependent Variable	Employment (log)			
	(1)	(2)	(3)	(4)
Treatment	0.195*** (0.017)	0.184*** (0.016)		
Treatment \times length			0.026*** (0.003)	0.026*** (0.003)
Observations	35,772	35,772	35,772	35,772
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

This table reports the effect of R&D tax credits on the number of different products exported, the sales (in log), and the level of employment (in log). Columns (1) reports the unconditional impact of enrolling in the program, column (2) includes sector fixed effects and trend; column (3) reports the unconditional impact of the length of exposure to the program and column (4) includes sector fixed effects and trend. Clustered standard errors are reported in parenthesis.

productivity metrics: total factor productivity, value added per worker and finally, sales per worker. The detailed information on how these metrics were computed can be found in the Appendix. Results of the estimation can be found in Table 6.

As illustrated in Table 6, firms that were supported by the program saw an increase in the three productivity metrics compared to the counterfactual. In column (1), it is estimated that the effect of the R&D tax incentives program is an increase in factor productivity of 9.6%, an increase in value-added per worker of 10.4% and an increase in sales per worker of 6.4%, all of which are statistically significant. In addition, as

Table 6: Effect of R&D Tax Credits on Productivity and Cost Efficiency

Dependent Variable	Total Factor Productivity (log)			
	(1)	(2)	(3)	(4)
Treatment	0.096*** (0.022)	0.091*** (0.02)		
Treatment \times length			0.009*** (0.003)	0.011*** (0.003)
Observations	35,740	35,740	35,740	35,740
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES

Dependent Variable:	Value Added per Worker (log)			
	(1)	(2)	(3)	(4)
Treatment	0.104*** (0.023)	0.105*** (0.022)		
Treatment \times length			0.018*** (0.003)	0.017*** (0.003)
Observations	35,772	35,772	35,772	35,772
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES

Dependent Variable:	Sales per Worker (log)			
	(1)	(2)	(3)	(4)
Treatment	0.064*** (0.016)	0.066*** (0.015)		
Treatment \times length			0.013*** (0.002)	0.012*** (0.002)
Observations	35,772	35,772	35,772	35,772
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

This table reports the effect of R&D tax credits on the total factor productivity (in log), the value added per worker (in log), and the sales per worker (in log). Column (1) reports the unconditional impact of enrolling in the program, column (2) includes sector fixed effects and trend; column (3) reports the unconditional impact of the length of exposure to the program and column (4) includes sector fixed effects and trend. Clustered standard errors are reported in parenthesis.

illustrated in columns (3) and (4), the effect is increasing in length of exposure to the program. A possible hypothesis to explain such results is the fact that firms may have leveraged the tax credits to engage in process innovation. In fact, process innovation would have a direct effect on labour productivity, as new methods of production are leveraged and allow firms to use more efficiently its inputs to produce output.

One would expect that the increase in productivity would concretely materialize itself as cost reductions in the firm. Increases in productivity allow firms to lower the marginal cost of production. In order to assess the effect on cost efficiencies, we compute a return on sales (RoS) metric by taking the ratio of operating profit to the sales of the firm. This efficiency metric assesses the ability of the firm to control costs and generate profits from

sales. Any reduction in costs generated through improvements in productivity would therefore have a direct positive effect on such metric. We estimate equations (1) and (2) using the RoS as a dependent variable. As illustrated in Table 6, firms that participated in the program saw a 3.4 percentage points increase in their RoS, which possibly may be the result of cost efficiencies driven by process-based innovation.

4.3 Heterogeneous Effects by Firms Size

Although we witness strong scale and productivity effects for the supported firms overall, the previous results may hide significant amount of heterogeneity between firms. One focal question is whether large and small firms exhibit different effects based on differentiated usage of the R&D tax credits. Indeed, it has been argued that firms of different sizes may leverage the tax credits for different purposes, larger firms for efficiency while smaller firms for growth (Conti et al., 2020). In order to verify this hypothesis, we split our treatment and control sample in three groups: small firms (between 10 and 50 employees), medium-size firms (between 51 and 149) and large firms (> 150 employees). We assess the scale and efficiency effects of the program on these sub-groups.

In Table 7, we can clearly observe that small firms exhibit very strong scale effects, both on sales and on employment. Interestingly, large firms also observe a material effect on sales, however, the effect on employment is almost null and non-statistically significant. The difference between large and small firms on employment is already illustrative of differences in the use of the program by both groups of firms: while the effect on sales and employment on small firms is consistent with firm growth, large firms aim to produce more (sales) without increasing the use of inputs (employment), which highlights the fact that large firms may be more seeking to enhance efficiency rather than scale.

Looking at efficiency, even though small firms see a slight effect on value added per worker, we do not observe any effect on the return on sales for small firms. By contrast, large firms see a material effect both on value-added per worker and on returns on sales, both stronger than small firms. This is consistent with the idea that large firms may have leveraged the tax credits in order to create new processes that are more efficient and allow them to better control costs, which would have a direct positive effect on value-added and RoS. Small firms, on the other hand, seem to have concentrated relatively more their R&D effort in order to scale-up, rather than improve efficiency, as illustrated by the strong effects on scale (sales, employment) and the muted effects on efficiency.

To reinforce the idea that large firms leverage the tax credits relatively more for efficiency while small firms leverage them relatively more for scale, we take a closer look at the effects of the program on low skill occupation. Although process innovation can take a variety of different forms, the emergence of new processes allows firms to increase efficiency through automation of tasks that were previously done manually. In fact,

Table 7: Impact of R&D Tax Credits by Firm Size

Dependant Variables	Sales (log)		Employment (log)		Value Added per Worker (log)		RoS	
	(1)		(2)		(3)		(4)	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Small Firms (10 to 50 employees)								
Treatment	0.236*** (0.036)	0.223*** (0.036)	0.208*** (0.027)	0.199*** (0.026)	0.07** (0.033)	0.068** (0.034)	0.006 (0.013)	0.007 (0.013)
Observations	13,754	13,754	13,754	13,754	13,754	13,754	13,726	13,726
Sector FE	NO	YES	NO	YES	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES	NO	YES	NO	YES
Medium-size Firms (51 to 149 employees)								
Treatment	0.188*** (.039)	0.199*** (.038)	0.141*** (.031)	0.144*** (.029)	0.061* (.036)	0.07** (.035)	0.032*** (.009)	0.033*** (.009)
Observations	10529	10529	10529	10529	10529	10529	10487	10487
Sector FE	NO	YES	NO	YES	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES	NO	YES	NO	YES
Large Firms (> 150 employees)								
Treatment	0.184*** (0.055)	0.164*** (0.052)	0.041 (0.036)	0.027 (0.032)	0.112** (0.052)	0.115** (0.052)	0.054** (0.024)	0.055** (0.023)
Observations	7,075	7,075	7,075	7,075	7,075	7,075	7,049	7,049
Sector FE	NO	YES	NO	YES	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES	NO	YES	NO	YES

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

This table reports the effect of R&D tax credits on sales (in log), employment (in log), value added per worker (in log) and return on sales. Column (1) reports the unconditional impact of enrolling in the program, column (2) includes sector fixed effects and trend. Clustered standard errors are reported in parenthesis.

process innovations aimed to control costs may displace workers at the bottom of the organizational distribution, who used to undertake routine tasks that can be re-invented or simply replaced through new technologies (Peters, 2004). However, we would not expect to see these results in the case of product innovation, where firms often need to scale-up operations to satisfy the customers increased demand for new products (Peters, 2004; Vivarelli, 2015). Therefore, looking at unskilled workers may provide a reasonable intuition on the type of innovation undertaken by the firm. We define unskilled workers as workers in categories 8 and 9 in the Classificação Portuguesa das Profissões in QP. These categories include non-qualified workers such as machine operators, warehouse workers, etc. all of which undertake routine and basic tasks that can be easily replaced through new processes. We estimate the effect of the program on such workers, both for small and large firms. Results are illustrated in Table 8.

A striking result is the difference in signs of the point estimates obtained for small and large firms. Small firms supported by the program saw, on average, an increase of 15-16% in unqualified workers compared to their peers, while large firms saw a decline of 4-6% in such workers compared to their counterfactual peers, although the effect is not statistically significant. Such discrepancy between both groups highlights again differences in use of the R&D tax credits: consistent with the idea that large firms aim for efficiency, such firms do not have any incentive to grow the number of employees engaging in little value-added routine tasks, while the opposite is the case for small firms focused on growth and scale.

Table 8: Impact of R&D of Tax Credits on Unskilled Workers, by Firm Size

Dependent Variable	Number of Unskilled Workers (log)	
	(1)	(2)
Small Firms		
Treatment	0.160*** (0.036)	0.152*** (0.036)
Observations	13,754	13,754
Sector FE	NO	YES
Sector Trend	NO	YES
Large Firms		
Treatment	-0.048 (0.090)	-0.056 (0.085)
Observations	7,075	7,075
Sector FE	NO	YES
Sector Trend	NO	YES

Overall, the results obtained in this section seem to point towards differentiated uses of the R&D tax credits by large and small firms. However, it is important to note that product and process innovations are not mutually exclusive: firms can engage both in creating new product lines and building more efficient processes. This may explain why, for instance, large firms still see a sizeable effect on sales while small firms see an increase in value-added. We should therefore nuance our hypothesis and say that small and large firms may have leveraged the R&D tax credits both for product and process innovation, but in different proportions depending on their size.

4.4 Robustness checks

As a robustness test, each regression was re-estimated by including sector dummies (to capture time-invariant heterogeneity at the sector level) and sectorial trends (which allows different sectors to be on their own trajectory). The results are robust to the introduction of both sector fixed effects and time trends.

Finally, we adopted, in the main part of the paper, a multivariate matching technique using mahalanobis as our distance metric (Abadie and Imbens, 2016; King and Nielsen, 2019). We test the robustness of our results using propensity score matching. We include, in the logistic regression, similar variables as the ones chosen in the main part of the paper and we match 1-5 with replacement using nearest neighbor matching. Results on some selected variables are illustrated in the Appendix. Interestingly, the sign, significance

and magnitude of the results are very similar to the ones obtained using MDM matching, which showcases the quality of our empirical setting. In addition, the results are also robust to the timing of the matching (whether we match one year or two years prior to support from the program).

4.5 Placebo test

One crucial identifying assumption in this paper is the fact that the increase in R&D-related activities experienced in the supported firms was entirely due to the R&D tax credits. If this condition did not hold, the results could not be interpreted as causal effects of the program. In order to verify this crucial identifying assumption, we undertake a placebo test where compute the effect of the treatment on R&D investment one year prior to participation. Results are illustrated in the Appendix. Importantly, there is not statistically significant effect of the tax credits scheme on R&D investment the year prior participation, which reinforces the credibility of our empirical setting.

5 Mechanisms

5.1 Adjusting the skill use towards skilled workers

The main challenge we face is how to define skilled and unskilled workers in our analysis. We follow [Bøler et al. \(2015\)](#); [Lindner et al. \(2021\)](#) and define skilled workers as those with a bachelor’s degree and/or higher education. Workers without a bachelor’s degree or higher are therefore classified as unskilled. Alternatively, we could have also used occupational categories in order to define skill groups. However, one can argue that educational attainment proxies relatively well the relationship between education and occupations within the firm: individuals with college degrees or more are more likely to occupy higher positions in the hierarchy. We compute and use the share of skilled workers out of the total workforce and the share of wage bills paid to skilled workers out of the total wage bill as our dependent variables in equations (1) and (2). Results are illustrated in Table 9.

As shown in columns (1) and (2), we see a material and statistically significant effect on the share of skilled workers out of the total workforce and the share of wage bills paid to skilled workers out of the total wage bill. These effects amount to around 1.5 to 2 percentage points and are increasing in length of exposure to the program as shown in columns (3) and (4). These results are consistent with the hypothesis that the increase in R&D, caused by the R&D tax credits, led to an increase in the relative skill demand in participating firms. This change in the workforce composition of the firm, tilted towards more educated workers is illustrative of the relationship between R&D, knowledge and

Table 9: Impact of R&D Tax Credits on Skill Use

Dependent variable	Share of Skilled Workers Out of Total Workforce			
	(1)	(2)	(3)	(4)
Treatment	0.016*** (0.003)	0.016*** (0.003)		
Treatment \times length			0.002*** (0.000)	0.002*** (0.000)
Observations	35,772	35,772	35,772	35,772
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES

Dependent Variable	Share of Skilled Workers Wage Bill Out of Total Wage Bill			
	(1)	(2)	(3)	(4)
Treatment	0.021*** (0.004)	0.021*** (0.004)		
Treatment \times length			0.003*** (0.001)	0.003*** (0.001)
Observations	35,772	35,772	35,772	35,772
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES

Dependent Variable	Presence of a Highly Skilled Worker in The Firm (0/1)			
	(1)	(2)	(3)	(4)
Treatment	0.084*** (0.014)	0.085*** (0.014)		
Treatment \times length			0.018*** (0.002)	0.018*** (0.002)
Observations	31,532	31,532	31,532	31,532
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

This table reports the effect of R&D tax credits on the share of skilled workers out of total workforce, the share of skilled workers wage bill out of total wage bill and the presence of highly skilled workers in the firms (Master or PhD level). Column (1) reports the unconditional impact of enrolling in the program, column (2) includes sector fixed effects and trend; column (3) reports the unconditional impact of the length of exposure to the program and column (4) includes sector fixed effects and trend. Clustered standard errors are reported in parenthesis.

skill-biased technological change, and is in line with recent evidence (Bøler et al., 2015; Lindner et al., 2021).

Is the skill use observed above driven by workers with a bachelor's degree? Or do we observe underlying growth in highly skilled individuals with a Master's and/or a PhD? Given that most firms in QP do not have workers with a Master's degree, we decide to estimate a linear probability model where we create a dummy equal to 1 if the firm has a highly skilled individual within its workforce and 0 otherwise. This will provide us the effect of the tax credits scheme on the probability of having highly skilled individuals within the firm. Results are also illustrated in Table 9.

As illustrated, we observe a statistically significant increase of 8.5 percentage points

in the probability of having a Master’s and/or PhD in the firm. In addition, the strength of the effect is also increasing in length of exposure of the program. Such results are consistent with the idea that the expertise provided by Master’s and PhDs is often crucial in the creation of new knowledge/ideas and in the overall development of the research process (OECD, 2015). We also provide, in the Appendix, the effect of the R&D incentives scheme on the share of Master’s/PhDs in the firm. The coefficients obtained are statistically significant, which reinforces the idea that firms who received the R&D tax credits saw underlying growth in highly skilled workers.

5.2 Adjusting the production function

One possible channel that may explain the increased human capital and expertise within supported firms is the adoption of new technologies by the participating firms, given the high complementarity between skill and technology (Card and DiNardo, 2002). New technologies require firms to adapt the composition of their workforce to tasks that are less routine-related and more knowledge-based. Therefore, in order to examine whether firms that were supported by the R&D tax credits exhibited stronger adoption of new technologies, we leverage the IUTICE dataset, a panel dataset which provides firm-level information on the adoption of new technologies. However, a major caveat of the use of this dataset is that it is a survey, not a census as the other datasets. In addition, some questions were only asked in some years. We estimate equation 1 of our empirical strategy on the matched sample using binary outcome variables on the adoption of technologies. Results are shown in Table 10.

Although the sample sizes are small, results indicate that firms that participated in the R&D tax credits scheme were more likely, on average, to adopt technologies such as enterprise resource management IT, industrial robots and radio frequency identification techniques. Such results, although not as robust as our previous findings, seem to reinforce the hypothesis of complementarity between skill and technology highlighted in the literature (Card and DiNardo, 2002). Moreover, the adoption of new technologies, combined with increased expertise in the workforce, provide evidence of a more structural, persistent change on the type of activities, workforce and resources used by the firms that received the R&D tax credits.

Table 10: Skill Bias and Technological Change

Dependent variable	Adoption of Customer Relationship Management IT (0/1)	
	(1)	(2)
Treatment	0.063 (0.04)	0.066* (0.04)
Observations	5,576	5,576
Sector FE	NO	YES
Sector Trend	NO	YES
Dependent Variable	Adoption of Enterprise Resource Planning IT (0/1)	
	(1)	(2)
Treatment	0.045* (0.026)	0.045* (0.026)
Observations	5,531	5,531
Sector FE	NO	YES
Sector Trend	NO	YES
Dependent Variable	Adoption of Radiofrequency Identification Techniques (0/1)	
	(1)	(2)
Treatment	0.096 (0.08)	0.099 (0.082)
Observations	2,202	2,202
Sector FE	NO	YES
Sector Trend	NO	YES
Dependent Variable	Adoption of Industrial Robots (0/1)	
	(1)	(2)
Treatment	0.088* (0.048)	0.086* (0.046)
Observations	575	575
Sector FE	NO	YES
Sector Trend	NO	YES

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

This table reports the effect of R&D tax credits on the adoption of Customer Relationship Management IT, the Adoption of Enterprise Resource Planning IT, the Adoption of Radiofrequency Identification Techniques and the Adoption of Industrial Robots. Column (1) reports the unconditional impact of enrolling in the program, column (2) includes sector fixed effects and trend. Clustered standard errors are reported in parenthesis.

6 Conclusion

This paper evaluated the causal effects of the R&D tax credits on the trajectory of firms, in terms of the overall R&D activity undertaken, firm performance and skill-biased technical change using micro-level Portuguese data. We show that the SIFIDE R&D tax incentives led to a significant increase in R&D activity in the firms supported by the program, especially at the extensive margin, even though the effect shows little persistence when firms are no longer supported. Firms seemed to have benefited in terms of scale and productivity, but these effects are very different for firms of different sizes: small firms seem to have leveraged the tax credits for growth purpose while large firms

seem to have focused their effort to improve efficiency. These results have important implications in terms of public policies. They suggest that R&D tax credit aiming at fostering employment should target small firms, while those aiming at improving production efficiency should be targeted towards larger firms.

Finally, we documented the existence of structural and persistent changes caused by the program: the increased human expertise, coupled with enhanced technological adoption, showcase the fact that the program may have far-reaching long-term implications for firms. Even though firms do not persist in increasing investment in R&D once outside the program, the impact of SIFIDE is likely to have lasting effects.

Although these results provide important insights, especially for policymakers, it is important to note that our analysis mostly focused on the firm and, to a smaller extent, on its workers. Further research could also enlarge the unit of analysis in order to focus on industry effects of R&D tax credits, and whether such program allows supported firms to gain a competitive advantage compared to their peers in terms of market share and pricing power, for instance. In addition, in this paper, we focused on the results/benefits of the program, without much analysis of the cost side of the program. Additional research would examine whether the benefits of the program, in terms of scale, productivity, and increased innovation, outweigh the financial costs of the program.

References

- Abadie, Alberto and Guido W Imbens, “Matching on the Estimated Propensity Score,” *Econometrica*, 2016, 84 (2), 781–807. (Cited on page(s) 22)
- Acemoglu, Daron, “Patterns of Skill Premia,” *The Review of Economic Studies*, 2003, 70 (2), 199–230. (Cited on page(s) 5)
- Aghion, Philippe, Antonin Bergeaud, Richard Blundell, and Rachel Griffith, “Innovation, firms and wage inequality,” *Department of Economics, Harvard University, Working Paper Series*, https://scholar.harvard.edu/files/aghion/files/innovations_firms_and_wage.pdf, 2017. (Cited on page(s) 6)
- Basto, Rita Bessone, Ana Martins, Guida Nogueira et al., “The Impact of R&D tax incentives in Portugal,” Technical Report, Gabinete de Estratégia e Estudos, Ministério da Economia 2021. (Cited on page(s) 4, 6, 7)
- Bastos, Paulo, Natália P Monteiro, and Odd Rune Straume, “Foreign acquisition and internal organization,” *Journal of International Economics*, 2018, 114, 143–163. (Cited on page(s) 10, 11)
- Blandinieres, Florence and Daniela Steinbrenner, “How Does the Evolution of R&D Tax Incentives Schemes Impact their Effectiveness? Evidence from a Meta-Analysis,” *ZEW-Centre for European Economic Research Discussion Paper*, 2021, (21-020). (Cited on page(s) 5)
- Bøler, Esther Ann, Andreas Moxnes, and Karen Helene Ulltveit-Moe, “R&D, International Sourcing, and the Joint Impact on Firm Performance,” *American Economic Review*, 2015, 105 (12), 3704–39. (Cited on page(s) 6, 12, 23, 24)
- Borusyak, Kirill and Xavier Jaravel, “Revisiting event study designs,” *Available at SSRN 2826228*, 2017. (Cited on page(s) 14)
- Card, David and John E DiNardo, “Skill-biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles,” *Journal of Labor Economics*, 2002, 20 (4), 733–783. (Cited on page(s) 5, 25)
- Conti, Raffaele, Miguel Godinho de Matos et al., “Big for Everyone? Big Data, Firm Size and Performance,” *Working Paper*, 2020. (Cited on page(s) 20)
- de Almeida Leitão, Martim Mingot, “And yet, they last: the employment and productivity effects of crises on firms in Portugal.” PhD dissertation 2021. (Cited on page(s) 33)
- Gaillard-Ladinska, Elina, Mariëlle Non, and Bas Straathof, “More R&D With Tax Incentives?*: A Meta-Analysis,” in “International Financial Markets,” Routledge, 2019, pp. 316–335. (Cited on page(s) 4, 5)
- Guceri, Irem and Li Liu, “Effectiveness of Fiscal Incentives for R&D: Quasi-experimental Evidence,” *American Economic Journal: Economic Policy*, 2019, 11 (1), 266–91. (Cited on page(s) 5)

- Ho, Daniel E, Kosuke Imai, Gary King, and Elizabeth A Stuart**, “Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference,” *Political Analysis*, 2007, 15 (3), 199–236. (Cited on page(s) 10)
- King, Gary and Richard Nielsen**, “Why propensity scores should not be used for matching,” *Political Analysis*, 2019, 27 (4), 435–454. (Cited on page(s) 22)
- Köhler, Christian, Philippe Laredo, and Christian Rammer**, “The impact and effectiveness of fiscal incentives for R&D,” 2012. (Cited on page(s) 4, 5)
- Lindner, Attila, Balázs Muraközy, Balazs Reizer, and Ragnhild Schreiner**, “Firm-level Technological Change and Skill Demand,” 2021. (Cited on page(s) 6, 23, 24)
- Mitchell, Jessica, Giuseppina Testa, Miguel Sanchez Martinez, Paul N Cunningham, and Katarzyna Szkuta**, “Tax incentives for R&D: supporting innovative scale-ups?,” *Research Evaluation*, 2020, 29 (2), 121–134. (Cited on page(s) 4, 5)
- OECD**, *Measurement of R&D Personnel: Persons employed and external contributors* 2015. (Cited on page(s) 25)
- Peters, Bettina**, “Employment Effects of Different Innovation Activities: Microeconomic Evidence,” *ZEW-Centre for European Economic Research Discussion Paper*, 2004, (04-073). (Cited on page(s) 21)
- Simões, António Carlos**, “Impact Evaluation of the Fiscal Incentive System for Corporate Research & Development.” PhD dissertation 2019. (Cited on page(s) 6)
- Toner, Phillip**, “Workforce Skills and Innovation: An Overview of Major Themes in the Literature,” 2011. (Cited on page(s) 5)
- Vivarelli, Marco**, “Innovation and Employment,” *IZA World of Labor*, 2015. (Cited on page(s) 21)

A Appendix

Table A1: Balance

Variable	Sample	Mean		%bias	& bias reduction	T-test		Variance Ratios V(T)/V(C)
		Treated	Control			T-Statistic	P-value	
Employment (log)	U	3.893	1.705	172.4		90.02	0.000	2.18
	M	3.881	3.851	2.4	98.600	0.59	0.552	1.01
Sales (log)	U	15.589	12.512	179.9		86.27	0.000	1.67
	M	15.571	15.513	3.4	98.100	0.95	0.343	1.03
TFP (log)	U	8.524	7.515	46.8		18.55	0.000	0.83
	M	8.292	8.228	3.0	93.700	0.92	0.358	0.98
Sales per Worker (log)	U	11.696	10.807	89.4		36.39	0.000	0.93
	M	11.690	11.661	2.9	96.700	0.96	0.336	1.03
R&D (log)	U	4.757	0.911	94.4		66.78	0.000	4.84
	M	4.278	4.249	0.7	99.200	0.16	0.876	1.02
Sales Growth	U	0.143	0.009	29.6		12.19	0.000	0.97
	M	0.093	0.082	2.5	91.500	1.10	0.272	1.11
TFP Growth	U	-0.052	-0.065	1.7		0.74	0.461	1.11
	M	-0.043	-0.048	0.6	62.900	0.38	0.704	1.08
Employment Growth	U	0.116	0.013	34.1		14.56	0.000	1.13
	M	0.088	0.042	15.0	55.900	5.66	0.000	1.42
Sales Growth (1 lag)	U	0.136	0.050	12.6		4.84	0.000	0.88
	M	0.109	0.062	6.7	46.500	2.60	0.009	0.62
TFP Growth (1 lag)	U	-0.142	-0.071	-9.8		-3.89	0.000	0.99
	M	-0.131	-0.136	0.6	93.700	0.21	0.832	1.27
Employment Growth (1 lag)	U	0.083	0.021	23.0		8.76	0.000	0.85
	M	0.076	0.054	8.0	65.300	2.26	0.024	0.79
Sales Growth (2 lags)	U	0.103	0.039	11.0		3.00	0.003	0.25
	M	0.091	0.064	4.6	54.300	1.74	0.082	0.60
TFP Growth (2 lags)	U	-0.134	-0.068	-10.1		-3.24	0.001	0.72
	M	-0.136	-0.155	3.0	70.300	0.91	0.364	0.87
Employment Growth (2 lags)	U	0.075	0.022	19.9		6.59	0.000	0.84
	M	0.067	0.043	9.1	54.300	2.38	0.018	1.00
Firm Age	U	20.875	15.448	34.3		16.89	0.000	1.83
	M	21.915	23.862	-12.3	64.100	-2.95	0.003	1.07
Number of Unskilled Workers	U	144.99	10.9	31.2		78.76	0.000	78.21
	M	103.81	101.84	0.5	98.500	0.24	0.809	1.47
Number of Masters/PhDs	U	0.947	0.054	14.8		45.98	0.000	122.74
	M	0.544	0.364	3.0	79.800	2.24	0.025	1.54

Table A2: Logit Estimation for Propensity Score Estimation

Received R&D Tax Credits	
Employment (log)	0.252*** (0.031)
Employment Growth	0.785*** (0.076)
Sales (log)	0.833*** (0.025)
Sales Growth	1.185*** (0.058)
TFP (log)	-0.062*** (0.016)
TFP Growth	-0.031 (0.036)
R&D (log)	0.086*** (0.005)
Firm Age	-0.01*** (0.002)
Observations	1,435,942
Pseudo R2	0.356
Sector Effects	YES
Year Effects	YES

Table A3: Effect of R&D Tax Credit Program on Selected Variables, using PSM 1-5

Dependent Variables:	R&D (log) (1)	Employment (log) (2)	VA per Worker (log) (3)	Share of Skilled Workers (4)	TFP (log) (5)
Treatment	0.965*** (0.116)	0.248*** (0.015)	0.134*** (0.026)	0.014*** (0.003)	0.093*** (0.026)
Sector FE	NO	NO	NO	NO	NO
Sector Trend	NO	NO	NO	NO	NO

Table A4: Placebo on R&D Investment One Year Prior to Participation

	Investment in R&D-Related Activities	
	(1)	(2)
One Year Prior to Participation		
Treatment	-0.105 (0.136)	-0.109 (0.136)
Observations	22,003	22,003
Sector FE	NO	YES
Sector Trend	NO	YES
First Year of Participation		
Treatment	0.898*** (0.157)	0.892*** (0.157)
Observations	22,003	22,003
Sector FE	NO	YES
Sector Trend	NO	YES

Computation of Productivity Metrics using SCIE

This section details the construction of three productivity metrics that are used in this thesis.

Sales per Worker This variable is constructed by dividing real sales by the number of employees in the firm:

$$\text{Sales per Worker}_t = (\text{Real Sales}_t) / (\text{Number of Employees}_t)$$

Value Added per Worker This variable is constructed by the dividing value added by the number of employees in the firm. Value added is the difference between sales (revenues) and costs of intermediate inputs used in the production.

$$\text{VA per Worker}_t = (\text{VA}_t) / (\text{Number of Employees}_t)$$

Total Factor Productivity (TFP) The computation of factor productivity using SCIE data follows exactly the procedure employed by [Leitão \(2021\)](#). Given the information on spending in inputs such as materials and labor provided in the dataset, [Leitão \(2021\)](#) computes a measure of factor productivity as a residual:

$$\begin{aligned} \ln(TFP_t) &= \ln(\text{Real Sales}_t) \\ &\quad - \text{Share of Materials in the Production}_t \times \ln(\text{Materials}_t) \\ &\quad - \text{Share of Wages in the Production}_t \times \ln(\text{Employees}_t) \end{aligned}$$

[Leitão \(2020\)](#) shows that the share of materials and wages out of production are relatively constant across years in Portugal, and therefore, TFP is computed as:

$$\ln(TFP_t) = \ln(\text{Real Sales}_t) - 0.54(\text{Materials}_t) - 0.14 \times \ln(\text{Employees}_t)$$