Better and Stronger? Theory and Evidence on the Effect of R&D Tax Credits on the Trajectory of Firms

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Abstract

This thesis examines the effect of R&D tax credits on the trajectory of firms, in terms of R&D, performance, workforce composition and technology adoption. We elaborate a theoretical model that links the effect of R&D tax credits on firms' decision to innovate and their differentiated effects based on firm size. Leveraging on the theoretical framework, we then estimate the causal effects of an R&D tax credits program in Portugal using rich micro-data on innovation and firms. By combining matching with a staggered adoption differences-in-differences, we show that tax credits have strong effects on the investment in R&D-related activities, especially at the extensive margin, although the effect is concentrated while funds are being received and not thereafter. Overall, such effect on R&D translates into better firm performance on scale and productivity. Yet, its nature depends heavily on firm size: consistent with different patterns of innovation, small firms exhibit very strong scale effects while large firms see significant productivity and efficiency gains. Importantly, firms that received the tax credits exhibit structural changes, both in terms of the increased share of skilled individuals within the firm and enhanced technological adoption, a finding consistent with the relationship between R&D, innovation and skill-biased technological change.

Keywords: R&D, Innovation, Impact Evaluation, Firm Performance, Scale, Productivity, Skill Bias, Technology

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Resumo

Esta tese examina o efeito dos créditos fiscais de I&D na trajetória das empresas, em termos de I&D, desempenho, composição da força de trabalho da empresa e tecnologia. Desenvolvemos um modelo teórico que identifica o efeito dos créditos fiscais de I&D na decisão das empresas de inovar e o impacto heterogêneo destes incentivos sobre empresas de diferentes tamanhos. Analisamos o efeito causal de um programa de créditos fiscais de apoio ao I&D implementado em Portugal, com dados sobre a inovação ao nível da empresa. Usando técnicas de emparelhamento com diferenças em diferenças, mostramos que os créditos fiscais têm fortes efeitos sobre o I&D, especialmente na margem extensiva, embora o efeito seja concentrado enquanto as empresas recebem os fundos e apresente muito pouco persistência. Tal efeito sobre o I&D traduz-se concretamente em melhor desempenho da empresa, tanto em escala como em produtividade, embora o efeito seja heterogêneo e dependa fortemente do tamanho da empresa: consistente com diferentes padrões de inovação, as pequenas empresas exibiram efeitos de escala muito fortes, enquanto as grandes empresas viram uma produtividade significativa e ganhos de eficiência. De modo geral, as empresas apoiadas pelo programa apresentam mudanças estruturais, tanto em termos de aumento da participação de indivíduos qualificados dentro da empresa como na adesão de novas tecnologia, um facto consistente com a relação entre o I&D, a inovação e os progressos técnicos com requisitos específicos em termos de qualificações.

Palavras-chave: I&D, Inovação, Avaliação de Impactos, Desempenho, Escala, Produtividade, Qualificações, Tecnologia

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1. Introduction

Since the Great Financial Crisis, investments in R&D have seen sustained growth in many countries around the world, outpacing the growth rate of real GDP (OECD, 2021). Even with the uncertainty created by the Covid-19 pandemic, a significant proportion of firms remained resilient in terms of their commitment to R&D (OECD, 2021). It has been argued that R&D plays a crucial role, not only for firm competitiveness, but most importantly for growth and productivity at the aggregate level (Jones & Williams, 2000). 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&D[1], there is still a dearth of evidence on how these incentives concretely impact the performance trajectory of firms, and whether such programs generate persistent and structural changes (Köhler et al., 2012; Mitchell et al., 2020). Yet, such knowledge is crucial in understanding not only the short-run but also 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?

In light of the questions above, this thesis develops theoretical foundations and 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 more importantly, 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 (Bessone 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. Matching allows to customize a control group with very similar observable characteristics to the treatment group prior to support from the R&D tax credits. The trajectory of the control

[1] See, for instance, Mitchell et al. (2020), Gaillard-Ladinska et al. (2015) for a meta-analysis on the large body of studies made.

group across time would then act as a counterfactual for firms that received the tax credits. Such methodology would therefore provide a robust estimate of the causal effect of R&D tax credits on the trajectory of the supported firms, as it accounts both for selection based on observables and for observable and unobservable characteristics that are invariant across periods (Bastos et al., 2018).

In order to understand the channels through which R&D tax credits impact firm performance and to guide the empirical analysis, we first elaborate a theoretical model where monopolistically competitive firms invest in R&D under uncertainty. The model predicts that R&D tax credits reduce the marginal cost of investing in knowledge within the firm, which incentivizes the firms to engage in more R&D activity. Yet, such increase in R&D leads to very different outcomes, depending on the pattern of innovation undertaken: firms that leverage the tax credits to create new products tend to see very strong effects on sales and employment, while firms that leverage the tax credits for process innovation experience stronger effects on productivity. Most importantly, the model predicts differentiated usages of the R&D tax credits based on firm size: larger firms are more likely to engage in enhancing efficiency through new processes while their smaller counterparts are more inclined to expand their size through product innovation. Such result relates to the seminal work of Cohen & Klepper (1996), which provides the micro-foundations on the relationship between firm size and innovation, and more recent works such as Conti & Godinho de Matos (2020), where the authors use panel data and matching methods to identify different patterns of big data innovation based on firm size.

Leveraging on the insights of the theoretical framework, we assess the causal effects of the SIFIDE R&D tax credits scheme using three different angles. This thesis first examines the relationship between R&D tax credits and 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. Although such result can be explained given the fact that tax credits reduce the marginal cost of investing in R&D, we document that a significant share of the effect is driven by the extensive margin, where firms that previously did not invest in R&D decided to opt in the program and start investing. This is an important finding, as it shows that the program pushes firms to overcome the initial barriers to engage in R&D and does not only cater to firms that already invested in R&D. Nevertheless, 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. By contrast to the direct relationship between tax credits and research and development spending, evidence on the effects of incentives on outcomes 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 mergeable microdata which would allow to follow firms for a variety of different performance metrics (WWCLEG, 2015). We bridge this gap by leveraging, in this thesis, more than five longitudinal mergeable datasets with data 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 while small firms tend to witness relatively stronger scale effects. Overall, these results are consistent with the predictions of the theoretical framework on different usage of R&D tax credits for innovation based on firm size.

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 (e.g. Acemoglu, 2003), and some studies leverage macro data to examine patterns of skill demand (e.g. Card & DiNardo, 2002). By contrast to these studies, this thesis explores the effect of R&D tax credits on skill bias 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. Levering *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 thesis 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 et al., 2021; Gaillard-Ladinska et al., 2015; 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 et al., 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. In addition, in contrast to most papers, this thesis bridges the gap between theory and empirics by providing the theoretical channels through which tax credits concretely impact firms.

Second, this thesis also contributes to the growing body of research that relates R&D to skill-biased technological change (SBTC). We follow verify closely recent studies that leveraged panel data to examine SBTC at the firm level. For instance, Aghion (2017) leverages UK employer-employee matched data to establish the relationship between R&D intensity, wage premia and the skill level of employees. Bøler (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) uses Hungarian data on innovation and workers to pin down the effect of different types of innovation on wage premia and skill bias at the firm level. Our work is perhaps most closely related to Bøler (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, this thesis distinguishes itself by leveraging a unique Portuguese dataset on firm-level technology. This thesis, therefore, provides additional evidence on the relationship between skill bias 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 thesis contributes to the very scarce literature on policy evaluations in Portugal. Very few evaluations of the SIFIDE program have been made in the literature. Simões and Mamede (2019) and Bessone Basto et al. (2021) provide first evaluations of the program, where the authors show that R&D tax credits generate strong effects on R&D investments. Yet, little has been explored on 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 thesis 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.

This thesis is organized as follows. Section II builds a theoretical model to explain the effect of R&D tax credits on firm outcomes. Section III presents the data and descriptive statistics. Section IV outlines the estimation strategy. Section V discusses the results. Section VI provides some robustness checks and Section VII concludes.

2. Conceptual Framework

In this section, we build a model that provides the theoretical foundation to invest in R&D and the resulting impact of R&D tax credits on firm outcomes. Leveraging on the works of Cohen & Klepper (1996) and Conti & Godinho de Matos (2020), we then endogenize the choice of innovation (whether product or process-based) based on firm size, in order to outline differentiated usages of R&D tax credits based on firm size. Details on the algebraic derivations are provided in Appendix I.

Basic Setting: Consider a profit-maximizing monopolistically competitive firm with an inverse demand function given by the following expression:

$$P_A = a - bQ_A \tag{1}$$

Where P_A is the price of the initial good A, Q_A is the quantity demanded of good A and a, b are demand parameters. The firm faces a production function that is linear in labor:

$$Q_A = \alpha_A L_A \tag{2}$$

Where L_A is the amount of labor used in the production of good A and α_A is a productivity parameter. The labor market is perfectly competitive and each unit of labor costs a wage w. Therefore, the marginal cost of firm A is constant and given by:

$$MC_A = \frac{w}{\alpha_A} = c_A \tag{3}$$

The firm can invest in R&D, which requires the acquisition of the R&D input I. The market for I is perfectly competitive and μ is the unitary cost of I. The accumulation of the R&D input leads to the production of knowledge K in the firm, according to the neoclassical function:

$$K = f(I) \tag{4}$$

Where $f(0) = 0, f'(I) > 0$, $f''(I) < 0$, and f is injective and invertible. Inverting equation (4), we can express the input demand of I as a function of K:

$$I = g(K) \tag{5}$$

Where $g(0) = 0, g'(K) > 0$, $g''(K) > 0$, and g is injective and invertible.

As more knowledge is accumulated, the probability that the firm successfully discovers an innovation increases. The probability function $p(K)$ provides the probability of successfully innovating given knowledge accumulated K. $p(K)$ has the following properties:

$$p(0) = 0 \tag{6}$$

$$p'(K) > 0 \tag{7}$$

$$p''(K) < 0 \tag{8}$$

$$\lim_{K \to \infty} p(K) = 1 \tag{9}$$

These properties imply that the more knowledge is accumulated, the probability of innovating increases but at a diminishing rate. The firm pays a proportional tax τ on its profits. R&D expenses in the input I are tax deductible. In addition, the firm can benefit from a tax credit rate on its R&D expenses, allowing to recover a portion λ of its R&D spending. We impose that:

$$\lambda\mu < (1 - \tau)\mu \tag{10}$$

Equation (10) states that the cost savings due to the tax credits from buying one unit of the R&D input I should not exceed the after-tax marginal cost of buying one unit of I. In our setting, the firm can only undertake two distinct forms of innovation. We analyze them sequentially in the following sections.

2.1. R&D Tax Credits & New Products

In this first setting, R&D activity and knowledge accumulation increases the probability of creating a new product line, product B, with the demand function:

$$P_B = d - eQ_B \tag{11}$$

Where P_B is the price of the newly created product B, Q_B is the quantity demanded of good B and d, e are demand parameters. The production function of product B is:

$$Q_B = \alpha_B L_B \tag{12}$$

Where L_B is the amount of labor used in the production of good B and α_B is a productivity parameter specific to product B. The marginal cost of producing product B is constant and equal to c_B.

The risk neutral firm maximizes expected profits by choosing the amount of R&D to undertake, the amount of knowledge to create, the price/quantity of both goods A and B:

$$\underset{\substack{P_A\\Q_A\\P_B\\Q_B\\K\\I}}{\text{Max}}\, E[\pi] = (1-\tau)\begin{pmatrix} p(K)[P_A Q_A + P_B Q_B - c_A Q_A - c_B Q_B] \\ +\big(1-p(K)\big)[P_A Q_A - c_A Q_A] - \mu I \end{pmatrix} + \lambda\mu I \tag{13}$$

$$s.t. \qquad P_A = a - bQ_A \tag{14}$$

$$P_B = d - eQ_B \tag{15}$$

$$I = g(K) \tag{16}$$

Substituting the constraints in the objective function and taking first-order conditions, we obtain:

$$\frac{\partial E[\pi]}{\partial Q_A} = 0 \Leftrightarrow Q_A = \frac{a - c_A}{2b} \tag{17}$$

$$\frac{\partial E[\pi]}{\partial Q_B} = 0 \Leftrightarrow Q_B = \frac{d - c_B}{2e} \tag{18}$$

$$\frac{\partial E[\pi]}{\partial K} = 0 \Leftrightarrow (1-\tau)p'(K)\pi_B = \mu g'(K)(1-\tau-\lambda) \tag{19}$$

In equations (17) and (18), the firm sets the marginal revenue of each product equal to the marginal cost of each product. In equation (19), the firm equates the marginal benefit of investing in an additional unit of knowledge equal to its marginal cost.

Effect of R&D Tax Credits on R&D Activity: Using equation (19), implicitly differentiating with respect to λ, and isolating $\frac{\partial K}{\partial \lambda}$, we obtain:

$$\frac{\partial K}{\partial \lambda} = \frac{\mu g'(K)}{\mu g''(K)(1-\tau-\lambda) - (1-\tau)p''(K)\pi_B} > 0 \quad (20)$$

The derivative in equation (20) in unambiguously positive, which implies that an increase in the tax credits leads to an increase in the amount of knowledge in the firm. As knowledge can only be accumulated through R&D activity, this implies that tax credits lead to an increase in R&D activity. Since the tax credits act as a reduction in the marginal cost of R&D, to re-equate the marginal benefit to the marginal cost, the firm needs to engage in more R&D.

Effect of R&D Tax Credits on Expected Sales and Employment: We denote the sales of products A and B, as:

$$S_A = (a - bQ_A)Q_A \quad (21)$$
$$S_B = (d - eQ_B)Q_B \quad (22)$$

The expected sales of the firm is given by:

$$E[S] = p(K)[S_A + S_B] + \big(1 - p(K)\big)[S_A] \quad (23)$$

Taking the derivative of equation (23) with respect to λ:

$$\frac{\partial E[S]}{\partial \lambda} = p'(K)\frac{\partial K}{\partial \lambda}S_B > 0 \quad (24)$$

We define expected employment as:

$$E[L_T] = p(K)[L_A + L_B] + \big(1 - p(K)\big)[L_A] \Leftrightarrow \quad (25)$$

Isolating L_i in equations (2) and (12) and plugging it in equation (25):

$$E[L_T] = \frac{Q_A}{\alpha_A} + p(K)\frac{Q_B}{\alpha_B} \tag{26}$$

Taking the partial derivative of equation (26) with respect to λ:

$$\frac{\partial E[L_T]}{\partial \lambda} = p'(K)\frac{\partial K}{\partial \lambda}\frac{Q_B}{\alpha_B} > 0 \tag{27}$$

Equations (24) and (27) show that the effect of R&D tax credits, through product innovation, is positive on sales and employment. As the firm engages in more R&D and more knowledge is accumulated in the firm, the probability of launching product B increases, which implies that the expected sales of the firm will increase. The firm will need to scale up the production of product B, thereby hiring more labor.

Effect of R&D Tax Credits on Expected Labor Productivity: What is the effect of R&D tax credits on efficiency gains through product innovation? To answer this question, we compute the expected average labor productivity:

$$E\left[\frac{Q}{L}\right] = p(K)\left[\frac{Q_A + Q_B}{L_A + L_B}\right] + \left(1 - p(K)\right)\left[\frac{Q_A}{L_A}\right] \tag{28}$$

Taking the derivative of equation (28) with respect to λ and solving, the effect of R&D tax credits in a setting where the firm engages in product innovation is positive on labor productivity if and only if:

$$\frac{\partial E\left[\frac{Q}{L}\right]}{\partial \lambda} > 0 \Leftrightarrow \frac{Q_B}{L_B} > \frac{Q_A}{L_A} \Leftrightarrow \alpha_B > \alpha_A \tag{29}$$

Equation (29) shows that the effect on labor productivity of firms that leverage the R&D tax credits to engage in product innovation is positive only if the production of product B is more efficient than A. Thus, the effect depends heavily on the cost structure of both product lines, which is *a priori* ambiguous.

2.2. R&D Tax Credits & Efficiency-Enhancing Process

In this section, firms can only leverage R&D tax credits to engage in process innovation, that is, change in the organizational processes to improve productivity. In order to understand the nature of process innovation, we start our discussion from the production function that was defined in the previous section:

$$Q_A = \alpha_A L_A \tag{30}$$

From this production function, we derive the marginal cost function:

$$MC_A = \frac{w}{\alpha_A} = c_A \tag{31}$$

If the firm manages to process innovate, this will yield an increase in the productivity parameter $\alpha_A' > \alpha_a$. Therefore, the production function if the firm successfully process innovates becomes:

$$Q_A = \alpha_A{}' L_A \tag{32}$$

The corresponding marginal cost function becomes:

$$MC_A' = \frac{w}{\alpha_A{}'} = c_A' < c_A \tag{33}$$

An important note is that, by construction, process innovation has a positive effect on productivity, whereas in the case of product innovation, the effect was ambiguous as shown in the previous section. The rest of the setting is identical to section A. The risk-neutral firm maximizes expected profits, by choosing the amount of R&D to undertake, the amount of knowledge to create and the price/quantity of good A:

$$\underset{\substack{P_A \\ Q_A \\ K \\ I}}{\text{Max}}\, E[\pi] = (1-\tau)\begin{pmatrix} p(K)[P_A Q_A - c_A{}' Q_A] \\ +\big(1-p(K)\big)[P_A Q_A - c_A Q_A] - \mu I \end{pmatrix} + \lambda\mu I \tag{34}$$

$$s.t. \qquad P_A = a - bQ_A \tag{35}$$

$$I = g(K) \tag{36}$$

Substituting the constraints in the objective function and taking first-order conditions, we obtain:

$$\frac{\partial E[\pi]}{\partial Q_A} = 0 \Leftrightarrow Q_A = \frac{a - [p(K)c_A' + \left(1 - p(K)\right)c_A]}{2b} \tag{37}$$

$$\frac{\partial E[\pi]}{\partial K} = 0 \Leftrightarrow (1-\tau)p'(K)(c_A - c_A')Q_A = (1 - \tau - \lambda)\mu g'(K) \tag{38}$$

In equation (37), the firm sets marginal revenue equal to expected marginal cost. In equation (38), the firm sets the marginal benefit from investing in an extra unit of knowledge equal to the marginal cost of doing so.

Effect of R&D Tax Credits on R&D Activity: We take the partial derivative of equation (38) with respect to λ:

$$\frac{\partial K}{\partial \lambda} = \frac{-\mu g'(K)}{(1-\tau)(c_A - c_A')\left(p''(K)Q_A + p'(K)\frac{\partial Q_A}{\partial K}\right) - (1 - \tau - \lambda)\mu g''(K)} \tag{39}$$

This derivative is positive if and only if:

$$p''(K)Q_A + p'(k)\frac{\partial Q_A}{\partial K} < 0 \tag{40}$$

Equation (40) needs to be imposed for the marginal benefit of accumulating K to be downward-slopping and to obtain an interior solution when equating marginal benefit to the marginal cost of knowledge accumulation. If equation (40) holds, the R&D tax credits lead to an increase in innovative activity, through more knowledge accumulated.

Effect of R&D Tax Credits on Sales: We define firm sales as:

$$S = (a - bQ_A)Q_A \tag{41}$$

Taking the derivative of equation (41) with respect to λ:

$$\frac{\partial S}{\partial \lambda} = \frac{\partial Q_A}{\partial K}\frac{\partial K}{\partial \lambda}(a - 2bQ_A) \Leftrightarrow \tag{42}$$

$$\frac{\partial S}{\partial \lambda} = \frac{\partial Q_A}{\partial K}\frac{\partial K}{\partial \lambda}P_A\left(\frac{1+\varepsilon}{\varepsilon}\right) \tag{43}$$

Where ε is the own-price elasticity of demand. The effect on sales of the R&D tax credits through process innovation depends on whether the demand is elastic or inelastic, a result that echoes the findings of Conti & Godinho de Matos (2020). If $\varepsilon < -1$, then the demand is elastic and as such, the effect on sales is positive. If, on the other hand, $\varepsilon > -1$, the demand is inelastic and as such, the effect on sales is negative.

Effect of R&D Tax Credits on Expected Employment: We define expected employment as:

$$E[L_T] = p(K)\left[\frac{Q_A}{\alpha_A{}'}\right] + \left(1 - p(K)\right)\left[\frac{Q_A}{\alpha_A}\right] \tag{44}$$

Taking the partial derivative with respect to λ and isolating, we obtain:

$$\frac{E[L_T]}{\partial\lambda} = \frac{\partial K}{\partial\lambda}\frac{[\alpha_A - \alpha_A']p'(K)Q_A + \left(p(K)\alpha_A + \left(1 - p(K)\right)\alpha_A'\right)\frac{\partial Q_A}{\partial K}}{\alpha_A'\alpha_A} \tag{45}$$

The sign of the derivative depends on the numerator of expression (45). The first term is negative while the second term is positive. On the one hand, the increase in knowledge leads to a decline in the expected marginal cost, an expansion of output and therefore, the firm requires more labor in order to scale-up. On the other hand, if the innovation succeeds, labor becomes more productive and as such, there is a need of less labor inputs to produce the same output. The scale effect and efficiency effect go in opposite directions. The effect on labor is negative if and only if:

$$\frac{E[L_T]}{\partial\lambda} < 0 \Leftrightarrow \frac{\alpha_A' - \alpha_A}{\alpha_A'} > \frac{\frac{\partial Q_A}{\partial K}}{p'(K)\frac{\partial K}{\partial\lambda}Q_A + p(K)\frac{\partial Q_A}{\partial K}\frac{\partial K}{\partial\lambda}} \tag{46}$$

Equation (46) tells us that if the productivity gains associated with process innovation are sufficiently large, then the effect on employment will be negative.

2.3. Differential Usage of R&D Tax Credits Based on Firm Size

In the previous two sections, we saw how R&D tax credits impacted differently firm outcomes depending on the type of innovation undertaken by the firm. In this section, we aim to understand how firm size influences the choice of the type of innovation undertaken by the firm. In order to answer this question, we will assume that the firm participates in the R&D tax credits scheme and can only invest in one type of innovation: either it invests in product or process innovation. In addition, we assume that firm invests a fixed amount of knowledge $\overline{K}$ and that the knowledge and probability functions, as defined in the previous section, are identical for both innovations.

The firm will decide to invest in the type of innovation that yields the highest expected increase in profits, compared to a scenario where the firm did not invest in R&D. The expected increase in profit from process innovation is given by:

$$E[\Delta\pi^{PROCESS}] = \frac{(1-\tau)(a-\bar{c})^2}{4b} - \frac{(1-\tau)(a-c_A)^2}{4b} - (1-\tau)\mu g(\overline{K}) + \lambda\mu g(\overline{K}) \quad (47)$$

Where $\bar{c} = p(\overline{K})c'_A + \left(1-p(\overline{K})\right)c_A$. Similarly, the expected increase in profit from product innovation is given by:

$$E[\Delta\pi^{PRODUCT}] = (1-\tau)p(\overline{K})\pi_B - (1-\tau)\mu g(\overline{K}) + \lambda\mu g(\overline{K}) \quad (48)$$

The firm will decide to invest in product innovation if and only if the expected increase in profits from undertaking product innovation is higher than the expected increase in profits from undertaking process innovation:

$$E[\Delta\pi^{PRODUCT}] > E[\Delta\pi^{PRODUCT}] \Leftrightarrow \quad (49)$$

$$\pi_B > \frac{(c_A - c'_A)(2a - \bar{c} - c_A)}{4b} \quad (50)$$

Equation (50) gives us a condition under which the firm would invest in product innovation instead of process innovation. Notice the role of the parameter a on the right-hand side of the inequality. The parameter a is a measure of size: it tells us the size of the demand that the firm faces for its initial product line. A small value of a implies that the demand that the firm faces is small, which in turn implies lower output and lower employment. On the other hand, a large value of a implies a large demand, larger output and therefore larger size overall.

Notice that a higher value of the scale parameter a makes the condition *more binding*, while a smaller value of a makes the constraint *less binding.* Intuitively, this means that for larger firms with a significant scale of operations, it is less likely that the inequality holds whereas for very small firms with small scale, it is much more likely that this inequality holds. Large firms benefit significantly from process innovation, as the decline in the marginal cost created by the innovation trickles down to a very large of amount of output. For small firms, this effect is not that apparent. This explains the differentiated patterns of innovation based on firm size.

2.4. Propositions

We can summarize the main findings of the model developed in this section in four main results presented below:

Proposition 1: Firms that receive R&D tax credits engage in more R&D-related investments.

Proposition 2: Product-based innovation incentivized by R&D credits has a positive effect on sales and employment while the effect on productivity is ambiguous and depends on how efficiently the new product is produced.

Proposition 3: Process-based innovation incentivized by R&D tax credits has a positive effect on productivity and improves efficiency, while the effect on sales and employment is ambiguous: the former depends on the elasticity of demand while the latter depends on the strength of the efficiency gains.

Proposition 4: Firms with a large scale of operations are more likely to engage in process-based than product-based innovation. The opposite is the case for firms with smaller size.

3. Data and Descriptive Statistics

3.1. Description of Datasets

We leverage five main datasets in this thesis. All the datasets are provided by the Portuguese governmental agency *Instituto National de Estastitica (INE)* responsible for the provision of high-quality data.

1) 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, at 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).

2) *Sistema de Contas Integradas das Empresas* (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 Bessone 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.

3) *Quadro de Pessoal* (QP) 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.

4) *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.

5) Finally, the *Inquérito à Utilização de Tecnologias da Informação e da Comunicação* (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.

3.2. Cleaning Procedure

The overall cleaning procedure follows very closely the cleaning procedure employed in the literature (see, for example, Carneiro et al. (2021) for QP, Leitão (2020) for SCIE and QP). In particular, and regarding SCIE, we drop firm-year observations where sales are negative. In addition, we use broad sectoral categories from the *CAE.Rev3* classification established by INE. The list of the sectoral categories is available in the Appendix. For QP, we keep only workers that are linked to firms. In addition, workers that have no regular remuneration are also dropped from the sample (for instance, these workers could have been interns or volunteers in the organization). We compute monthly wage bills paid to workers as the sum of the base (monthly) salary received by the worker and regular/non-regular incremental earnings. When divided by the number of hours worked, this variable provides us with the hourly wage paid to the worker. We then collapse QP at the firm level, taking an average of the relevant outcome variables for our analysis. Monetary variables in both datasets are deflated using CPI data and expressed in real terms. Finally, we merge QP, SCIE and SIFIDE using the common key present in all three datasets. We then identify firms that benefited from the tax credits in the combined dataset.

Importantly, the SIFIDE dataset also provides us with information on firms denied support from the program. These firms are not considered in our analysis, and we focus solely on successful participations of the firms. In addition, since in this thesis, we are interested on evaluating the effect of R&D credits on the trajectory of the firms in terms of various outcomes of interest, firms that first received tax credits in 2017 onwards are not included in the analysis and are dropped from the data. The rationale behind this decision is that we do not have sufficient data on these firms from the moment they participate to the program onwards in order to accurately evaluate the effect of the program on their trajectory. For instance, a firm that first participated in 2019 will have no observations after that period as it is the last year available in our sample.

3.3. 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. This important issue will be detailed in the next section.

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	

Note: Author's computations using SCIE, QP and SIFIDE. Mean values are expressed with standard deviations in parentheses in columns 1 and 2. T-static and p-value for the differences in means are reported in column 3.

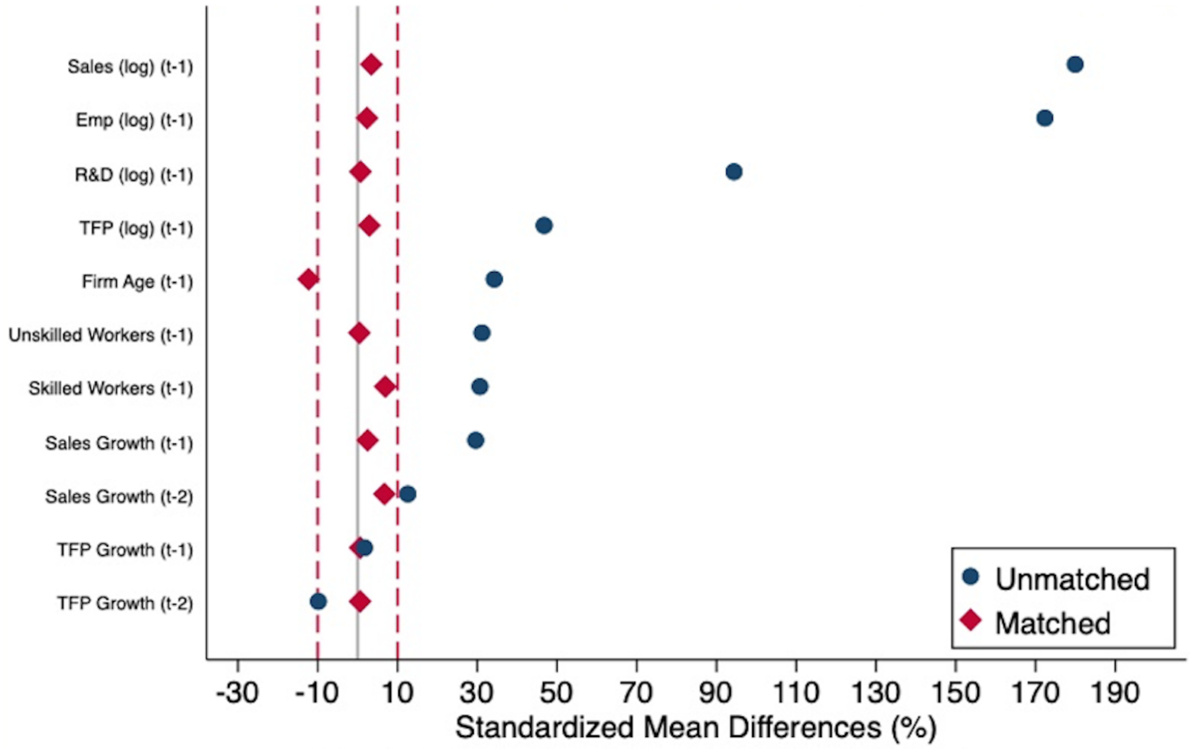
4. Estimation Strategy

Since we have, in our estimation sample, firms that received the R&D tax credits and firms that did not, a first alternative would be to analyse the evolution of the firms that benefited from the incentives with the entire pool of firms that never received them in order to isolate the causal effect of R&D tax credits. Yet, such approach would be flawed as it would assume that firms that participated to the tax incentives program would follow the same trajectory as the entire pool of firm that never participated in the absence of the tax credits, i.e., that the parallel trend assumption would hold. Such assumption, however, is unlikely given the substantial differences in observable characteristics illustrated in table 1.

To bypass this 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. In fact, matching would allow us to create a customized control group with very similar observable characteristics to those of the firms that participated in the tax credits program. We use one-to-one distance matching[2] 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. The SMD is the most important metric to evaluate matching quality (Ho et al., 2007).

[2] The 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 have been replicated for other forms of matching and are qualitatively similar (see section VI).

Figure 1: SMD for the Matched and Unmatched Sample



Note: the dashed lines represent the 10% threshold for balance.

As shown above, the matching managed to reduce a significant amount of observable 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. Additional information on the balance is provided in the Appendix.

Following Bastos et al. (2018), we use the matched groups and estimate the following two-way fixed effects model[3]:

$$y_{it} = \alpha_i + \delta_t + \beta_1 D_{it} + \epsilon_{it} \tag{1}$$

[3] Specification derived from Borusyak & Jaravel (2017).

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 onwards[4] 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 onwards, 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):

$$y_{it} = \alpha_i + \delta_t + \beta_2 D_{it} \times Lenght_i + \epsilon_{it} \tag{2}$$

where $Lenght_i$ 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 sectoral 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] In a sense, we are defining two periods: a "pre" period before support and a "post" period from the moment the firm is first supported.

5. Results

5.1. Effect of R&D Tax Credits on R&D Activity

We first examine the effect of the R&D incentives scheme on the research and development activity of the firms supported by the program[5]. We estimate equations (1) and (2) using the log investments in R&D-related activities as the outcome variable. Results are shown in Table 2 below.

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***	0.949***		
	(0.132)	(0.132)		
Treatment × length			0.158***	0.159***
			(0.022)	(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***	2.608***		
	(0.207)	(0.204)		
Treatment × length			0.523***	0.520***
			(0.038)	(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**	0.312**		
	(0.151)	(0.151)		
Treatment × length			0.066***	0.065***
			(0.023)	(0.024)
Observations	30,337	30,337	30,337	30,337
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES

Note: Clustered standard errors are shown. *** p<0.01, ** p<0.05, * p<0.1. A firm is a classified as "engaged in R&D prior to program" if the firm has at least one year pre-participation where the firm invested in R&D while a firm is classified as "never engaged in R&D prior to program" if the firm has never invested in R&D before the program.

[5] The results for the pooled regressions (excluding tables 7-8) include micro-firms. Regressions have been re-run excluding micro-firms, and the results remain robust (available under request).

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. These results are entirely consistent with Proposition I derived from the theoretical framework: as the tax credits reduce the marginal cost of investing in R&D, this 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[6], 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 (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.

[6] More precisely, we are using the log of the variable plus 1 in order to accommodate the concentration at 0 that exists from firms that did not undertake R&D.

Effect at the Extensive Margin: As shown by the magnitude of the coefficients in panel B, 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:

$$Innovation_{it} = \begin{cases} 0 \; if \; RD_{it} = 0 \\ 1 \; if \; RD_{it} > 0 \end{cases}$$

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.

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***	0.084***		
	(0.013)	(0.013)		
Treatment × length			0.016***	0.016***
			(0.002)	(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***	0.272***		
	(0.021)	(0.021)		
Treatment × length			0.055***	0.055***
			(0.004)	(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	0.009		
	(0.015)	(0.015)		
Treatment × length			0.006***	0.006**
			(0.002)	(0.002)
Observations	30,337	30,337	30,337	30,337
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES

Note: Clustered standard errors are shown. *** p<0.01, ** p<0.05, * p<0.1.

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 persistency 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 onwards. 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 & Jaravel, 2017):

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

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

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

Note: Clustered standard errors are shown. *** p<0.01, ** p<0.05, * p<0.1.

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.

5.2. Effect of R&D Tax Credits on Firm Performance

How does the increase in R&D activity caused by the program translate concretely in firm outcomes and innovation? In this section, we aim to assess the effects of the program on firm performance and document the heterogeneous effects of the program based on firm size[7].

Effect on Product Variety: As illustrated in Section II, one possible use of the R&D tax credits is product innovation. This would allow firms to reach new customers and expand their product line. This raises the question of whether participation in the R&D tax credits program led to an increase in product variety within the firm. Such task is, however, difficult to undertake as we do not have information on product variety in QP, nor in SCIE. In order to solve this issue, we leverage the *Comércio Internacional* dataset, which contains detailed information on exporting firms in Portugal. We recover, from this dataset, the number of product varieties that are exported by firms every year. In a sense, this thesis follows Goldberg et al. (2010) by linking trade data at the firm-level with information on firm product lines. Such data is particularly

[7] From this section onwards, we estimate equations (1) and/or (2) using the full sample rather than using the dynamic specification with a reduced sample (table 4). Given the fact that firms have very different lengths of exposure to the program, keeping firms with similar exposure to estimate the dynamic specification would significantly reduce the size of the treatment group, which is problematic. In addition, specifications (1) and (2) provide a straightforward way of interpreting the causal effects of the program.

relevant to assess the effect of the program on product diversification, as we can use the number of exported varieties by the firms as a proxy for the effect of the program on product variety. We merge *CI* with *QP, SCIE* and *SIFIDE* and estimate equations (1) and (2) using the number of exported product varieties as a dependent variable. Results are shown in the first panel of Table 5.

As illustrated in column (1), firms that participated in the program saw an increase of 3.4 more products exported compared to the counterfactual control group, and this effect is statistically significant. This suggests that R&D tax credits impact positively the product variety of supported firms, possibly through product innovation. Importantly, it is crucial to note that the first panel of Table 5 was estimated only using exporting firms that were matched. Therefore, the number of observations used in the estimation is lower than in the previous regressions.

<u>*Effect on Firm Scale:*</u> 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, as illustrated in Proposition II, 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.

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

Dependent Variable:	**Number of Different Products Exported**			
	(1)	(2)	(3)	(4)
Treatment	3.402***	3.129***		
	(0.886)	(0.861)		
Treatment × length			0.651***	0.675***
			(0.175)	(0.176)
Observations	26,526	26,526	26,526	26,526
Industry FE	NO	YES	NO	YES
Industry Trend	NO	YES	NO	YES
Dependent variable:	**Sales (log)**			
	(1)	(2)	(3)	(4)
Treatment	0.261***	0.252***		
	(0.024)	(0.022)		
Treatment × length			0.04***	0.038***
			(0.004)	(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***	0.184***		
	(0.017)	(0.016)		
Treatment × length			0.026***	0.026***
			(0.003)	(0.003)
Observations	35,772	35,772	35,772	35,772
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES

Note: Clustered standard errors are shown. *** p<0.01, ** p<0.05, * p<0.1

Effect on 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 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 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, as illustrated in Section II, 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. As shown in Section II, 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.

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***	0.091***		
	(0.022)	(0.02)		
Treatment × length			0.009***	0.011***
			(0.003)	(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***	0.105***		
	(0.023)	(0.022)		
Treatment × length			0.018***	0.017***
			(0.003)	(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***	0.066***		
	(0.016)	(0.015)		
Treatment × length			0.013***	0.012***
			(0.002)	(0.002)
Observations	35,772	35,772	35,772	35,772
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES
Dependent Variable:	**Return on Sales (RoS)**			
	(1)	(2)	(3)	(4)
Treatment	0.034***	0.035***		
	(0.009)	(0.009)		
Treatment × length			0.006***	0.006***
			(0.001)	(0.001)
Observations	35,664	35,664	35,664	35,664
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES

Note: Clustered standard errors are shown. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Differentiated Effects by Firm 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. Indeed, it is possible that the previous results are only driven by a subset of firms and not by all the firms that received tax credits. 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 & Godinho de Matos, 2020). Such finding is also theoretically illustrated by Proposition IV. In order to verify this hypothesis, we split our treatment and control sample in two groups: small firms (between 10 and 50 employees) and large firms[8] (>150 employees). We assess the scale and efficiency effects of the program on both 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[9], 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.

[8] We do not have enough firms in the treated group above 250 employees, hence we decide to use the 150 employees threshold. Results are robust if we use the 100 employees threshold instead.

[9] We use value-added per worker and RoS as our main efficiency metrics as any cost reduction driven by process innovation would directly impact both variables.

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

Dependant Variables:	Sales (log) (1)		Employment (log) (2)		Value Added per Worker (log) (3)		RoS (4)	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Small Firms								
Treatment	0.236***	0.223***	0.208***	0.199***	0.07**	0.068**	0.006	0.007
	(0.036)	(0.036)	(0.027)	(0.026)	(0.033)	(0.034)	(0.013)	(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
Large Firms								
Treatment	0.184***	0.164***	0.041	0.027	0.112**	0.115**	0.054**	0.055**
	(0.055)	(0.052)	(0.036)	(0.032)	(0.052)	(0.052)	(0.024)	(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

Note: Clustered standard errors are shown. *** p<0.01, ** p<0.05, * p<0.1 Results of equation (1) are provided in this table.

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 workers at the bottom layers of the organizational structure. 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, 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 bottom-layer workers may provide a reasonable intuition on the type of innovation undertaken by the firm[10]. We define *bottom-layer 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.

[10] See Caliendo et al. (2020), where the authors link the idea of firm restructuring to changes in the internal structure and re-organization of layers. Following Caliendo et al. (2020), this thesis proxies process innovation through changes in the bottom layer of the organization.

Table 8: Effect of R&D Tax Credits on Bottom-Layer Workers, by Firm Size

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

Note: Clustered standard errors are shown. *** p<0.01, ** p<0.05, * p<0.1. Results of equation (1) are provided in this table.

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.

5.3. Effect of R&D Tax Credits on Skill-Biased Technological Change

Although R&D tax credits impact firm performance, as illustrated in the previous section, it is important to note that firms do not operate in a vacuum. Any effect of innovation and R&D may trickle down to workers and influence the composition of the workforce in the firm. Given the well-documented relationship between human capital (skill) and knowledge capital generated through R&D (see Toner, 2011), and in light of recent theories on the importance of skill-biased technical change (Card & DiNardo, 2002), we explore, in this section, the effect of R&D tax on the skill composition of firms.

Effect on Skill Bias: The main challenge we face is how to define skilled and unskilled workers in our analysis. In this thesis, we follow Bøler (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 skill-biased technological change, and is in line with recent evidence (Bøler, 2015; Lindner et al., 2021).

Effect on Master's and PhDs: Is the skill bias 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[11]. 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.

Table 9: Effect of R&D Tax Credits on Skill Intensity

Dependent variable:	**Share of Skilled Workers Out of Total Workforce**			
	(1)	(2)	(3)	(4)
Treatment	0.016***	0.016***		
	(0.003)	(0.003)		
Treatment × length			0.002***	0.002***
			(0.000)	(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***	0.021***		
	(0.004)	(0.004)		
Treatment × length			0.003***	0.003***
			(0.001)	(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***	0.085***		
	(0.014)	(0.014)		
Treatment × length			0.018***	0.018***
			(0.002)	(0.002)
Observations	31,532	31,532	31,532	31,532
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES

Note: Clustered standard errors are shown. Highly skilled workers refer to workers with a Master's degree of more. *** p<0.01, ** p<0.05, * p<0.1

[11] Data not available in 2004 and 2005.

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.

Skill Bias and Technological Adoption: 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 & 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 radiofrequency 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 & 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 & Technological Change

Dependent variable:	Adoption of Customer Relationship Management IT (0/1)	
	(1)	(2)
Treatment	0.063	0.066*
	(0.04)	(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*	0.045*
	(0.026)	(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	0.099
	(0.08)	(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*	0.086*
	(0.048)	(0.046)
Observations	575	575
Sector FE	NO	YES
Sector Trend	NO	NO

Note: Clustered standard errors are shown. *** p<0.01, ** p<0.05, * p<0.1. For Industrial Robots, the regression is cross-sectional and does not include firm fixed effects nor time effects.

6. Placebo Test and Robustness Checks

In this thesis, we test the robustness of the results obtained in our analysis in the following ways:

First, one crucial identifying assumption in this thesis 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.

Second, as highlighted throughout the paper, 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 (see Abadie & Imbens, 2004; King & Nielson, 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).

7. Conclusion

This thesis evaluated the effects of 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. Building on a theoretical framework, where we linked the effects of R&D tax credits on firm outcomes, as a guide for the analysis, we assessed the causal effects of the SIFIDE tax credits program on the supported firms. We found that the 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 persistency 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, a finding consistent with the theoretical predictions of our model. 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.

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 thesis, 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.

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9. Appendix

9.1. Appendix I – Conceptual Framework

We present the algebraic derivations of some of the results obtained in the main part of the paper.

A. R&D Tax Credits & New Products

Effect of R&D tax credits on R&D Activity: We implicitly derivative the expression $(1-\tau)p'(K)\pi_B = \mu g'(K)(1-\tau-\lambda)$ and isolate the partial derivative with respect to λ. We obtain:

$$(1-\tau)p''(K)\frac{\partial K}{\partial \lambda}\pi_B = \mu\left[g''(K)\frac{\partial K}{\partial \lambda}(1-\tau-\lambda) - g'(K)\right] \Leftrightarrow$$

$$\frac{\partial K}{\partial \lambda} = \frac{\mu g'(K)}{\mu g''(K)(1-\tau-\lambda)-(1-\tau)p''(K)\pi_B} > 0$$

Which is the exact same expression obtained in the main part of the paper.

Effect of R&D tax credits on Expected Sales: We denote the sales of products A and B, respectively as:

$$S_A = (a - bQ_A)Q_A$$

$$S_B = (d - eQ_B)Q_B$$

The expected sales of the firm is given by the following expression:

$$E[S] = p(K)[S_A + S_B] + \left(1 - p(K)\right)[S_A] \Leftrightarrow$$

$$E[S] = S_A + p(K)S_B$$

Taking the derivative of the previous expression with respect to λ, we obtain:

$$\frac{\partial E[S]}{\partial \lambda} = p'(K)\frac{\partial K}{\partial \lambda}S_B > 0$$

<u>*Effect of R&D tax credits on Expected Employment:*</u> We define expected employment as:

$$E[L_T] = p(K)[L_A + L_B] + \left(1 - p(K)\right)[L_A] \Leftrightarrow$$

$$E[L_T] = L_A + p(K)L_B \Leftrightarrow$$

$$E[L_T] = \frac{Q_A}{\alpha_A} + p(K)\frac{Q_B}{\alpha_B}$$

Taking the partial derivative with respect to λ, we obtain:

$$\frac{\partial E[L_T]}{\partial \lambda} = p'(K)\frac{\partial K}{\partial \lambda}\frac{Q_B}{\alpha_B} > 0$$

<u>*Effect of R&D tax credits on Expected Labor Productivity:*</u> We compute the expected average labor productivity:

$$E\left[\frac{Q}{L}\right] = p(K)\left[\frac{Q_A + Q_B}{L_A + L_B}\right] + \left(1 - p(K)\right)[\frac{Q_A}{L_A}]$$

Taking the derivative of with respect to λ, we obtain:

$$\frac{\partial E[\frac{Q}{L}]}{\partial \lambda} = p'(K)\frac{\partial K}{\partial \lambda}[\frac{Q_A + Q_B}{L_A + L_B} - \frac{Q_A}{L_A}]$$

The sign of the derivative depends on the sign of the expression $\frac{Q_A+Q_B}{L_A+L_B} - \frac{Q_A}{L_A}$. Putting under the same denominator and simplifying, we obtain:

$$\frac{Q_A + Q_B}{L_A + L_B} - \frac{Q_A}{L_A} = \frac{Q_B L_A - Q_A L_B}{(L_A + L_B) L_A}$$

The sign of which depends on the numerator $Q_B L_A - Q_A L_B$. The effect of the R&D tax credits on expected labor productivity will positive if and only if:

$$\frac{\partial E[\frac{Q}{L}]}{\partial \lambda} > 0 \Leftrightarrow \; Q_B L_A - Q_A L_B > 0 \; \Leftrightarrow \frac{Q_B}{L_B} > \frac{Q_A}{L_A}$$

Which provides a straightforward and intuitive condition under which the R&D tax credits will increase expected output per worker. For product innovation to increase efficiency as measured by output per worker, the output per worker under new product line B should be higher than the output per worker under existing product line A.

To understand better what factors impact the ratio of output per worker, we simply and we obtain the following condition:

$$\frac{\partial E[\frac{Q}{L}]}{\partial \lambda} > 0 \Leftrightarrow \frac{Q_B}{L_B} > \frac{Q_A}{L_A} \; \Leftrightarrow \frac{\alpha_B}{\alpha_A} > 1$$

This condition specifies that the relative productivity in the production of goods A and B, as measured by α_A, α_B is the main determinant of average labor productivity.

B. R&D Tax Credits & Efficiency-Enhancing Process

*Effect on R&D Activity***:** In order to find the effect of R&D tax credits when the firm can engage into process innovation, we take the partial derivative of equation $(1-\tau)p'(k)(c_A - c_A')Q_A = (1-\tau-\lambda)\mu g'(k)$ with respect to λ:

$$(1-\tau)(c_A - c_A')(p''(K)\frac{\partial K}{\partial \lambda}Q_A + p'(K)\frac{\partial Q_A}{\partial K}\frac{\partial K}{\partial \lambda}) = (1-\tau-\lambda)\mu g''(K)\frac{\partial K}{\partial \lambda} - \mu g'(K)$$

$$\Leftrightarrow$$

$$\frac{\partial K}{\partial \lambda} = \frac{-\mu g'(K)}{(1-\tau)(c_A - c_A')\left(p''(K)Q_A + p'(K)\frac{\partial Q_A}{\partial K}\right) - (1-\tau-\lambda)\mu g''(K)}$$

Effect on Sales: We define firm sales as:

$$S = (a - bQ_A)Q_A$$

Taking the derivative with respect to λ:

$$\frac{\partial S}{\partial \lambda} = -b\frac{\partial Q_A}{\partial K}\frac{\partial K}{\partial \lambda}Q_A + (a - bQ_A)\frac{\partial Q_A}{\partial K}\frac{\partial K}{\partial \lambda} \Leftrightarrow$$

$$\frac{\partial S}{\partial \lambda} = \frac{\partial Q_A}{\partial K}\frac{\partial K}{\partial \lambda}(a - 2bQ_A)$$

Knowing that $MR_A = a - 2bQ_A$ and that $MR_A = P_A\left(\frac{1+\varepsilon}{\varepsilon}\right)$, where ε is the own-price elasticity of demand, we obtain:

$$\frac{\partial S}{\partial \lambda} = \frac{\partial Q_A}{\partial K}\frac{\partial K}{\partial \lambda}P_A\left(\frac{1+\varepsilon}{\varepsilon}\right)$$

Effect on Employment: We define expected employment as:

$$E[L_T] = p(K)\left[\frac{Q_A}{\alpha_A'}\right] + \big(1 - p(K)\big)\left[\frac{Q_A}{\alpha_A}\right] \Leftrightarrow$$

$$E[L_T] = \frac{\alpha_A p(K)Q_A + \big(1-p(K)\big)\alpha_A' Q_A}{\alpha_A'\alpha_A} \Leftrightarrow$$

$$E[L_T] = \frac{p(K)Q_A[\alpha_A - \alpha_A'] + \alpha_A' Q_A}{\alpha_A'\alpha_A}$$

Taking the partial derivative with respect to λ:

$$\frac{E[L_T]}{\partial\lambda} = \frac{[\alpha_A - \alpha_A'] \left(p'(K)\frac{\partial K}{\partial\lambda}Q_A + p(K)\frac{\partial Q_A}{\partial K}\frac{\partial K}{\partial\lambda}\right) + \alpha_A' \frac{\partial Q_A}{\partial K}\frac{\partial K}{\partial\lambda}}{\alpha_A'\alpha_A} \Leftrightarrow$$

$$\frac{E[L_T]}{\partial\lambda} = \frac{\partial K}{\partial\lambda}\frac{[\alpha_A - \alpha_A'] \left(p'(K)Q_A + p(K)\frac{\partial Q_A}{\partial K}\right) + \alpha_A' \frac{\partial Q_A}{\partial K}}{\alpha_A'\alpha_A} \Leftrightarrow$$

$$\frac{E[L_T]}{\partial\lambda} = \frac{\partial K}{\partial\lambda}\frac{[\alpha_A - \alpha_A']p'(K)Q_A + \left(p(K)\alpha_A + \left(1 - p(K)\right)\alpha_A'\right)\frac{\partial Q_A}{\partial K}}{\alpha_A'\alpha_A}$$

C. Differential Use of R&D Tax Credits Based on Firm Size

The firm will decide to invest in the type of innovation that yields the highest expected increase in profits, compared to a scenario where the firm did not invest in R&D (counterfactual scenario). The expected increase in profit from a process-based innovation is given by:

$$E[\Delta\pi^{PROCESS}] = (1-\tau)\begin{pmatrix} p(\overline{K})\left[\left(a - bQ'_A\right)Q'_A - c_A{}'Q'_A\right] \\ +\left(1 - p(\overline{K})\right)\left[\left(a - bQ'_A\right)Q'_A - c_A Q'_A\right] - \mu g(\overline{K}) \end{pmatrix}$$
$$+\lambda\mu g(\overline{K}) - (1-\tau)([(a - bQ_A)Q_A - c_A Q_A])$$
$$\Leftrightarrow$$
$$E[\Delta\pi^{PROCESS}] = \frac{(1-\tau)(a-\bar{c})^2}{4b} - \frac{(1-\tau)(a-c_A)^2}{4b} - (1-\tau)\mu g(\overline{K}) + \lambda\mu g(\overline{K})$$

Where $\bar{c} = p(\overline{K})c_A' + \left(1 - p(\overline{K})\right)c_A$ in equation. Similarly, the expected increase in profit from a product-based innovation is given by:

$$E[\Delta\pi^{PRODUCT}] = (1-\tau)\begin{pmatrix} p(k)[(a - bQ_A)Q_A + (d - eQ_B)Q_B - c_A Q_A - c_B Q_B] \\ +\left(1 - p(k)\right)[(a - bQ_A)Q_A - c_A Q_A] - \mu g(\overline{K}) \end{pmatrix}$$
$$+\lambda\mu g(\overline{K}) - (1-\tau)([(a - bQ_A)Q_A - c_A Q_A])$$
$$\Leftrightarrow$$
$$E[\Delta\pi^{PRODUCT}] = (1-\tau)p(\overline{K})\pi_B - (1-\tau)\mu g(\overline{K}) + \lambda\mu g(\overline{K})$$

The firm will decide to invest in product innovation if and only if the expected increase in profits from undertaking product innovation is higher than the expected increase in profits from undertaking process innovation:

$$E[\Delta\pi^{PRODUCT}] > E[\Delta\pi^{PROCESS}] \iff$$

$$\frac{(1-\tau)(a-\bar{c})^2}{4b} - \frac{(1-\tau)(a-c_A)^2}{4b} - (1-\tau)\mu g(\bar{K}) + \lambda\mu g(\bar{K}) <$$

$$(1-\tau)p(\bar{K})\pi_B - (1-\tau)\mu g(\bar{K}) + \lambda\mu g(\bar{K})$$

$$\iff$$

$$p(\bar{K})\pi_B > \frac{(a-\bar{c})^2}{4b} - \frac{(a-c_A)^2}{4b} \iff$$

$$p(\bar{K})\pi_B > \frac{(a-\bar{c}-a+c_A)(a-\bar{c}+a-c_A)}{4b} \iff$$

$$p(\bar{K})\pi_B > \frac{p(\bar{K})(c_A-c_A')(2a-\bar{c}-c_A)}{4b} \iff$$

$$\pi_B > \frac{(c_A-c_A')(2a-\bar{c}-c_A)}{4b}$$

Which is the same condition derived in the main part of the paper.

9.2. Appendix II – Data, Variables and Definitions

Computation of Productivity Metrics using SCIE

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

1. Sales per Worker

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

$$Sales\ per\ Worker_t = \frac{Real\ Sales_t}{Number\ of\ Employees_t}$$

2. 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.

$$VA\ per\ Worker_t = \frac{VA_t}{Number\ of\ Employees_t}$$

3. ***Total Factor Productivity (TFP)***

In this thesis, the computation of factor productivity using SCIE data follows exactly the procedure employed by Leitão (2020). Given the information on spending in inputs such as materials and labor provided in the dataset, Leitão (2020) computes a measure of factor productivity as a residual:

$$\begin{aligned}\ln(TFP_t) = {} & \ln(Real\ Sales_t) \\ & - Share\ of\ Materials\ in\ the\ Production_t \times \ln(Materials_t) \\ & - Share\ of\ Wages\ in\ the\ Production_t \times \ln(Employees_t)\end{aligned}$$

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:

$$\ln(TFP_t) = \ln(Real\ Sales_t) - 0.54 \times \ln(Materials_t) - 0.14 \times \ln(Employees_t)$$

Sectoral Definition

This thesis uses broad sectoral classification stemming from the *CAE Rev.3* classification. The following categories are used to define sectors, as defined by INE (2007):

Table A1: Sectoral Divisions from CAE Rev.3

Sector	Label
A	Agriculture & Fishing
B	Extractive Industries
C	Manufacturing
D	Energy, Electricity & Gas
E	Water Sanitization & Depollution
F	Construction
G	Retail
H	Transports
I	Restauration & Tourism
J	Information, Communication and Technology
K	Finance & Insurance
L	Real Estate
M	Consulting & Scientific Research
N	Administrative Support
Other Residual Sectors	Education, health, etc.

Source: Instituto Nacional de Estatística INE. (2007). *Classificação Portuguesa das Atividades Económicas Rev.3*. Retrieved from https://www.ine.pt/ine_novidades/semin/cae/CAE_REV_3.pdf. In this thesis, categories D & E are combined due to the similarity in their activities.

9.3. Appendix III – Matching Balance

Table A2: Covariates Balance, Matched Sample, 2004-2019

		Mean				T-Test		Variance Ratios
Variable	Sample	Treated	Control	%bias	& bias reduction	T-Statistic	P-value	V(T)/V(C)
Employment (log)	U	3.893	1.705	172.4	98.600	90.02	0.000	2.18
	M	3.881	3.851	2.4		0.59	0552	1.01
Sales (log)	U	15.589	12.512	179.9	98.100	86.27	0.000	1.67
	M	15.571	15.513	3.4		0.95	0.343	1.03
TFP (log)	U	8.524	7.515	46.8	93.700	18.55	0.000	0.83
	M	8.292	8.228	3.0		0.92	0.358	0.98
Sales per Worker (log)	U	11.696	10.807	89.4	96.700	36.39	0.000	0.93
	M	11.690	11.661	2.9		0.96	0.336	1.03
R&D (log)	U	4.757	0.911	94.4	99.200	66.78	0.000	4.84
	M	4.278	4.249	0.7		0.16	0.876	1.02
Sales Growth	U	0.143	0.009	29.6	91.500	12.19	0.000	0.97
	M	0.093	0.082	2.5		1.10	0.272	1.11
TFP Growth	U	-0.052	-0.065	1.7	62.900	0.74	0.461	1.11
	M	-0.043	-0.048	0.6		0.38	0.704	1.08
Employment Growth	U	0.116	0.013	34.1	55.900	14.56	0.000	1.13
	M	0.088	0.042	15.0		5.66	0.000	1.42
Sales Growth (1 lag)	U	0.136	0.050	12.6	46.500	4.84	0.000	0.88
	M	0.109	0.062	6.7		2.60	0.009	0.62
TFP Growth (1 lag)	U	-0.142	-0.071	-9.8	93.700	-3.89	0.000	0.99
	M	-0.131	-0.136	0.6		0.21	0.832	1.27
Employment Growth (1 lag)	U	0.083	0.021	23.0	65.300	8.76	0.000	0.85
	M	0.076	0.054	8.0		2.26	0.024	0.79
Sales Growth (2 lags)	U	0.103	0.039	11.0	54.300	3.00	0.003	0.25
	M	0.091	0.064	4.6		1.74	0.082	0.60
TFP Growth (2 lags)	U	-0.134	-0.068	-10.1	70.300	-3.24	0.001	0.72
	M	-0.136	-0.155	3.0		0.91	0.364	0.87
Employment Growth (2 lags)	U	0.075	0.022	19.9	54.300	6.59	0.000	0.84
	M	0.067	0.043	9.1		2.38	0.018	1.00
Firm Age	U	20.875	15.448	34.3	64.100	16.89	0.000	1.83
	M	21.915	23.862	-12.3		-2.95	0.003	1.07
Number of Unskilled Workers	U	144.99	10.9	31.2	98.500	78.76	0.000	78.21
	M	103.81	101.84	0.5		0.24	0.809	1.47
Number of Masters/PhDs	U	0.947	0.054	14.8	79.800	45.98	0.000	122.74
	M	0.544	0.364	3.0		2.24	0.025	1.54

Note : the balance by year and by industry is exact and therefore, it is not illustrated in the table

9.4. Appendix IV – Results

Table A3: Effect of R&D Tax Credits on the Share of Highly Skilled Workers

Dependent variable:	**Share of Highly Skilled Workers Out of Total Workforce**			
	(1)	(2)	(3)	(4)
Treatment	0.007***	0.007***		
	(0.002)	(0.002)		
Treatment × length			0.001***	0.001***
			(0.000)	(0.000)
Observations	31,532	31,532	31,532	31,532
Industry FE	NO	YES	NO	YES
Industry Trend	NO	YES	NO	YES
Dependent Variable:	**Share of Highly Skilled Workers Wage Bill Out of Total Wage Bill**			
	(1)	(2)	(3)	(4)
Treatment	0.011***	0.011***		
	(0.002)	(.002)		
Treatment × length			0.002***	0.002***
			(0.000)	(0.000)
Observations	31,532	31,532	31,532	31,532
Industry FE	NO	YES	NO	YES
Industry Trend	NO	YES	NO	YES

Note: Clustered standard errors are shown. *** p<0.01, ** p<0.05, * p<0.1 Highly-skilled workers are workers with a Masters and/or a PhD.

Effect on Wage Premia: Finally, we examine more closely the effects of the R&D incentives scheme on the average wage paid in the firm, distinguishing between skilled and unskilled workers. Results are showcased in Table A4.

The effect on wages is overall muted. Even though we observe a slight positive effect on the wages paid to the skilled workers, the magnitude of the effect is relatively small (2.4%). In addition, we do not seem to observe any effect on the average wage paid to unskilled workers nor on the overall average wage paid in the firm. These results are puzzling, as Aghion (2017) documented a significant wage premium driven by innovation, especially amongst unskilled workers, while Lindner et al. (2021) documented a significant wage premium to skilled workers. In our study, it does not seem that firms supported by R&D tax credits changed significantly the wages paid to their workers, compared to the control group. One possible explanation for this result is the fact that the productivity gains associated with the program were kept at the firm level and did not trickle down as wage gains to worker. In addition, such hypothesis would be consistent with the assumption of competitive labor markets: given that wages are set by the overall market, firms may decide to hire the workers at the market wage, which is the same wage faced by its peers. This would explain why the wage evolution of the firms supported by the tax credits tracks very closely the evolution of the control group.

Table A4: Effect of R&D Tax Credits on Average Wages (Hourly), by Skilled Group

Dependent Variable:	**Average Hourly Wage (log)**			
	(1)	(2)	(3)	(4)
All Workers (Pooled Skilled/Unskilled)				
Treatment	0.009	0.01*		
	(0.005)	(0.005)		
Treatment × length			0.001	0.001
			(0.001)	(0.001)
Observations	35,772	35,772	35,772	35,772
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES
Skilled Workers Only				
Treatment	0.024***	0.022**		
	(0.009)	(0.009)		
Treatment × length			0.002*	0.003*
			(0.001)	(0.001)
Observations	30,836	30,836	30,836	30,836
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES
Unskilled Workers Only				
Treatment	0.003	0.003		
	(0.005)	(0.005)		
Treatment × length			0.000	0.001
			(0.001)	(0.001)
Observations	34,745	34,745	34,745	34,745
Sector FE	NO	YES	NO	YES
Sector Trend	NO	YES	NO	YES

Note: Clustered standard errors are shown. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

9.5. Appendix V – Robustness Checks

Placebo Test

In order to verify that the effect on R&D investment is indeed driven by the program, we follow firms that were supported by the tax credits pre-participation until they receive the tax credits (t=0). We use an event-study specification with leads, impute a placebo shock the year prior to participation and compare with the treatment effect on the year the firms truly receive the tax credits. We can clearly see that the effect of the treatment is null and non-statistically significant the year prior to participation. Yet, on impact, there is a very strong level effect on R&D investment, which is consistent with the results obtained in the main part of the paper.

Table A5: Placebo on R&D Investment One Year Prior to Participation

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

Note: Clustered standard errors are shown. *** p<0.01, ** p<0.05, * p<0.1

Propensity Score Matching (PSM)

In the main part of the paper, we decided to opt for distance matching using *mahalanobis* as our distance metric (see King & Nielson, 2019; Abadie & Imbens, 2004). We chose this matching technique as it provided us with good balance while selecting a relatively large number of supported firms and their respective counterfactuals. In addition, given that MDM matching matches on a covariate distance indicator, the pairs of firms that are formed are relatively similar in all aspects in terms of the matched covariates (Imbens, 2004), which makes sub-sample analysis (for instance, splitting by firm size) much easier to undertake (Jann, 2017). In this section, we leverage propensity score matching (PSM) in order to build our control and treatment groups. We estimate a logit with the main variables used in the paper. Results are provided below.

Table A6: 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 R^2	0.356
Sector Effects	YES
Year Effects	YES

Note: Standard errors are shown. *** p<0.01, ** p<0.05, * p<0.1.

The pseudo R-squared of this regression is around 0.36, which is very high and shows that a significant amount of heterogeneity between participating firms and control firms is due to the variables included in the regression. Note, however, that some variables are the opposite signs that what we would have expected. For instance, TFP and growth of TFP have negative signs. This is due to significant amount of collinearity between the variables included in the regression. If we were to remove sales and the growth of sales from the regression, both signs would turn positive. We then estimate the propensity score and match nearest neighbor 1-5 with replacement. We decided to match each beneficiary of the tax credits scheme to the most similar five control firms as it is the method that provided us with the best balance amongst all the other PSM algorithms. Equation (1) of our empirical strategy is then run on some selected covariates using the matched groups. Results are shown below.

Table A7: 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***	0.248***	0.134***	0.014***	0.093***
	(0.116)	(0.015)	(0.026)	(0.003)	(0.026)
Sector FE	NO	NO	NO	NO	NO
Sector Trend	NO	NO	NO	NO	NO

Note: Clustered standard errors are shown. *** p<0.01, ** p<0.05, * p<0.1. Results are obtained using PSM, 1-5, with replacement.

Importantly, the results obtained in the table are extremely close to the coefficients we obtained in the main part of the paper. This reinforces the credibility of our experimental design, as the way we select the control and the treatment groups does not impact materially the results.