ISCTE Business School
INSTITUTO UNIVERSITÁRIO DE LISBOA

# IMPACT EVALUATION OF THE FISCAL INCENTIVE SYSTEM FOR CORPORATE RESEARCH & DEVELOPMENT

António Simões

Dissertation submitted as partial requirement for the conferral of

MSc. in Economics

Supervisor:
Prof. Ricardo Paes Mamede, Assistant Professor, ISCTE-IUL, Department of Political Economy

Co-supervisor:
Prof. Thomas Greve, Assistant Professor, ISCTE-IUL, Department of Economics

September, 2019

# Abstract

The Fiscal Incentive Scheme for Corporate Research and Development (R&D), more commonly known by its acronym SIFIDE has been in force since 1997 with only a small interruption in the fiscal years of 2004 and 2005. Yet, despite its relevance, both financial and institutional, it remains largely unstudied. Using firm-level microdata from four different sources, this dissertation aims fill the gap in the empirical literature and study the impact the incentive has had on the R&D effort of supported firms through the usage of a matching estimator. The findings suggest that SIFIDE had a positive and significant impact while, at the same time, being a cost-effective policy. During the period analysed, from 2006 to 2007, for each euro of forgone tax revenue, between 1.26 and 1.88 euros were spent by the firms which benefited from these tax credits in R&D activities. The results are in line with those of several authors who, in recent years, studied similar incentive schemes in other countries.

**Key words:** Fiscal incentives, Research and Development - R&D, Matching, Counterfactual impact evaluation
**JEL - Codes:** H32, C14, O31

# Resumo

O Sistema de Incentivos Fiscais à Investigação e Desenvolvimento (I&D) Empresarial, mais conhecido pelo seu acrónimo SIFIDE está em vigor desde 1997 com apenas uma pequena interrupção nos anos fiscais de 2004 e 2005. No entanto, apesar da sua relevância quer financeira quer institucional, mantém-se fundamentalmente por estudar. Utilizando microdados ao nível da empresa de quatro fontes diferentes, esta dissertação procura preencher o espaço vazio na literatura empírica estudando o impacto que este incentivo tem tido no esforço de I&D das empresas por ele apoiadas, utilizando para o efeito um estimador de emparelhamento. As conclusões do estudo sugerem que o SIFIDE teve um impacto significativo e positivo conseguindo, simultaneamente, ser uma política custo-eficaz. Durante o período analisado, de 2006 a 2007, por cada euro perdido em coleta fiscal não efetuada, entre 1,26 e 1,88 euros foram gastos, pelas empresas que beneficiaram desses créditos fiscais, em atividades de I&D. Os resultados encotram-se em linha com os outros autores que, em anos recentes, estudaram sistemas de incentivo semelhantes noutros países.

**Palavras-chave:** Incentivos fiscais, Investigação e desenvolvimento - I&D, Emparelhamento, Avaliação de impacto contrafactual
**JEL - Códigos:** H32, C14, O31

# Acknowledgements

Throughout this journey, never did I walk alone. I want to acknowledge the support of the many who walked alongside me.

My supervisor, who jumped on-board from the very first day and did everything he could to unlock all the necessary doors and go thorugh all the necessary hoops.

My co-supervisor, who put up with my over-the-moon ambitions with a smile.

All my colleagues at ANI, particularly those who had to unfortunate luck of sharing an office with me. Moreover my direct supervisors, António Bob Santos and Ana Ponte, as well as Paulo Madeira and the rest of the team managing SIFIDE, Ana, Dina, Inês and Francisco, all of whom helped me shine light on the inner-workings of it all.

All the staff at INE, and in particular Ana Chumbau, who provided me with all the resources necessary to carry this project forward.

My friends, who heard me trying to explain the subject of my dissertation over and over again without much success and particularly Henrique who lost countless hours of his own time to helped me, both in person and not, even when across different time-zones.

Finally my mum, who still supports me unconditionally despite having more than enough reasons no to do so.

I thank all of the above. For all the time spent on me I am deeply grateful.

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# 1. Introduction

Even as time goes by, some things seem to stay the same. The Fiscal Incentive Scheme for Corporate R&D, more commonly known by its acronym: SIFIDE (from the Portuguese designation, “Sistema de Incentivos Fiscais à I&D Empresarial”) was first established in 1997 (Decree-Law no. 292/97 of 22nd October) following the implementation of article 50 of the 1997 State Budget (Law no. 52-C/96 of 27th December) which laid out, in 1996, the plans for the system’s implementation in the following year. I too was born in 1996 and, throughout my lifetime, I recall much of the debate which brought SIFIDE to life being played out repeatedly, without many noticeable changes.

SIFIDE is a tax incentive system for private firms which aims to boost the competitiveness of said firms by supporting their R&D efforts through a corporate tax deduction applied to expenditure of such nature, stimulating the participation of the business sector in the national R&D effort. The program has been in force since 1997 until today with only a small interruption in the fiscal years of 2004 and 2005 where it was replaced by another program, the Fiscal Reserve for Investment.

The wording of the Law itself provides a few clues on the objectives of the program stating the following, in its preamble:

> “Firms’ productivity and, subsequently, their competitiveness are dependent of their innovative capacity which, in turn, depends largely on the results of the R&D activities they promote.
>
> In Portugal, the participation of the private sector in the country’s global R&D effort is very reduced, and urgent measures are needed to stimulate this activity. This endeavour is even more needed as Portugal is one of very few OECD countries where there is no R&D fiscal incentive mechanism, resulting in a penalising situation when competing for knowledge-intensive investments with neighbouring Spain.
>
> Being the intention of the Government to contribute and modify the current situation with respect to corporate R&D activities it is only natural, not excluding other measures, to use classic mechanisms which is susceptible to induce short-term results: fiscal incentives.”
>
> Decree-Law no. 292/97 of 22nd October

It is quite remarkable how up to date the challenges pointed out in this preamble still remain to this day. While the incentive has been in place for over 20 years and despite having since undergone several revisions aimed at increasing its generosity, at first glance it seems that very little has changed. But did the incentive actually change anything? This is precisely why it may still be relevant to revisit SIFIDE in 2019. This research aims to contribute to the literature by expanding the empirical evidence collected on the impact of public support for private R&D[1] to include an analysis of SIFIDE which, despite its relative importance and long-standing presence in the Portuguese policy toolbox, has been largely ignored by academia over the last two decades.

This analysis is twofold as not only should the impact of the policy be investigated but, given its fiscal nature, it is also crucial to understand if this impact, if it actually exists, was worth the loss in tax revenue, which we already know exists. This question is of great importance as, according to the OECD's 1-B-index[2], as of March 2019, Portugal's R&D tax credit scheme is the second most generous in the world. Only France provides a more competitive regime. In light of these facts, this dissertation focuses on answering these two central questions: What is the impact of SIFIDE? And is the policy cost-effective?

The first question is that of causal inference and therefore will be analysed within a counterfactual impact evaluation framework. It is absurd to simply compare directly the group of firms which benefit from the incentive (deemed "treated") with the group of those who do not (deemed "non-treated" or "control") given that both groups exhibit dissimilar distributions among several key characteristics (deemed "counfounders") which impact the performance of such groups as well as the their likelihood of using the incentive itself, and whose effect thus must be isolated from that of the policy itself. The unobserved, counterfactual scenario will be estimated using both propensity score matching and multivariate matching techniques. These match treated firms to suitable non-treated firms whose similarity warrants them as viable controls for the first group thus serving as their hypothetical outcome had they not been treated, the so-called counterfactual outcome.

The remainder of this dissertation is structured as follows: chapter 2 presents a brief compendium of evidence regarding the impact of R&D tax credit schemes similar to that of SIFIDE; chapter 3 dives into the detail of the incentive scheme being analysed and presents the data available to do so; chapter 4 presents the methodology used and the empirical strategy employed in the evaluation; chapter 5 presents the main empirical results and, finally, chapter 6 concludes.

[1]For a recent review on the matter refer to Becker (2015).

[2]Developed by Warda (2002), the B-index is a measure of the level of the pre-tax profit a "representative" company needs to generate to break even on a marginal, unitary outlay on R&D.

# 2. A brief survey of the literature

The rationale behind all forms of public support for private R&D is to correct the under-investment in innovation activities as these (as well as other activities generally related to the production of knowledge) exhibit market failures stemming from a set of characteristics of this quasi-public good, among which those of indivisibility, inappropriability and uncertainty (Arrow, 1962). These characteristics lead private firms to invest less in R&D than what is socially desirable. As firms cannot appropriate all the benefits associated with an innovation (which may have a high rate of social return despite having a low rate of private return) it then becomes socially desirable to reduce the cost these firms incur when performing R&D activities, letting society carry some of the burden in the hope of fomenting a higher (and hopefully optimal) supply of R&D (Nelson, 1959).

R&D tax incentives are not new. Canada implemented them first in 1944, Japan did so in 1966 and the United States of America in 1981. As of the 2018 fiscal year, the usage of fiscal incentives as a tool to stimulate corporate R&D grew considerably with, at least, 30 of the 35 OECD countries and 21 of 28 EU countries having similar schemes[1]. R&D tax incentives are also offered by a plethora of non-OECD countries including Brazil, China, India, Russia, Singapore and South Africa.

R&D tax incentives (be it in the form of tax credits, tax allowances, accelerated depreciation schemes, etc) all function by reducing a firm's tax burden by a given amount. Usually this amount is a function of the volume of R&D expenditure, the increment of such expenditure, or both. They constitute an indirect means of supporting R&D, contrasting with direct government funding of business R&D through grants or contracts.

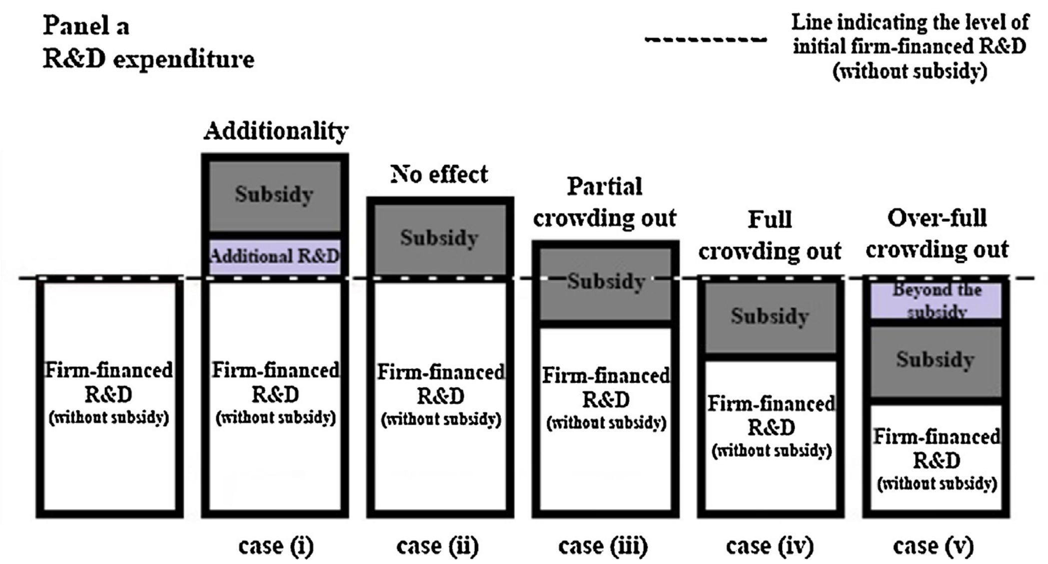
The simplicity (and thus the low administrative costs) of implementation is arguably one of the main reasons for the popularity of these type of instruments. Other advantages over direct R&D incentives include the neutrality of the incentive, meaning that all types of firms as well as all forms of R&D are supported. This may also be interpreted as a drawback given that firms will first invest in projects with highest private, rather than social, rates of return.

The literature on the impact of fiscal incentives to R&D is split in two different branches which focus on two different ways of measuring the effectiveness of the policy

[1] OECD R&D Tax Incentive Database, http://oe.cd/rdtax

being evaluated. Studies on the impact of R&D incentives usually focus on either one or the other. These two major strands emerging from the literature are:

- **Input additionality:** This set of studies analyses the impact of the R&D tax incentives on R&D spending by firms and, as such, their focus is exclusively on the change in the supply of R&D attributable to the presence of the incentive. Admittedly, the most basic rationale behind R&D tax incentives is the presence of a less than optimal supply of this quasi-public good, however it is extraordinarily difficult to access whether the level of the good supplied after the implementation of the policy is still below, above or at the social optimum as “this would necessarily involve comparing the marginal return to industrial R&D dollars at the societal level to the opportunity cost of using the extra tax dollars in another way” (Hall and Van Reenen, 2000). Faced with this challenge, the most common approach employed when conducting evaluation of fiscal incentive for R&D relies on comparing, on one hand, the amount of incremental expenditure induced by the incentive to, on the other hand, the loss in tax revenue. The ratio of these two quantities is usually defined as the additionality effect and if, and only if, it is greater than one, can the tax credit be deemed as cost-effective. The interpretation of this metric is quite straightforward: the amount of additional R&D expenses for each unit of forgone tax revenue. Some studies also call this additionality effect the fiscal credit multiplier. Furthermore, one assumes that if it is the case that the increment in R&D expenditure is smaller than the lost revenue in non-collected taxes (an additionality effect of less than 1), some degree of crowding out occurs. Dimos and Pugh (2016) summarise the possible effects of an R&D subsidy in figure 2.1.




Source: Dimos and Pugh (2016)

Figure 2.1: The possible effects of R&D subsidies on R&D expenditure

- **Output additionality:** The question of output additionality surges naturally given that, often, the legislative bodies who put in place the R&D tax incentive explicitly set out policy goals which go beyond that of simply increasing the amount of R&D expenditure and may include further goals like, for example, the support of Small and Medium Enterprises (SMEs), the promotion of cooperation between industry and the respective national scientific system, or, as is the case with SIFIDE, increase the country's competitiveness in attracting business with R&D activities from abroad. This branch of studies analyses the impact of the R&D tax incentives in many different indicators including firm productivity, firm growth, likelihood of introducing new products, likelihood of applying for intellectual property rights (IPR) and export intensity, among others.

In this chapter, I'll mostly review the state of the input additionality literature as not only this the most broad of the two branches but also the focus of this particular dissertation. For fairly recent review including studies of both input and output additionality, NESTA's Compendium of Evidence on the Effectiveness of Innovation Policy Intervention[2], features an article by Köhler et al. (2012) which surveys a number of such studies on both sides of the additionality argument and provides a collection of country-based reviews summarising their findings.

Most of the early empirical evidence on the impact of fiscal incentives toward corporate R&D comes from studies analysing the introduction, in 1981[3], of the Research and Experimentation Tax Credit, in the USA. While some of these very early studies like that of Eisner et al. (1984) can claim to be the pioneers of this branch of studies, theses studies were plagued by criticism. Notably, in the case of Eisner's report, critics pointed to model misspecification as evidenced by lack of a variable to capture the effect of the tax credit (Hall and Van Reenen, 2000).

In his article entitled "Explicit and implicit effects of the R&D tax credit", Berger (1993) uses *Compustat* data from publicly listed manufacturing enterprises in the USA from 1975 until 1989 and estimates R&D demand through a Pooled OLS model with fixed effects in cross sections and featuring a shift parameter for the R&D tax credit while simultaneously including controls for non-tax factors which may determine R&D demand, at the firm level. At the time of inception, the tax credit's original rate was 25% of new R&D expenditure (defined in the legislation as all R&D expenditure above the average level of R&D expenditure carried out in the previous three years). In 1986, the rate for the tax credit was reduced to 20%. The model pointed to an average increase in R&D intensity (here defined as the ratio of R&D expenditure over turnover) of at least

[2] http://www.innovation-policy.org.uk/compendium/

[3] The Research and Experimentation Tax Credit was introduced by the Economic Recovery Tax Act of 1981, also known as the "Kemp–Roth Tax Cut", introduced a major tax cut designed to promote economic growth during the presidency of Ronald Reagan.

2.9%, during 1981-89 and as much as 8.5% during 1982-85, when the rate of the tax credit was at its highest, estimating an input additionally effect of 1.74 during this second period. Crucially, the study looks also at firms which were unable to utilise the credit in subsequent years and finds that they did not increase their R&D expenditure after 1981 "beyond that expected for nontax reasons".

Published in the same year, a similar study by Hall (1993) came to a only slightly different conclusion ("spending stimulated in the short run was about $2 billion (1982 dollars) per year, while the foregone tax revenue was about $1 billion (1982 dollars) per year") and, while implying a larger additionally effect of 2, the study largely validates the conclusions of the aforementioned study, which is not unexpected given that the data was collect from the same source and much of the period analysed (1980 until 1991) overlaps. After estimating a model for the tax price elasticity of R&D using a generalised method of moments estimator the author finds that, regardless of model specification, the tax price elasticity of R&D turns out to always be either unity or slightly higher, in absolute terms.

Also published in 1993, Hines (1993) looks at a group of multinational corporations which were affected by a slew of new regulations, coming into law from 1986 to 1990, which introduced a more generous tax treatment to R&D performed in the United States. The researcher estimated that R&D spending responded to changes in the after-tax price of R&D with an elasticity somewhere between - 1.6 and - 1.2 using different OLS and IV estimators. As the author points out, "the changes in R&D that would accompany the reforms slightly exceed the tax revenue changes they would induce" and estimates an input additionally effect in the neighbourhood of 1.2 to 1.9.

A final article from 1993, but whose focus is admittedly narrower, only taking into account the pharmaceutical sector, reaches a different conclusion. McCutchen (1993) also models R&D demand and finds that, "while significant changes occurred in the R&D spending patterns in each of the strategic groups in the pharmaceutical industry after the tax credit went into effect", the input additionally effect is less than unity at 0.29 to 0.35, during 1982 to 1985. This contrasts with the studies above mentioned and, even though it may be tempting to dismiss this result as being mainly due to the choice of a specific industry, broader studies done around the same time period reach a similar conclusion. Most notably among these is the U.S. General Accounting Office (1989) report comparing 219 corporations for which they had not only *Compustat* R&D spending data but also confidential tax data. The GAO report concludes that the R&D tax credit stimulated between 1 billion and 2.5 billion dollars in additional R&D spending at a cost in foregone revenue of approximately 7 billion dollars, between 1981 and 1985. This would put the additionally effect in the same ballpark as McCutchen (1993), which indeed finds a value between 0.15 and 0.36, and again at a level which, while still positive, is lower than unity.

A review of the literature from around this era by Hall and Van Reenen (2000) concludes that, while there is a lot of heterogeneity in the findings regarding the magnitude of the additionally effect itself, the results suggest that the introduction of the tax credit in the US had an impact which, at the very least, was both significant and positive. This means that one can safely assume that the complete crowding-out hypothesis does not verify, at least in the USA. The author also surveys a few studies conducted, at the time, outside the USA, which mostly replicate the US findings.

For example, Dagenais et al. (1997) reaches a similar result, estimating an additionality effect of 0.98 for Canadian firms using a generalised Tobit model and data from 1975 until 1992. This value rises to 1.04 when calculations are done only with firms which are not subject to a ceiling in their use of the tax credit.

In Europe, for example, the Norwegian R&D Tax Credit Scheme, introduced in 2002, was also subject to an evaluation (Cappelen et al., 2010) which includes, among others, the study done by Haegeland and Møen (2007) on the subject of input additionality. The author uses a difference-in-differences regression approach and data from 1993 until 2006 to find an effect spanning from 1.3 to 2.9.

This study does stand out as being on the high-end of estimates in the literature but, then again, values vary significantly across different countries and sectors. Case in point, an article by Castellacci and Lie (2015), who performed meta-regression analysis of the 34 articles dated between 1993 and 2012, pointed exactly to this heterogeneity of results. For example, studies which focused on high tech industries usually obtain a smaller estimated additionality effect while the opposite stands true for studies focusing on SMEs, service industries, and low-tech sectors. Nonetheless, Corchuelo and Martínez-Ros (2010) utilises data on Spanish firms and matching techniques to reach an opposite conclusion, namely, that "in the estimation of the counterfactual situation... average tax policy fosters R&D technological effort, but the increase is significant only for large firms", proving that even broader generalisations don't necessarily hold across all countries, time periods or sectors.

While focused on output-additionality, noteworthy of mention is also the article by Czarnitzki et al. (2011) which examines the effect of R&D tax credits on innovation activities of Canadian manufacturing firms during 1993-1997 and concludes that indeed tax credits lead to additional innovation output. The methodology employed by Czarnitzki et al. (2011) was an advance in the literature and will be closely followed in this study as it uses a non-parametric matching approach in order to control for a possible selection bias. Matching techniques tend to offer more conservative estimates of the additionality effect than IV or difference-in-difference estimators (Castellacci and Lie, 2015).

More recent studies like those of Duguet (2012), Bodas Freitas et al. (2017) and Sterlacchini and Venturini (2018) also make use of matching estimators. In the first, the author examines a panel of French firms with data from 1993 to 2003. In an effort to identify the impact of the R&D tax incentive scheme, the author matches firms using the R&D tax credit with similar firms not taking advantage of the fiscal incentive, ending up with an estimated additionality effect of 2.33.

Bodas Freitas et al. (2017) analyse Norway, Italy and France using data from multiple editions of the Community Innovation Survey carried out in these countries in 2004, 2006 and 2008 and, using a combination of matching with difference-in-differences methods, find combined effects raging from 0.26, in France during the 2004-2006 period, to 3.20, in Italy during the 2006-2008 period.

Finally, in a similar study, Sterlacchini and Venturini (2018) also analyse France and Italy, as well as the UK. Making use of a propensity score matching technique, they estimate an addtionality effect in the order of 0.73, 1.49 and 1.58, respectively for France, Italy and the UK, during the 2007-2009 period.

In Portugal, only the 2010 report by SIFIDE's Certifying Commission (FCT; GPEARI; AdI, 2010) attempts to measure the impact of SIFIDE by calculating a naïve "fiscal multiplier" which is obtained by computing the ratio of the average change in approved R&D expenditure over the change in approved tax credit, from 2006 to 2007, for which the authors find an average value of 2.5 of increased approved R&D expenditure for each additional euro of tax credit approved, in the year 2007. Of course, there are a multitude of issues regarding this value among which the obvious problem arising from the fact that the amount of tax credit approved on any given year is a direct consequence of the amount of R&D expenditure approved on the same year.

# 3. On SIFIDE and data availability

## 3.1 SIFIDE

### 3.1.1 Design and implementation

From its inception in 1997 (Decree-Law no. 292/97 of 22nd October), the Fiscal Incentive Scheme for Corporate Research and Development, SIFIDE (from the Portuguese designation "Sistema de Incentivos Fiscais à Investigação e Desenvolvimento Empresarial"), took the form of a tax credit against corporate income tax following an hybrid scheme, that is, it features both a limitless volume deduction and a capped incremental deduction.

The limitless volume deduction means valid R&D expenditure can be deducted against corporate income tax at some defined rate. The incremental deduction was set up so valid R&D expenditure in excess of the geometrical average expenditure from the last two exercises, up to a certain ceiling, could be deducted at higher rate. The porpuse of hybrid or purely incremental schemes is quite obvious: to benefit firms which continuously grow expand their R&D activities and to further promote this continued growth.

The design, at the time of introduction in 1997, was characterised by having a base rate of 8%, an incremental rate of 30%, an incremental rate cap of 250 000€ and unused claims could be carried forward into the following 3 fiscal years. At the time no preferential treatment was given to SMEs and all expenditure needed to be related to activities done exclusively in Portuguese territory.

The program has been in force since 1997 until today with only a small interruption in the fiscal years of 2004 and 2005 where it was replaced by another program, the Fiscal Reserve for Investment, before being re-introduced in 2006. The generosity of the scheme has since grown significantly and the incentive, as of the fiscal year of 2018, features a base rate of 32.5%, an incremental rate of 50%, an incremental rate cap of 1 500 000€ and unused claims can now be carried forward into the following 8 fiscal years. In addition, SMEs (according to the definition given in article 2 of Decree-Law no. 372/2007 of 6th November) which have not yet completed two exercises and that did not benefit from the incremental rate set, benefit from a bonus of 15 p.p. on base rate and the R&D activities outside Portuguese territory are now also eligible.

Over the years, SIFIDE was subject to several changes which are summarised in table 3.1, below. The table encompasses all major design changes over the past two decades.

Table 3.1: SIFIDE: Design changes

| Fiscal Year | Base Rate | Incremental Rate | Incremental Rate Limit | Carry-forward Option |
|---|---|---|---|---|
| 1997 | 8% | 30% | 250 000 € | 3 years |
| 1998 | | | | |
| 1999 | | | | |
| 2000 | | | | |
| 2001 | 20% | 50% | 500 000 € | 6 years |
| 2002 | | | | |
| 2003 | | | | |
| 2004 | SIFIDE was inactive for the fiscal years of 2004 and 2005, replaced by the Fiscal Reserve for Investment (RFI) | | | |
| 2005 | | | | |
| 2006 | 20% | 50% | 750 000 € | 6 years |
| 2007 | | | | |
| 2008 | | | | |
| 2009 | 32.50% | | 1 500 000 € | |
| 2010 | | | | |
| 2011 | | | | |
| 2012 | | | | |
| 2013 | | | | |
| 2014 | | | | 8 years |
| 2015 | | | | |
| 2016 | | | | |
| 2017 | | | | |
| 2018 | | | | |

A more complete version of the above mentioned table with all changes to the legislation, including Decree-Law no. 292/97, Decree-Law no. 197/2001, Law no. 40/2005, Law no. 10/2009, Law no. 3-B/2010, Law no. 55-A/2010, Law no. 4-B/2011, Decree-Law no. 82/2013, Law no. 83-C/2013, Decree-Law no. 162/2014, Law no. 42/2016 and Law no. 114/2017, can be found in the appendix to this dissertation.

### 3.1.2 Application and tax credit history

To be eligible to qualify for the tax credit, a firm must have R&D expenditure not covered (meaning it may not have been subcontracted or subsidised by another entity other than the firm itself); its taxable profit must be directly assessed, thus not determined by indirect methods; and have accomplished all obligations towards both the Tax and Customs Authority and Social Security. If all conditions are met a firm may then submit an application for SIFIDE, addressed to the National Innovation Agency (ANI) until the end of the fifth month of the year following the fiscal year in question.

Following the application, an expert appointed by the National Innovation Agency checks the R&D nature of the declared expenditure following the Frascati Manual (OECD, 2002, 2015) and its eligibility according to SIFIDE's rules (FCT; GPEARI; AdI, 2010).

Eligible expenditure included that incurred with the goal of achieving new scientific or technical knowledge; and the exploitation of research results or other scientific or technical knowledge with the aim to discover or substantially improve raw materials, products, services or manufacturing processes. Nine categories of expenditure were eligible in the 1997 piece of legislation, namely:

(a) Acquisition of tangible fixed assets, apart from buildings, built or acquired new and use directly in R&D activities;

(b) Expenditure with personnel directly involved in the R&D activities

(c) Expenditure related to the participation of personnel in the management of R&D institutions;

(d) Operating expenses up to a maximum of 55% of the expenditure on wages and salaries of personnel directly involved in the R&D activities in the fiscal year;

(e) Expenditure on R&D activities outsourced to public entities and entities recognised by the Ministries of the Economy, and Science and Technology as suitable with regard to R&D activities.

(f) Equity stakes in R&D institutions or contributions to funds intended for the financing of R&D;

(g) Expenditure with the filing and maintenance of patents;

(h) Expenditure with the acquisition of patents for use in R&D activities;

(i) Expenditure with audits to R&D.

The application history for which we have data available (since the re-introduction of SIFIDE, in 2006) is detailed in table 3.2, below.

Table 3.2: SIFIDE: Application history

| Fiscal Year | Applications | $1^{st}$ Time Applications | Approved Applications | Failed Applications | Approval Rate |
|---|---|---|---|---|---|
| 2006 | 442 | 442 | 419 | 23 | 95% |
| 2007 | 680 | 333 | 622 | 58 | 91% |
| 2008 | 931 | 354 | 827 | 104 | 89% |
| 2009 | 1 090 | 336 | 907 | 183 | 83% |
| 2010 | 1 033 | 206 | 851 | 182 | 82% |
| 2011 | 1 004 | 150 | 813 | 191 | 81% |
| 2012 | 943 | 203 | 880 | 63 | 93% |
| 2013 | 1 059 | 235 | 958 | 101 | 90% |
| 2014 | 1 075 | 217 | 1 009 | 66 | 94% |
| 2015 | 1 174 | 229 | 1 105 | 69 | 94% |
| Grand Total | 9431 | 2705 | 8391 | 1040 | 89% |

Here you may notice the growth in applications from 2006 until 2008 was followed by stagnation thereafter. This may be interpreted as a sign that the incentive had reached by then most firms which partake in R&D activities on a regular basis.

Besides information on applications, it may also be interesting to look at data regarding the amount of R&D expenditures declared as well as the amount of tax credit given to firms in the same time period. This information can be found in table 3.3. Here, also after 2008, the growth of declared R&D expenses far outpaced that of approved R&D expenses until the year 2012. Relabelling of expenditure phenomena are in fact well documented in the literature going as far back as the 1980s (Eisner et al., 1984; Oxera, 2006) and are arguably a normal result of firms becoming familiar with both the eligibility criteria of expenditure as well as the level of enforcement of these criteria by the authority governing the incentive.

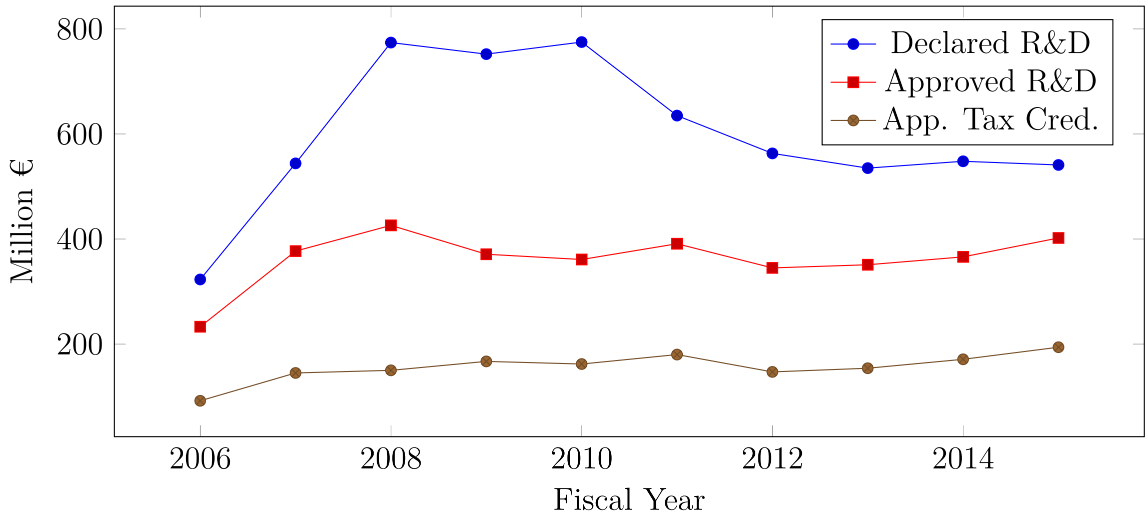
The amount of R&D expenditure actually approved has plateaued from 2008 onwards on an amount usually just shy of 400M €. Inversely, the amount of tax credit approved grew year-over-year (with the only exception being in the fiscal year of 2012) but this is mostly a result of the increase in the generosity of the scheme which occurred in 2009, when the base rate increased from 20% to 32.5% and the incremental rate limit was doubled to 1 500 000€, as showed previously on table 3.1.

Table 3.3: SIFIDE: Credit history

| Fiscal Year | Declared R&D | Approved R&D | Approved R&D w/o Subsidies | Requested Tax Credit | Approved Tax Credit |
|---|---|---|---|---|---|
| 2006 | 322.8M € | 232.6M € | 257.1M € | 117.2M € | 92M € |
| 2007 | 543.6M € | 376.7M € | 407.9M € | 178.5M € | 145.1M € |
| 2008 | 774.3M € | 425.8M € | 468.2M € | 219.3M € | 149.7M € |
| 2009 | 751.6M € | 370.9M € | 398.9M € | 257.7M € | 167.2M € |
| 2010 | 774.9M € | 361.5M € | 423.6M € | 230.1M € | 162.1M € |
| 2011 | 635M € | 391.4M € | 450.3M € | 258M € | 179.8M € |
| 2012 | 562.5M € | 344.9M € | 396.7M € | 188.9M € | 147.2M € |
| 2013 | 534.6M € | 350.5M € | 411.8M € | 186.7M € | 153.7M € |
| 2014 | 548M € | 366.4M € | 423.4M € | 190.9M € | 170.7M € |
| 2015 | 541.4M € | 402.1M € | 439.1M € | 215.8M € | 193.6M € |
| Grand Total | 5 988.7M € | 3 622.6M € | 4 076.9M € | 2 043.1M € | 1 561.1M € |

When plotted in a time series, as done in figure 3.1, the gap between the amount of declared R&D expenditure and the approved amount of R&D expenditure from 2008 until 2012 becomes even more apparent.

Figure 3.1: SIFIDE: Credit history



## 3.2 Data

This dissertation uses firm-level, annual data from four different sources. The underlying database, their respective sources and their anual availability are listed below:

1. **National Innovation Agency (ANI)**: Data regarding SIFIDE applications and tax credit approved, from 2006 until 2015.

2. **National Institute of Industrial Property (INPI)**: Data regarding Intellectual Property Rights, from 2004 until 2015.

3. **Directorate-General for Education and Science Statistics (DGEEC)**: Survey to National Scientific and Technological Potencial (IPCTN), from all years where the survey was conducted (2005 and all years between 2007 and 2015).

4. **National Institute of Statistics (INE)**: Integrated Firm Accounting System (SCIE), including further data retrieved from firm data collected using the Official Accounting Plan (POC) and later the Simplified Firm Information (IES) submissions, from 2004 until 2015.

The different sources were merged together using firms' unique tax identification number (this unique number was anonymised by the National Institute of Statistics in order to assure the confidentiality of the data was not compromised). The number of individual firms for which data existed in the several databases is detailed in table 3.4, below:

Table 3.4: Number of individual firms recorded in each database

| Database | Number of firms | ... which are corporations | ... which are in SCIE | ... which are in IPCTN |
|---|---|---|---|---|
| SCIE | 2 654 274 | 663 079 | - | - |
| IPCTN | 28 782 | 28 782 | 27 586 | - |
| SIFIDE | 2 705 | 2 695 | 2 642 | 2 605 |

While the universe of individual firms in excess of 2.5 million, only 27 586 firms are simultaneously present in both the databases of SCIE and IPCTN, of which 2 605 also took benefited from SIFIDE sometime between 2006 and 2015. Furthermore, only 6 517 of the former declared R&D expenditure of any type in IPCTN, at least once. All of the remaining firms that participated in the IPCTN survey declared to have never financed, hired or developed R&D activities.

Given this information, it is possible to divide the sample in three groups of firms:

1. Those who never participated in R&D activities. This group is irrelevant in the context of a counterfactual impact evaluation as they are not eligible for the treatment and thus are automatically invalid controls.

2. Those who participated in R&D activities yet have not benefited from SIFIDE. This is the group from which a set of controls can be extracted. These firms, while eligible for SIFIDE, did not apply for the incentive.

3. Those who participated in R&D activities and have taken advantage of SIFIDE (i.e., the treated firms)

Table 3.5: Mean value of key variables for different groups of firms

| Variable | Firms without R&D activities | ... with R&D, not in SIFIDE | ... with R&D, in SIFIDE |
|---|---|---|---|
| Employees | 6.46 | 74.55 | 204.84 |
| R&D Personnel | 0.01 | 0.66 | 6.41 |
| Turnover | 584 040.80 € | 13 125 364.21 € | 62 755 205.39 € |
| EBT | 13 996.55 € | 520 825.52 € | 5 695 754.85 € |
| Profit | 9 731.47 € | 421 230.39 € | 4 846 429.98 € |
| Assets | 988 860.95 € | 20 631 174.67 € | 109 483 154.88 € |
| Equity | 291 930.08 € | 6 627 263.10 € | 40 270 446.49 € |
| Operating margin | 57 644.41 € | 856 268.71 € | 1 504 827.57 € |
| GVA (at market prices) | 133 477.08 € | 3 124 080.39 € | 15 566 894.45 € |
| GFCF | 28 888.93 € | 762 341.15 € | 4 158 575.56 € |
| Industrial designs | 0.002 | 0.057 | 0.104 |
| Registered trademarks | 0.134 | 2.869 | 10.033 |
| Active patents | 0.004 | 0.059 | 0.225 |
| Patent requests | 0.004 | 0.011 | 0.069 |
| Developed R&D | - | 121 358.75 € | 842 127.67 € |
| Total R&D expenditure | - | 169 766.37 € | 923 586.15 € |
| App. labour productivity | 19 838.34 € | 43 020.14 € | 70 196.99 € |

The three different groups of firms are indeed very distinct. As expected, firms which participate in R&D activities are, on average, larger, more profitable, more productive and more IPR-intensive than their counterparts. The same applies when comparing firms which take advantage of SIFIDE with both the aforementioned group. The stark contrast between both groups who perform R&D anticipates difficulties in finding an homogeneous group of firms which differ only in their usage of the incentive scheme (often called common support) from which to extract balanced treated and control groups from.

# 4. On the empirical strategy

## 4.1 Methodology

As discussed in chapter two, the vast majority of evaluations of the effectiveness of R&D tax credit schemes have been conducted as benefit–cost analyses, however, the method employed by researchers to identify the amount of additional R&D induced by the tax credit does diverge across studies.

In order to estimate the causal effect SIFIDE has on firms which take advantage of the scheme it would, in principle, be necessary to know how these firms would have behaved in the absence of this fiscal incentive. The impossibility of simultaneously observing, for each firm, their performance both when they take advantage of SIFIDE and when they do not makes it necessary to estimate this potential outcome, the so-called the counterfactual scenario. The causal effect is defined thus as the difference between an observed outcome and its counterfactual. This framework, which conceptualises causal inference in terms of potential outcomes under treatment and control, was developed throughout the years in several publications (Rubin, 1974, 1979, 1980) and its often called the Rubin causal model (Holland, 1986). It serves as baseline for our model as well.

For $N$ units of index $i$ ranging from 1 to $N$ let $T_i$ denote a binary variable describing the treatment assignment (assuming 1 for treated and 0 otherwise). The potential outcomes $Y_i(1)$, for the event of treatment, and $Y_i(0)$ otherwise, are realised and observed depending on treatment assignment $T_i$ as

$$Y_i = \begin{cases} Y_i(0) & \text{if } T_i = 0 \\ Y_i(1) & \text{if } T_i = 1 \end{cases} \tag{4.1}$$

Accordingly, $Y_i(1) - Y_i(0)$ is the treatment effect for unit $i$ however the quantity of interest of the model is the average treatment effect on the treated $ATT$, defined as:

$$ATT = \mathbf{E}[Y_i(1) - Y_i(0)|T_i = 1] \tag{4.2}$$

As pointed out by Athey and Imbens (2017), the gold standard for causal inference are randomised control trials and, in an ideal world, the impact of any public policy would be accessed by conducting a randomised controlled trial (RCT). However this approach is not always possible or, in fact, adequate. As such, the impact of any given policy is, more often than not, estimated from a given set of observational data[1]. This is the case for fiscal incentives.

The issue which arises from this lack of randomised treatment assignment is that it leads to selections bias (auto-selection in the case of SIFIDE) and likely implies confoundedness. This pehnomena occurs when the treatment assignment variable $T_i$ is correlated with other variables which are also correlated with the potential outcomes $Y_i(1)$ and $Y_i(0)$. In a RCT, randomisation of the selection process would eliminate the correlation between any potential confounder and $T_i$ but, in the absence of randomisation, treatment identification can be heavily confounded. For an illustration of this, the reader should have in mind the extremely different characteristics of firms which take advantage of SIFIDE in comparison with those observed in all other firms, even those who also perform R&D activities. Evidence of this is provided in table 3.5.

Several modern econometric techniques have been developed to measure treatment effects when in the presence of selection bias. The program evaluation literature offers a few different estimation strategies to correct for selection bias[2]. These methods include the difference-in-differences (DiD) estimator, structural modelling, instrumental variables estimation and non-parametric matching. For the application of IV estimators one needs valid instruments for the treatment identification.

It is very difficult, in the case of SIFIDE, to find suitable instruments which comply with the essential properties of exogeneity and relevance. Structural models suffer from much of the same issue and, while they allow the estimation of deep structural parameters of theoretical models, the heavy reliance on assumptions makes them unattractive. In our case, the best approach is matching.

Matching promotes balance on covariates, reduces model dependence and thus potentially helps removing bias (Rubin, 1973). In addition, we're using differenced outcome variables which, given equal trends between treatment and control groups, helps to remove the effects of time-invariant confounding factors following the logic behind the DiD approach. Notice that, even when the equal trends assumption does not verify, using first differences for the outcome variables does no harm to the matching process. While we cannot prove this assumption, there is reason to believe that the firms selected by the matching process could indeed exhibit equal trends.

[1] A second best case scenario happens when the treatment is as-if randomly assigned in the population of interest (this is usually called a "natural experiment"). In this scenario, selection is not an issue and one can simply consider the treatment itself as an experiment and find comparison group to mimic the control and identify treatment effects.

[2] See Imbens and Wooldridge (2009) or Athey and Imbens (2017) for recent literature reviews on the subject matter.

### 4.1.1 The matching estimator

Fortunately matching can be used to estimate $ATT$ if the confounders are observed. These observed confounders for unit $i$ will be denoted by $X_i$, a vector of dimension $k$, with $j^{th}$ element $X_{ij}$. Abadie and Imbens (2011) set out four assumptions for this estimate to hold validity, these are:

**Assumption 1** *Let $X$ be a random vector of dimension $k$ of continuous covariates distributed on $\mathbb{R}^k$ with compact and convex support $\mathbb{X}$, with (a version of the) density bounded and bounded away from zero on its support;*

**Assumption 2** *For almost every $x \in X$,*
*(i) $T$ is independent of $Y(0)$ conditional on $X = x$;*
*(ii) $Pr(T = 1|X = x) < 1 - \eta$, for some $\eta > 0$;*

**Assumption 3** *Conditional on $T_i = t$ the sample consists of independent draws from $Y, X|T = t$, for $t = 0, 1$. For some $r \geq 1$ , $N_1^r/N_0 \to \theta$ , with $0 < \theta < \infty$ ;*

**Assumption 4** *Let $\mu_t(x) = \mathbf{E}[Y_i(t)|X_i = x]$ and $\sigma_t^2(x) = \mathbf{E}[(Y_i - \mu_t(x))^2|X_i = x]$. Then, (i) $\mu_t(x)$ and $\sigma_t^2$ are Lipschitz in $X$ for $t = 0, 1$, (ii) $\mathbf{E}[(Y_i(t))^4|X_i = x] \leq C$ for some finite $C$, for almost all $x \in X$, and (iii) $\sigma_t(x)$ is bounded away from zero.*

Assumption 1 requires that all variables in $X$ have a continuous distribution however "discrete covariates with a finite number of support points (e.g., binary variables) can be accommodated by conditioning on their values" (Abadie and Imbens, 2011).

Assumption 2.i is that of unconfoundness and it states that, conditional on $X_i$, the treatment $T_i$ is "as good as randomized," therefore independent of the potential outcomes, $Y_i(1)$ and $Y_i(0)$ (Rosenbaum and Rubin, 1983) and Assumption 2.ii is that of overlap, or of existence of common support, and it requires that the support of $X$ for the treated be a subset of the support of $X$ for control observations (meaning that treated and control group most have overlapping distribution of their covariates). The combination of both is usually referred to as the strong ignorability assumption.

Assumption 3 refers to the sampling process and assumption 4 sets regularity conditions. In practical implementations, these assumptions usually follow directly from the type of data employed and from the model of $\mu_t(x)$.

We will utilise the bias-corrected matching estimator proposed by Abadie and Imbens (2011). This estimator consists of two steps. Firstly, all units are matched, both treated and controls, then, some of the remaining bias is removed through regression on a subset of the covariates where the difference within the matches is regression-adjusted for the difference in covariate values.

This estimator is, under assumptions 1 to 4, a $N^{1/2}$-consistent and asymptotically normal estimator of $ATT$ defined by:

$$\hat{ATT}_{bcm} = \frac{1}{N_1} \sum_{T_i=1} (Y_i - \hat{Y}_i(0)) \tag{4.3}$$

being $J_M(i)$ the matched sample of $i$ with size $M_i$ and $\hat{\mu}_0$ an unbiased estimator of $\mathbf{E}[Y_i(0)|X_i = x]$, for every $i \in N_1$ and for every $j \in J_M(i)$, the estimator $\hat{Y}_i(0)$ is given by:

$$\hat{Y}_i(0) = \frac{1}{M_i} \sum_{j \in J_M(i)}^{M_i} (Y_j + \hat{\mu}_0(X_i) - \hat{\mu}_0(X_j)), \tag{4.4}$$

The estimate $\hat{\mu}_0(X_i)$ is a linear least squares estimate of the model of $\mu_0(X_i)$ and is estimated only on the sub-sample of matched controls. It is expected that the linear approximation done after matching will be adequate. Moreover, the bias of this estimate brings little noise to the estimation of the quantity of interest (Abadie and Imbens, 2011) while allowing multiple continuous covariates and a large $N$.

Robust variances were estimated following Abadie and Imbens (2006).

### 4.1.2 Matching techniques

Two different nearest-neighbour matching techniques were utilised: propensity score matching and multivariate matching based on Mahalanobis distance, both of which are implemented in *R* (R Core Team, 2017) through the **Matching** package (Sekhon, 2011). Note that the difference between these techniques is related to the choice of distance metric used in the matching procedure.

Regardless of the technique used, matching was done one-to-one and with replacement, only allowing one matched control per treated unit but allowing each possible control observation to be used as a match for more than one single treated observation, thus meaning that the order in which the units are matched does not matter and hopefully improving overall balance.

In addition, overlap was enforced by the usage of a caliper of 0.25 standard deviations in the matching process (meaning that only when observations which fell within 0.25 standard deviations of the given distance metric used for matching of a treated observation were these observations used in the sampling of treatment and control groups).

#### 4.1.2.1 Propensity score matching

Propensity score matching (PSM) is the most widely used matching method in the literature and has been in use for the last 50 years. The basic principle behind it is simple: reduce $k$ elements of the covariate vector $X$ to a scalar, the propensity score $\pi$ such that

$$\pi_i = Pr(T_i = 1|X_i = x) = \mathbf{E}[T_i|X_i = x] \tag{4.5}$$

Afterwards, each treated unit is matched to the nearest control unit in the unidimensional metric of the propensity score vector (letting $d$ denote the distance):

$$d(X_i, X_j) = |\pi_i - \pi_j| \tag{4.6}$$

Given, howerver, that $\pi_i = \pi_j$ does not imply $X_i = X_j$, PSM may paradoxically lead to imbalance. Rosenbaum and Rubin (1983) argue that, given a large enough sample size, matching on the propensity score indeed produces covariate balance but, in reality, sample size may not even come into play as a slight misspecification of the propensity score model is enough to result in biased estimations of treatment effect.

We used two distinct methods of estimating the propensity score:

1. A **logistical regression**, which is the most commonly used model in the literature, whose regressors were the chosen control variables (more on this on the next section).

2. A **"Covariate Balancing Propensity Score"**, utilising the same regressors, which implements an estimation method described by Imai and Ratkovic (2014).

Imai and Ratkovic (2014) propose both a just-identified and an overidentified CBPS. We'll use the overidentified CBPS so that we can use Hansen's J-statistic test of overidentifying restrictions as a specification test for the propensity score model (where the null hypothesis is that the propensity score model is correctly specified). This method targets a set of moment conditions that are implied by the covariate balancing property in addition to the score condition for the maximum likelihood and estimates the propensity score using the generalized method of moments (GMM). The CBPS estimation method is also relatively robust to model misspecificaiton given that it selects the parameter values that maximize the resulting covariate balance, reducing model dependency. The method can be implemented in $R$ (R Core Team, 2017) through the **CBPS** package (Fong et al., 2019).

To avoid the issue of compression of the propensity scores near zero and one, extreme values (<0.1 and >0.9) were trimmed from the sample prior to matching.

#### 4.1.2.2 Multivariate matching

A popular technique in the literature (Rubin, 1979, 1980), multivariate matching is more often than not based on the Mahalanobis distance, defined as:

$$md(X_i, X_j) = \sqrt{(X_i - X_j)^T S^{-1} (X_i - X_j)} \tag{4.7}$$

where $S$ is the sample covariance matrix of $X$.

When performing multivariate matching one must take into account that, if $X$ consists of more than a single continuous variable, multivariate matching estimates will contain a bias term that converges to zero at a rate that may be slower than $N^{1/2}$ (Abadie and Imbens, 2006). Hence the choice of the bias-corrected matching estimator proposed by Abadie and Imbens (2011).

There are a few advantages of this distance metric when compared to propensity score. Firstly, multivariate matching is not "blind" in higher dimensions where it usually has an easier time achieving balance between individual coordinates of $X$. Secondly, unlike the propensity score which must be estimated, usually through a parametric regression model, this approach is non-parametric throughout and therefore does not risk exacerbating model dependence.

Note that it is advisable to include the propensity score in the set of covariates used for multivariate matching so as to minimise the discrepancy along both the propensity score itself and the individual coordinates of $X$, orthogonal to the propensity score (Rosenbaum and Rubin, 1985).

We used two distinct techniques of multivariate matching:

1. **Mahalanobis distance matching**, as described above, where matching was done across all control variables, including also the propensity scores estimated by the CBPS model.

2. **Genetic matching**, as proposed by Diamond and Sekhon (2013).

The Genetic matching algorithm builds atop of the outcome of the Mahalanobis distance matching procedure and applies an evolutionary genetic search algorithm in order to optimise post-matching covariate balance by assigning a set of weights $W$ for all matching variables, weighting each variable according to their relative importance for achieving the best overall balance. The new distance function becomes a generalized version of Mahalanobis distance with the additional weight parameter $W$:

$$d(X_i, X_j, W) = \sqrt{(X_i - X_j)^T (S^{-1/2})^T W S^{-1/2} (X_j - X_i)} \tag{4.8}$$

where $W$ is a $k \times k$ positive definite weight matrix and $S^{-1/2}$ is the Cholesky decomposition of $S = (S^{-1/2})^T S^{-1/2}$.

Implemented in *R* (R Core Team, 2017) through the function *GenMatch* of the **Matching** package, the iterative procedure minimises a loss function defined as the minimum p-value observed across a series of standardised statistics (paired t-tests and nonparametric KS tests). In *GenMatch*, all elements of $W$ are set to zero except for those in the main diagonal meaning only the $k$ parameters of main diagonal may be chosen. The optimisation problem is then solved using a genetic algorithm which attempts to maximise the smallest p-value at each generation.

Its important to underline that if one includes the propensity score $\pi(X_i)$ as one the covariates, as we do, propensity score matching will be special case of Genetic Matching (where all other covariates are weighted with weight 0).

## 4.2 Empirical application

### 4.2.1 Outcome variables

The following variables were selected as outcome variables. The absolute variation of each variable was used when estimating the average treatment effect on the treated.

- **R&D personnel** (SCIE)
- **In-house R&D expenditure**, includes personnel, current expenditures, equipment and, real-estate and other fixed capital (IPCTN)
- **Total R&D expenditure**, includes expenditures with development, hiring and financing of R&D (IPCTN)
- **In-house R&D intensity** $= \frac{\text{In-house R\&D expenditures}}{\text{Turnover}}$ (IPCTN/SCIE)
- **Total R&D intensity** $= \frac{\text{Total R\&D expenditures}}{\text{Turnover}}$ (IPCTN/SCIE)

### 4.2.2 Control variables

The following variables were selected as control variables:

- **Turnover**, log-transformed (SCIE)
- **Turnover growth rate** (SCIE)
- **Financial autonomy $< 30\%$** $= \frac{\text{Equity}}{\text{Assets}}$ (SCIE), a binary variable
- **Earnings before taxes** (SCIE)
- **Apparent labour productivity** $= \frac{\text{GVA (at market prices)}}{\text{Personnel}}$ (SCIE)
- **Firm has an active patent or industrial design** (INPI), a binary variable
- **R&D personnel** (SCIE)
- **In-house R&D expenditure** (IPCTN)
- **Total R&D expenditure** (IPCTN)
- **In-house R&D intensity** (IPCTN/SCIE)
- **Total R&D intensity** (IPCTN/SCIE)

### 4.2.3 Absolute restrictions

Some absolute restrictions were made during the matching process with regards to firms of the same Statistical classification of economic activities, as defined by NACE Rev. 2. As such, only firms with the same classification (at one letter level) were matched with each other. Furthermore, only firms of NACE C, J and G, respectively "Manufacturing", "Information and Communication" and "Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles", were left in the sample, before matching.

### 4.2.4 Evaluation period

Ideally, the evaluation of a program with the characteristics of SIFIDE would focus on the firms which applied for the program in the very beginning, when it was introduced (in this case, 1997) however there is no data available for 1997. Fortunately though, SIFIDE has a very singular characteristic: the program effectively ended in 2003 and was then reintroduced in 2006. Furthermore, 2006 also exhibits a few characteristics which make it suitable for conducting an impact assessment:

- The design of the program remained unchanged for the three following fiscal years (2006, 2007 and 2008), as can be seen in table 3.1.
- The number of firms that applied for the incentive for the first time was the highest for which there is data available (given that the program was reintroduced this year, all firms which participated effectively did it for the first time), as can be seen in table 3.2.
- The gap between the declared and the certified R&D expenditure is somewhat narrow (20.3%). The opposite occurred with the rate of approval (95%), as can be seen in tables 3.3 and 3.2.
- Relative macroeconomic stability, crucially preceding the Great Recession of 2008.

Unfortunately, the year 2006 also imposes a few additional challenges given that the survey from which four of the five outcome variables is collected from (IPCTN) was not conducted in 2006 and, as such, measuring the contemporaneous effects of the incentive becomes effectively impossible. To address this challenge the following year of 2007 (in which IPCTN was conducted) was added to the sample. The inclusion of and extra year in the measurement of the treatment effect does come with some associated costs given that only firms which benefited from the incentive in both 2006 and 2007 can now be considered for the treatment group and, similarly, only firms which did not benefit from SIFIDE in both years can be used for the purposes of building a control group.

Table 4.1: Data availability for matching and evaluation periods

| Database | 2004 | 2005 | 2006 | 2007 |
|---|---|---|---|---|
| SIFIDE | - | - | X | X |
| SCIE | X | X | X | X |
| INPI | X | X | X | X |
| IPCTN | - | X | - | X |

Using the years of 2006 and 2007 as the evaluation period makes it necessary to match firms in the period immediately before this one. Thus, data from the years 2004 and 2005 was included in the sample for matching purposes. All control variables are measured in 2005, year for which data is available. The inclusion of the year 2004 is done in order to calculate the growth rate of the firms' turnover (SCIE) in the subsequent year, which is then used as a control variable in the matching process. Matching was conducted using 2005 data (pre-treatment) and the results were measured mainly in 2007 (post-treatment).

### 4.2.5 Final sample

The following table summarises the characteristics of both treated and non-treated firms present in the final sample. From the initial set of eligible firms 828 were observed in the four relevant years (2004-2007), of which 171 firms apllied for SIFIDE in both 2006 and 2007, the treatment group, and 657 firms which did not apply in either of those years, the group of possible controls.

Table 4.2: Mean values for treated and non-treated firms' characteristics

| Sample decompostion | Treated | Non-treated |
|---|---|---|
| Observations | 171 | 657 |
| NACE C | 69.59% | 65.14% |
| NACE J | 25.15% | 17.35% |
| NACE G | 5.26% | 17.50% |
| **Variable** | **Treated** | **Non-treated** |
| Turnover | 21 776 428.37 € | 4 922 967.31 € |
| Turnover growth rate | 12.29% | 7.42% |
| Financial autonomy <30% | 22.22% | 38.36% |
| Earnings before taxes | 9 577 016.69 € | 1 223 156.79 € |
| Apparent labour productivity | 66 056.79 € | 39 985.13 € |
| Firm has an active patent or industrial design | 11.11% | 2.74% |
| R&D personnel | 4.84 | 0.82 |
| In-house R&D expenditure | 668 763.83 € | 65 916.99 € |
| Total R&D expenditure | 766 531.36 € | 129 715.71 € |
| In-house R&D intensity | 4.17% | 12.93% |
| Total R&D intensity | 4.42% | 13.24% |

# 5. Results

## 5.1 Balance and estimated impacts

In this section we will present balance statistics and the estimated treatment effects on the treated for each of the matching procedures described in the previous chapter. A comparative analysis of these, as well as a section on the estimated additionality effect, can be found in the end of the chapter.

While reading the next pages one should be mindful of the balance statistics of the pre-matched sample, presented in table 5.1, as these serve as the baseline from which any matching procedure must improve on. In an ideal scenario, treatment and control groups would be exactly equal in which case the standard mean difference would be 0, the variance ratio would be 1 and the T-test p-value would also be 1, for all control variables. In reality, values are expected to fall somewhere in between these and the baseline.

Table 5.1: Pre-matching: Balance statistics

| Control Variable | Balance Statistics | | |
|---|---|---|---|
| | Std. Mean Diff. | Var. Ratio | T-test P-value |
| log(Turnover) | 0.828 | 0.76 | 0.00000 |
| Turnover growth rate | 0.181 | 0.53 | 0.05291 |
| Financ. auton. <30% | -0.387 | 0.73 | 0.00002 |
| EBT | 0.229 | 18.66 | 0.00342 |
| App. labour product. | 0.348 | 1.02 | 0.00006 |
| Patent/Ind. design | 0.266 | 3.72 | 0.00095 |
| R&D personnel | 0.350 | 19.49 | 0.00001 |
| In-house R&D exp. | 0.287 | 75.30 | 0.00025 |
| Total R&D exp. | 0.289 | 3.97 | 0.00033 |
| In-house R&D intensity | -1.108 | 0.00 | 0.38052 |
| Total R&D intensity | -1.085 | 0.00 | 0.37765 |

The tables shown below present the balance statistics resulting from propensity score matching using the logistical model[1] and the results of the treatment effect estimation obtained from this matched sample.

Table 5.2: PSM - Logit: Balance statistics

| Control Variable | Balance Statistics | | |
|---|---|---|---|
| | Std. Mean Diff. | Var. Ratio | T-test P-value |
| log(Turnover) | -0.078 | 1.63 | 0.41731 |
| Turnover growth rate | -0.193 | 0.19 | 0.36919 |
| Financ. auton. <30% | -0.168 | 0.80 | 0.18814 |
| EBT | 0.246 | 2.06 | 0.02302 |
| App. labour product. | -0.069 | 0.22 | 0.72441 |
| Patent/Ind. design | -0.054 | 0.86 | 0.63784 |
| R&D personnel | -0.072 | 0.62 | 0.50671 |
| In-house R&D exp. | 0.167 | 0.53 | 0.15019 |
| Total R&D exp. | 0.246 | 1.07 | 0.01418 |
| In-house R&D intensity | 0.313 | 5.81 | 0.00069 |
| Total R&D intensity | 0.316 | 5.08 | 0.00061 |
| Propensity Score | 0.000 | 1.01 | 0.94757 |
| Matched Observations | | 135 | |

Table 5.3: PSM - Logit: Average treatment effect on the treated

| Outcome Variable | ATT | | Std. Error |
|---|---|---|---|
| Δ R&D personnel (2005-2006) | 3.28 | *** | 1.08 |
| Δ R&D personnel (2005-2007) | 6.61 | *** | 2.13 |
| Δ In-house R&D exp. (2005-2007) | 746 230.07 € | *** | 224 283.75 € |
| Δ Total R&D exp. (2005-2007) | 813 128.55 € | *** | 229 388.61 € |
| Δ Int. of in-house R&D exp. (2005-2007) | 0.0232 p.p. | *** | 0.0090 p.p. |
| Δ Int. of total R&D exp. (2005-2007) | 0.0272 p.p. | *** | 0.0097 p.p. |

*** p <0.01; ** p <0.05; * p <0.1

[1] After trimming the extreme values (<0.1 and >0.9) of the estimated propensity score the sample was left with 560 observations, of which 144 were treated.

The tables shown below present the balance statistics resulting from propensity score matching using the CBPS model[2] and the results of the treatment effect estimation obtained from this matched sample.

Table 5.4: PSM - CBPS: Balance statistics

| Control Variable | Balance Statistics | | |
|---|---|---|---|
| | Std. Mean Diff. | Var. Ratio | T-test P-value |
| log(Turnover) | 0.105 | 1.37 | 0.23352 |
| Turnover growth rate | -0.117 | 0.24 | 0.53843 |
| Financ. auton. <30% | -0.036 | 0.95 | 0.78520 |
| EBT | 0.134 | 2.59 | 0.19717 |
| App. labour product. | 0.055 | 0.27 | 0.76467 |
| Patent/Ind. design | 0 | 1 | 1 |
| R&D personnel | -0.218 | 0.45 | 0.06989 |
| In-house R&D exp. | 0.181 | 0.84 | 0.05623 |
| Total R&D exp. | 0.159 | 0.99 | 0.11298 |
| In-house R&D intensity | 0.305 | 1.69 | 0.00539 |
| Total R&D intensity | 0.317 | 1.79 | 0.00345 |
| Propensity Score | 0.004 | 0.99 | 0.34411 |
| Matched Observations | 136 | | |

Table 5.5: PSM - CBPS: Average treatment effect on the treated

| Outcome Variable | ATT | | Std. Error |
|---|---|---|---|
| Δ R&D personnel (2005-2006) | 4.93 | *** | 1.26 |
| Δ R&D personnel (2005-2007) | 7.83 | *** | 2.09 |
| Δ In-house R&D exp. (2005-2007) | 625 030.43 € | *** | 233 666.87 € |
| Δ Total R&D exp. (2005-2007) | 708 132.38 € | *** | 240 359.16 € |
| Δ Int. of in-house R&D exp. (2005-2007) | 0.0104 p.p. | | 0.0077 p.p. |
| Δ Int. of total R&D exp. (2005-2007) | 0.0118 p.p. | | 0.0078 p.p. |

*** p <0.01; ** p <0.05; * p <0.1

[2] After trimming the extreme values (<0.1 and >0.9) of the estimated propensity score the sample was left with 560 observations, of which 144 were treated.

The tables shown below present the balance statistics resulting from multivariate Mahalanobis distance matching and the results of the treatment effect estimation obtained from this matched sample.

Table 5.6: Multivariate Matching - MDM: Balance statistics

| Control Variable | Balance Statistics | | |
|---|---|---|---|
| | Std. Mean Diff. | Var. Ratio | T-test P-value |
| log(Turnover) | 0.015 | 0.93 | 0.59455 |
| Turnover growth rate | 0.104 | 1.07 | 0.35946 |
| Financ. auton. <30% | 0 | 1 | 1 |
| EBT | 0.102 | 1.63 | 0.09109 |
| App. labour product. | 0.037 | 0.68 | 0.58984 |
| Patent/Ind. design | 0 | 1 | 1 |
| R&D personnel | 0 | 1 | 1 |
| In-house R&D exp. | 0.104 | 1.19 | 0.10794 |
| Total R&D exp. | 0.122 | 1.21 | 0.06964 |
| In-house R&D intensity | 0.021 | 1.16 | 0.80190 |
| Total R&D intensity | 0.029 | 1.19 | 0.72277 |
| Propensity Score | 0.022 | 0.97 | 0.36608 |
| Matched Observations | | 62 | |

Table 5.7: Multivariate Matching - MDM: Average treatment effect on the treated

| Outcome Variable | ATT | | Std. Error |
|---|---|---|---|
| Δ R&D personnel (2005-2006) | 1.47 | *** | 0.39 |
| Δ R&D personnel (2005-2007) | 2.79 | *** | 0.35 |
| Δ In-house R&D exp. (2005-2007) | 326 043.96 € | *** | 26 295.21 € |
| Δ Total R&D exp. (2005-2007) | 335 434.49 € | *** | 27 827.17 € |
| Δ Int. of in-house R&D exp. (2005-2007) | 0.0301 p.p. | *** | 0.0064 p.p. |
| Δ Int. of total R&D exp. (2005-2007) | 0.0312 p.p. | *** | 0.0067 p.p. |

*** p <0.01; ** p <0.05; * p <0.1

The tables shown below present the balance statistics resulting from genetic matching[3] and the results of the treatment effect estimation obtained from this matched sample.

Table 5.8: Multivariate Matching - GM: Balance statistics

| Control Variable | Balance Statistics | | |
|---|---|---|---|
| | Std. Mean Diff. | Var. Ratio | T-test P-value |
| log(Turnover) | 0.005 | 0.92 | 0.86159 |
| Turnover growth rate | 0.122 | 1.27 | 0.27084 |
| Financ. auton. <30% | 0 | 1 | 1 |
| EBT | 0.088 | 1.61 | 0.16443 |
| App. labour product. | 0.054 | 0.65 | 0.47211 |
| Patent/Ind. design | 0 | 1 | 1 |
| R&D personnel | 0 | 1 | 1 |
| In-house R&D exp. | 0.058 | 1.14 | 0.34830 |
| Total R&D exp. | 0.077 | 1.17 | 0.21938 |
| In-house R&D intensity | 0.01 | 1.16 | 0.90192 |
| Total R&D intensity | 0.018 | 1.19 | 0.82398 |
| Propensity Score | 0.009 | 0.97 | 0.68468 |
| Matched Observations | | 62 | |

Table 5.9: Multivariate Matching - GM: Average treatment effect on the treated

| Outcome Variable | ATT | | Std. Error |
|---|---|---|---|
| Δ R&D personnel (2005-2006) | 1.63 | *** | 0.39 |
| Δ R&D personnel (2005-2007) | 2.90 | *** | 0.35 |
| Δ In-house R&D exp. (2005-2007) | 331 986.42 € | *** | 26 423.65 € |
| Δ Total R&D exp. (2005-2007) | 340 930.15 € | *** | 27 903.59 € |
| Δ Int. of in-house R&D exp. (2005-2007) | 0.0327 p.p. | *** | 0.0064 p.p. |
| Δ Int. of total R&D exp. (2005-2007) | 0.0338 p.p. | *** | 0.0067 p.p. |

*** p <0.01; ** p <0.05; * p <0.1

[3] The genetic algorithm ran for 7 generations with a population size of 1000 and reached convergence after the $2^{nd}$ generation. Further information, including the weights assigned to each covariate can be found in the appendix to this dissertation.

Regarding balance it is immediately obvious the trade-off made between internal and external validity when comparing the results of propensity score matching and multivariate matching. Regardless of the method used to estimate the propensity score, both propensity score matching procedures had a much larger number of matched observations (135 and 136 respectively for the logistical regression and the CBPS) than the multivariate matching procedures (with only 62 matches), however this gain in external validly coming from a larger matched sample comes at the cost of lower internal validity as manifested by the worse balance statistics when compared to the multivariate matching procedures.

When comparing only the two propensity score models it is not unreasonable to argue that the CBPS[4] achieves slightly better balance given that the matching it produces leads us not reject the null hypothesis of the paired T-test, at significance level of 5%, for ten of the twelve control variables variables (as opposed to just eight). In addition, the variance ratios for the control variables "In-house R&D intensity" and "Total R&D intensity" also improve significantly.

Nonetheless, the two propensity score matching methods mostly produce similar results with a notable exception of the change in intensity of both in-house and total R&D expenditure, which is found to be significant at a 1% significance level when matching is done on the logistic estimated propensity score yet is not significant (even at a 10% level of significance) when the CBPS is used. In fact, only the CBPS matching procedure deviated with regard to estimated treatment effects as all other methods found as statistically significant (at a 1% level of significance, no less) impact on all outcome variables, including the change in intensity of in-house R&D expenditure and change in intensity of in total R&D expenditure. The different magnitude of the effects of the propensity score matching and the multivariate matching estimations stems from the differences in the matched sample between the two methods, with the multivariate matching procedures selecting a sample composed of smaller (but more homogeneous) firms.

In sum, going back to the questions posed in the introduction of this dissertation: "What is the impact of SIFIDE?" The evidence points to a positive and significant impact on the beneficiary firms, at least with regard to the assignment of additional employees to R&D activities and to the increase in R&D expenditure, both in-house and overall.

To answer the second question ( "Is the policy cost-effective?") we'll focus on the question of input additionally, addressed in the next section of this chapter.

[4]Hansen's J-statistic for the CBPS model was 0.0002, we therefore do not reject the null hypothesis of correct specification of the propensity score model. This statistic as well as the model's output table can be found in the appendix.

## 5.2 Additionality effect

Using the estimated counterfactuals and their estimated average treatment effect values in conjunction with the volume of the tax credit approved for the treated firms in the fiscal years of 2006 and 2007 it is possible to calculate an average additionally effect for SIFIDE. The results are shown in the table below:

Table 5.10: Average input additionality effect

| Additionality effect | Logit | CBPS | MDM | GM |
|---|---|---|---|---|
| In-house R&D expenditure | 1.73 | 1.29 | 1.23 | 1.25 |
| Total R&D expenditure | 1.88 | 1.46 | 1.26 | 1.28 |

Regardless of the type of R&D expenditure and of the matching procedure utilised, the estimated average input additionality effect is larger than unity. This means that the amount of R&D expenditure induced by the incentive is indeed higher than the forgone revenue in non-collected taxes. We can thus also safely set aside the crowding out (both full and partial) and no effect hypotheses. In short, for each euro of forgone tax revenue, between 1.26 and 1.88 euros were spent by private firms in R&D activities, during the period of 2006-2007.

Focusing on the in-house R&D expenditure alone the estimates are even closer. We obtain an estimated addditionality effect ranging from 1.23 to 1.73, a range which is even more compact if we only take into account the estimates from both the multivariate matching methods and the CBPS matching procedure which, together, vary only between 1.23 and 1.29.

These values are in line with those found in recent studies (Haegeland and Møen, 2007; Duguet, 2012; Bodas Freitas et al., 2017; Sterlacchini and Venturini, 2018). Furthermore, may even provide us a glimpse of the regularity noted by Corchuelo and Martínez-Ros (2010) in their study of Spanish firms. The reason is the following, the matched sample resulting from the multivariate matching methods consist of a group of smaller firms when in comparison with the propensity score matching derived samples. Combining this with the fact that the same sample yields lower estimates of the additionality effect when compared to the propensity score matching sample estimates, it is not unreasonable to extrapolate that this effect is larger the larger the firms benefiting from the incentive which, in turn, is the what Corchuelo and Martínez-Ros (2010) reports.

# 6. Concluding Remarks

SIFIDE has been a significant part of the national R&D effort with a remarkable tenure. Yet despite its relevance, both financial and institutional, it remained largely unstudied. While many researchers have studied similar incentives schemes in other countries, to the best of our knowledge, no evidence has ever been collected for the Portuguese R&D tax credit. This dissertation aims to change this by filling this unexplored literature gap with an analysis on the impact of the fiscal incentive on firms' R&D activities. In the process, we also try to advance the methodological frontier by using both the tried and tested conventional methods and some more recent techniques (examples of this are the use of a Covariate Balancing Propensity Score in addition to the conventional approach of estimating a logistic regression or, similarly, the application of the genetic matching algorithm in addition to the conventional Mahalanobis distance matching technique it is based upon).

The findings of this study suggest that SIFIDE had a positive and significant impact on firms' R&D input while, at the same time, being a cost-effective policy. During the period analysed, from 2006 until 2007, for each euro of forgone tax revenue, between 1.26 and 1.88 euros were spent in R&D activities by the firms who benefited from these tax credits. This result seems consistent with the findings of several authors who, in recent years, studied similar incentives in other countries.

Notwithstanding this result it is important to point out some limitations of the analysis. While the methodology chosen is sound for the strict purpose of this dissertation, a few challenges remain unaddressed. The lack of a longer post-treatment follow up period made it impossible to assess the long-term effects of the incentive, which are of particular relevance since the literature points to high adjustment costs faced by firms wishing to change their level of R&D expenditure (Hall, 1993). The limitations of the matching methodology and the data available made it extremely difficult to "follow" firms for more than the two fiscal years considered in the present analysis without losing a significant part of the available observations. Also absent from this dissertation is a meaningful impact heterogeneity assessment, an area which is rapidly becoming a very prominent topic of this literature (Castellacci and Lie, 2015; Sterlacchini and Venturini, 2018) and which holds significant relevance for policy implication, given the efforts being made by legislators to give special treatment to some types of firms (in SIFIDE this is evident for the case of SMEs, firms with personnel holding a PhD and firms with projects in ecological product design). This study does not addressed either the issue of policy complementarity: while being a relevant part of the innovation policy toolbox, tax credits are only one of many incentives being deployed to promote firms' R&D activities. Finally, the lack of control for actual usage of the tax credit, for which there was no data available, but which is relevant given that, for example, some applications take as three or more years to be approved.

In conclusion, undeterred by its several challenges and limitations I sincerely believe this dissertation may help to shed some light into the world of SIFIDE and its importance and furthermore go back to the assertion I made in the introduction of this study ("even as time goes by, some things seem to stay the same") to conclude in the following manner: when change occurs continuously around us we may not perceive it as such, nonetheless, looking back on it, it seems as if it may have been change itself what stayed the same thorough. A constant, uniform, sustained, admittedly slow, rhythm of change.

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# Appendix

## Rosenbaum sensitivity test for Wilcoxon signed rank p-value

| Output Variable | Γ | Logit | | CBPS | | MDM | | GM | |
|---|---|---|---|---|---|---|---|---|---|
| | | Lower | Upper | Lower | Upper | Lower | Upper | Lower | Upper |
| Δ R&D personnel (2005-2006) | 1.5 | 0.000 | 0.059 | 0.000 | 0.001 | 0.001 | 0.105 | 0.000 | 0.048 |
| | 2 | 0.000 | 0.414 | 0.000 | 0.041 | 0.000 | 0.263 | 0.000 | 0.137 |
| | 2.5 | 0.000 | 0.796 | 0.000 | 0.225 | 0.000 | 0.435 | 0.000 | 0.251 |
| | 3 | 0.000 | 0.954 | 0.000 | 0.516 | 0.000 | 0.587 | 0.000 | 0.370 |
| Δ R&D personnel (2006-2007) | 1.5 | 0.000 | 0.002 | 0.000 | 0.000 | 0.000 | 0.008 | 0.000 | 0.006 |
| | 2 | 0.000 | 0.056 | 0.000 | 0.000 | 0.000 | 0.040 | 0.000 | 0.031 |
| | 2.5 | 0.000 | 0.276 | 0.000 | 0.005 | 0.000 | 0.101 | 0.000 | 0.081 |
| | 3 | 0.000 | 0.585 | 0.000 | 0.031 | 0.000 | 0.184 | 0.000 | 0.151 |
| Δ In-house R&D exp. (2005-2007) | 1.5 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | 2 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | 2.5 | 0.000 | 0.000 | 0.000 | 0.002 | 0.000 | 0.000 | 0.000 | 0.000 |
| | 3 | 0.000 | 0.000 | 0.000 | 0.016 | 0.000 | 0.000 | 0.000 | 0.000 |
| Δ Total R&D exp. (2005-2007) | 1.5 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | 2 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | 2.5 | 0.000 | 0.000 | 0.000 | 0.003 | 0.000 | 0.000 | 0.000 | 0.000 |
| | 3 | 0.000 | 0.000 | 0.000 | 0.027 | 0.000 | 0.000 | 0.000 | 0.000 |
| Δ Int. of in-house R&D exp. (2005-2007) | 1.5 | 0.000 | 0.000 | 0.000 | 0.081 | 0.000 | 0.000 | 0.000 | 0.000 |
| | 2 | 0.000 | 0.000 | 0.000 | 0.555 | 0.000 | 0.000 | 0.000 | 0.000 |
| | 2.5 | 0.000 | 0.004 | 0.000 | 0.908 | 0.000 | 0.002 | 0.000 | 0.002 |
| | 3 | 0.000 | 0.029 | 0.000 | 0.990 | 0.000 | 0.008 | 0.000 | 0.007 |
| Δ Int. of total R&D exp. (2005-2007) | 1.5 | 0.000 | 0.000 | 0.000 | 0.102 | 0.000 | 0.000 | 0.000 | 0.000 |
| | 2 | 0.000 | 0.001 | 0.000 | 0.608 | 0.000 | 0.000 | 0.000 | 0.000 |
| | 2.5 | 0.000 | 0.013 | 0.000 | 0.930 | 0.000 | 0.003 | 0.000 | 0.002 |
| | 3 | 0.000 | 0.082 | 0.000 | 0.993 | 0.000 | 0.010 | 0.000 | 0.008 |

## CBPS output

```
Call:
CBPS(formula = Tr ~ ., data = psmodeldata, iterations = 5000,
    method = "over")

Coefficients:
                                   Estimate  Std. Error z value   Pr(>|z|)
(Intercept)                        -6.35     2.98e-10   -2.13e+10 0.000    ***
`logTurnover.-1`                   0.29      1.02e-08   28500000  0.000    ***
`Low_financial_autonomy.-1`        -0.685    5.28e-11   -1.3e+10  0.000    ***
`Personnel_RD.-1`                  0.115     5.34e-10   2.15e+08  0.000    ***
`EBT.-1`                           9.11e-09  3.94       2.32e-09  1
`Apparent_labor_productivity.-1`   1.47e-07  3.48       4.23e-08  1
`IPR.-1`                           0.806     1.47e-12   5.48e+11  0.000    ***
`Developed_RD_expenditure.-1`      1.51e-06  9.32       1.62e-07  1
`All_RD_expenditure.-1`            -6.36e-07 9.71       -6.55e-08 1
`RD_intensity_Turnover.-1`         -0.977    3.04e-11   -3.21e+10 0.000    ***
`All_RD_intensity_Turnover.-1`     0.991     3.13e-11   3.16e+10  0.000    ***
`Turnover_growth.-1`               0.572     1.38e-11   4.16e+10  0.000    ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

J - statistic:   0.0002087951
Log-Likelihood:  -336.5652
```

## Genetic matching iterative search algorithm

```
Domains:
 0.000000e+00   <=  X1   <=    1.000000e+03
 0.000000e+00   <=  X2   <=    1.000000e+03
 0.000000e+00   <=  X3   <=    1.000000e+03
 0.000000e+00   <=  X4   <=    1.000000e+03
 0.000000e+00   <=  X5   <=    1.000000e+03
 0.000000e+00   <=  X6   <=    1.000000e+03
 0.000000e+00   <=  X7   <=    1.000000e+03
 0.000000e+00   <=  X8   <=    1.000000e+03
 0.000000e+00   <=  X9   <=    1.000000e+03
 0.000000e+00   <=  X10  <=    1.000000e+03
 0.000000e+00   <=  X11  <=    1.000000e+03
 0.000000e+00   <=  X12  <=    1.000000e+03
```

```
 0.000000e+00   <=  X13  <=    1.000000e+03
 0.000000e+00   <=  X14  <=    1.000000e+03

Data Type: Floating Point
Operators (code number, name, population)
(1) Cloning..........................  122
(2) Uniform Mutation.................  125
(3) Boundary Mutation................  125
(4) Non-Uniform Mutation.............  125
(5) Polytope Crossover...............  125
(6) Simple Crossover.................  126
(7) Whole Non-Uniform Mutation........  125
(8) Heuristic Crossover..............  126
(9) Local-Minimum Crossover..........  0

SOFT Maximum Number of Generations: 100
Maximum Nonchanging Generations: 4
Population size       : 1000
Convergence Tolerance: 1.000000e-03

Not Using the BFGS Derivative Based Optimizer on the Best Individual
Each Generation.
Not Checking Gradients before Stopping.
Using Out of Bounds Individuals.

Maximization Problem.
GENERATION: 0 (initializing the population)
Lexical Fit..... 1.436113e-01  1.958560e-01  1.958560e-01  2.474658e-01
3.900168e-01  3.962507e-01  4.445360e-01  5.308221e-01  5.589588e-01
6.446126e-01  8.242774e-01  8.361015e-01  9.141126e-01  9.877167e-01
9.877167e-01  9.877167e-01  9.877167e-01  9.995087e-01  1.000000e+00
1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
#unique......... 1000, #Total UniqueCount: 1000
var 1:
best............ 8.268188e+02
mean............ 4.973552e+02
variance........ 8.481421e+04
var 2:
```

```
best............ 7.549588e+02
mean............ 4.938416e+02
variance........ 8.577322e+04
var 3:
best............ 9.805137e+02
mean............ 5.112892e+02
variance........ 8.330387e+04
var 4:
best............ 7.573235e+02
mean............ 5.030558e+02
variance........ 8.226378e+04
var 5:
best............ 7.953184e+02
mean............ 4.985651e+02
variance........ 8.315866e+04
var 6:
best............ 3.013860e+02
mean............ 4.997917e+02
variance........ 8.318592e+04
var 7:
best............ 5.653959e+02
mean............ 4.875403e+02
variance........ 8.243502e+04
var 8:
best............ 3.531693e+02
mean............ 5.091513e+02
variance........ 8.731443e+04
var 9:
best............ 1.392154e+02
mean............ 5.007512e+02
variance........ 8.445964e+04
var 10:
best............ 1.861956e+02
mean............ 5.006787e+02
variance........ 8.379620e+04
var 11:
best............ 1.604613e+02
mean............ 4.823151e+02
variance........ 8.456197e+04
```

```
var 12:
best............ 9.460863e+02
mean............ 5.022998e+02
variance........ 8.324891e+04
var 13:
best............ 4.346489e+02
mean............ 5.086838e+02
variance........ 8.242287e+04
var 14:
best............ 4.768758e+02
mean............ 5.090747e+02
variance........ 8.177651e+04

GENERATION: 1
Lexical Fit..... 1.566912e-01  1.958560e-01  1.958560e-01  2.391381e-01
2.791079e-01  3.778421e-01  4.388808e-01 5.308221e-01  6.808581e-01
8.242774e-01  8.352111e-01  8.470325e-01  9.132192e-01  9.877167e-01
9.877167e-01  9.877167e-01  9.995087e-01  9.995087e-01  1.000000e+00
1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
#unique......... 775, #Total UniqueCount: 1775
var 1:
best............ 3.842716e+02
mean............ 6.421826e+02
variance........ 4.996918e+04
var 2:
best............ 2.839333e+02
mean............ 5.240018e+02
variance........ 7.823153e+04
var 3:
best............ 5.517747e+02
mean............ 6.901376e+02
variance........ 8.626654e+04
var 4:
best............ 2.593281e+02
mean............ 7.028425e+02
variance........ 3.436999e+04
var 5:
best............ 9.638785e+02
```

```
mean............ 6.205247e+02
variance........ 6.102974e+04
var 6:
best............ 2.711449e+02
mean............ 3.366735e+02
variance........ 3.785950e+04
var 7:
best............ 1.574928e+02
mean............ 4.871187e+02
variance........ 3.705725e+04
var 8:
best............ 2.458407e+02
mean............ 4.354987e+02
variance........ 3.292092e+04
var 9:
best............ 5.265136e+02
mean............ 2.945819e+02
variance........ 4.828381e+04
var 10:
best............ 7.995448e+01
mean............ 2.522696e+02
variance........ 2.882688e+04
var 11:
best............ 8.511373e+01
mean............ 2.080847e+02
variance........ 2.653426e+04
var 12:
best............ 2.484905e+02
mean............ 6.702002e+02
variance........ 7.949414e+04
var 13:
best............ 6.456003e+02
mean............ 4.079534e+02
variance........ 5.106067e+04
var 14:
best............ 3.103218e+02
mean............ 5.067129e+02
variance........ 3.922010e+04
```

```
GENERATION: 2
Lexical Fit..... 1.644327e-01  1.958560e-01  1.958560e-01  2.193849e-01
2.708374e-01  3.482977e-01  4.721134e-01  5.308221e-01  6.846824e-01
8.239805e-01  8.242774e-01  8.615913e-01  9.019192e-01  9.336023e-01
9.336023e-01  9.877167e-01  9.995087e-01  9.995087e-01  1.000000e+00
1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
#unique......... 765, #Total UniqueCount: 2540
var 1:
best............ 6.987709e+02
mean............ 5.245990e+02
variance........ 4.232004e+04
var 2:
best............ 2.839333e+02
mean............ 4.255660e+02
variance........ 4.899655e+04
var 3:
best............ 5.517747e+02
mean............ 6.281900e+02
variance........ 5.634700e+04
var 4:
best............ 2.216843e+02
mean............ 5.698037e+02
variance........ 6.745933e+04
var 5:
best............ 9.638785e+02
mean............ 7.509891e+02
variance........ 4.842733e+04
var 6:
best............ 2.711449e+02
mean............ 2.793403e+02
variance........ 9.690860e+03
var 7:
best............ 5.382053e+02
mean............ 3.354107e+02
variance........ 3.356993e+04
var 8:
best............ 2.458407e+02
mean............ 3.050496e+02
```

```
variance........ 9.372147e+03
var 9:
best............ 3.209486e+02
mean............ 3.561267e+02
variance........ 3.033966e+04
var 10:
best............ 7.572074e+01
mean............ 1.553863e+02
variance........ 9.601147e+03
var 11:
best............ 8.453907e+01
mean............ 1.536960e+02
variance........ 1.052323e+04
var 12:
best............ 2.456310e+02
mean............ 5.313041e+02
variance........ 7.856869e+04
var 13:
best............ 6.192084e+02
mean............ 4.379937e+02
variance........ 4.816057e+04
var 14:
best............ 3.256369e+02
mean............ 4.459503e+02
variance........ 1.809487e+04

GENERATION: 3
Lexical Fit..... 1.644327e-01  1.958560e-01  1.958560e-01  2.193849e-01
2.708374e-01  3.482977e-01  4.721134e-01  5.308221e-01  6.846824e-01
8.239805e-01  8.242774e-01  8.615913e-01  9.019192e-01  9.336023e-01
9.336023e-01  9.877167e-01  9.995087e-01  9.995087e-01  1.000000e+00
1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
#unique......... 750, #Total UniqueCount: 3290
var 1:
best............ 6.987709e+02
mean............ 5.196474e+02
variance........ 3.268416e+04
var 2:
```

```
best............ 2.839333e+02
mean............ 3.081260e+02
variance........ 1.107131e+04
var 3:
best............ 5.517747e+02
mean............ 5.325623e+02
variance........ 8.806700e+03
var 4:
best............ 2.216843e+02
mean............ 2.776521e+02
variance........ 2.646656e+04
var 5:
best............ 9.638785e+02
mean............ 8.932013e+02
variance........ 2.622854e+04
var 6:
best............ 2.711449e+02
mean............ 2.863324e+02
variance........ 8.651773e+03
var 7:
best............ 5.382053e+02
mean............ 4.086643e+02
variance........ 4.284928e+04
var 8:
best............ 2.458407e+02
mean............ 2.613198e+02
variance........ 7.717235e+03
var 9:
best............ 3.209486e+02
mean............ 4.291812e+02
variance........ 1.716661e+04
var 10:
best............ 7.572074e+01
mean............ 1.085850e+02
variance........ 1.026125e+04
var 11:
best............ 8.453907e+01
mean............ 1.126672e+02
variance........ 8.157821e+03
```

```
var 12:
best............ 2.456310e+02
mean............ 3.006496e+02
variance........ 1.611370e+04
var 13:
best............ 6.192084e+02
mean............ 5.998278e+02
variance........ 2.231831e+04
var 14:
best............ 3.256369e+02
mean............ 3.360757e+02
variance........ 8.303426e+03

GENERATION: 4
Lexical Fit..... 1.644327e-01  1.958560e-01  1.958560e-01  2.193849e-01
2.708374e-01  3.482977e-01  4.721134e-01  5.308221e-01  6.846824e-01
8.239805e-01  8.242774e-01  8.615913e-01  9.019192e-01  9.336023e-01
9.336023e-01  9.877167e-01  9.995087e-01  9.995087e-01  1.000000e+00
1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
#unique......... 684, #Total UniqueCount: 3974
var 1:
best............ 6.987709e+02
mean............ 5.550259e+02
variance........ 3.219970e+04
var 2:
best............ 2.839333e+02
mean............ 3.115542e+02
variance........ 9.830900e+03
var 3:
best............ 5.517747e+02
mean............ 5.399250e+02
variance........ 6.208779e+03
var 4:
best............ 2.216843e+02
mean............ 2.406733e+02
variance........ 8.825222e+03
var 5:
best............ 9.638785e+02
```

```
mean............ 9.166650e+02
variance........ 1.263222e+04
var 6:
best............ 2.711449e+02
mean............ 2.901840e+02
variance........ 8.450521e+03
var 7:
best............ 5.382053e+02
mean............ 4.698289e+02
variance........ 3.784805e+04
var 8:
best............ 2.458407e+02
mean............ 2.617123e+02
variance........ 7.711741e+03
var 9:
best............ 3.209486e+02
mean............ 4.167505e+02
variance........ 1.646255e+04
var 10:
best............ 7.572074e+01
mean............ 1.038135e+02
variance........ 9.593500e+03
var 11:
best............ 8.453907e+01
mean............ 1.063727e+02
variance........ 7.579367e+03
var 12:
best............ 2.456310e+02
mean............ 2.942639e+02
variance........ 1.215460e+04
var 13:
best............ 6.192084e+02
mean............ 6.215929e+02
variance........ 7.552027e+03
var 14:
best............ 3.256369e+02
mean............ 3.285176e+02
variance........ 5.361468e+03
```

```
GENERATION: 5
Lexical Fit..... 1.644327e-01  1.958560e-01  1.958560e-01  2.193849e-01
2.708374e-01  3.482977e-01  4.721134e-01  5.308221e-01  6.846824e-01
8.239805e-01  8.242774e-01  8.615913e-01  9.019192e-01  9.336023e-01
9.336023e-01  9.877167e-01  9.995087e-01  9.995087e-01  1.000000e+00
1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
#unique......... 680, #Total UniqueCount: 4654
var 1:
best............ 6.987709e+02
mean............ 5.610808e+02
variance........ 2.971906e+04
var 2:
best............ 2.839333e+02
mean............ 3.115362e+02
variance........ 9.431114e+03
var 3:
best............ 5.517747e+02
mean............ 5.420045e+02
variance........ 4.956885e+03
var 4:
best............ 2.216843e+02
mean............ 2.334501e+02
variance........ 6.060687e+03
var 5:
best............ 9.638785e+02
mean............ 9.160521e+02
variance........ 1.515056e+04
var 6:
best............ 2.711449e+02
mean............ 2.880847e+02
variance........ 8.004539e+03
var 7:
best............ 5.382053e+02
mean............ 4.451658e+02
variance........ 3.574788e+04
var 8:
best............ 2.458407e+02
mean............ 2.618967e+02
```

```
variance........ 6.546774e+03
var 9:
best............ 3.209486e+02
mean............ 4.153136e+02
variance........ 1.583299e+04
var 10:
best............ 7.572074e+01
mean............ 9.562692e+01
variance........ 6.960855e+03
var 11:
best............ 8.453907e+01
mean............ 1.098129e+02
variance........ 9.629512e+03
var 12:
best............ 2.456310e+02
mean............ 2.831118e+02
variance........ 1.081959e+04
var 13:
best............ 6.192084e+02
mean............ 6.201441e+02
variance........ 8.190920e+03
var 14:
best............ 3.256369e+02
mean............ 3.289016e+02
variance........ 5.292858e+03

GENERATION: 6
Lexical Fit..... 1.644327e-01  1.958560e-01  1.958560e-01  2.193849e-01
2.708374e-01  3.482977e-01  4.721134e-01  5.308221e-01  6.846824e-01
8.239805e-01  8.242774e-01  8.615913e-01  9.019192e-01  9.336023e-01
9.336023e-01  9.877167e-01  9.995087e-01  9.995087e-01  1.000000e+00
1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
#unique......... 671, #Total UniqueCount: 5325
var 1:
best............ 6.987709e+02
mean............ 5.674726e+02
variance........ 2.919560e+04
var 2:
```

```
best............ 2.839333e+02
mean............ 3.088971e+02
variance........ 8.386479e+03
var 3:
best............ 5.517747e+02
mean............ 5.427982e+02
variance........ 5.631956e+03
var 4:
best............ 2.216843e+02
mean............ 2.373547e+02
variance........ 6.557646e+03
var 5:
best............ 9.638785e+02
mean............ 9.135706e+02
variance........ 1.532359e+04
var 6:
best............ 2.711449e+02
mean............ 2.825350e+02
variance........ 5.477573e+03
var 7:
best............ 5.382053e+02
mean............ 4.598647e+02
variance........ 3.645807e+04
var 8:
best............ 2.458407e+02
mean............ 2.572398e+02
variance........ 4.964164e+03
var 9:
best............ 3.209486e+02
mean............ 4.143885e+02
variance........ 1.538027e+04
var 10:
best............ 7.572074e+01
mean............ 1.055306e+02
variance........ 1.080330e+04
var 11:
best............ 8.453907e+01
mean............ 1.106647e+02
variance........ 1.005138e+04
```

```
var 12:
best............ 2.456310e+02
mean............ 2.929286e+02
variance........ 1.348660e+04
var 13:
best............ 6.192084e+02
mean............ 6.207422e+02
variance........ 5.529425e+03
var 14:
best............ 3.256369e+02
mean............ 3.320948e+02
variance........ 5.895367e+03

GENERATION: 7
Lexical Fit..... 1.644327e-01  1.958560e-01  1.958560e-01  2.193849e-01
2.708374e-01  3.482977e-01  4.721134e-01  5.308221e-01  6.846824e-01
8.239805e-01  8.242774e-01  8.615913e-01  9.019192e-01  9.336023e-01
9.336023e-01  9.877167e-01  9.995087e-01  9.995087e-01  1.000000e+00
1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
#unique......... 662, #Total UniqueCount: 5987
var 1:
best............ 6.987709e+02
mean............ 5.606813e+02
variance........ 3.032525e+04
var 2:
best............ 2.839333e+02
mean............ 3.114772e+02
variance........ 9.827387e+03
var 3:
best............ 5.517747e+02
mean............ 5.416673e+02
variance........ 4.782532e+03
var 4:
best............ 2.216843e+02
mean............ 2.360032e+02
variance........ 6.555078e+03
var 5:
best............ 9.638785e+02
```

```
mean............ 9.224278e+02
variance........ 1.182664e+04
var 6:
best............ 2.711449e+02
mean............ 2.851592e+02
variance........ 6.417764e+03
var 7:
best............ 5.382053e+02
mean............ 4.628284e+02
variance........ 3.455594e+04
var 8:
best............ 2.458407e+02
mean............ 2.636130e+02
variance........ 6.090733e+03
var 9:
best............ 3.209486e+02
mean............ 4.169117e+02
variance........ 1.625389e+04
var 10:
best............ 7.572074e+01
mean............ 1.041233e+02
variance........ 9.623536e+03
var 11:
best............ 8.453907e+01
mean............ 1.084443e+02
variance........ 8.520166e+03
var 12:
best............ 2.456310e+02
mean............ 2.848530e+02
variance........ 1.032279e+04
var 13:
best............ 6.192084e+02
mean............ 6.196767e+02
variance........ 6.095630e+03
var 14:
best............ 3.256369e+02
mean............ 3.295832e+02
variance........ 4.577088e+03
```

```
'wait.generations' limit reached.
No significant improvement in 4 generations.

Solution Lexical Fitness Value:
1.644327e-01  1.958560e-01  1.958560e-01  2.193849e-01  2.708374e-01
3.482977e-01  4.721134e-01  5.308221e-01  6.846824e-01  8.239805e-01
8.242774e-01  8.615913e-01  9.019192e-01  9.336023e-01  9.336023e-01
9.877167e-01  9.995087e-01  9.995087e-01  1.000000e+00  1.000000e+00
1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
1.000000e+00  1.000000e+00  1.000000e+00

Parameters at the Solution:

 X[ 1] : 6.987709e+02
 X[ 2] : 2.839333e+02
 X[ 3] : 5.517747e+02
 X[ 4] : 2.216843e+02
 X[ 5] : 9.638785e+02
 X[ 6] : 2.711449e+02
 X[ 7] : 5.382053e+02
 X[ 8] : 2.458407e+02
 X[ 9] : 3.209486e+02
 X[10] : 7.572074e+01
 X[11] : 8.453907e+01
 X[12] : 2.456310e+02
 X[13] : 6.192084e+02
 X[14] : 3.256369e+02

Solution Found Generation 2
Number of Generations Run 7

Total run time : 0 hours 1 minutes and 14 seconds
```

## Balance PSM - Logit

```
Original number of observations.............  560
Original number of treated obs...............  144
Matched number of observations...............  135
Matched number of observations  (unweighted).  169
```

```
Number of obs dropped by 'exact' or 'caliper'  9


***** (V1) `logTurnover.-1` *****
                       Before Matching     After Matching
mean treatment........     16.843          16.766
mean control..........      16.38          16.895
std mean diff.........     27.506          -7.847

mean raw eQQ diff.....    0.53689         0.27702
med  raw eQQ diff.....    0.56009         0.22651
max  raw eQQ diff.....     1.1529           1.307

mean eCDF diff........   0.095799        0.040605
med  eCDF diff........    0.11098         0.04142
max  eCDF diff........    0.18884         0.10651

var ratio (Tr/Co).....      1.457          1.6322
T-test p-value........  0.0033477         0.41731
KS Bootstrap p-value.. < 2.22e-16           0.268
KS Naive p-value...... 0.00097234         0.29314
KS Statistic..........    0.18884         0.10651


***** (V2) `Low_financial_autonomy.-1` *****
                       Before Matching     After Matching
mean treatment........    0.17361         0.18519
mean control..........    0.21875         0.25062
std mean diff.........    -11.876         -16.782

mean raw eQQ diff.....   0.048611        0.029586
med  raw eQQ diff.....          0               0
max  raw eQQ diff.....          1               1

mean eCDF diff........   0.022569        0.014793
med  eCDF diff........   0.022569        0.014793
max  eCDF diff........   0.045139        0.029586
```

```
var ratio (Tr/Co).....    0.84334         0.80343
T-test p-value........    0.23122         0.18814


***** (V3) `Personnel_RD.-1` *****
                       Before Matching     After Matching
mean treatment........      2.9028          2.6593
mean control..........      1.1394          3.0015
std mean diff.........      33.999         -7.2444

mean raw eQQ diff.....      1.7153         0.55621
med  raw eQQ diff.....           1               0
max  raw eQQ diff.....          11              10

mean eCDF diff........    0.073393        0.019295
med  eCDF diff........    0.061699        0.017751
max  eCDF diff........     0.24332        0.094675

var ratio (Tr/Co).....      2.7605         0.62244
T-test p-value........   0.0001665         0.50671
KS Bootstrap p-value.. < 2.22e-16           0.148
KS Naive p-value......   6.309e-06         0.43504
KS Statistic..........     0.24332        0.094675


***** (V4) `EBT.-1` *****
                       Before Matching     After Matching
mean treatment........     5608057         4562888
mean control..........     1799641         1645863
std mean diff.........      25.018          24.607

mean raw eQQ diff.....     4090219         2546395
med  raw eQQ diff.....      750828          378892
max  raw eQQ diff.....    55184661        43108061

mean eCDF diff........     0.14663        0.071821
med  eCDF diff........     0.16987        0.071006
max  eCDF diff........     0.23397         0.14793
```

```
var ratio (Tr/Co).....     2.2632          2.0643
T-test p-value........  0.0057108        0.023021
KS Bootstrap p-value.. < 2.22e-16           0.048
KS Naive p-value...... 1.6388e-05        0.049534
KS Statistic..........    0.23397         0.14793


***** (V5) `Apparent_labor_productivity.-1` *****
                       Before Matching     After Matching
mean treatment........      60649           56958
mean control..........      49195           60581
std mean diff.........     19.481         -6.9015

mean raw eQQ diff.....      18798           13341
med  raw eQQ diff.....      12396          5779.9
max  raw eQQ diff.....     676661          676661

mean eCDF diff........    0.15161        0.073708
med  eCDF diff........    0.17041        0.076923
max  eCDF diff........    0.27003         0.16568

var ratio (Tr/Co).....    0.54826            0.22
T-test p-value........   0.068099         0.72441
KS Bootstrap p-value.. < 2.22e-16            0.02
KS Naive p-value...... 3.3572e-07        0.019334
KS Statistic..........    0.27003         0.16568


***** (V6) `IPR.-1` *****
                       Before Matching     After Matching
mean treatment........   0.083333        0.081481
mean control..........   0.043269        0.096296
std mean diff.........     14.445         -5.3952

mean raw eQQ diff.....   0.041667        0.011834
med  raw eQQ diff.....          0               0
max  raw eQQ diff.....          1               1

mean eCDF diff........   0.020032       0.0059172
```

```
med  eCDF diff........   0.020032      0.0059172
max  eCDF diff........   0.040064       0.011834

var ratio (Tr/Co).....     1.8537        0.86003
T-test p-value........    0.11315        0.63784


***** (V7) `Developed_RD_expenditure.-1` *****
                       Before Matching     After Matching
mean treatment........     289694         227927
mean control..........      70678         183568
std mean diff.........     56.143         16.741

mean raw eQQ diff.....     214404          94936
med  raw eQQ diff.....     144571          88042
max  raw eQQ diff.....    1051787         933824

mean eCDF diff........    0.32341        0.16152
med  eCDF diff........    0.36886        0.16272
max  eCDF diff........    0.46902        0.31953

var ratio (Tr/Co).....     4.4561        0.53341
T-test p-value........ 9.5346e-10        0.15019
KS Bootstrap p-value.. < 2.22e-16     < 2.22e-16
KS Naive p-value...... < 2.22e-16     6.4198e-08
KS Statistic..........    0.46902        0.31953


***** (V8) `All_RD_expenditure.-1` *****
                       Before Matching     After Matching
mean treatment........     358571         298972
mean control..........      96185         203669
std mean diff.........     55.554         24.556

mean raw eQQ diff.....     269006         107284
med  raw eQQ diff.....     202295         101728
max  raw eQQ diff.....    1162150         456801

mean eCDF diff........    0.32397        0.17738
```

```
med  eCDF diff........    0.37313         0.18935
max  eCDF diff........    0.46795          0.3432

var ratio (Tr/Co).....     2.9553          1.0714
T-test p-value........ 2.1879e-09        0.014179
KS Bootstrap p-value.. < 2.22e-16      < 2.22e-16
KS Naive p-value...... < 2.22e-16      4.5317e-09
KS Statistic..........    0.46795          0.3432


***** (V9) `RD_intensity_Turnover.-1` *****
                       Before Matching     After Matching
mean treatment........   0.038998        0.036564
mean control..........   0.012414        0.012865
std mean diff.........     34.389          31.264

mean raw eQQ diff.....   0.032382        0.022736
med  raw eQQ diff.....  0.0064582       0.0042229
max  raw eQQ diff.....    0.61379         0.27037

mean eCDF diff........    0.24546         0.16908
med  eCDF diff........    0.28205         0.20118
max  eCDF diff........    0.32933         0.27219

var ratio (Tr/Co).....     1.3023          5.8146
T-test p-value........ 0.00030566      0.00068845
KS Bootstrap p-value.. < 2.22e-16      < 2.22e-16
KS Naive p-value...... 1.6746e-10      7.3005e-06
KS Statistic..........    0.32933         0.27219


***** (V10) `All_RD_intensity_Turnover.-1` *****
                       Before Matching     After Matching
mean treatment........   0.041411         0.03902
mean control..........   0.014055        0.014382
std mean diff.........     34.407          31.556

mean raw eQQ diff.....   0.033801        0.024157
med  raw eQQ diff.....  0.0080059       0.0054978
```

```
max  raw eQQ diff.....    0.61379        0.27502

mean eCDF diff........    0.25238        0.18453
med  eCDF diff........    0.29808        0.23077
max  eCDF diff........    0.34749        0.29586

var ratio (Tr/Co).....       1.22         5.0849
T-test p-value........ 0.00033198     0.00060796
KS Bootstrap p-value.. < 2.22e-16     < 2.22e-16
KS Naive p-value...... 1.2071e-11     7.5258e-07
KS Statistic..........    0.34749        0.29586


***** (V11) `Turnover_growth.-1` *****
                       Before Matching     After Matching
mean treatment........    0.14035        0.13895
mean control..........    0.10752         0.1936
std mean diff.........     11.543        -19.253

mean raw eQQ diff.....   0.073843        0.10008
med  raw eQQ diff.....   0.041974        0.02708
max  raw eQQ diff.....     2.6414         2.6414

mean eCDF diff........   0.066042       0.056143
med  eCDF diff........   0.059829       0.032544
max  eCDF diff........     0.1469         0.1716

var ratio (Tr/Co).....    0.53253        0.19089
T-test p-value........    0.28166        0.36919
KS Bootstrap p-value..       0.01          0.008
KS Naive p-value......   0.019767       0.013799
KS Statistic..........     0.1469         0.1716


***** (V12) pscore *****
                       Before Matching     After Matching
mean treatment........    0.34566        0.31407
mean control..........    0.20687        0.31402
std mean diff.........     65.145        0.02666
```

```
mean raw eQQ diff.....    0.13839     0.0032233
med  raw eQQ diff.....    0.10526    0.00074635
max  raw eQQ diff.....    0.40965      0.034045

mean eCDF diff........    0.23503     0.0067558
med  eCDF diff........    0.25788     0.0059172
max  eCDF diff........    0.39183      0.035503

var ratio (Tr/Co).....     3.3713        1.0111
T-test p-value........ 4.3725e-12       0.94757
KS Bootstrap p-value.. < 2.22e-16             1
KS Naive p-value......  1.088e-14       0.99993
KS Statistic..........    0.39183      0.035503


Before Matching Minimum p.value: < 2.22e-16
Variable Name(s): `logTurnover.-1` `Personnel_RD.-1` `EBT.-1`
`Apparent_labor_productivity.-1` `Developed_RD_expenditure.-1`
`All_RD_expenditure.-1` `RD_intensity_Turnover.-1`
`All_RD_intensity_Turnover.-1` pscore  Number(s): 1 3 4 5 7 8 9 10 12

After Matching Minimum p.value: < 2.22e-16
Variable Name(s): `Developed_RD_expenditure.-1`
`All_RD_expenditure.-1` `RD_intensity_Turnover.-1`
`All_RD_intensity_Turnover.-1`  Number(s): 7 8 9 10
```

## Balance PSM - CBPS

```
Original number of observations.............  560
Original number of treated obs..............  144
Matched number of observations..............  136
Matched number of observations  (unweighted).  172

Number of obs dropped by 'exact' or 'caliper'  8


***** (V1) `logTurnover.-1` *****
                       Before Matching     After Matching
```

```
mean treatment........     16.92          16.832
mean control..........    16.385          16.662
std mean diff.........    32.425           10.46

mean raw eQQ diff.....   0.57861         0.31109
med  raw eQQ diff.....    0.6182         0.28451
max  raw eQQ diff.....     1.322          1.3861

mean eCDF diff........    0.1059        0.049419
med  eCDF diff........   0.12433        0.052326
max  eCDF diff........   0.20726         0.10465

var ratio (Tr/Co).....    1.3973          1.3741
T-test p-value........ 0.00059822        0.23352
KS Bootstrap p-value.. < 2.22e-16          0.286
KS Naive p-value...... 0.00020396          0.303
KS Statistic..........   0.20726         0.10465


***** (V2) `Low_financial_autonomy.-1` *****
                       Before Matching     After Matching
mean treatment........   0.18056         0.18382
mean control..........   0.21394         0.19779
std mean diff.........   -8.6496         -3.5935

mean raw eQQ diff.....  0.034722        0.017442
med  raw eQQ diff.....         0               0
max  raw eQQ diff.....         1               1

mean eCDF diff........  0.016693       0.0087209
med  eCDF diff........  0.016693       0.0087209
max  eCDF diff........  0.033387        0.017442

var ratio (Tr/Co).....   0.88381         0.94555
T-test p-value........   0.37974          0.7852


***** (V3) `Personnel_RD.-1` *****
                       Before Matching     After Matching
```

```
mean treatment........     2.7569          2.5882
mean control..........     1.1779          3.5661
std mean diff.........     33.441         -21.796

mean raw eQQ diff.....      1.625         0.98256
med  raw eQQ diff.....          1               0
max  raw eQQ diff.....         10              11

mean eCDF diff........   0.067726        0.035437
med  eCDF diff........    0.05235        0.034884
max  eCDF diff........    0.23851        0.098837

var ratio (Tr/Co).....     2.2122         0.45316
T-test p-value........ 0.00025139        0.069887
KS Bootstrap p-value.. < 2.22e-16            0.12
KS Naive p-value...... 1.0356e-05         0.37026
KS Statistic..........    0.23851        0.098837


***** (V4) `EBT.-1` *****
                       Before Matching     After Matching
mean treatment........    5355184         4490720
mean control..........    1809155         2919475
std mean diff.........     22.749            13.4

mean raw eQQ diff.....    3953519         1583101
med  raw eQQ diff.....     735342          470538
max  raw eQQ diff.....   55184661        43108061

mean eCDF diff........    0.14748        0.093273
med  eCDF diff........    0.16653        0.072674
max  eCDF diff........    0.23825         0.20349

var ratio (Tr/Co).....      2.376          2.5943
T-test p-value........   0.011563         0.19717
KS Bootstrap p-value.. < 2.22e-16      < 2.22e-16
KS Naive p-value...... 1.0642e-05       0.0016142
KS Statistic..........    0.23825         0.20349
```

```
***** (V5) `Apparent_labor_productivity.-1` *****
                       Before Matching     After Matching
mean treatment........      60893            57353
mean control..........      49373            54524
std mean diff.........     19.581           5.5111

mean raw eQQ diff.....      18875            11325
med  raw eQQ diff.....      12899           6455.7
max  raw eQQ diff.....     676661           676661

mean eCDF diff........    0.15251         0.087754
med  eCDF diff........    0.17014         0.075581
max  eCDF diff........    0.27698          0.19186

var ratio (Tr/Co).....    0.54915          0.26562
T-test p-value........   0.066624          0.76467
KS Bootstrap p-value.. < 2.22e-16            0.004
KS Naive p-value...... 1.4895e-07        0.0035591
KS Statistic..........    0.27698          0.19186


***** (V6) `IPR.-1` *****
                       Before Matching     After Matching
mean treatment........    0.10417         0.095588
mean control..........   0.043269         0.095588
std mean diff.........     19.866                0

mean raw eQQ diff.....     0.0625                0
med  raw eQQ diff.....          0                0
max  raw eQQ diff.....          1                0

mean eCDF diff........   0.030449                0
med  eCDF diff........   0.030449                0
max  eCDF diff........   0.060897                0

var ratio (Tr/Co).....     2.2645                1
T-test p-value........   0.027594                1
```

```
***** (V7) `Developed_RD_expenditure.-1` *****
                       Before Matching     After Matching
mean treatment........     349561          287441
mean control..........      83113          199307
std mean diff.........     46.464          18.117

mean raw eQQ diff.....     261920          132280
med  raw eQQ diff.....     154251          110811
max  raw eQQ diff.....    1494206         1211975

mean eCDF diff........    0.32429         0.19265
med  eCDF diff........     0.3754         0.21512
max  eCDF diff........    0.46661         0.37791

var ratio (Tr/Co).....     4.6444         0.84246
T-test p-value........  2.534e-07        0.056227
KS Bootstrap p-value.. < 2.22e-16      < 2.22e-16
KS Naive p-value...... < 2.22e-16      4.2958e-11
KS Statistic..........    0.46661         0.37791


***** (V8) `All_RD_expenditure.-1` *****
                       Before Matching     After Matching
mean treatment........     444345          385933
mean control..........     110154          259553
std mean diff.........     40.189          15.929

mean raw eQQ diff.....     317212          179371
med  raw eQQ diff.....     206839          133120
max  raw eQQ diff.....    2438636         3258061

mean eCDF diff........    0.32656         0.19817
med  eCDF diff........    0.37767         0.22674
max  eCDF diff........    0.47035         0.38372

var ratio (Tr/Co).....     4.6709         0.99106
T-test p-value........ 6.6826e-06         0.11298
KS Bootstrap p-value.. < 2.22e-16      < 2.22e-16
```

```
KS Naive p-value...... < 2.22e-16     2.0057e-11
KS Statistic..........    0.47035        0.38372


***** (V9) `RD_intensity_Turnover.-1` *****
                       Before Matching     After Matching
mean treatment........   0.037589       0.037906
mean control..........   0.012207       0.014227
std mean diff.........     33.315         30.455

mean raw eQQ diff.....   0.031072       0.029114
med  raw eQQ diff.....  0.0064582       0.005814
max  raw eQQ diff.....    0.61379        0.61379

mean eCDF diff........    0.24443        0.18386
med  eCDF diff........    0.28205        0.19186
max  eCDF diff........    0.33173        0.31395

var ratio (Tr/Co).....     1.2862         1.6906
T-test p-value........ 0.00047134      0.0053858
KS Bootstrap p-value.. < 2.22e-16     < 2.22e-16
KS Naive p-value......  1.192e-10     8.6741e-08
KS Statistic..........    0.33173        0.31395


***** (V10) `All_RD_intensity_Turnover.-1` *****
                       Before Matching     After Matching
mean treatment........   0.040373        0.04081
mean control..........   0.015207       0.015285
std mean diff.........     31.946         31.744

mean raw eQQ diff.....   0.032936       0.030779
med  raw eQQ diff.....  0.0080391       0.007219
max  raw eQQ diff.....    0.61379        0.61379

mean eCDF diff........    0.25288        0.19268
med  eCDF diff........    0.30075        0.19767
max  eCDF diff........     0.3523        0.31977
```

```
var ratio (Tr/Co).....     1.0262          1.7908
T-test p-value........  0.0010545       0.0034533
KS Bootstrap p-value.. < 2.22e-16      < 2.22e-16
KS Naive p-value......  5.877e-12      4.6026e-08
KS Statistic..........     0.3523         0.31977


***** (V11) `Turnover_growth.-1` *****
                       Before Matching     After Matching
mean treatment........     0.1377          0.1445
mean control..........    0.10675         0.17857
std mean diff.........     10.911         -11.733

mean raw eQQ diff.....     0.0717        0.093976
med  raw eQQ diff.....   0.039531        0.040588
max  raw eQQ diff.....     2.6414          2.6414

mean eCDF diff........   0.063358        0.063477
med  eCDF diff........   0.058226        0.075581
max  eCDF diff........    0.14209         0.13953

var ratio (Tr/Co).....    0.53519         0.24055
T-test p-value........    0.30832         0.53843
KS Bootstrap p-value..      0.016           0.074
KS Naive p-value......   0.026609        0.070247
KS Statistic..........    0.14209         0.13953


***** (V12) pscore *****
                       Before Matching     After Matching
mean treatment........    0.33371         0.30866
mean control..........    0.20805         0.30936
std mean diff.........     61.149        -0.38491

mean raw eQQ diff.....    0.12545       0.0032848
med  raw eQQ diff.....    0.09016      0.00057285
max  raw eQQ diff.....     0.3847        0.035335

mean eCDF diff........    0.21935       0.0058821
```

```
med  eCDF diff........    0.24265       0.005814
max  eCDF diff........    0.37447       0.023256

var ratio (Tr/Co).....     2.8878        0.99086
T-test p-value........ 7.2241e-11        0.34411
KS Bootstrap p-value.. < 2.22e-16              1
KS Naive p-value...... 1.8718e-13              1
KS Statistic..........    0.37447       0.023256


Before Matching Minimum p.value: < 2.22e-16
Variable Name(s): `logTurnover.-1` `Personnel_RD.-1` `EBT.-1`
`Apparent_labor_productivity.-1` `Developed_RD_expenditure.-1`
`All_RD_expenditure.-1` `RD_intensity_Turnover.-1`
`All_RD_intensity_Turnover.-1` pscore  Number(s): 1 3 4 5 7 8 9 10 12

After Matching Minimum p.value: < 2.22e-16
Variable Name(s): `EBT.-1` `Developed_RD_expenditure.-1`
`All_RD_expenditure.-1` `RD_intensity_Turnover.-1`
`All_RD_intensity_Turnover.-1`  Number(s): 4 7 8 9 10
```

## Balance Multivariate Matching - Mahalanobis distance matching

```
Original number of observations..............  828
Original number of treated obs...............  171
Matched number of observations...............  62
Matched number of observations  (unweighted).  62

Number of obs dropped by 'exact' or 'caliper'  109


***** (V1) `logTurnover.-1` *****
                       Before Matching     After Matching
mean treatment........     16.896         16.268
mean control..........     15.409         16.247
std mean diff.........     82.798         1.5332

mean raw eQQ diff.....     1.5466        0.12544
```

```
med  raw eQQ diff.....     1.4246        0.09294
max  raw eQQ diff.....     15.141        0.76221

mean eCDF diff........    0.20514       0.023776
med  eCDF diff........    0.23043       0.016129
max  eCDF diff........    0.30337       0.080645

var ratio (Tr/Co).....    0.75729        0.92591
T-test p-value........ < 2.22e-16        0.59455
KS Bootstrap p-value.. < 2.22e-16          0.984
KS Naive p-value...... 2.8465e-11        0.98772
KS Statistic..........    0.30337       0.080645


***** (V2) `Low_financial_autonomy.-1` *****
                       Before Matching     After Matching
mean treatment........    0.22222        0.27419
mean control..........    0.38356        0.27419
std mean diff.........    -38.694              0

mean raw eQQ diff.....    0.16374              0
med  raw eQQ diff.....          0              0
max  raw eQQ diff.....          1              0

mean eCDF diff........    0.08067              0
med  eCDF diff........    0.08067              0
max  eCDF diff........    0.16134              0

var ratio (Tr/Co).....    0.73418              1
T-test p-value........ 1.8832e-05              1


***** (V3) `Personnel_RD.-1` *****
                       Before Matching     After Matching
mean treatment........     4.8421        0.58065
mean control..........     0.8204        0.58065
std mean diff.........     35.046              0

mean raw eQQ diff.....     3.9474              0
```

```
med  raw eQQ diff.....          1              0
max  raw eQQ diff.....         64              0

mean eCDF diff........   0.098286              0
med  eCDF diff........   0.084435              0
max  eCDF diff........    0.30489              0

var ratio (Tr/Co).....     19.488              1
T-test p-value........ 9.9058e-06              1
KS Bootstrap p-value.. < 2.22e-16              1
KS Naive p-value...... 2.2141e-11              1
KS Statistic..........    0.30489              0


***** (V4) `EBT.-1` *****
                       Before Matching     After Matching
mean treatment........    9577017        1543420
mean control..........    1223157        1205656
std mean diff.........     22.853          10.17

mean raw eQQ diff.....    7961342         429367
med  raw eQQ diff.....     957238         152960
max  raw eQQ diff.....  190814192        5590675

mean eCDF diff........    0.22392       0.063821
med  eCDF diff........    0.24081       0.064516
max  eCDF diff........    0.39245        0.17742

var ratio (Tr/Co).....     18.659         1.6312
T-test p-value........  0.0034202       0.091093
KS Bootstrap p-value.. < 2.22e-16          0.234
KS Naive p-value...... < 2.22e-16         0.2833
KS Statistic..........    0.39245        0.17742


***** (V5) `Apparent_labor_productivity.-1` *****
                       Before Matching     After Matching
mean treatment........      66057          42263
mean control..........      39985          41462
```

```
std mean diff.........     34.814          3.6989

mean raw eQQ diff.....      31570          3745.6
med  raw eQQ diff.....      18976          3198.9
max  raw eQQ diff.....     717417           28333

mean eCDF diff........    0.21921        0.056452
med  eCDF diff........    0.25523        0.048387
max  eCDF diff........    0.36522         0.14516

var ratio (Tr/Co).....     1.0161         0.67787
T-test p-value........ 6.4243e-05         0.58984
KS Bootstrap p-value.. < 2.22e-16           0.506
KS Naive p-value...... 3.3307e-16         0.53082
KS Statistic..........    0.36522         0.14516


***** (V6) `IPR.-1` *****
                       Before Matching     After Matching
mean treatment........    0.11111               0
mean control..........   0.027397               0
std mean diff.........      26.56               0

mean raw eQQ diff.....   0.081871               0
med  raw eQQ diff.....          0               0
max  raw eQQ diff.....          1               0

mean eCDF diff........   0.041857               0
med  eCDF diff........   0.041857               0
max  eCDF diff........   0.083714               0

var ratio (Tr/Co).....     3.7226             NaN
T-test p-value........  0.0009455               1


***** (V7) `Developed_RD_expenditure.-1` *****
                       Before Matching     After Matching
mean treatment........     668764           71848
mean control..........      65917           62495
```

```
std mean diff.........     28.672          10.425

mean raw eQQ diff.....     598498           10667
med  raw eQQ diff.....     165996          4919.5
max  raw eQQ diff.....   21322542           75104

mean eCDF diff........    0.37032        0.041345
med  eCDF diff........     0.4118        0.032258
max  eCDF diff........    0.50741          0.1129

var ratio (Tr/Co).....       75.3          1.1913
T-test p-value........ 0.00024807         0.10794
KS Bootstrap p-value.. < 2.22e-16           0.682
KS Naive p-value...... < 2.22e-16         0.82428
KS Statistic..........    0.50741          0.1129


***** (V8) `All_RD_expenditure.-1` *****
                       Before Matching     After Matching
mean treatment........     766531           79534
mean control..........     129716           67912
std mean diff.........     28.866          12.153

mean raw eQQ diff.....     558765           12485
med  raw eQQ diff.....     213096            6210
max  raw eQQ diff.....    5287227           75104

mean eCDF diff........    0.36951        0.043656
med  eCDF diff........    0.41096        0.032258
max  eCDF diff........    0.51382         0.14516

var ratio (Tr/Co).....     3.9677          1.2104
T-test p-value........ 0.00032942        0.069642
KS Bootstrap p-value.. < 2.22e-16           0.416
KS Naive p-value...... < 2.22e-16         0.53082
KS Statistic..........    0.51382         0.14516


***** (V9) `RD_intensity_Turnover.-1` *****
```

```
                       Before Matching     After Matching
mean treatment........   0.041716        0.020723
mean control..........    0.12932        0.019475
std mean diff.........    -110.75          2.1314

mean raw eQQ diff.....    0.40004       0.0058041
med  raw eQQ diff.....  0.0076192      0.00023435
max  raw eQQ diff.....     64.999         0.10284

mean eCDF diff........    0.18075        0.032258
med  eCDF diff........    0.22286        0.016129
max  eCDF diff........    0.31178          0.1129

var ratio (Tr/Co).....  0.0009591          1.1588
T-test p-value........    0.38052          0.8019
KS Bootstrap p-value.. < 2.22e-16            0.68
KS Naive p-value...... 6.9903e-12         0.82428
KS Statistic..........    0.31178          0.1129


***** (V10) `All_RD_intensity_Turnover.-1` *****
                       Before Matching     After Matching
mean treatment........   0.044246        0.021423
mean control..........    0.13239         0.01968
std mean diff.........    -108.45          2.9453

mean raw eQQ diff.....    0.40209       0.0057578
med  raw eQQ diff.....  0.0085002      0.00056505
max  raw eQQ diff.....     64.999         0.10284

mean eCDF diff........    0.18534         0.03828
med  eCDF diff........     0.2195        0.032258
max  eCDF diff........    0.30297          0.1129

var ratio (Tr/Co).....  0.0010125          1.1878
T-test p-value........    0.37765         0.72277
KS Bootstrap p-value.. < 2.22e-16           0.696
KS Naive p-value...... 3.0405e-11         0.82428
KS Statistic..........    0.30297          0.1129
```

```
***** (V11) `Turnover_growth.-1` *****
                       Before Matching      After Matching
mean treatment........     0.1229         0.078795
mean control..........   0.074204         0.062054
std mean diff.........      18.13           10.412

mean raw eQQ diff.....    0.08157         0.026757
med  raw eQQ diff.....    0.04584         0.024516
max  raw eQQ diff.....     2.6414         0.079217

mean eCDF diff........   0.079666         0.051332
med  eCDF diff........   0.075903         0.048387
max  eCDF diff........    0.17688          0.19355

var ratio (Tr/Co).....    0.53105           1.0685
T-test p-value........   0.052912          0.35946
KS Bootstrap p-value..      0.002            0.156
KS Naive p-value...... 0.00041092          0.19586
KS Statistic..........    0.17688          0.19355


***** (V12) pscore *****
                       Before Matching      After Matching
mean treatment........    0.37207          0.18756
mean control..........    0.15594          0.18593
std mean diff.........      78.75           2.1674

mean raw eQQ diff.....    0.21543        0.0055042
med  raw eQQ diff.....     0.1364        0.0034049
max  raw eQQ diff.....    0.62923         0.021866

mean eCDF diff........    0.29639         0.019188
med  eCDF diff........    0.33413         0.016129
max  eCDF diff........    0.47088         0.064516

var ratio (Tr/Co).....     4.9385          0.97248
T-test p-value........ < 2.22e-16          0.36608
```

```
KS Bootstrap p-value.. < 2.22e-16             1
KS Naive p-value...... < 2.22e-16       0.99951
KS Statistic..........    0.47088      0.064516


Before Matching Minimum p.value: < 2.22e-16
Variable Name(s): `logTurnover.-1` `Personnel_RD.-1` `EBT.-1`
`Apparent_labor_productivity.-1` `Developed_RD_expenditure.-1`
`All_RD_expenditure.-1` `RD_intensity_Turnover.-1`
`All_RD_intensity_Turnover.-1` `Turnover_growth.-1`
pscore  Number(s): 1 3 4 5 7 8 9 10 11 12

After Matching Minimum p.value: 0.069642
Variable Name(s): `All_RD_expenditure.-1`  Number(s): 8
```

## Balance Multivariate Matching - Genetic matching

```
Original number of observations.............  828
Original number of treated obs..............  171
Matched number of observations..............  62
Matched number of observations  (unweighted).  62

Number of obs dropped by 'exact' or 'caliper'  109


***** (V1) `logTurnover.-1` *****
                       Before Matching     After Matching
mean treatment........     16.896          16.268
mean control..........     15.409          16.261
std mean diff.........     82.798         0.48798

mean raw eQQ diff.....     1.5466         0.11471
med  raw eQQ diff.....     1.4246         0.10036
max  raw eQQ diff.....     15.141         0.76221

mean eCDF diff........    0.20514        0.020954
med  eCDF diff........    0.23043        0.016129
max  eCDF diff........    0.30337        0.064516
```

```
var ratio (Tr/Co).....    0.75729        0.92279
T-test p-value........ < 2.22e-16        0.86159
KS Bootstrap p-value.. < 2.22e-16          0.998
KS Naive p-value...... 2.8465e-11        0.99951
KS Statistic..........    0.30337       0.064516


***** (V2) `Low_financial_autonomy.-1` *****
                       Before Matching     After Matching
mean treatment........    0.22222        0.27419
mean control..........    0.38356        0.27419
std mean diff.........    -38.694              0

mean raw eQQ diff.....    0.16374              0
med  raw eQQ diff.....          0              0
max  raw eQQ diff.....          1              0

mean eCDF diff........    0.08067              0
med  eCDF diff........    0.08067              0
max  eCDF diff........    0.16134              0

var ratio (Tr/Co).....    0.73418              1
T-test p-value........ 1.8832e-05              1


***** (V3) `Personnel_RD.-1` *****
                       Before Matching     After Matching
mean treatment........     4.8421        0.58065
mean control..........     0.8204        0.58065
std mean diff.........     35.046                0

mean raw eQQ diff.....     3.9474              0
med  raw eQQ diff.....          1              0
max  raw eQQ diff.....         64              0

mean eCDF diff........   0.098286              0
med  eCDF diff........   0.084435              0
max  eCDF diff........    0.30489              0
```

```
var ratio (Tr/Co).....     19.488              1
T-test p-value........ 9.9058e-06              1
KS Bootstrap p-value.. < 2.22e-16              1
KS Naive p-value...... 2.2141e-11              1
KS Statistic..........    0.30489              0


***** (V4) `EBT.-1` *****
                       Before Matching     After Matching
mean treatment........    9577017         1543420
mean control..........    1223157         1252220
std mean diff.........     22.853           8.768

mean raw eQQ diff.....    7961342          428759
med  raw eQQ diff.....     957238          151487
max  raw eQQ diff.....  190814192         5590675

mean eCDF diff........    0.22392        0.068927
med  eCDF diff........    0.24081        0.080645
max  eCDF diff........    0.39245         0.19355

var ratio (Tr/Co).....     18.659          1.6057
T-test p-value........  0.0034202         0.16443
KS Bootstrap p-value.. < 2.22e-16           0.164
KS Naive p-value...... < 2.22e-16         0.19586
KS Statistic..........    0.39245         0.19355


***** (V5) `Apparent_labor_productivity.-1` *****
                       Before Matching     After Matching
mean treatment........      66057           42263
mean control..........      39985           41096
std mean diff.........     34.814           5.391

mean raw eQQ diff.....      31570          4498.4
med  raw eQQ diff.....      18976          3901.7
max  raw eQQ diff.....     717417           28333

mean eCDF diff........    0.21921        0.070168
```

```
med  eCDF diff........    0.25523       0.096774
max  eCDF diff........    0.36522        0.14516

var ratio (Tr/Co).....     1.0161        0.64641
T-test p-value........ 6.4243e-05        0.47211
KS Bootstrap p-value.. < 2.22e-16          0.488
KS Naive p-value...... 3.3307e-16        0.53082
KS Statistic..........    0.36522        0.14516


***** (V6) `IPR.-1` *****
                       Before Matching     After Matching
mean treatment........    0.11111                  0
mean control..........   0.027397                  0
std mean diff.........      26.56                  0

mean raw eQQ diff.....   0.081871              0
med  raw eQQ diff.....          0              0
max  raw eQQ diff.....          1              0

mean eCDF diff........   0.041857              0
med  eCDF diff........   0.041857              0
max  eCDF diff........   0.083714                  0

var ratio (Tr/Co).....     3.7226            NaN
T-test p-value........  0.0009455              1


***** (V7) `Developed_RD_expenditure.-1` *****
                       Before Matching     After Matching
mean treatment........     668764          71848
mean control..........      65917          66603
std mean diff.........     28.672         5.8464

mean raw eQQ diff.....     598498         8010.7
med  raw eQQ diff.....     165996         5001.5
max  raw eQQ diff.....   21322542          75104

mean eCDF diff........    0.37032       0.028281
```

```
med  eCDF diff........     0.4118       0.016129
max  eCDF diff........    0.50741       0.080645

var ratio (Tr/Co).....       75.3         1.1359
T-test p-value........ 0.00024807         0.3483
KS Bootstrap p-value.. < 2.22e-16          0.924
KS Naive p-value...... < 2.22e-16        0.98772
KS Statistic..........    0.50741       0.080645


***** (V8) `All_RD_expenditure.-1` *****
                       Before Matching     After Matching
mean treatment........     766531          79534
mean control..........     129716            72193
std mean diff.........     28.866         7.6763

mean raw eQQ diff.....     558765         9686.5
med  raw eQQ diff.....     213096           5964
max  raw eQQ diff.....    5287227          75104

mean eCDF diff........    0.36951       0.031621
med  eCDF diff........    0.41096       0.024194
max  eCDF diff........    0.51382         0.1129

var ratio (Tr/Co).....     3.9677         1.1696
T-test p-value........ 0.00032942        0.21938
KS Bootstrap p-value.. < 2.22e-16          0.658
KS Naive p-value...... < 2.22e-16        0.82428
KS Statistic..........    0.51382         0.1129


***** (V9) `RD_intensity_Turnover.-1` *****
                       Before Matching     After Matching
mean treatment........   0.041716       0.020723
mean control..........    0.12932       0.020111
std mean diff.........    -110.75         1.0457

mean raw eQQ diff.....    0.40004      0.0056227
med  raw eQQ diff.....  0.0076192     0.00026176
```

```
max  raw eQQ diff.....     64.999        0.10284

mean eCDF diff........    0.18075       0.025851
med  eCDF diff........    0.22286       0.016129
max  eCDF diff........    0.31178       0.096774

var ratio (Tr/Co)..... 0.0009591          1.1608
T-test p-value........    0.38052        0.90192
KS Bootstrap p-value.. < 2.22e-16          0.832
KS Naive p-value...... 6.9903e-12         0.9336
KS Statistic..........    0.31178       0.096774


***** (V10) `All_RD_intensity_Turnover.-1` *****
                       Before Matching     After Matching
mean treatment........   0.044246       0.021423
mean control..........    0.13239       0.020332
std mean diff.........    -108.45         1.8435

mean raw eQQ diff.....    0.40209      0.0054838
med  raw eQQ diff..... 0.0085002     0.00048297
max  raw eQQ diff.....     64.999        0.10284

mean eCDF diff........    0.18534       0.028069
med  eCDF diff........     0.2195       0.016129
max  eCDF diff........    0.30297       0.096774

var ratio (Tr/Co)..... 0.0010125          1.1903
T-test p-value........    0.37765        0.82398
KS Bootstrap p-value.. < 2.22e-16          0.852
KS Naive p-value...... 3.0405e-11         0.9336
KS Statistic..........    0.30297       0.096774


***** (V11) `Turnover_growth.-1` *****
                       Before Matching     After Matching
mean treatment........     0.1229       0.078795
mean control..........   0.074204       0.059208
std mean diff.........      18.13         12.181
```

```
mean raw eQQ diff.....    0.08157       0.033284
med  raw eQQ diff.....    0.04584       0.027713
max  raw eQQ diff.....     2.6414        0.15588

mean eCDF diff........   0.079666        0.06104
med  eCDF diff........   0.075903       0.048387
max  eCDF diff........    0.17688        0.19355

var ratio (Tr/Co).....    0.53105         1.2745
T-test p-value........   0.052912        0.27084
KS Bootstrap p-value..      0.002          0.168
KS Naive p-value...... 0.00041092        0.19586
KS Statistic..........    0.17688        0.19355


***** (V12) pscore *****
                       Before Matching     After Matching
mean treatment........    0.37207        0.18756
mean control..........    0.15594        0.18685
std mean diff.........      78.75        0.93402

mean raw eQQ diff.....    0.21543      0.0056243
med  raw eQQ diff.....     0.1364       0.003462
max  raw eQQ diff.....    0.62923       0.021866

mean eCDF diff........    0.29639       0.019438
med  eCDF diff........    0.33413       0.016129
max  eCDF diff........    0.47088       0.064516

var ratio (Tr/Co).....     4.9385        0.97266
T-test p-value........ < 2.22e-16        0.68468
KS Bootstrap p-value.. < 2.22e-16          0.998
KS Naive p-value...... < 2.22e-16        0.99951
KS Statistic..........    0.47088       0.064516


Before Matching Minimum p.value: < 2.22e-16
Variable Name(s): `logTurnover.-1` `Personnel_RD.-1` `EBT.-1`
```

```
`Apparent_labor_productivity.-1` `Developed_RD_expenditure.-1`
`All_RD_expenditure.-1` `RD_intensity_Turnover.-1`
`All_RD_intensity_Turnover.-1` `Turnover_growth.-1`
pscore  Number(s): 1 3 4 5 7 8 9 10 11 12

After Matching Minimum p.value: 0.164
Variable Name(s): `EBT.-1`  Number(s): 4
```

## Control variables, before matching

| Control Variable | Treated | | Non-treated | |
|---|---|---|---|---|
| | Mean | Std. Dev. | Mean | Std. Dev. |
| log(Turnover) | 16.90 | 1.80 | 15.41 | 2.06 |
| Turnover growth rate | 0.12 | 0.27 | 0.07 | 0.37 |
| Financ. auton. <30% | 0.22 | 0.42 | 0.38 | 0.49 |
| EBT | 9 577 016.69 | 36 554 828.80 | 1 223 156.79 | 8 462 465.76 |
| App. labour product. | 66 056.79 | 74 888.89 | 39 985.13 | 74 294.29 |
| Patent/Ind. design | 0.11 | 0.32 | 0.03 | 0.16 |
| R&D personnel | 4.84 | 11.48 | 0.82 | 2.60 |
| In-house R&D exp. | 668 763.83 | 2 102 537.19 | 65 916.99 | 242 296.64 |
| Total R&D exp. | 766 531.36 | 2 206 072.82 | 129 715.71 | 1 107 523.55 |
| In-house R&D intensity | 0.04 | 0.08 | 0.13 | 2.55 |
| Total R&D intensity | 0.04 | 0.08 | 0.13 | 2.55 |

## SIFIDE: Legislation changes

| Fiscal Year | Legislation (Law in force in **Bold**) | Designation | Base Rate | Incremental Rate | Incremental Rate Limit | Carry-forward Option |
|---|---|---|---|---|---|---|
| 1997 | **Decree-Law no. 292/97** | SIFIDE | 8% | 30% | 250 000€ | 3 years |
| 1998 | | | | | | |
| 1999 | | | | | | |
| 2000 | | | | | | |
| 2001 | Decree-Law no. 197/2001 [a] | | 20% | 50% | 500 000€ | 6 years |
| 2002 | | | | | | |
| 2003 | | | | | | |
| 2004 | Decree-Law no. 23/2004 | SIFIDE was inactive for the fiscal years of 2004 and 2005, replaced by the Fiscal Reserve for Investment (RFI) | | | | |
| 2005 | | | | | | |
| 2006 | **Law no. 40/2005** [b,c] | | | | 750 000€ | |
| 2007 | | | | | | |
| 2008 | | | | | | |
| 2009 | Law no. 10/2009 | | 32,50% | | 1 500 000€ | |
| 2010 | Law no. 3-B/2010 [d] | | | | | |
| 2011 | Law no. 55-A/2010 [e] | SIFIDE II | | | | |
| 2012 | Law no. 4-B/2011 [f,g,h] | | | | | |
| 2013 | Decree-Law no. 82/2013 [i,j,k] | | | | | |
| 2014 | Law no. 83-C/2013 | | | | | 8 years |
| 2015 | & | | | | | |
| 2016 | **Decree-Law no. 162/2014** [l,m,n] | | | | | |
| 2017 | Law no. 42/2016 [o] | | | | | |
| 2018 | Law no. 114/2017 | | | | | |

[a] Purchased land stopped being an eligible expense
[b] Activities outside Portuguese territory made eligible
[c] Expenses with the filing and maintenance of patents become deductible for SMEs only
[d] The incremental rate for expenses related to the hiring of personnel holding a PhD increases by 20 points with the limit being increased to 1 800 000€
[e] The base rate is bonified by 10% for SMEs who have yet to complete two fiscal years and, therefore, don't benefit from the incremental rate
[f] Eligible operating expenses are capped at 55% of expenses with personnel directly involved in R&D
[g] Expenses with the acquisition of patents and expenses with audits to R&D become deductible for SMEs only
[h] Expenses with personnel directly involved in R&D are only deductible at a rate of 90% for non-SMEs
[i] Only expenses with employees holding higher education degrees become eligible as expenses with personnel directly involved in R&D
[j] Expenses with personnel without higher education may be taken into account as operational expenses up to the limit set in ($f$)
[k] The base rate is bonified by 15% for SMEs who have yet to complete two fiscal years and, therefore, don't benefit from the incremental rate
[l] Expenses with the filing and maintenance of patents and expenses with audits to R&D become again deductible for large enterprises
[m] Expenses with personnel holding a PhD start being considered as 120% of their total amount
[n] Expenses with personnel directly involved in R&D become once more deductible in full for non-SMEs
[o] Expenses with R&D linked to projects related to ecological product design start being considered as 110% of their total amount