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Abstract:

This objective of this paper is to evaluate and examine the impact of technological platforms used as technology transfer tools on the financial and employment variables of SMEs. To do so, it considers the French Technological Research Institute (TRI) known as "Nanoelec", which is an interdisciplinary thematic institute which uses technological platforms to accelerate the transfer of innovation in companies. Using a matched difference-in-difference approach with the individual effects on panel data observed over the 2008–2016 period, empirical analysis shows that the TRI had a homogenous and significant effect on equity but no effect on employment variables. When cross-referenced against the length of participation in the TRI however, more heterogenous results emerged, showing that the TRI had an additional effect on all financial variables (turnover, equity and financial autonomy) and that this effect appears to concentrate on companies which have participated for longer (two to three years). Furthermore, the evaluation shows a clear positive effect on equity and financial autonomy among firms that collaborate with an Atomic Energy Commission (CEA) laboratory and a weak negative effect on net turnover for firms which receive "expertise" type treatment. Additional analysis indicates that the type of treatment has a more significant role to play than the length of involvement in the TRI.

Keywords:

Science-industry relationships, Technological platforms, Difference-in-differences approach, SME, Impact evaluation

JEL codes:
C21, C53, D04, H23, O36

Working Paper

Evaluation of the effectiveness of technological platforms as a technology transfer tool: the impact of French Technological Research Institutes on the socio-economic performance of SMEs

Ruben Fotso[1]

March 2020

Abstract

This objective of this paper is to evaluate and examine the impact of technological platforms used as technology transfer tools on the financial and employment variables of SMEs. To do so, it considers the French Technological Research Institute (TRI) known as “Nanoelec”, which is an interdisciplinary thematic institute which uses technological platforms to accelerate the transfer of innovation in companies. Using a matched difference-in-difference approach with the individual effects on panel data observed over the 2008–2016 period, empirical analysis shows that the TRI had a homogenous and significant effect on equity but no effect on employment variables. When cross-referenced against the length of participation in the TRI however, more heterogenous results emerged, showing that the TRI had an additional effect on all financial variables (turnover, equity and financial autonomy) and that this effect appears to concentrate on companies which have participated for longer (two to three years). Furthermore, the evaluation shows a clear positive effect on equity and financial autonomy among firms that collaborate with an Atomic Energy Commission (CEA) laboratory and a weak negative effect on net turnover for firms which receive “expertise” type treatment. Additional analysis indicates that the type of treatment has a more significant role to play than the length of involvement in the TRI.

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Code JEL: C21, C53, D04, O36

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1. Introduction

In recent years, many empirical studies have sought to assess the impact of innovation policies based on science-industry relationships, on corporate performance. However, this work has largely focused on the impact of direct assistance from these policies (Lundmark and Power, 2008; Giuliani and Arza, 2009; Dessertine, 2014; Brossard and Moussa, 2014; Dujardin *et al.*, 2015; Ben Hassine and Mathieu, 2017; Nishimura and Okamuro, 2016; Eom and Lee, 2010; Chai and Shih, 2016; Bellucci *et al.*, 2018), totally ignoring the impact of science-industry transfer technological platforms. However, the question of the effectiveness of these platforms is important for public authorities, which would like to know whether it is more effective to provide direct financial support to companies or to fund platforms that in turn interact with companies.

In addition, given the specificity of these platforms, they could be more effective than other science-industry transfer policy instruments, in that they induce public researchers and private actors to work on a daily basis using shared equipment in the same location, which facilitates and increases the exchange of formal and informal information and knowledge between scientific actors and their industry counterparts. Such co-location of skills and knowledge does not exist for the other instruments involved in science-industry transfer policies, where the partners of a collaborative R&D project meet occasionally to inform one another of progress on the project without significant knowledge transfer. Moreover, technological platforms play a key role in the commercialisation of innovative products by reducing the time-to-market. This type of tool is particularly useful for SMEs as they do not have enough resources to develop a new idea until it is commercialised. Technological platforms also play a key role in regional innovation systems, in that they are widely used by local authorities as local development tools (France-Clusters, 2014).

In France, platforms are an important part of the national innovation system. According to the Innovation-Factory and BPIFrance-Le-Lab (2018) which reported on the role of platforms in regional innovation ecosystems, "platforms are developing all over France. France is original in two ways: the proliferation of initiatives and the establishment of mega-platforms." This report also states that "platforms are distinguished by the size of the physical location and investments and the ambitions they pursue, most often in terms of regional and/or societal impact(s)." Despite the significance of these measures, the real impact of platforms on the economic activities of companies and regions remains an open question (Innovation-Factory and BPIFrance-Le-Lab 2018). This question is all the more important as local authorities devote significant financial resources to the development of these platforms. In this context, it seems relevant to evaluate the impact of technological platforms on the performance of SMEs.

The main objective of this paper is to evaluate and analyse the impact of technological platforms used as technology transfer tools on the socio-economic performance of SMEs. For this, we consider the French Technological Research Institute known as "Nanoelec" which was created in 2012 in Grenoble and is based on technological platforms. A Technological Research Institute (TRI) is defined as an interdisciplinary thematic research institute that brings together higher education and research institutions, major groups and SMEs working together on technological platforms around a common technological research agenda, in order to accelerate the transfer of scientific knowledge from the public to the private sector. The TRIs are original in several ways. In terms of the legal status of the TRIs, there is no pre-defined legal form. However, these structures must respect at least six conditions.[2] In terms of how their activities are funded, TRIs form part of a co-investment approach in which 50% of activities are financed by public stakeholders and the other half by private stakeholders. Compared with existing innovation support mechanisms, the TRIs encourage cooperation between a variety of different actors working on R&D projects in a multilateral (as opposed to a bilateral) way. In addition, the creation of the TRIs is based on the principle of regionality. This is how eight TRIs were

[2] The first condition is that the form of the TRI must allow it to directly receive public and private funds. The second condition is that the development model of the TRI is compatible with the Community framework for State aid. The third condition stipulates that the TRI must have its own legal personality. The fourth condition is that the distribution of contributions and governance between the public and the private sector must be balanced. The fifth condition stipulates that the TRI has the possibility of deriving revenue from its activities either through the direct or indirect exploitation of intellectual property rights or through invoicing services. The sixth condition states that the TRI must have sufficient flexibility in terms of recruitment and personnel management to allow a certain fluidity in the constitution of teams from the public and the private sectors.

established in eight different French regions as part of the vast national programme known as the Programme d'Investissement d'Avenir (Investment in the future programme, PIA). For example, one of these eight TRIs, Nanoelec, specialises in nanoelectronics and was established in Grenoble because this city is recognised as being the electronics hub of France. Powered by CEA[3] through its LETI institute[4], Nanoelec concentrates mainly on the three-dimensional integration of chips and photonics on silicon, which are key technologies for the integrated circuits of the future.

As part of its activities, Nanoelec has set up a programme solely intended for SMEs wishing to integrate intelligence into their products. Known as "Easytech", this programme aims to help SMEs create new products or develop existing products to accelerate the development of their innovative products, services or processes, and to give the company a competitive advantage as a result of the know-how available in the Grenoble area. To this end, it offers personalised support enabling companies to identify product or process innovation pathways, to better manage the different stages of the innovation process, and to access new sources of financing. Three types of support are proposed: "Expertise", "INP R&D" and "CEA R&D" (see *Subsection 5.4.* for more details). Unlike direct R&D aid, where the company receives a financial incentive to engage in R&D cooperation, under this form of support, the company pays an R&D service in order to collaborate on a multilateral basis with public and private scientific stakeholders through the platform. The peculiarity of science-industry transfer platforms is that they accelerate the transfer of knowledge and technologies within companies, thus reducing the shift from R&D to industrial production.

This impact evaluation study is based on the fixed effects estimator applied to a difference-in-differences model, combined with matching methods to select the appropriate control group. Given that the objective of technological platforms is to accelerate the transfer of innovation within companies and consequently reduce the time-to-market, this study focuses, despite the short time scale, on financial variables (turnover, financial autonomy and equity) and employment variables (total employment, number of managers and proportion of managers). The evaluation results show that, overall, the TRI has additional effects on both financial and employment variables and that these effects are fairly heterogeneous. Overall, the results tend to indicate that firms that participated in the TRI significantly improve their equity relative to the control firms. However, by studying the heterogeneity of these effects, the results become more precise. By analysing the heterogeneity of the treatment in terms of the length of participation in the TRI, the results show an effect on all the financial variables (turnover, equity and financial autonomy) which seems to focus on companies that have participated for longer (two to three years). On the other hand, no effect was found for the employment variables. Moreover, by examining the heterogeneity in terms of the type of support provided, the evaluation results show a positive effect on equity and financial autonomy which seems to be concentrated on companies which received the "CEA R&D" type of support (collaboration with a CEA laboratory). No effect was identified in companies that benefited from the other two types of support ("Expertise" and "INP R&D"). No effects were identified for employment variables. By distinguishing the beneficiary companies on the basis of the combination of length of treatment and type of treatment, the results indicate that only companies that received the "CEA R&D" type of treatment for one year significantly improve their total employment. Other analyses indicate, overall, that the type of treatment that a company receives plays a greater role than the length of treatment in terms of the effectiveness of the TRI. However, these results should be interpreted with great caution due to the exploratory nature of this study and, particularly due to the small sample size.

This paper makes three major contributions. First, science-industry transfer policies are generally based on geographic proximity and interactions between scientific and industrial actors; what is referred to in the

[3] The Commission for Atomic Energy and Alternative Energies is a French public scientific research organisation in the fields of energy, defense, information technologies, material sciences, and life and health sciences, based in ten sites across France. Historically known as the Atomic Energy Commission (CEA), it changed its name in 2010 and expanded its scope to alternative energies.

[4] The Laboratory of Electronics and Information Technology (LETI) is one of the world's leading applied research centres for microelectronics and nanotechnology. Based in the scientific polygon in Grenoble, France, it is one of the 34 members of the network of Carnot institutes to promote innovation and economic dynamism in collaboration with industry.

literature as the "regional innovation system". According to the concept of a regional innovation system, many countries have adopted a regional development model that gives local governments a central role in strengthening private R&D. Regional governments therefore devote significant financial resources to corporate R&D activities, encouraging the formation of research networks and cooperation between the different components of local innovation systems (Martin *et al.*, 2011, Bellucci *et al.*, 2018). Despite the importance of this concept, there is still little empirical evidence on the effectiveness of place-based policies, and our paper aims to fill this gap. Secondly, technological platforms are among the preferred tools in France for strengthening links between science and industry and accelerating the transfer of technology within companies, especially SMEs. As a result, local authorities devote significant financial resources to the development of these platforms. However, the real impact of the platforms on the economic activities of companies remains unevaluated. To our knowledge, there are no empirical studies evaluating the effectiveness of these tools. This article fills this gap by contributing to the literature on the evaluation of technological platforms with regards to the performance of SMEs. Finally, this study constitutes the first quantitative evaluation of the impact of TRI policy since its implementation in France in 2012. As such, this study contributes to a better understanding of the real effectiveness of science-industry transfer policies, in that the TRIs exclusively carry out science-industry type R&D projects.

The remainder of the paper is structured as follows. Section 2 presents a literature review focusing, one the hand, on the empirical work related to the impact of science-industry measures on SMEs and, on the other, on the roles and expected benefits of platforms. Section 3 explains the empirical strategy while Section 4 presents the data and the outcome variables. Section 5 focuses on the main results and Section 6 on the robustness tests. Section 7 provides the conclusion and some policy recommendations.

2. Literature review

2.1. Empirical studies: Impact of science-industry type measures

The purpose of this subsection is to analyse the bulk of the empirical studies that seek to assess the impact of science-industry type measures on the performance of SMEs.

An analysis of empirical studies identified different types of policy measures based on science-industry relationships. These measures can be grouped into two categories. On the one hand are measures that encompass not only R&D projects involving science and industry actors but also inter-firm R&D projects (industry-industry). This category includes clusters (Lundmark and Power, 2008; Giuliani and Arza, 2009; Dessertine, 2014; Brossard and Moussa, 2014; Dujardin *et al*., 2015; Ben Hassine and Mathieu, 2017), science and technology parks (Autant-Bernard, 2015) and collaborative research grant programmes (Bellucci *et al*., 2018). On the other hand are measures that exclusively include science-industry type R&D projects, i.e., R&D projects including at least one firm and one university and/or public research organisation. This second category mainly includes R&D consortiums (Nishimura and Okamuro, 2016; Chai and Shih, 2016; Eom and Lee, 2010).

In this review, we solely focus on this second category of empirical studies to gain a better understanding of the specificities of government-led science-industry relationships.

Over the 2000–2001 period, Eom and Lee (2010) evaluated the effects of a policy initiated by the Korean government in the 1990s to exclusively promote science-industry R&D consortia. By applying an instrumental variables method without "matching" to a sample of 538 firms, the authors found a positive and significant effect of the science-industry cooperation on patents. However, no effect was identified as to the probability of innovation, nor of labour productivity, and even less of sales. They explain the lack of results by the fact that university-industry cooperation cannot guarantee the success of technological innovation; rather, it can influence the selection or direction of the company's research projects. No details were given on the category of companies studied, but the average size of these companies was around 200 employees suggests that the companies analysed were SMEs.

Nishimura and Okamuro (2016) used a heterogeneous sample (SMEs and large enterprises) of 584 companies to evaluate the direct effects of an R&D consortia support programme funded by the Japanese government. This programme exclusively sponsored science-industry type R&D projects for two years (1997–1998) and exclusively targeted applied research and development for commercialisation. Contrary to the previous study, the authors created a group of control firms using the propensity score method and compared the performances of treated companies and control companies. Approximately 10 years after treatment (in 2007 and 2008), the authors found that only SMEs that were members of the consortium had significantly improved their labour productivity, total factor productivity, and product sales compared to non-consortium firms.

The Danish National Advanced Technology Foundation (DNATF) is the only Danish government source of funding that has exclusively supported science-industry research partnerships, with the aim of developing products that are commercialised in private companies. Chai and Shih (2016) investigated whether firms that received funding from the foundation between 2005–2010 (the treatment period) improved their innovative performance (number of patents, number of publications, proportion of inter-institutional publications) compared to non-recipient companies. The results obtained using the matched difference-in-differences method on a sample of 126 firms indicated that for 2010, participation in university-industry partnerships where mediation was active improved the number of peer-reviewed publications and the proportion of inter-institutional publications for SMEs, but not the number of patents. These authors tried to explain this lack of effect on patents by referring to the shared idea that science-industry partnerships influence the selection or direction of research projects from the company to basic research. The change in research direction suggests that public financial support for university-industry partnerships bridges the gap between science and technology and enables firms to invest more in risky and basic innovative activities to increase their stock of knowledge.

The difference-in-differences method is difficult to apply when the sample of beneficiaries is limited, and the temporal depth is reduced. In this context, the French Cour des Comptes (2018) developed a methodology called "the method of individual comparison to the FNA[5] set" in an attempt to assess the socio-economic impact of the Jules Verne TRI[6] on a group of 11 SMEs and of the TTAC[7] on a group of 15 companies which had concluded a licensing agreement. Using turnover as a socio-economic indicator, this method consisted in analysing the evolution of the turnover of the treated companies and comparing it with that of companies in the same sector of activity. Instead of estimating the effect of these tools, the aim of this method was to determine whether the fact that a firm belongs to the TRI or has concluded a licensing agreement with the TTAC could be correlated with an improvement in the turnover of the firm under study compared with the turnover of all firms in the same FNA code. In other words, this method does not establish a causal relationship but rather a significant correlation between participation in a programme and changes in the result variables. This method shows that the conclusion of a patent licence with a TTAC is correlated with an improvement in the turnover of the treated firm of at least 4% in the short term. The results of this analysis for the TRI show that participation of a firm in the TRI is correlated with a 2% improvement in turnover in the short term.

It is notable that there are very few empirical studies on the impact of science-industry transfer-type policies that exclusively look at R&D science-industry projects. It is, therefore, very difficult to draw definitive conclusions. Nevertheless, the results of the analysis suggest that the effectiveness of the science-industry transfer devices would be observable on output indicators (patents, labour productivity, total factor productivity, etc.) and on economic indicators (sales, etc.) at least under two conditions. The first condition is that they must be evaluated over a long-term period (10 years after treatment for Eom and Lee (2010) and Nishimura and Okamuro (2016)). The second condition is that the purpose of these instruments should be to develop applied research and marketed products (as in the case of Nishimura and Okamuro (2016) and Chai and Shih (2016)), unless the public authorities strive to make companies more risky by investing in R&D projects based on fundamental research. A number of important points can be raised with regard to these studies. The first point relates to the methodology used. Evaluation does not seem to be robust for the first two studies (Eom and Lee, 2010; Nishimura and Okamuro, 2016). For the first study, the authors did not set up a control group that would have enabled them to establish the counterfactual situation of treated companies. This represents a methodological limitation in that it is impossible to know what performance companies would have experienced if had they not been treated. This limitation was taken into account by Nishimura and Okamuro (2016), who constructed a control group using the propensity score matching method. However, these authors use the first difference method to estimate the effect of treatment. This method consists in identifying the difference between the performances of treated and control companies. Unlike the difference-in-differences method, this method does not control for unobserved variables that are stable over time and that may have an impact upon treatment and performance.

The second remark concerns the sample. To the best of our knowledge, there is no empirical study that specifically focuses on the evaluation of SMEs. Rather, evaluations have been conducted on heterogeneous samples often composed of SMEs, mid-size companies and large firms. Having an extremely heterogeneous sample could have an impact on the estimated average effect that would be strongly influenced by the values of large enterprise and mid-size companies. This could explain why the estimation results are usually not stable for SMEs. It would be better to have a completely homogeneous sample composed only of SMEs. Last but not

[5] French Nomenclature of Activities.

[6] The Jules Verne TRI is a shared industrial research centre dedicated to advanced production technologies. Focused on the needs of strategic industrial sectors (aeronautics, automotive, energy and naval), its teams work on the development of innovative technologies that will be deployed in plants in the short and medium term in three major areas: integrated product/process design / innovative processes / flexible and intelligent production systems.

[7] A Technology Transfer Accelerator Company (TTAC) is a subsidiary company created by one or more institutions (universities and research organisations), responsible for detecting and evaluating inventions from public research laboratories to support them until they are transferred to companies.

least, a point can be raised about the evaluation of technological platforms. To the best of our knowledge, there is no empirical study that has evaluated the impact of technological platforms on business performance.

2.2. Roles and expected benefits of platforms

Several studies in the academic literature (See Gawer and Cusumano, 2014) have studied platforms and tried to give a definition of this phenomenon. The common factor in these different definitions is, above all, the pooling of equipment for the benefit of companies, in particular SMEs/SMIs (France-Clusters, 2014). Analysis of their composition shows that they consist of at least five elements (France-Clusters, 2014): *a) A partnership research infrastructure* (hosting infrastructure[8] and general services); *b) Training* (training to and through research[9] and technical training[10]); *c) Economic real estate* (incubator and development of start-ups from platform projects); *d) Basic service* (host function[11]) and *e) Specialised services* (tertiary functions)[12], R&D technological[13] and event hosting.

Contrary to direct support for science-industry collaborations, science-industry transfer platforms have a peculiarity that is to induce public researchers and private actors to work together on a daily basis with shared equipment, in the same location, which has the consequence of facilitating and increasing the exchange of formal and informal information and knowledge between scientific and industrial actors. This co-location of skills and knowledge does not exist for the other science-industry transfer policy instruments, where the partners in a collaborative R&D project meet occasionally to inform one another of progress on the project. This context leads us to believe that technological platforms would be more efficient than other devices.

The objective of the platform is to accelerate the transfer of technologies and knowledge within companies and introduce innovation into the market (France-Clusters, 2014). It is based on a logic of narrowing the gap between the results of research and industrial production on the one hand and between industrial production and socio-economic performance on the other. Platforms play a bigger role for SMEs, as these companies do not have the financial resources to undertake R&D until commercialisation. For example, these platforms make it easier for SMEs to access equipment and skills that are often pooled, which SMEs alone cannot finance, or which are not accessible locally within the regional area (France-Clusters, 2014). Moreover, they make it possible to strengthen the competitiveness of SMEs/SMIs, in the sense that they provide them with high added-value services, a network of experts and advanced technologies. For Gawer and Cusumano (2014), they play an intermediary role between applicants (companies most often) and suppliers (other companies, laboratories, technical centres, etc.). The report sponsored by Innovation-Factory and BPIFrance-Le-Lab (2018) states that "innovation platforms provide mid-size companies and SMEs with a mean of relaying their strategic diversification and digitalisation, as is the case for large companies."

If the platforms play their roles fully, one would expect a number of potential benefits cited in the Gawer and Cusumano (2014) study. The first potential benefits for firms using the platforms are fixed cost savings. Indeed, one of the characteristics of R&D activities is the presence of very high unrecoverable fixed costs (sunk costs) which constitutes a barrier to R&D, especially for SMEs. These fixed costs mainly consist of expenses related to the acquisition of sophisticated equipment and machinery, researchers' wages, etc. If an SME decides, despite this barrier, to acquire the equipment and machinery or to hire the researchers, it exposes itself to a risk of bankruptcy in the event that the project does not succeed, since it will be obliged to use its own funds which are

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[8] Hosting projects, conference room, cafeteria, etc.
[9] Reception, PhD student management.
[10] Internship hosting, continuing education.
[13] Technical platforms: known and open equipment for testing, operation, partnership research contracts.
[12] Consulting in marketing study, legal services and business plan.
[13] Technological development, assembly of collaborative R&D projects.

already low, to cover its expenses. In this context, easy access to the equipment and skills offered by the platform enables SMEs to save money and avoid possible bankruptcy. Since technological platforms are usually organised around shared technological equipment and research tools, they represent a means of sharing costs and risks (France-Clusters, 2014).

These fixed cost savings are not without consequence on the socio-economic performance of companies using platforms. They may result in a consolidation of companies' equity insofar as they no longer need to mobilise their own funds to provide equipment and machinery. In addition, the decrease in fixed costs has a negative direct impact on total cost, which will increase the company's profit margin, strengthen its cash flow and thus repay its debts. We should therefore expect to see an improvement in the financial health of the company through an increase in its financial autonomy. It is also possible that the company can use this decrease in total cost to reduce its sale prices in order to increase turnover. With regard to the employment performance of the company, the use of the platform may initially be accompanied by a decrease in the qualified workforce, since companies already have access to qualified skills around the platform. In the industrial production phase, increased employment may be observed.

The second potential benefit of using the platforms is the reduction in time-to-market, in that access to the platform reduces the gap between research results and industrial production (France-Clusters, 2014). This implies that the support platforms provide to companies is likely to reduce the time scale for financial return and thus have an impact upon socio-economic performance in the short or medium term. In addition, other benefits such as efficiency gains in product development through the reuse of common areas and "modular" designs; in particular the ability to produce a large number of derivatives with limited resources, flexibility in designing product features, increasing the degree of innovation on complementary products and services, etc. (Gawer and Cusumano, 2014).

3. Empirical strategy

The objective of this empirical study is to evaluate the causal effect of the TRI on financial and employment variables of SMEs. Without loss of generality, it is assumed that participation in the TRI is the "treatment"; companies involved in TRI actions are "treated" firms and companies that did not participate are "untreated" firms, and the variables potentially affected by the TRI are the outcome variables. This study uses a matched difference-in-differences approach with individual effects to compare treated and untreated firms and to evaluate changes in outcomes before and after participation in the TRI. The choice of the difference-in-differences model with individual effects is justified by the fact that the treated companies enter and leave the TRI on different dates. This assumes that the treated companies did not have the same length of treatment. In addition, companies do not benefit from the same type of treatment, which means that treatment is not homogeneous. This specificity corresponds to what the evaluation literature calls "difference-in-differences with multiple treatment effects at different time periods". Therefore, applying a standard difference-in-differences approach that would consist of observing the results of groups of treated and untreated firms at two time points (before and after treatment) is neither adaptable nor effective in our study case. This is why we used panel data that will take into account the specificities of the treatment mentioned above. Furthermore, the value of the panel data is to integrate the individual effects into the difference-in-differences model in order to take this specificity into account. Given that treated and untreated firms were not randomly selected, because the evaluation is ex-post, it is highly likely that the direct comparison between the results of the treated and non-treated groups causes a selection bias. In our total sample, *Table 6* shows that there is a strong heterogeneity between the treated and untreated companies. For this reason, setting up a valid control group is essential to reduce selection bias issues. As a result, the difference-in-differences approach with individual effects was combined with nearest neighbour propensity score matching. Propensity score matching ensures that the distribution of observable characteristics is identical between the two groups (treated and untreated companies). The matched difference-in-differences model with individual effects takes into account time-invariant factors, such as individual fixed characteristics and trend effects, and thus allows variables that are observable and unobservable over time to influence outcome variables. (Khandker *et al.*, 2010; Bellucci *et al.*, 2018). Moreover, it makes it possible to control for annual fixed effects that are likely to influence the results even in the absence of treatment. Formally, the model is specified as follows:

$$Y_{it} = \beta_0 + \beta_1 TRI_{it} + c_i + \theta_t + \varepsilon_{it} \quad (1)$$

where *i* is the statistical individual and *t* is the year. In this study, the statistical individuals are the treated and control companies that are observed over the period (2008–2016). The parameter θ_t represents an indicator variable which makes it possible to take into account the annual fixed effects, in particular the effects of the financial crisis, which can have an influence on corporate performance. This specification also includes the individual effect c_i thus controlling for all unobservable features within the enterprise that do not change over time, but which may be correlated to participation in the TRI. The introduction of this parameter is very useful because it partially addresses the self-selection problem. The reasons for participating or not participating in the TRI could be correlated to and thus influence corporate performance. Therefore, it is important to separate them from the effect of the TRI. In this regard, the strategies of the company can be easily identified, the intelligence of the managers, the mode of organisation of the company, etc. It is therefore assumed that these unobservable variables are stable over time and specific to each company. TRI_{it}: indicates the treatment variable that takes the value 1 if the company *i* participated in the actions of the TRI, at the year *t* (year of treatment: 2012, 2013, 2014, 2015) and 0 otherwise. Y_{it}: outcome variables of firm *i* at time *t*. ε_{it}: a random disturbance. β_1: is our parameter of interest, it measures the mean effect of the TRI on firm performance indicators.

The estimation procedure is carried out in two steps: the first step consists of estimating the propensity score based on the observable characteristics of the companies in the reference year. Since treatment started in 2012, we chose 2011 as the reference year, i.e., the year before the treatment takes place. This choice is guided by the evaluation literature. The second step simply estimates the equation (1) using the fixed effects estimator to identify the permanent mean impact of the TRI on the financial and employment variables of SMEs. "Permanent mean effect" is defined as the effect over the period going from the first year of entrance in the measure to the last year of observation.

4. Data and outcome variables

4.1. Data

This empirical work uses panel data observed over the 2008–2016 period for the financial variables and 2008–2015 for the employment variables. The choice of these study periods is justified by the availability of data. Our impact study is based on an original database from several data sources. The data relating to the beneficiary companies are collected by the Nanoelec TRI and supplemented by EuroLIO.[14] They mainly contain information on the company name, the identifier, post code, industry, number of projects carried out by company, the year of the beginning and the end of the project, etc. The financial and accounting data relating to the beneficiary and non-beneficiary companies come from the DIANE database. This is a database produced by Bureau van Dijk which collects general, financial and stock market information on French companies. The study also uses DADS data from INSEE. This contains employment information (total number of employees, number of managers, employer information, etc.). The final database of the beneficiary companies contains 170 observations corresponding to the different projects carried out by Nanoelec within the framework of the Easytech programme. As this study focuses on completed projects, we removed all projects that have not yet

[14] European Localised Innovation Observatory.

been completed, resulting in a database of 161 projects carried out by 117 companies. More precisely, these are projects started and ended between 2012 and 2017.

Tables 1 and 2 present the distribution of the companies and completed projects between 2012 and 2017. *Table 1* presents the distribution of projects carried out within the TRI during the 2012–2017 period. A total of 161 projects started and were completed between 2012 and 2017. It can be seen that at the beginning of the programme in 2012, only five projects were started and the measure was subsequently ramped up in 2013 and stabilised at around forty projects a year. The decrease observed in 2016 is due to the fact that several projects launched in 2016 have not yet been completed. The data for the year 2017 are partial. Of the 161 projects, 93 started and were completed the same year and 65 were completed the year after their launch. Only three projects lasted longer (between two and four years). This suggests that the effects of this measure could be observable in the short and medium term, given that the R&D projects carried out are in the applied research stage. *Table 2* presents the distribution of TRI companies over the 2012–2017 period, by only counting the companies that have repeatedly benefited from TRI. In other words, it is the number of distinct companies that benefit from the TRI. A reading of this table shows that of the 117 beneficiary companies, more than half entered the scheme before 2016. 2015 was the year with the highest number of new entrants. The majority of companies only benefited once from the services of the TRI (84 out of 117), but some benefited three or even four times (see Table 3).

Given that the last year of observation of the DIANE database was 2016, in our database we decided to select only the projects that started and ended between 2012 and 2015 in order to have a temporal decline for the evaluation. This led to 46 companies that completed 62 projects (see Tables 4 and 5). In addition, all companies that were not very small firms or SMEs were eliminated since this empirical work focuses on these categories. This resulted in a final sample of 30 beneficiary companies.

Table 1: Distribution of projects starting and ending between 2012 and 2017

End	2012	2013	2014	2015	2016	2017*	Total
2012	**1**						**1**
2013	**3**	**14**					**17**
2014	**1**	**14**	**30**				**45**
2015	**0**	**0**	**13**	**24**			**37**
2016	**0**	**0**	**2**	**20**	**21**		**43**
2017*	**0**	**1**	**0**	**0**	**14**	**3**	**18**
Total	**5**	**29**	**45**	**44**	**35**	**3**	**161**

*Partial data for 2017 at the time of carrying out the study

Table 2: Distribution of firms according to the date of their entrance and exit from the TRI (Only one entrance and one exit)

Start / End	2012	2013	2014	2015	2016	2017*	Total
2012	**1**						**1**
2013	**3**	**13**					**16**
2014	**1**	**11**	**13**				**25**
2015	**0**	**0**	**9**	**20**			**29**
2016	**0**	**0**	**2**	**12**	**18**		**32**
2017*	**0**	**1**	**0**	**0**	**10**	**3**	**14**
Total	**5**	**25**	**24**	**32**	**28**	**3**	**117**

*Partial data for 2017 at the time of carrying out the study

Table 3: Number of participations of firms

Number of projects	1	2	3	4
Number of firms	84	23	9	1

Table 4: Distribution of projects started and ended between 2012 and 2015

Entrance year / Exit year	2012	2013	2014	2015	Total
2012	1				1
2013	3	12			15
2014	1	7	18		26
2015			9	11	20
Total	5	19	27	11	62

Table 5: Distribution of firms according to the date of their entrance and exit from the TRI

Entrance year / Exit year	2012	2013	2014	2015	Total
2012	0				0
2013	3	8			11
2014	2	6	9		17
2015		1	8	9	18
Total	5	15	17	9	46

4.2 Outcome variables

Unlike most empirical studies (see Zuniga-Vicente *et al.*, 2014; Chai and Shih, 2016; Ben Hassine - and Mathieu, 2017; Bellucci *et al.*, 2018; Kapetaniou and Lee, 2018; etc.) which focus on innovation variables (R&D expenditure, R&D workforce, publications, patents, etc.) when the analysis is carried out within a short and medium term time-scale, we focus on socio-economic variables. The choice of long-term variables while the analysis is carried out in the short and medium term is justified by the fact that platforms are intended to accelerate the transfer of innovation in companies and consequently to reduce the time from R&D to industrial production and from production to corporate economic performance.

The outcome variables are divided into two categories: financial variables (turnover, equity and financial autonomy) and employment variables (total employment, number of managers and proportion of managers). The turnover is the sum of a company's sales of goods or services over an accounting period. It gives an indication of the level of activity and allows comparisons and analysis in time and space. As the financial resources owned by the company (excluding debt), equity is an interesting indicator. Its evolution makes it possible in particular to give an account of the development of the company, but also of its financial health insofar as having a high level of equity capital limits the risk of bankruptcy. Financial autonomy is an indicator which determines the level of dependence of a company on external financing, in particular bank loans. It also makes it possible to assess debt capacity. It is measured by the ratio between equity and long-term financial debt. The higher this ratio, the more independent a firm is from its lenders. The total number of employees of a company is an interesting quantitative indicator that shows whether the TRI has a direct effect on the number of people hired. The number of managers is an indicator that takes into account the quality of the job, while the proportion of managers aims to capture changes in the structure of the job.

5. Results

This section presents the results of the effects of technological platforms framed by Nanoelec on SMEs, including the matching results, the difference-in-differences results and the robustness tests in order to corroborate the obtained results.

5.1 Matching

The sample of counterfactual firms is usually constructed using matching methods. In the evaluation literature, there are several matching methods (nearest neighbour matching, stratification matching, exact matching, optimal matching, etc.). Given the small size of the sample of treated companies (30 companies), it seemed essential to choose a matching method that could select the counterfactual companies while retaining all the treated companies. As a result, the nearest neighbour matching method was chosen, as this method finds similar untreated firms for each treated firm, on the basis of an estimated distance. Like other matching methods, nearest neighbour matching is implemented in two steps. The first step is to calculate the propensity score for each firm, which is defined as the probability that a company, given its characteristics, participates in the TRI, regardless of whether it participates or not. The propensity score is a quantitative value that summarises the initial characteristics of firms and its linkage to the indication of treatment to constitute a posteriori groups of comparable companies that differ only in treatment. More specifically, it involves estimating a statistical model (Probit or Tobit model) for the entire sample (treated and untreated firms) that provides an estimate of the probability of participating in each unit, regardless of whether or not it participates in treatment. This is a method was developed by Rosenbaum and Rubin (1983) in order to estimate the effect of treatment in a non-randomised comparative study, by taking into account initial unbalanced characteristics. In this study, the pre-treatment characteristics used to estimate the propensity score are the approximate size of the firm by turnover and total workforce, age, industry, geographical location (French department), proportion of managers and financial autonomy. In other words, it is a question of estimating for any firm, whether or not they are a beneficiary, the probability that it participates in the TRI, given its size, its age, its industry, its location, its proportion of managers and its financial autonomy. The choice of these variables was guided by the impact evaluation literature of innovation policies.

Once the propensity score is calculated based on pre-treatment characteristics, the second step is to match each treated company with one or more companies in the control group, according to the propensity score. By implementing the nearest neighbour matching method, it is strongly recommended to select more than one control unit. In this study, for each treated company we chose to select five best control companies, making a total sample of 180 companies (30 treated companies and 150 control companies). These control companies were selected from our total database of 2,306 potentially counterfactual companies. The quality of the matching was evaluated through the balancing test, which consists of comparing the TRI companies (treated) to control companies (untreated) in terms of characteristics and performance, before and after matching.

Table 6 presents the results of the comparison between TRI and non-TRI firms before matching. It indicates that the differences in average values between TRI and non-TRI firms are large and statistically significant for almost all characteristics. However, it would appear that the two groups are significantly identical in terms of age. As regards the outcome variables, the TRI group of firms and the non-TRI group of firms are significantly different in terms of turnover, financial autonomy and total employment. However, it is significant that these two groups are identical in terms of equity, the proportion and number of managers. In sum, the group of non-TRI companies (2,306 companies) do not appear to constitute a valid control group, due to the significant differences between the TRI group of companies and the group of non-TRI companies. This justifies the use of a matching method. *Table 7* presents the results of the comparison between the TRI and non-TRI firms after matching. It can be seen that the differences in the values of the treatment and control group variables decreased significantly after matching. Tests of difference in means/proportions show that, significantly, the two groups (treated and control) are identical, with respect to all characteristics and outcome variables. These results suggest that the quality of matching is good. Therefore, it can be said that nearest neighbour matching resulted in a valid group of 150 counterfactual firms. Furthermore, we find that matching balanced the values of the non-matching variables such as the proportion of firms receiving RTC (Research Tax Credit), the amount of RTC, equity, and so on.

Table 6: Mean comparison between TRI firms and non-TRI firms, before matching

	TRI firms	Non-TRI firms	
Characteristics	**Average or Proportion**	**Average or Proportion**	**Test of difference**
Turnover	5,088,879	2,428,420	2,660,459*
Equity	2,404,542	1,174,493	1,230,049
Financial autonomy	40.02	17.16	22.86***
Total employment	46.78	18.5	25.79**
Number of managers	11.35	4.22	7.13
Proportion of managers	0.19	0.14	0.05
Proportion of RTC Firms	0.6	0.11	0.49***
Research Tax Credit	397,549	59,255	338,294*
Age	22.3	21.32	0.98
Typology			
VSE[14]	0.17	0.6	-0.43***
SME	0.83	0.4	0.43***
Location			
Isère	0.5	0.11	0.39***
Outside Isère	0.5	0.89	-0.39***
Auvergne-Rhône-Alpes	0.8	0.48	0.32***
Outside Auvergne-Rhone-Alpes	0.2	0.52	-0.32***
Industries			
Most frequent industries	0.83	0.62	0.21***
Least frequent industries	0.17	0.38	-0.21***
Number of firms	30	2306	Total = 2,336

Notes: The signs ***. ** and * respectively match to the statistically significant coefficients at 1%. 5% and 10%.

Table 7: Mean comparison between TRI firms and control firms after matching

	TRI firms	Control firms	
Characteristics	**Average or Proportion**	**Average or Proportion**	**Test of difference**
Turnover	5,088,879	6,023,587	-934,708
Equity	2,404,542	2,234,076	170,466
Financial autonomy	40.02	37.71	2.31
Total employment	46.78	40.15	6.63
Number of managers	11.35	7.035	4.315
Proportion of managers	0.19	0.16	0.03
Proportion of RTC Firms	0.6	0.52	0.08
Research Tax Credit	397,549	120,933	276,616
Age	22.3	22.46	-0.16
Typology			
VSE	0.17	0.17	0
SME	0.83	0.83	0
Location			
Isère	0.5	0.43	0.07
Outside Isère	0.5	0.57	-0.07
Auvergne-Rhône-Alpes	0.8	0.73	0.07
Outside Auvergne-Rhone-Alpes	0.2	0.27	-0.07
Industry			
Most frequent industries	0.83	0.93	-0.01
Least frequent industries	0.17	0.07	0.01
Number of firms	30	150	Total = 180

Notes: The signs ***, ** and * respectively match to the statistically significant coefficients at 1%, 5% and 10%.

5.2 The homogeneous impact of the TRI on SME performance

The evaluation results of the impact of TRI are presented in *Table 8*. For each performance indicator, we present the mean effects, the number of observations, the number of beneficiary firms, the number of control firms and the study period. Overall, the results indicate that Nanoelec had positive homogeneous effects[15] on only one financial variable (equity) and no effect on the employment variables of the recipient firms.

With respect to the financial variables, the estimation results show that the TRI had a positive and significant effect on equity. More specifically, firms that benefited from the TRI's R&D services recorded a significant increase in their equity, by EUR 623,349 compared to non-recipient firms but this was statistically similar to recipient firms. Furthermore, there is a non-significant but positive effect on the financial autonomy of the beneficiary firms compared to the control firms. On the other hand, the TRI had a non-significant negative effect on turnover. A negative and significant effect on turnover was also found in the evaluation study by Bellucci *et al*. (2018). No theoretical explanation has been put forward to justify this negative effect.

With respect to the employment variables, the evaluation results suggest that the TRI had no significant effect on these variables. On the other hand, it should be noted that these non-significant effects were all negative, regardless of the employment variable selected. It should be noted that the difficulty in identifying significant effects on the employment variables could be explained by the lack of time scale in this study. If the negativity of the effects on the employment variables were to be confirmed over a great time scale, it could be explained

[15] Regardless of the length and type of treatment.

by the fact that access to the TRI's skilled labour by treated firms does not provide an incentive for treated firms to hire skilled labour compared to untreated firms that do not have access to the TRI's skilled labour.

Beyond the problem of time scale, it is possible that these effects hide a certain heterogeneity in that not only did the firms not have the same length of treatment, but they also did not benefit from the same type of treatment. Consequently, it would be interesting to analyse the heterogeneity in order to better understand the meaning of the estimated effects. This is what we propose to explore in the following subsections.

Table 8: The effect of TRI on SME performance - summary of impact evaluation

Outcome variables		Outcome variables	
Financial variables	Estimated effects	**Employment variables**	Estimated effects
Turnover		**Total employment**	
	-563,406		-1.487
Permanent mean effect	(388,229)	Permanent mean effect	(2.141)
Number of observations	1,586	Number of observations	1,104
Equity		**Number of managers**	
	623,349*		-0.678
Permanent mean effect	(328,626)	Permanent mean effect	(0.676)
Number of observations	1,587	Number of observations	1,104
Financial autonomy		**Proportion of managers**	
	1.137		-0.001
Permanent mean effect	(1.937)	Permanent mean effect	(0.013)
Number of observations	1,585	Number of observations	1,104
Study period	2008–2016		2008–2015
Number of firms treated/ controls	30/150		23/115

Notes: The signs ***, ** and * correspond to statistically significant coefficients at 1%, 5% and 10% respectively. Standard errors in parentheses are robust to both heteroscedasticity and autocorrelation.

5.3. Heterogeneity in the treatment intensity: the relationship between length of treatment and effects of TRI

The length of participation in the TRI is not the same for all companies, as it varies according to the number of projects. In addition, each project does not present the same type and degree of difficulty. Consequently, each R&D project does not take the same length of time to be carried out. In this context, it can be expected that companies with different lengths of treatment could experience different developments in terms of performance, since the longer a company lasts in the TRI scheme, the more it will be able to benefit from knowledge externalities. Thus, the mean effect of the treatment estimated above may not take into account any heterogeneity in the length of participation in the TRI.

To determine whether some firms benefited more than others from the collaborative research supervised by the TRI, we estimated the effect of the treatment by distinguishing different subgroups of firms. Three subgroups were formed according to length of treatment. The first subgroup consists of firms with one year of treatment,

while the second subgroup includes firms with two years of treatment and the third group consists of firms with three years of treatment. A general disadvantage of this subgroup approach is that each subgroup includes very few observations, which may prevent the results from being generalised (Bellucci *et al*., 2018). In our case, using panel data increases the number of observations. This approach lets us understand whether there is a relationship between treatment intensity measured by treatment duration and treatment effect. To understand the role played by the length of participation, the analysis must be done by subgroup. The research question is whether firms which have participated for longer benefit more from treatment effects than those which have participated for less time.
The results of this analysis are summarised in *Table 9*.

5.3.1 The impact analysis on financial variables

The impact analysis of the treatment on the firms that remained in the TRI for one year (see column 1 of *Table 9*) shows that the programme had no significant effect on this category of firms, regardless of the financial variable chosen. For companies with two years of participation (see column 2 of *Table 9*), the results indicate that the programme had a positive and significant effect on equity. More specifically, the TRI had an additional effect of EUR 916,195 on the equity of companies that remained within the TRI scheme for two years compared to non-TRI companies but similar to beneficiary companies. Although not significant, there was still a positive effect on financial autonomy. As regards firms that participated in the scheme for three years (see column 3 of *Table 9*), we observe significant additional effects on two financial variables: turnover (EUR 495,552) and financial autonomy (9.82). In other words, the results tend to indicate that the companies that stayed in Nanoelec for about three consecutive years significantly improved their turnover and financial autonomy, respectively by EUR 495,552 and 9.82 compared to the non-treated companies but identical to the treated companies. In the light of the results obtained, it must be noted that the additional effects are focused on companies that remained within the TRI for two or three years. This leads us to believe that the length of participation could play an important role in the effectiveness of Nanoelec insofar as the longer a firm remains in the scheme, the more likely it is to benefit from knowledge externalities and consequently to improve its performance. However, these results must be interpreted with caution due to the small size of the sub-groups of companies. This work is still at an exploratory stage, so it would be interesting to continue this analysis with a large sample in order to check the stability of the results.

5.3.2 The impact analysis on employment variables

The impact analysis of the treatment on firms that remained in the TRI for one year (see column 1 of *Table 9*) shows that the programme had no significant effect on this category of firms, regardless of the variable studied. Non-significant negative effects on this category of firms can be observed on all employment variables. For firms with two years of participation (see column 2 of *Table 9*), similar results are observed. The results are slightly different for companies with three years of participation (see column 3 of *Table 9*). Indeed, no significant effect is observed on the employment variables. In contrast to the other two categories of companies there is, nonetheless, a non-significant positive effect on the proportion of managers. In the light of the results obtained, it is difficult to give an interpretation. Nevertheless, the failure to identify significant effects could be explained by the small sample size and the short time scale.

Table 9: Heterogeneity in the effect of the TRI: the impact on groups with different lengths of participation

	(1) Group 1: one year of participation	(2) Group 2: two years of participation	(3) Group 3: three years of participation	(4) Number of observations
Financial variables				
Turnover				1,586
Permanent mean effect	-280,834 (423,900)	-916,958 (639,241)	495,552* (280,107)	
Equity				1,587
Permanent mean effect	(280,107 (517,853)	916,194** (406,470)	-338,004 (196,005)	
Financial autonomy				1,585
Permanent mean effect	-0.093 (2.77)	1.095 (2,8)	9.82** (4.937)	
Number of beneficiary firms	13/30	15/30	2/30	
Employment variables				
Total employment				1,104
Permanent mean effect	-1.474 (4.109)	-1.857 (2,31)	-0.084 (2.693)	
Number of managers				1,104
Permanent mean effect	-1.117 (0.937)	-0.217 (1.176)	-0.774 (0534)	
Proportion of managers				1104
Permanent mean effect	-0.001 (0.014)	-0.009 (0.024)	0.029 (0.022)	
Number of beneficiary firms	11/23	10/23	2/23	

Notes: The signs ***, ** and * correspond to statistically significant coefficients at 1%, 5% and 10% respectively. Standard errors in parentheses are robust to both heteroscedasticity and autocorrelation.

5.4. Heterogeneity in the treatment type: the relationship between treatment type and effects of TRI

As explained in the introduction, companies do not receive the same types of treatment. There are three types of treatment: *i) Expertise.* This involves writing or approving the specifications on the basis of the right technical choices, prior to an R&D collaboration. The underlying idea is to secure the planned development at as early a stage as possible. This support lasts approximately one month for an average amount of EUR 12,000. This is the type of support that is, a priori, least important for the company; *ii) Creativity sessions.* Here, the TRI team explores paths of diversification in relation with the objectives and ambitions of the company. Having defined the company's innovative project, the team presents the most relevant actors and, if necessary, suggests referring the company towards other networks. The purpose of this is to find new product ideas and ideas for diversification in order to regain a competitive advantage over competitors. The team consists mainly of engineering students who are assigned to a company as part of an internship to, for example, lead to proof of concept. This personalised support, known as “INP R&D”, can take about six months for an amount of EUR 35,000. The third type of treatment is *iii) Implementation.* These are significant R&D collaboration contracts, between the company and a CEA laboratory, with an average duration of about one year and for an average amount of EUR 150,000. This is the type of project that is, a priori, likely to have the greatest impact on the company. Through this type of support, the Easytech programme teams and the company work together on a daily basis on the technological platforms and use technologies developed in the laboratories or specific skills, in order to develop products, processes or services which are significantly improved by taking into account the business and know-how of the company. These teams follow the different stages of the company’s project. This accompanying support is known as “CEA R&D”.

It is to be expected that the treatment does not affect companies in the same way depending on whether they benefit from an expertise, an INP R&D project or a collaboration contract with a CEA laboratory. Corporate performance may vary depending on the type of treatment. The mean effect of treatment may not take into account the possible heterogeneity in corporate performance between treated companies. In order to explore whether some firms benefited more than others from the collaborative research supported by the TRI, we estimated the effect of the treatment by distinguishing different sub-groups of firms. Three subgroups were formed according to the type of treatment. The first subgroup is made up of companies that have only benefited from “expertise”. The second subgroup includes all companies that worked with students within the framework of an “INP R&D” contract. The third group are companies that signed a collaboration contract with a “CEA R&D” laboratory. We encountered cases where the company has benefited from both “expertise” and an “INP R&D” contract, or “expertise” and a “CEA R&D” contract. In the first case, we include the company in the “INP R&D” sub-group since the INP R&D contract is more important financially than simple “expertise”. In the second case, the company is included in the “CEA R&D” group, for the same reason as in the first case. The estimated results are presented in *Table 10*.

5.4.1. The impact analysis on financial variables

The evaluation results indicate that companies that received the "expertise" treatment did not benefit from the economic effects of the programme (see column 1 of Table 10). Worse, these companies experienced a significant fall in turnover. As regards the companies that used the "INP R&D" type of aid, the evaluation results show that the programme had no significant effect on this category of companies, regardless of the chosen variable (see column 2 of Table 10). On the other hand, the results seem to be more interesting for enterprises that benefited from the "CEA R&D" type of treatment, in that the TRI had positive and significant effects on equity capital (EUR 1,351,865) and financial autonomy (5.436) (see column 3 of Table 10). In other words, companies which collaborated with a CEA laboratory experienced an increase in their equity and financial autonomy, by EUR 1,351,865 and 5.436 respectively compared to control firms. These results seem to be consistent because, unlike the other two types of aid, the "CEA R&D" type of aid represents true collaboration between the company and the CEA laboratories with the aim of mobilising technologies and skills already developed and/or available in the TRI to incorporate them into products or processes in order to make them smarter. The impact of this type of aid was the most expected. On the other hand, the effects of the "expertise" and "INP R&D" types of treatment were less expected. It is tempting to think that the impact of the "INP R&D" action could be more visible on employment variables, insofar as this treatment allows companies to access a qualified and less expensive workforce, represented by engineering students.

5.4.2. The impact analysis on employment variables

The evaluation results indicate that Nanoelec had no significant effect on companies that benefited from the "expertise" type of aid (see column 1 of Table 10). Specifically, there was a non-significant positive effect on the proportion of managers and a non-significant negative effect on total employment and the number of managers. For companies that used the "INP R&D" type of treatment, the evaluation results show that the TRI had no significant effect on the employment variables. More clearly, there was a positive non-significant effect on total employment and the number of managers and a negative non-significant effect on the proportion of managers (see column 2 of Table 10). For companies that benefited from the "CEA R&D" type aid, no significant effect was identified regardless of the chosen variable (see column 3 of Table 10). In this category of companies, a non-significant positive effect is observed on total employment and the proportion of managers and a non-significant negative effect on the number of managers. In view of these results, it is difficult to reach a clear interpretation and draw definitive conclusions. However, there is a strong belief that the absence of significant effects is due to the short time scale and the small size of the subgroups. One possible explanation may lie in the greater heterogeneity of the firms participating in the TRI.

It would be interesting to explore a broader heterogeneity by cross-referencing length and type of treatment. Although this analysis would increase the number of subgroups and thus further reduce the sample size, it has important implications in that it would reveal whether treatment duration or treatment type appear to play a more important role in the effectiveness of the TRI. This analysis is explored in the next subsection.

Table 10: Heterogeneity of treatment: the impact of each treatment type

Types of treatment	**(1) Treatment 1: "EXPERTISE"**	**(2) Treatment 2: "INP R&D"**	**(3) Treatment 3: "CEA R&D"**	(4) Number of observations
Financial variables				
Turnover				1,586
Permanent	-1,055,127*	26,491	-725,560	
mean effect	(553 509)	(304 827)	(778 777)	
Equity				1,587
Permanent	-169,056	260,147	1,351,865**	
mean effect	(346,268)	(360,414)	(600,034)	
Financial autonomy				1,585
Permanent	0.422	-3.93	5.436*	
mean effect	(2.53)	(3.14)	(3.007)	
Number of beneficiary firms	8/30	9/30	13/30	
Employment variables				
Total employment				1,104
Permanent	-8.816	0.404	1.276	
mean effect	(6.268)	(2.123)	(2.634)	
Number of managers				1,104
Permanent	-1.887	0.109	-0.519	
mean effect	(1.486)	(1.25)	(0.899)	
Proportion of managers				1,104
Permanent	0.014	-0.025	0.004	
mean effect	(0.018)	(0.033)	(0.014)	
Number of beneficiary firms	10/23	6/23	7/23	

Notes: The signs ***, ** and * correspond to statistically significant coefficients at 1%, 5% and 10% respectively. Standard errors in parentheses are robust to both heteroscedasticity and autocorrelation.

5.5. Heterogeneity in the interaction between treatment intensity and treatment type

We distinguished the participants in the TRI based on the interaction between the length of treatment and the type of treatment. This distinction led to five subgroups. The first group is made up of companies that received "expertise" within the TRI for one year. The second sub-group was composed of firms which benefited from collaboration with a CEA laboratory for one year. The third subgroup includes companies that worked with "INP" engineering trainees for two years. The fourth subgroup includes the companies which benefited from a collaboration with a CEA laboratory over a two-year treatment period. The last subgroup is made up of companies that benefited from collaboration with a CEA laboratory for a period of three years of treatment. The research question is to determine which of the two factors of the length of treatment or the type of treatment plays a greater role in the effectiveness of the TRI. The results are presented in Table 11.

5.5.1. The impact analysis on financial variables

The combination of length of treatment and type of treatment reveals new results. The first result concerns companies that have been in the TRI for two years. The analysis of the effect of the treatment according to the length of participation revealed that the TRI had a positive and significant effect only on equity (see *Section 5.3.1*). Cross-referencing the length and type of treatment yields two sub-groups of firms. The first subgroup represents companies that benefited from the "INP R&D" type of treatment for two years (column 3 of *Table 11*). The second subgroup consists of companies that received the "CEA R&D" type of treatment for two years (column 4 of *Table 11*). Three new results are to be noted. Firstly, it is clear that the positive and significant effects are concentrated only on the second subgroup (column 4 of *Table 11*). Secondly, we observe that the number of significant financial variables increases. The effects no longer concern only equity but also financial autonomy. Thirdly, the size of the effect on equity doubles (from EUR 916,194 to EUR 2,046,252). These results suggest that companies that have remained in the TRI for only two years can only benefit fully from the economic effects if they receive CEA R&D support. In view of these new results, it is tempting to say that the "CEA R&D" type of treatment would play a more important role than the length of treatment.

5.5.2. The impact analysis of employment variables

Another interesting finding is based on the subgroup that benefited from a collaboration with a CEA laboratory for one year. Analyses of mean effect, heterogeneity in the length of treatment, and heterogeneity in the type of treatment all indicated that the TRI had no effect on employment variables (see *Section 5.2*, *Section 5.3.2*, and *Section 5.4.2*). By cross-referencing the two factors (length of treatment and type of treatment), the results become more precise, indicating that firms that received the "CEA R&D" treatment for one year significantly improved total employment. More clearly, Nanoelec had a positive effect of 7.87 on total employment. In other words, this category of companies increased its total workforce by about eight employees. However, this new result should be interpreted with great caution as it concerns only one company. Despite the small sample size, it is tempting to think that the "CEA R&D" type of treatment plays a more important role than the length of treatment. For future research, it would be important to carry out the same analyses with a larger sample size in order to verify the veracity and stability of the results.

Table 11: Heterogeneity in the interaction between length and type of treatment

Types of treatment	**(1) Group Benefiting from "EXPERTISE" for one year**	**(2) Group Benefiting from "CEA R&D" for one year**	**(3) Group Benefiting from "INP R&D" for two years**	**(4) Group Benefiting from "CEA R&D" for two years**	**(5) Group Benefiting from "CEA R&D" for three years**
Financial variables					
Turnover					
Permanent mean effect	-1,054,636* (553,373)	799,779 (502,809)	28,998 (304,920)	-2,518,659 (1,577,126)	483,499* (281,985)
Equity					
Permanent mean effect	-167,461 (346,323)	1,203,681 (1,083,636)	262,028 (360,407)	2,046,252** (800,532)	-335,238 (196,270)
Financial autonomy					
Permanent mean effect	0.408 (2.53)	-0.829 (4.488)	-3.95 (3.14)	10.105** (4.495)	9.874** (4.932)
Number of beneficiary Firms	8/30	6/30	9/30	5/30	2/30
Employment variables					
Total employment					
Permanent mean effect	-8.77 (6.26)	7.87** (3.52)	0.433 (2.12)	-6.097 (4.92)	-0.092 (2.68)
Number of managers					

Permanent mean effect	-1.88 (1.48)	-0.132 (0.841)	0.111 (1.25)	-0.825 (2.42)	-0.775 (0.533)
Proportion of managers					
Permanent mean effect	0.014 (0.018)	-0.021 (0.019)	-0.025 (0.033)	0.020 (0.026)	0.029 (0.022)
Number of beneficiary firms	10/23	1/23	6/23	4/23	2/23

Notes: The signs ***, ** and * correspond to statistically significant coefficients at 1%, 5% and 10% respectively. Standard errors in parentheses are robust to both heteroscedasticity and autocorrelation.

6. Robustness checks

6.1. Testing for a common trend hypothesis

To ensure the robustness of our results, we tested for the underlying assumption of the difference-in-differences method, which states that, in the absence of a programme, outcomes in the treatment group would have followed the same trend as outcomes in the control group. In other words, outcomes should increase or decrease at the same rate in both groups. If the trends in outcomes are different between the two groups, then the estimates provided by the double difference method would be biased. In order to test for this hypothesis, commonly referred to as the "common trend hypothesis", it is often advisable to check how the trends in outcomes in the treatment and control groups changed a few years prior to the programme. For example, if it turns out that the two trends are parallel, then it could be inferred that, in the absence of treatment, outcomes in the treatment group would have followed the same trend as outcomes in the control group. This can be done graphically or statistically. We chose the second option, following the recommendation by Gertler *et al.* (2011), who suggested that the validity of this hypothesis of common trends can be assessed by comparing changes in outcome variables for the treatment and control groups in the years prior to joining the programme. In our context, Nanoelec began in 2012, so we used data from 2011, 2010, 2009 and 2008 to calculate changes in outcome variables. Subsequently, we performed a mean difference test to compare the changes in outcome variables for the treatment and control groups. The results presented in *Table 12* show that the differences in changes in outcome variables between the treated group and the control group are not significant. Therefore, we can conclude that the common trend hypothesis holds.

Table 12: Test for common trend assumption

	TRI firms	**Non-TRI firms**		
Outcome Variables	**Variations mean**	**Variations mean**	Test of Difference	P-value
Financial variables				
Turnover	198,982	288,199	-89,217	0.7544
Equity	152,743	126,132	26,611	0.7775
Financial autonomy	-1.33	2.2	-3.53	0.3965
Employment variables				
Total employment	-0.623	-0.0608	-0.5622	0.7791
Number of managers	0.159	0.0057	0,1537	0.815
Proportion of managers	-0.0061	-0.00364	-0.00246	0.8884

6.2. Sensitivity analysis: using a different control group

Another way to test for the robustness of the results is to estimate the treatment effect using a different control group constructed through a different matching method. The impact evaluation is robust if the effects estimated with another control group are similar to those obtained with the original control group. In this study, we used the optimal matching method to construct a new control group. This matching method selects control units and matches them to treated units on the basis of the smallest mean absolute distance (Zepeda, 2015). Using this method, we selected the five best control firms, resulting in a sample of 180 firms, of which 150 were control firms. We replicated the same analyses. Overall, the results are similar in terms of the significance of the variables and order of magnitude, with some very small differences (the different results are in Tables 13, 14, 15 and 16 in the Appendix).

6.3. Sensitivity analysis: intertemporal analysis of effects

Our intertemporal analysis of effects is based on the assumption that some variables would be impacted by the treatment (TRI measure) in the short term (during treatment) while others would be impacted in the medium or long term (after treatment). To test for this hypothesis, our approach consisted in disaggregating the mean permanent effect into two effects: an *instantaneous effect* which represents the effect of the TRI during the treatment period and a *post-treatment effect* which represents the effect of the TRI after the treatment period.

The results of this analysis are presented in *Tables* 17, 18, 19 and 20 in the Appendix, representing respectively the homogeneous effect of treatment, the heterogeneous effect as a function of the length of treatment, the heterogeneous effect as a function of the type of treatment, and the heterogeneous effect as a function of the interaction between duration and type of treatment. Concerning financial variables, the results tend to show that, overall, the TRI has a mean instantaneous effect on financial autonomy and a mean post-treatment effect on turnover. This result seems to corroborate the effectiveness of the TRI, as the observation of the effects of treatment on turnover requires time for the transition from R&D activities to financial performance. Furthermore, financial autonomy is a short-term performance indicator. Regarding employment variables, the results seem to show a negative instantaneous effect on total employment and the number of managers and a positive post-treatment effect on total employment. Similarly, this observation seems to confirm the results we found in the previous sections and the effectiveness of the TRI, in that employment variables are generally long-term performance indicators. On the other hand, the negative instantaneous effect that was found could be justified by the fact that during the treatment period, firms benefiting from R&D services would have less incentive to hire, in the sense that they already had access to the TRI workforce to carry out their activities.

7. Conclusion

The objective of this paper was to evaluate and examine the impact of technological platforms used as technology transfer tools on the financial and employment variables of small and medium-sized enterprises (SMEs). For this, we considered the French Technological Research Institute (TRI) known as Nanoelec, which is an interdisciplinary thematic institute that uses technological platforms to help SMEs create new products or develop existing products, to accelerate the development of their products, services or innovative processes, and to give the company a competitive advantage, through the know-how available in the Grenoble area. Three main research questions were addressed by our evaluation analysis. The first research question was to determine whether the Nanoelec TRI platform as a technology diffusion tool had additionality effects on financial and employment variables. The second research question was to know whether these effects were heterogeneous with regard to the length of participation on the one hand and, on the other, with regard to the type of aid proposed by the TRI. In other words, could the length of participation and the type of aid have a significant impact on the role in the effectiveness of the TRI? Finally, did the length of treatment or the type of treatment play a more important role in the effectiveness of the TRI?

Using a matched difference-in-differences approach to the panel data observed over the 2008–2016 period, the evaluation results indicate that the TRI had positive effects on financial variables. It would appear that the TRI was successful in stimulating equity growth in recipient firms taken as a whole, compared to control companies. By distinguishing beneficiary enterprises according to the length of their participation, the results tend to show that the estimated impact is heterogeneous. Indeed, the positive effects on turnover, equity and financial autonomy appear to be concentrated on firms which participated for a longer time (two to three years). No effect is detected on firms which stayed in the TRI for only one year. This suggests that the longer a company participates, the more likely it is to benefit from the economic impact of the TRI. This result could be explained by the fact that the assimilation of knowledge takes some time, especially for SMEs that do not have a sufficiently large absorption capacity to understand and assimilate information from their external environment quickly. By distinguishing between recipient companies according to the type of treatment received, the results suggest that the TRI has had a positive impact on equity and financial autonomy and that these effects seem to be restricted to enterprises which have real collaborated with CEA laboratories within the framework of the platform. A slightly significant negative effect on sales was identified, which focuses only on companies that have benefited from the "expertise" treatment. No effect was found on companies that received the "INP R&D" treatment. The positive effect of the "CEA R&D" type of aid is in line with expectations insofar as the collaboration with a CEA laboratory was by far the most important a priori treatment for the impact compared to other treatments.

With respect to the employment variables, the evaluation results show that, overall, the TRI has no effect on these variables compared to control firms. By distinguishing recipient firms based on the length of treatment on the one hand and, on the other, based on the type of treatment received, no effect is always identified. By distinguishing these firms according to the combination of length and type of treatment, a positive and significant effect on total employment was observed which seems to focus on firms which benefited from the "CEA R&D" type of treatment for one year. However, all these results must be interpreted with great caution due to the small sample size of the beneficiary enterprises. Analyses of the heterogeneity of the treatment showed that the length of treatment and the type of treatment chosen seem to play an important role in the effectiveness of the TRI, with the type of treatment playing a major role.

It would be interesting to compare our results with those of studies on direct support for science-industry collaborations to determine whether the impact seems stronger (or, on the contrary, less strong) when support is provided by the platforms. We identified only three studies in the empirical literature on direct support for science-industry collaborations in the strict sense. Moreover, these studies did not choose exactly the same performance variables as our study, which makes comparison difficult. The only common variable is turnover. This is found in two evaluation studies (Eom and Lee, 2010; Nishimura and Okamuro, 2016) but the significant effect on this indicator is only identified in the study by Nishimura and Okamuro (2016). This impact was estimated at 3.2% in 2007 and 2.6% in 2008, which averages 2.9%. Comparing this figure to our effect reported in terms of percentage, it can be seen that the effect identified in our study, which is about 9.7%, is much higher than the effect reported by Nishimura and Okamuro (2016) even if the time scales are different. Based on these figures alone, it would be premature to think that platforms would be more effective than direct support for science-industry collaborations.

The results of this study allowed us to consider some recommendations in terms of public policy. The first recommendation concerns the length of participation. Our analysis of the evaluation highlighted the key role played by duration of treatment. It has been shown that the longer a company remains in the TRI, the more it is likely to benefit from the economic effects. Therefore, it would be worthwhile to improve the design of this policy by including a longer duration of treatment as a prerequisite for participation in the TRI. The second recommendation relates to the type of treatment. Our analyses showed that the R&D collaboration contract with a CEA laboratory was the most effective treatment. Therefore, we recommend increasing this type of treatment in the TRI scheme.

This evaluation study is not without limitations. It would be interesting to take them into consideration for future research. First, one of the most common limitations encountered in innovation policy impact evaluations is the use of an indicator variable as a measure of the treatment variable (Bellucci *et al*., 2018). This is due to the difficulty of accessing all information on the size of the subsidies received each year of treatment by the treated company. Our study is no exception to this limitation. Although we have information on the total amount spent per project, we are unable to know exactly how much is spent annually, making it difficult to use this information in this evaluation. Second, the sample size of the firms treated is not very large. It is even smaller when we subdivided the sample in order to study heterogeneity. It would therefore be interesting to conduct the same analyses with a larger sample size in order to see whether the results remain stable. Third, our evaluation study relies primarily on the additionality of financial and employment variables. These variables may not be sufficient to assess the effectiveness of collaborative research programmes. According to Bellucci *et al.* (2018), R&D cooperation can have a more general impact on the R&D strategy of SMEs and, in particular, on their ability to assimilate and exploit the external knowledge and internal capacities required to establish new collaborations with companies and research centres. All these effects, identified by the literature under the general concept of behavioural additionality, are of particular importance for place-based innovation policies and need to be carefully considered in future research. Finally, it is impossible at this stage to draw conclusions on the comparison between the effectiveness of technological platforms and that of other forms of direct support to enterprises. This would be an interesting perspective for future research.

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Appendix

Table 13: The impact of TRI on the performance of SMEs - Summary results of impact evaluation (with another control group constructed using optimal matching)

Outcome variables		**Outcome variables**	
Financial variables	Estimated effects	Employment variables	Estimated effects
Turnover		Total employment	
	-597,998		-1.398
Permanent mean effect	(387,549)	Permanent mean effect	(2.138)
Number of observations	1,586	Number of observations	1,104
Equity		Number of managers	
	511,635*		-0.758
Permanent mean effect	(333,113)	Permanent mean effect	(0.676)
Number of observations	1,587	Number of observations	1,104
Financial autonomy		Proportion of managers	
	0.535		-0.012
Permanent mean effect	(2.008)	Permanent mean effect	(0.013)
Number of observations	1585	Number of observations	1104
Study period	2008–2016		2008–2015
Number of treated/ controls	30/150		23/115

Notes: The signs ***, ** and * correspond to statistically significant coefficients at 1%, 5% and 10%, respectively. Standard errors in parentheses are robust to both heteroscedasticity and autocorrelation.

Table 14: Heterogeneity in the effect of TRI: the impact on groups at different lengths of participation (another control group constructed using optimal matching)

	(1) Group 1: one year of participation	**(2) Group 2: two years of participation**	**(3) Group 3: three years of participation**	(4) Number of observations
Financial variables				
Turnover				1,586
Permanent mean effect	-320,992	-951,078	497,189*	
	(423,265)	(638,247)	(276,412)	
Equity				1,587
Permanent mean effect	288,097	810,166**	-413,117	
	(522,550)	(409,460)	(214,556)	
Financial autonomy				1,585
Permanent mean effect	-0.562	0.426	8.858*	
	(2.547)	(2.854)	(4.912)	

Number of beneficiary Firms	13/30	15/30	2/30	
Employment variables				
Total employment				1,104
Permanent mean effect	-1.535 (4.106)	-1.713 (2.299)	0.376 (2.741)	
Number of managers				1,104
Permanent mean effect	-1.205 (0.938)	-0.295 (1.175)	-0.827 (0.55)	
Proportion of managers				1,104
Permanent mean effect	-0.010 (0.014)	-0.021 (0.024)	0.015 (0.022)	
Number of beneficiary Firms	11/23	10/23	2/23	

Notes: The signs ***, ** and * correspond to statistically significant coefficients at 1%, 5% and 10%, respectively. Standard errors in parentheses are robust to both heteroscedasticity and autocorrelation.

Table 15: Heterogeneity in the treatment type: impact of each treatment type (another different control group constructed using optimal matching)

Types of treatment	**Treatment 1: "EXPERTISE"**	**Treatment 2: "INP R&D"**	**Treatment 3: "CEA R&D"**	Number of observations
Financial variables				
Turnover				1,586
Permanent	-1,087,835**	-14,212	-756,623	
Mean effect	(553 388)	(304 378)	(777 715)	
Equity				1,587
Permanent	-289,779	151,810	1,242,781**	
Mean effect	(350,124)	(363,271)	(603,709)	
Financial autonomy				15,85
Permanent	-0.085	-4.527	4.773	
mean effect	(2.622)	(3,2)	(3.047)	
Number of beneficiary firms	8/30	9/30	13/30	
Employment variables				
Total employment				1,104
Permanent	-8.796	0.474	1.414	
mean effect	(6.264)	(2.137)	(2.616)	
Number of managers				1,104
Permanent	-1.966	0.025	-0.597	
mean effect	(1.487)	(1.247)	(0.900)	
Proportion of managers				1,104
Permanent	0.005	-0.035	-0.006	
mean effect	(0.018)	(0.034)	(0.014)	
Number of beneficiary Firms	10/23	6/23	7/23	

Notes: The signs ***, ** and * correspond to statistically significant coefficients at 1%, 5% and 10%, respectively. Standard errors in parentheses are robust to both heteroscedasticity and autocorrelation.

Table 16: Heterogeneity in the interaction between treatment duration and treatment type (another different control group constructed via optimal matching)

Types of treatment	(1) Group benefiting from "EXPERTISE" for one year	(2) Group Benefiting from "CEA R&D" for one year	(3) Group Benefiting from "CEA R&D" for two years	(4) Group Benefiting from "INP R&D" for two years	(5) Group Benefiting from "CEA R&D" for three years
Financial variables					
Turnover					
Permanent	-1,087,439**	749,378	-11,824	-2,541,438	485,232*
mean effect	(553,246)	(503,176)	(304,449)	(1,575,709)	(278,045)
Equity					
Permanent	-288,269	1,075,303	153,575	1,944,389**	-410,317*
mean effect	(350,176)	(1,089,114)	(363,275)	(802,813)	(214,933)
Financial autonomy					
Permanent	-0.098	-1.247	-4.548	9.304**	8.912*
mean effect	(2.619)	(4.534)	(3.2)	(4.542)	(4.906)
Number of beneficiary firms	8/30	6/30	9/30	5/30	2/30
Employment variables					
Total employment					
Permanent	-8.753	7.716**	0.501	-5.811	0.369
mean effect	(6.263)	(3,561)	(2.137)	(4.869)	(2.736)
Number of managers					
Permanent	-1.963	-0.232	0.027	-0.893	-0.828
mean effect	(1.487)	(0.843)	(1.248)	(2.427)	(0.548)
Proportion of managers					
Permanent	0.005	-0.029	-0.036	0.007	0.015
mean effect	(0.018)	(0.019)	(0.034)	(0.026)	(0.022)
Number of beneficiary firms	10/23	1/23	6/23	4/23	2/23

Notes: The signs ***, ** and * correspond to statistically significant coefficients at 1%, 5% and 10%, respectively. Standard errors in parentheses are robust to both heteroscedasticity and autocorrelation.

Table 17: The effect of TRI on the performance of SMEs - Results summary of impact evaluation (mean instantaneous effect and mean post-treatment effect)

Outcome Variables		**Outcome variables**	
Financial variables	Estimated Effects	Employment variables	Estimated effects
Turnover		**Total employment**	
Mean instantaneous Effect	27,849 (263,657)	Mean instantaneous Effect	-3.083* (1.684)
Mean post-treatment effect	-923,828 (574,686)	Mean post-treatment effect	2.823 (4.226)
Number of observations	1,586	Number of observations	1104
Equity		**Number of managers**	
Mean instantaneous Effect	389,499 (295,817)	Mean instantaneous Effect	-0.928* (0.529)
Mean post-treatment effect	542,996 (441,464)	Mean post-treatment effect	0.271 (1.344)
Number of observations	1,587	Number of observations	1104
Financial autonomy		**Proportion of managers**	
Mean instantaneous effect	0.524 (1.855)	Mean instantaneous Effect	0.002 (0.012)
Mean post-treatment effect	1.198 (2.535)	Mean post-treatment effect	-0.008 (0.026)
Number of observations	1,585	Number of observations	1104
Study period	2008–2016		2008–2015
Number of treated/controls	30/150		23/115

Notes: The signs ***, ** and * correspond to statistically significant coefficients at 1%, 5% and 10%, respectively. Standard errors in parentheses are robust to both heteroscedasticity and autocorrelation.

Table 18: Heterogeneity in the effect of TRI: The impact on groups with different lengths of participation

	(1) Group 1: one year participation	(2) Group 2: two years participation	(3) Group 3: three years participation	(4) Number of observations
Financial variables				
Turnover				1,586
Mean Instantaneous effect	-40,500 (324,506)	27,754 (395,916)	314,157 (261,518)	
Mean post-treatment effect	-363,176 (546,518)	-1,569,461 (990,859)	708,528** (278,995)	
Equity				1,587
Mean Instantaneous effect	(876,921 (652,660)	171,035 (317,038)	-94,452 (175,248)	
Mean post-treatment effect	(-110,043 (602,706)	1,285,715** (570,807)	-505,419* (293,651)	
Financial autonomy				1,585
Mean Instantaneous effect	2.474 (2.845)	-1.823 (2.463)	7.849** (3.957)	
Mean post-treatment effect	-2.035 (3.135)	3.996 (3.842)	4.952 (5.102)	
Number of beneficiary firms	13/30	15/30	2/30	
Employment variables				
Total employment				1,104
Mean Instantaneous Effect	-1.726 (3.597)	-4.482** (1.838)	-1.872 (2.365)	
Mean post-treatment effect	-0.283 (6.714)	6.572 (4.427)	7.738*** (1.83)	
Number of managers				1,104
Mean Instantaneous effect	-0.752 (0.676)	-1.120 (0.930)	-0.737 (0.558)	
Mean post-treatment effect	-1.155 (1.547)	2.462 (2.563)	-0.188 (0.346)	
Proportion of managers				1,104
Mean Instantaneous Effect	-0.001 (0.014)	-0.009 (0.024)	0.029 (0.022)	
Mean post-treatment effect	0.002 (0.02)	-0.027 (0.062)	0.017 (0.023)	
Number of beneficiary				

Firms	11/23	10/23	2/23

Notes: The signs ***, ** and * correspond to statistically significant coefficients at 1%, 5% and 10%, respectively. Standard errors in parentheses are robust to both heteroscedasticity and autocorrelation.

Table 19: Heterogeneity in treatment type: the impact of each treatment type

Types of treatment	**(1) Treatment 1: "EXPERTISE"**	**(2) Treatment 2: "INP R&D"**	**(3) Treatment 3: "CEA R&D"**	(4) Number of observations
Financial variables				
Turnover				1,586
Mean	-327,038	109,352	132,476	
Instantaneous effect	(465,376)	(226,431)	(526,520)	
Mean	-1,349,907*	-76,255	-1,151, 106	
post-treatment effect	(696,196)	(546,311)	(1,033,421)	
Equity				1,587
Mean	59,261	35,176	892,605	
Instantaneous effect	(247,906)	(353,870)	(602,339)	
Mean	-363,829	427,475	1,057,653	
post-treatment effect	(430,468)	(444,109)	(744,858)	
Financial autonomy				1,585
Mean	1.378	-4.185	4.708	
Instantaneous effect	(2.8)	(2.823)	(2.895)	
Mean	-0.634	-1.415	3.466	
post-treatment effect	(2.874)	(4.489)	(3.984)	
Number of beneficiary firms	8/30	9/30	13/30	
Employment variables				
Total employment				1,104
Mean	-6.596	-1.408	-2.531	
Instantaneous effect	(5.389)	(1.509)	(2.294)	
Mean	-9.031	6.796	8.232**	
post-treatment effect	(10.782)	(5.450)	(3.634)	
Number of managers				1,104
Mean	-0.881	-0.384	-1.335*	
Instantaneous effect	(1.077)	(1.058)	(0.697)	
Mean	-2.701	1.887	1.388	
post-treatment effect	(2.332)	(2.721)	(1.831)	
Proportion of managers				1,104
Mean	0.002	-0.007	0.008	
Instantaneous effect	(0.012)	(0.029)	(0.015)	
Mean	0.030	-0.071	-0.005	
post-treatment effect	(0.030)	(0.107)	(0.019)	
Number of beneficiary firms	10/23	6/23	7/23	

Notes: The signs ***, ** and * correspond to statistically significant coefficients at 1%, 5% and 10%, respectively. Standard errors in parentheses are robust to both heteroscedasticity and autocorrelation.

Table 20: Heterogeneity in the interaction between length and type of treatment

Types of treatment	**(1)** **Group benefiting from "EXPERTISE" for one year**	**(2)** **Group benefiting from "CEA R&D" for one year**	**(3)** **Group benefiting from "INP R&D" for two years**	**(4)** **Group benefiting from "CEA R&D" for two years**	**(5)** **Group benefiting from "CEA R&D" for three years**
Financial variables					
Turnover					
Mean instantaneous effect	-327,833 (465,379)	422,039 (333,062)	111,713 (226,563)	-117,001 (1,022,100)	315,016 (261,574)
Mean post-treatment effect	-1,054,636* (553,373)	799,779 (502,809)	28,998 (304,920)	-2,518,659 (1,577,126)	483,499* (281,985)
Equity					
Mean instantaneous effect	56,488 (247,885)	2,187,269 (1,516,993)	44,086 (353,450)	445,973 (600,496)	-88,135 (175,865)
Mean post-treatment effect	-167,461 (346,323)	1,203,681 (1,083,636)	262,028 (360,407)	2,046,252** (800,532)	-335,238 (196,270)
Financial autonomy					
Mean instantaneous effect	1.379 (2.8)	4.18 (5.759)	-4.189 (2.823)	3.515 (4.232)	7.894** (3.952)
Mean post-treatment effect	0.408 (2.53)	-0.829 (4.488)	-3.95 (3.14)	10.105** (4.495)	9.874** (4.932)
Number of beneficiary Firms	8/30	6/30	9/30	5/30	2/30
Employment variables					
Total employment					
Mean instantaneous effect	-6.603 (5.394)	5.225* (3.121)	-1.355 (1.506)	-10.531*** (3.307)	-1.838 (2.353)
Mean post-treatment effect	-9.03 (10.784)	9.534* (4.918)	6.808 (5.540)	6.475 (7.058)	7.856*** (1.823)
Number of managers					
Mean instantaneous effect	-0.882 (1.076)	-0.551 (0.573)	-0.378 (1.058)	-2.584 (1.735)	-0.735 (0.555)
Mean post-treatment effect	-2.703 (2.333)	0.578 (1.659)	1.875 (2.721)	3.132 (4.476)	-0.172 (0.349)
Proportion of managers					
Mean	0,002	-0.011	-0.007	0.012	0.026

instantaneous effect	(0.012)	(0.026)	(0.029)	(0.023)	(0.023)
Mean post-treatment effect	0.03 (0.03)	-0.029* (0.016)	-0.072 (0.107)	0.021 (0.043)	0.016 (0.024)
Number of beneficiary Firms	10/23	1/23	6/23	4/23	2/23

Notes: The signs ***, ** and * correspond to statistically significant coefficients at 1%, 5% and 10%, respectively. Standard errors in parentheses are robust to both heteroscedasticity and autocorrelation.