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Macro and micro impacts evaluation of public innovation policies : evidence from European regions and French firms

Modou Mar

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THESIS

To obtain the title of

DOCTOR OF PHILOSOPHY OF THE COMMUNAUTÉ UNIVERSITÉ GRENOBLE ALPES

Spécialité : **Sciences Économiques**

Arrêté ministériel : 25 mai 2016

Presented by

Modou MAR

Thesis carried out at the **Grenoble Applied Economic Laboratory
(GAEL)** at the **École Doctorale Sciences Economiques**

Macro and Micro Impacts Evaluation of Public Innovation Policies: Evidence from European Regions and French Firms

The public defense has taken place on **September 7th, 2018**
in front of a jury composed of:

Anne PLUNKET

Professor, Université Paris-Sud (Paris XI)

(Chair)

Emmanuel DUGUET

Professor, Université Paris Est Créteil

(Reviewer)

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Professor, Université de Lorraine

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THÈSE

Pour obtenir le grade de

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Thèse préparée au sein du **Laboratoire d'Économie Appliquée de
Grenoble (GAEL)** dans l'**École Doctorale Sciences Economiques**

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*“I prefer to be true to myself,
even at the hazard of incurring the ridicule of others,
rather than to be false, and to incur my own abhorrence.”*

Frederick Douglass

Dedication

*This thesis is dedicated to my mother and father,
to my beloved wife Ramatoulaye and children,
to my uncle Wilane, brothers, sisters, and all my family.
Thank you for your kindness, love and endless support.*

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MAR Modou - JUNE 2018

The University of Grenoble Alpes intends to give no approval and no disapprobation to the opinions emitted in this thesis. These must be considered as appropriate to their author.

Thesis Abstract

My dissertation aims at investigating empirically the macro and micro impacts of public innovation policies. To do so, it focuses especially on two specific policies respectively implemented in Europe and France. To evaluate the effect of European innovation policy, we use macro-level (European regions) panel data covering 218 EU-27 regions for the 1995-2012 period. And for evaluating the French clusters policy, we use micro-level (French firms) panel data covering the 2004-2005 period. The chapter 1 brings an overview of the economy of innovation. It presents the rationales for public intervention to support R&D and innovation and the main public instruments but also the limits of public intervention. Finally, it presents a large literature review on the econometric evaluation of innovation policies and discusses the evidence of public innovation policy.

The chapter 2 is a macro-econometric study on the impacts of the EU Fifth and Sixth Framework Programmes policy on regional innovation using a panel data set covering the 1995-2012 period and 218 regions of the entire EU-27. We estimate a regional knowledge production function by using a random-trend model and a translog specification in order to take into account the complementarity and substitution effects between factors but also the threshold effects and the initial endowments of innovative factors. Findings suggest that, while the FP5 expenditure seems to have no impact on regional innovation, the FP6 spending impacts positively regional innovation. However, the effects are heterogeneous across countries. While the FP5 has a positive effect on regional innovation in the top 11 countries, only the FP6 spending affects regional innovation in the other 16 European countries. Further, results show complementarity between human capital and FP6 or the FP5-FP6 amounts (SumFP5-6), and on the contrary substitution between R&D spending and FP6 or the SumFP5-6 spending.

For methodological issues, we decided to separate the micro-level study on the French competitiveness clusters into two parts. The chapter 3 examines the effectiveness of the French competitiveness clusters policy on the SMEs' innovation input and output additionality. We use firm-level data set covering the 2005-2012 period and an original strategy to construct different treatment options distinguishing cluster membership and participation in FUI projects. We first analyze the selection process before using the conditional difference-in-difference (CDiD) estimator to control for unobserved heterogeneity effects and to test the additionality hypothesis. The findings suggest the rejection of any crowding-out effect, no matter what treatment option is used and indicate substantial input additionality effects. With regard to output additionality, there are positive effects on employment, but weak or nonexistent effect on other types of economic performance. Moreover, results reveal that the effects are larger for the joint participation (clusters adhesion and FUI projects participation) and smaller for participation only in FUI projects.

The chapter 4 examines the effectiveness of the same French clusters policy on mid-sized and large firms' performance. Using firm-level data over the 2004-2012 period, we adopt a two-way fixed effects model to overcome selection bias by controlling not only for the unobserved time-invariant heterogeneity but also for heterogeneity in firms' observed characteristics over a multiple-periods. The findings suggest that clusters have no effect on private R&D but FUI projects participation leads to crowding-out effects. Contrary to what one might expect, the effects on R&D staff and researchers are surprisingly very low even nonexistent. Both instruments increase innovation. On total employment, the impacts of both instruments are strongly positive but are slightly stronger for the FUI projects participation. Furthermore, adhesion to clusters has positive effects on turnover and export. However, the effects of FUI projects participation are negative on turnover and added value but null for exports. We find that the effects are heterogeneous according to the type of clusters but also depending on the number of years a firm has been participating in the policy.

Keywords: Innovation policies, R&D subsidies, Collaborative R&D, EU Framework Programmes, Cluster policies, Firms' performance, Policy evaluation, Panel data, Random trend Model, Conditional Difference-in-Difference, Two-way fixed effects model

List of abbreviations

2SLS	Two-Stage Least Squares
AAP	Call for projects (Appel à projets)
AII	Agency of the Industrial Innovation
AMADEUS	Analyse Major Databases from European Sources
ANR	National Agency of Research
ATE	Average Treatment Effect
ATENT	Average Treatment Effect on the Non-treated
ATET	Average Treatment Effect on the Treated
Bpifrance	French Public Investment Bank
CDC	Caisse des dépôts et consignations
CDiD	Conditional Difference-in-Difference
CF	Control Function
CGET	Commissariat général à l'égalité des territoires
CIA	Conditional Independence Assumption
CIADT	French administration in charge of spatial planning and regional policy
CIR	Research tax credit (Crédit Impôt Recherche)
CIS	Community Innovation Surveys
CORDIS	Community Research and Development Information Service
CS3	Number of employees in executives, managers and high intellectual professions
CSA	Common Support Assumption
DADS	Annual declarations of social data
DATAR	Délégation interministérielle à l'aménagement du territoire et à l'attractivité régionale

DERD	External research and development expenditures
DGCIS	Direction Générale de la compétitivité, de l'industrie et des services
DGE	Direction Générale des Entreprises
DGFIP	Direction Générale des Finances Publiques
DIACT	Délégation interministérielle à l'aménagement et à la compétitivité des territoires
DID	Difference-in-Difference
DIRD	Internal research and development expenditures
DIRECCTE	Directions régionales des entreprises, de la concurrence, de la consommation, du travail et de l'emploi
EBITDA	Earnings Before Interest, Taxes, Depreciation, and Amortization
EC	European Commission
EESD	Energy, environment and sustainable development
EPO	European Patent Office
ERA	European Research Area
ETIs	Midsized firms
EU	European Union
EuroLIO	European Localized Innovation Observatory
Eurostat	Statistical Office of the European Union
FICUS	Fichier complet unifié de Suse
FP5	Fifth European Union Framework Programmes
FP6	Sixth European Union Framework Programmes
FPs	European Union Framework Programmes
FUI	Unique Interministerial Fund
GDP	Gross Domestic Product
GE	Large firms
GROWTH	Competitive and sustainable growth
HK	Human capital
ICP	Industrial Cluster Projects Policy
INCO2	Confirming the international role of community research
INSEE	French National Institute for Statistics

IR	Income tax
ISCED	International Standard Classification of Education
ISF	Solidarity tax on wealth
ISI	Industrial Strategic Innovation
IST	User-friendly Information Society
IT	Information technology
IV	Instrumental Variables
JEI	Young Innovative Enterprise
JRC	Joint Research Centre
KPF	Knowledge Production Function
LIFI	Financial Links
LPS	Local Productive Systems
MAR	Marshall Arrow Romer
MESR	French Ministry of Research and High Education
NEG	New Economic Geography
NN	Nearest-neighbor
NUTS	Nomenclature of territorial units for statistics
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
PIA	Programme des Investissements d’Avenir
PS	Propensity Score
PSM	Propensity Score Matching
R&D	Research and development
RD	Regression Discontinuity
RGM	Random trend (growth) model
RKPF	Regional Knowledge Production Function
RSA	Regional Selective Assistance
RTD	Research and Technological Development
SMEs	Small and Medium-sized Enterprises
TFP	Total factor productivity

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Introduction

Innovation as engine of economic growth

Since the pioneering work of [Schumpeter \(1942\)](#), the understanding of the important role of knowledge for economic progress is accompanied by a significant evolving consideration of the concept of innovation and research and development (R&D) for the industry, economists and governments. Due to its influence on economic progress, industrial change and international competitiveness ([Romer, 1986](#); [Grossman and Helpman, 1991](#); [Romer, 1994](#); [Barro and Sala-i Martin, 1995](#); [Aghion et al., 1998](#); [Encaoua et al., 2004](#)), the concept of innovation has become a widely-debated subject and attracted a raising interest, not only within firms, but also at the national levels. For nations, innovation helps to drive economic growth and to address global challenges, such as living standard, health, pollution, climate change and sustainable development ([OECD, 2015b](#)). And for firms, it is the best way to have a market power and to improve their dynamics of growth ([Schumpeter, 1942](#)). According to [Fagerberg \(2004\)](#), if firms learn from interacting with external sources, they increase the pressure on other firms to follow and this greatly enhances the innovativeness of both individual firms and the economic systems to which they belong (regions or countries).

Innovation policy: what, why and how?

Firms invest in R&D however, because of the complex, and uncertain environment of innovation, they face several problems inhibiting innovation and therefore causing private sector under-investment in R&D. The most accepted argument among other (see chapter 1) is the market failures due to the incapacity of firms to appropriate the returns of R&D they undertake because of markets failures related to knowledge externalities or spillovers. In response to the under-investment in R&D and innovation activities, [Nelson \(1959\)](#) and

Arrow (1962) have provided a seminal argument suggesting that government intervention is necessary to support private R&D effort for innovation. Several other rationales for innovation policies including capital market imperfections due to information asymmetry, imperfect competition, coordination problem and systemic failures have been proposed in the economic literature (Martin and Scott, 2000; Edler et al., 2016; Georghiou et al., 2014).

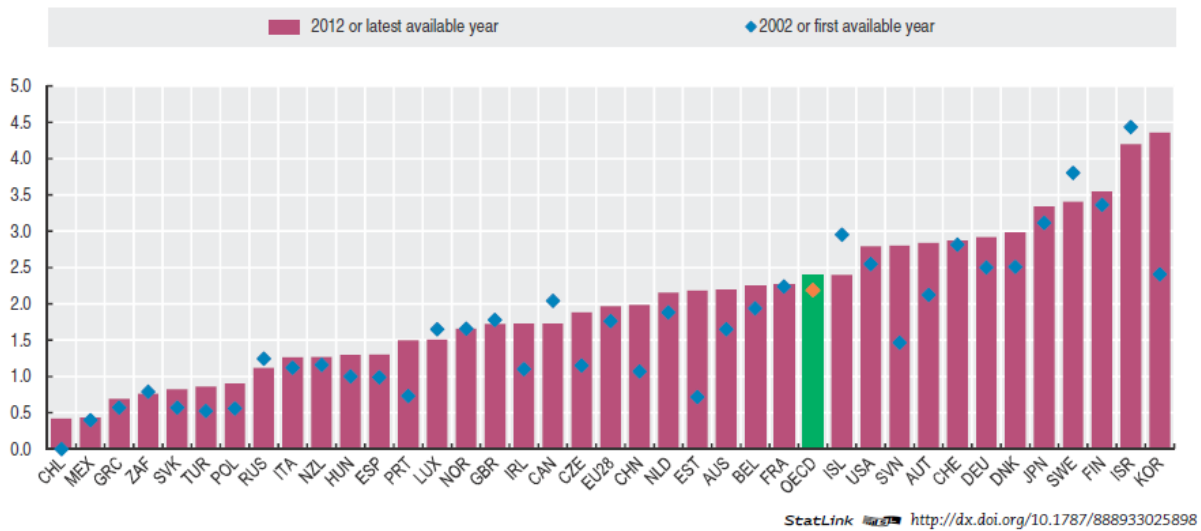
Public intervention for R&D through direct/indirect instruments (more or less accepted) can overcome issues faced by the private sector and thus foster technology breakthroughs and innovation. We distinguish supply-side instruments which include direct funding, R&D award, fiscal incentives for innovation activities and debt and risk-sharing schemes, from demand-side instruments which include legislation, public procurement, supporting private demand and systemic policies (Edler and Georghiou, 2007). Moreover, instruments may be linked or complementary with other instruments and result into mixed policies and collaborative R&D (including cluster policies, network policies and support for R&D cooperation) (Edler et al., 2013).

Comparison of R&D expenditure to GDP ratio

International comparison

At the world level, several countries have recognized the benefits of supporting R&D investment and started to implement various direct and indirect public policies in order to stimulate private R&D and innovation. Most of the developed and developing countries have spent public resources to boost their innovation and economic system and increase the level of welfare. According to the OECD statistics presented in figure 1, over the 2002-2012 period, R&D intensity grew in the OECD countries (from 2.19% to 2.40%), in the EU-28 (from 1.76% to 1.97%), in the United States (from 2.55 to 2.79%) and in Japan (from 3.12% to 3.34%). Countries like Estonia (more than tripled, from 0.72% to 2.18%), Portugal (doubled), Slovenia (almost doubled), South Korea, Czech Republic and Turkey were the fastest growing OECD countries while in the same period, R&D intensity in China almost doubled, increasing from 1.07% 1.98% and surpassed the EU-28 for the first time in 2012.

Figure 1: Gross domestic spending on R&D Total, % of GDP, 2002-2012



Source: From OECD Factbook 2014. https://www.oecd-ilibrary.org/economics/oecd-factbook-2014_factbook-2014-en

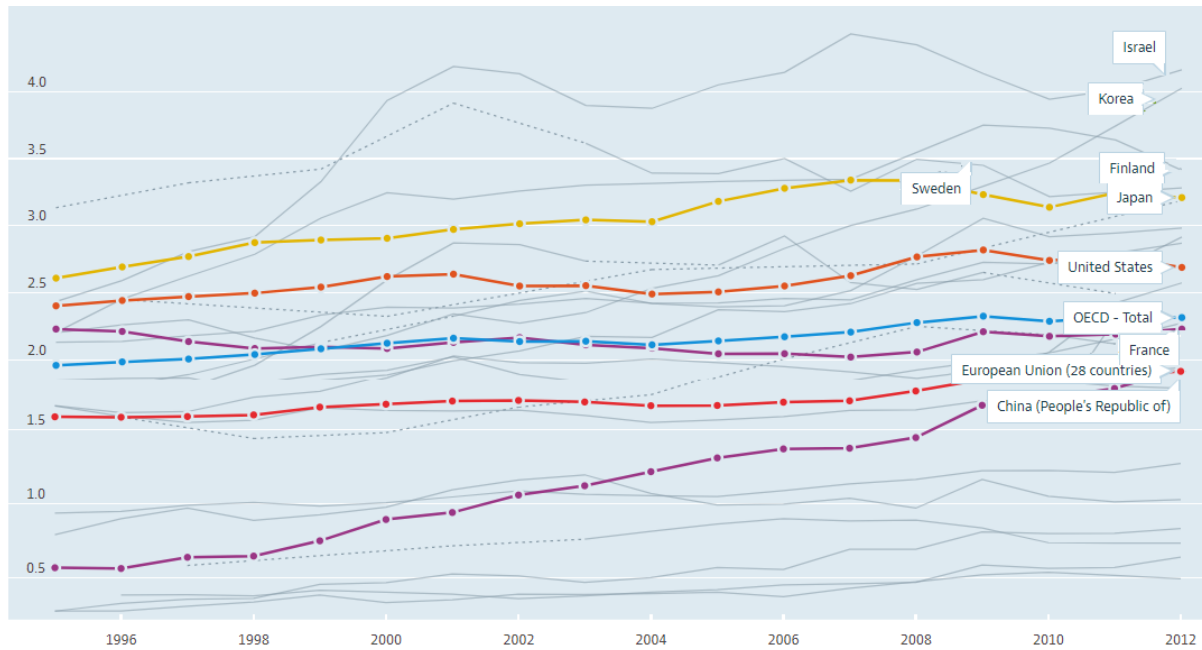
European innovation strategy

At the European level, over the last three decades, the EU has developed its systems of innovation with respect to the strategic orientation of its technology and innovation policies. The main instruments of the EU are the Framework Programmes (FPs) on Research and Technological Development (RTD) which have funded thousands of collaborative R&D projects to support transnational cooperation and mobility for training purposes. Based on the Maastricht treaty, the FPs were implemented in 1984 to strengthen the scientific and technological bases of industry and to promote research activities (CORDIS, 2002)¹. Since their implementation, the FPs have known strong rise in their budgets from €3.75 billion for the first phase (FP1) to €80 billion for the Horizon 2020 program (FP8).

Moreover, through the Lisbon strategy at the European Council in 2000, the European Commission set a target of investing 3% of Gross domestic product (GDP) on R&D by 2010. However, the Eurostat statistics (figure 1) indicate that although the ratio of R&D expenditures to the GDP has increased in certain European countries (Estonia, Portugal, Slovenia for example), in several other member states, it has decreased (Sweden) or stagnated (France, United Kingdom). As consequence, the average R&D expenditure has increased slightly but has never reached 2% of the GDP in the EU-28 as a whole in this period.

¹Community Research and Development Information Service (CORDIS)

Figure 2: Gross domestic spending on R&D Total, % of GDP, 1995-2012



Source: Main Science and Technology Indicators, April 2018. <https://data.oecd.org/rd/gross-domestic-spending-on-r-d.htm>

Figure 2 shows the changes in Gross domestic expenditure on R&D to GDP ratio for EU28 compared to USA, Japan, China and OECD countries over the 1995-2012 period. According to the official data (OECD, 2018), in 2010, R&D amounted to 2.2% of GDP for the OECD as a whole and amounted only to 1.8% of GDP in average for the EU-28. Therefore, as shown by the figure 2, when making a comparison, we see that only Denmark, Finland, Israel, Japan, South Korea and Sweden were the countries whose R&D-to-GDP ratio exceeded 3%. On average, although some EU countries such as Finland, Sweden and Denmark were among the most performing in the world, the EU-28 as a whole performed lower than Japan, USA, and average OECD countries. Therefore, it may be understandable that the EU needs to increase its R&D effort in order to become more competitive and to catch up the most performing countries like Japan and USA for example.

French innovation policy strategy

In France, one of the largest economies in the EU, the government have spent a lot of public resources to support innovation. Indeed, France is one of the three European leading countries in terms of R&D volume, but have spent between 2% and 2.23% of its GDP over

the 1995-2012 period to support innovation. Figure 1 shows that between 2002 and 2012, the French R&D-to-GDP ratio has stagnated (from 2.24 to 2.26%). Although France did not meet the 3% target set by the EU, French public R&D expenditures as a percentage of GDP is always above the EU average but remains below the levels of countries like Finland, Sweden, Denmark, and Germany. According to French Ministry of Research, in 2012, French funding of R&D was about €48.4 billion of which 41% of public contribution. In France, as in several other developed countries, there is a mix of several intervention instruments including the clusters policy implemented in 2004 to develop networking between companies and research and training organizations.

Research questions

The economic and social context issues as well as the challenges of growth and sustainable development push public policymakers to support R&D and innovation. In struggling to improve the performance of innovation systems policymakers who spend a lot of public resources need to know about the effectiveness of the policies they implement.

The increasing interest in innovation and the importance of resources devoted to the R&D policies led to a great number of researches which addressed the evaluation of the effectiveness of public innovation policies using several econometric methods. The R&D policies impact evaluation remains subject to key methodological and empirical concern for economic researchers because the complexity of innovation systems and innovation process make it difficult to identify the real effects of a policy. The impacts found in the literature and their magnitude vary depending on the geographical scope, the data used and their level of aggregation, the estimation method and model specification (David et al., 2000; Cerulli and Poti, 2012).

The main objective of this thesis is to empirically investigate the effectiveness of public innovation policies. The basic idea that motives this thesis is that lot of public resources are spent at the European level but also in France to support R&D and innovation, and therefore evaluations are needed to know how much money should be invested, in what sectors and under what conditions to better reach the targets when supporting innovative activities. This thesis focuses on two specific policies, one of which was implemented at the European level and the other was implemented in France.

In the literature, many studies have used econometric techniques to analyze the effects of the EU Framework Programmes (FPs) policy on firms' innovation and performance. Nevertheless, these studies have focused on micro-data (firm level) and the question asking if the FPs policy has positive effects on innovation at the macro-level (regional) has not been addressed. The first purpose of this thesis is to analyze the impacts of the EU Fifth and Sixth Framework Programmes policy on the regional innovation of the EU-27 countries.

Furthermore, in the literature, there are few studies assessing the impacts of the French competitiveness clusters policy. Globally, these studies focus on the effects of this policy on the performance of small and medium-sized enterprises (SMEs) and on mid-sized firms (ETIs). Their findings suggest a rejection of the crowding-out hypothesis and suggest weak positive impact on innovation input additionality (private R&D and employment in R&D) but no substantial effects in terms of output additionality (innovation and market performance) are found. However, there is no study controlling at the same more than one instrument. Knowing that in France there is a mix of several public innovation instruments, it may make sense to control some instruments (clusters adhesion and FUI projects participation) when evaluating the effects of the clusters policy. Indeed, the lack of conclusive results on the effectiveness of the policy may be partly attributable to the lack of adequate data and methodology but also to the simultaneity of several instruments of innovation policies. Moreover, we see that almost all the different studies partly disregard or remove systematically from their evaluations the large firms which undertake a huge share of total R&D spending (48.5% in 2012) and which are the main beneficiary of subsidies. Therefore, the second purpose of this thesis is to examine and better understand the effectiveness of the French Competitiveness clusters policy on the innovation and performance of small and medium-sized enterprises, mid-sized firms but also large firms by controlling two innovation instruments.

Because of the two main purposes of the thesis, it makes sense to separate the research questions into specific research questions. With respect to the two different policies analyzed in this thesis, we have two sets of main research questions addressed.

The first set of main research questions addressed in this thesis and which focus on the EU innovation policy are: *Have the EU Fifth and Sixth Framework Programmes impacted positively the European regional innovation? How the effects, if any, of these programs vary between leading and lagging EU countries? What are the improvements that need to be done in order to make the policy more effective?*

The second set of main research questions addressed in this thesis and which focus on the French clusters policy are: *What are the factors that determine the participation of firms in the clusters policy? What are the impacts of clusters adhesion on firms' performance? What are the impacts of FUI projects participation on firms' performance? Do firms perform better when they jointly belong to clusters and participate in projects? Do the effects of the policy differ between SMEs and ETIs and large firms. What are the improvements that need to be done in order to make the policy more effective?*

In this thesis, I use a variety of empirical models in order to answer the different research questions. In the following work we use the new development of empirical models and particularly natural experiments studies approach, in order to evaluate the impacts of innovation policies at both macro-level (European regions) and micro-level (French SMEs, ETIs, and large firms).

To answer the first set of main research questions, we use macro-data to evaluate, in one complete empirical chapter, how the two phases (Fifth and Sixth) of the EU Framework Programmes policy have impacted the regional innovation of the EU-27 countries. we also account for the simultaneity of the two instruments.

Thereafter, to answer the second set of research questions, we use micro-data to evaluate the effects of the French competitiveness clusters policy on firms' innovation and performance (input and output additionality). To do so, because of methodological issues, we divide the work into two different chapters. The first chapter as commonly done in the literature evaluates the effects of the clusters policy on small and medium-sized enterprises' innovation and performance (input and output additionality). The other chapter goes further and proposes an adequate methodology to bring a deep analysis of the effectiveness of this clusters policy on midsized and large firms' performance in terms of incentives for private R&D investments, innovation, job creation and market competitiveness. As in the first empirical chapter, in these two empirical chapters, we consider two policy instruments (adhesion to clusters and participation in FUI projects), account for their simultaneity and compare them.

The thesis is organized into four chapters, one of which is reserved for the theoretical and empirical literature review of innovation policy evaluations and the three others are empirical contributions to public innovation policy evaluations.

Chapters synthesis and contributions to literature

The **first chapter** presents a literature review of public innovation policies and examines the empirical evidence on the effectiveness of public interventions to support R&D and innovation. We review the economics of innovation literature by taking theoretical and empirical perspectives on the relation of innovation and economic growth, innovation and technical change, and innovation and firms. We discuss some indicators used to measure innovation. Moreover, the chapter gives an overview of the theoretical rationales of public intervention to support private R&D and innovation and the main public intervention instruments. Finally, we review the major econometric method of evaluation of public innovation policies and present a literature review on the evidence of several public intervention instruments stimulating private R&D spending and innovation. The empirical literature overview highlights the great heterogeneity in results of empirical studies that tried to evaluate the effects of public support for R&D and there is no consensus in the literature. Although some crowding-out effects have been found in former studies and particularly in the USA, recent empirical evidence on input and output additionality at the firm level suggests that R&D subsidies may mostly stimulate private R&D investment and positively impact innovation outcomes and firms' performance. However, the studies analyzing the effectiveness of cluster policies on the firms' R&D and performance are mixed and non-conclusive. The results found in the literature vary depending on the geographical scope, the data used and their level of aggregation, and the estimation method and model specification (David et al., 2000; Cerulli and Potì, 2012). As explained by Cerulli and Potì (2012), even if the majority of models focus on testing private R&D additionality, much attention should be devoted to the effects of R&D effort on firms' performance. In general, the literature confirms the existence of a positive relationship between innovation policies and firms' innovation, but the effect on economic performance is not so evident. In the following chapters, we use the new development of empirical models and particularly natural experiments studies to evaluate the impacts of innovation policies on private R&D and firms' performance. Our contribution to this on-going R&D and innovation policy evaluation consists of empirical analyses conducted in three studies.

In the **chapter 2**, we use macro-data (regional panel) covering the 1995-2012 period and 218 regions of the entire EU-27 and adopt a knowledge production function (KPF) with a translog function specification. We use a random trend model specification that controls

for all the unobserved heterogeneity of regions that can affect innovation. It is a panel model approaches which deal with unobservables and endogeneity to study the effects of the European Union Framework Programmes (FPs) policy on regional innovation. This study contributes to the literature in terms of methodology and findings. In terms of methodology, differently from other studies which generally use firm-level data to evaluate the effects of the FPs policy, it proposes the use of macro-level data and a relevant macroeconomic method controlling for main innovation inputs, i.e. human capital (HK) and R&D and the FP5 and FP6 spending, as well as main unobserved factors that may affect the innovation process. The use a translog function specification for the production function allows taking into account the complementarity and substitution effects between factors but also the threshold effects and the initial endowments of innovative factors. In terms of findings, the results bring new evidence on the impacts of the FP5 and FP6 programmes on innovation output at the macro-level in EU-27. Moreover, results reveal for complementarity but also for substitution between factors. Further, a comparison of the impacts between leading countries (EU top 11 performer countries) and lagging countries (EU low 16) shows strong heterogeneity of these results.

In the **chapter 3**, we use micro-level data and adopt a quasi-experiments design² and combine propensity score matching and difference-in-difference approaches also known as conditional difference-in-difference (CDiD) to evaluate the effects of the French competitiveness clusters policy on the innovation and performance of small and medium-sized enterprises (SMEs). This study uses firm-level data and contributes to the literature in terms of methodology and findings. In France, all the studies analyzing the competitiveness clusters policy impacts on firms' performance control for one instrument at the same time (clusters adhesion or FUI projects participation). Differently from these latter, to our knowledge this study is the first study proposing a relevant methodology by considering multiple treatments and controlling for two instruments (clusters adhesion and FUI projects participation). In terms of findings, it brings new evidence on input additionality and on output additionality effects of SMEs but also compares these effects according to the three treatment options.

²Quasi-experiments do not rely on randomization but on other principles for establishing participant and control groups (which are generally considered as inferior to randomization in terms of their potential to generate unbiased estimates of impact) (Leeuw and Vaessen, 2009).

In the **chapter 4**, we use micro-level data and the two-way fixed effects model to overcome selection bias by controlling not only for the unobserved time-invariant heterogeneity but also for heterogeneity in firms' observed characteristics over a multiple-periods and analyze the effects of this same French clusters policy on the innovation and performance of mid-sized and large firms. With respect to the fact that large firms are the main actors of this policy, this study contributes greatly to the literature in terms of methodological aspects but also in terms of new findings. As explained in the previous section, in France and generally at the international level, there is a lack of evaluation of clusters policy on large firms using econometric techniques because of methodological issues and more especially the lack of counterfactuals. In terms of methodological aspects, to our knowledge, this study is the first econometric study evaluating the effects of the competitiveness clusters policy on large firms' performance. Moreover, as in the previous chapter, it analyzes the impacts by controlling for two instruments and compares them. In terms of findings, it proposes new evidence on input additionality and output additionality effects. It goes further and shows that these effects are heterogeneous according to the type of clusters to which a firm belongs but also depending on the number of years a firm has been participating in the policy.

We conclude this thesis by presenting the synthesis of findings and discussing the implications of public interventions for innovation policies and making recommendations to governments concerning public policy impacts. We also make recommendations for further research on the efficiency of public innovation policies.

Chapter 1

Public innovation policy evaluation: theoretical and empirical literature

Abstract

This chapter examines the empirical evidence on the impact and effectiveness of public intervention to support R&D and innovation. It first brings an overview of the economy of innovation by discussing the definitions of innovation and highlights the relationship between innovation and economic growth and innovation and firms' activities and competitiveness. Moreover, it gives an overview of the theoretical justification and rationales of public intervention to support private R&D and innovation and presents the main public intervention instruments supporting innovation but also the limits of public intervention. Finally, it brings a large literature review on the econometric evaluation of innovation policies and discusses the evidence of public innovation policy.

Surveying the literature of innovation and public R&D policies enables to address more comprehensively the theoretical and empirical issues related to public innovation policy and their evaluation. This enables understanding the complexity of innovation and its different aspects especially with regard to firms' development but also the difficulties related to its measurement. An overview of the main econometric models used in the literature and the different impact evaluation reveals that, although some crowding-out effects have been found in former studies, recent empirical evidence suggests that R&D subsidies may mostly stimulate private R&D investment and may positively impact innovation outcomes but also the productivity and competitiveness of firms. Moreover, the literature reveals that studies focusing on R&D tax incentives, generally conclude for positive effects but for cluster policies, findings are mixed and non-conclusive. Furthermore, reviewing the empirical literature reveals a great heterogeneity and a lack of consensus in results depending on the geographical scope, type of data, estimation method and model specification. Indeed, in observational studies approach data are subject to bias and make it challenging to evaluate innovation policies. Finally, the literature highlights the concentration of evaluation on testing R&D input additionality and the lack of studies evaluating the effects on firms' output performance.

Keywords: R&D policy rationales, Innovation policy instruments, R&D subsidies, Tax credits, Collaborative policy, Policy evaluation, Treatment effects

JEL classification: O30, O32, O38, C01, C14, C2, C3, C5, D22, D4, D04, E62, G14

1.1 Introduction

During the past decades, the understanding of the important role of knowledge for economic progress is accompanied by a significant evolving consideration of the concept of innovation and research and development (R&D) for the industry, economists, and governments. The concept of innovation has become a widely-debated subject and attract a raising interest, not only within firms but also at the regional and national levels due to its effects on economic progress, industrial change (Romer, 1986) and international competitiveness. The innovative effort (including formal research and development) remains the *sine qua non* of growth and is important to help address global challenges (OECD, 2007).

Innovation, technological or not, influences most of the economic mechanisms and is at the top priorities of the strategies of firms and nations. The role of innovation in the economy has considerably strengthened during the last decades because of the globalization and the technological development. The economic theory has evolved strongly in the understanding of its various aspects, since the pioneering works of Schumpeter (1942) until the new theories of competition, of labor market, of growth or international trade. The globalization of the economy accompanied with the technological development intensified the competition and lead firms and States to rely on innovation.

The firms consider innovation as a priority to strengthen their positions on the market and to improve their growth. Firms make the investments that drive innovation, but they face several problems that inhibit innovation and leading to private sector under-investment in R&D. Over the last decades, governments have recognized the role of R&D in economic growth and have been engaged in providing R&D support for firms. The seminal argument for public R&D subsidies to correct this private under-investment has been provided by Nelson (1959) and Arrow (1962). Several rationales more or less accepted for innovation policies have been proposed by policy-makers and academics. These rationales include among others, markets failures related to knowledge externalities or spillovers, capital market imperfections due to information asymmetry, imperfect competition, coordination problem and systemic failures. There is a huge debate among economists about the desirability of these public supports toward firms. Some economists (Wolf, 1993; Hospers et al., 2009) argue that public subsidies may be inefficient because public resources may crowd-out private financing because of the firms' selfishness but also public resources may be allocated to the less efficient sector

and thus become inefficient.

There is a new approach of policies for innovation in many countries, where governments increasingly act as a facilitator in the face of complexity and uncertainty, enabling coordination between individual economic agents. R&D policies for innovation operate in a complex, and uncertain environment, where government action will not always get it right. The impact of policies for innovation depends heavily on their governance and implementation, including the trust in government action and the commitment to learn from experience (OECD, 2015b). Most of the OECD countries have spent public resources directly to boost their economic system and increase the level of welfare. Such policies may be effective but may harm technological performance. Regarding the complex relationships between public policies implemented to enhance innovation and their expected positive impacts, but also their potential negative effects on innovation process, it is critical to evaluate these policies.

In recent years economists and econometricians have provided studies aiming at understanding the functioning of firms R&D strategies and the efficiency of public subsidies and supports for private R&D. Several econometric models have been used to measure the effect of public intervention supporting private R&D. The originality of this chapter lies on the regrouping of a large literature on the economy of innovation based on theoretical and empirical perspectives on innovation policies, their rationales, their efficiency and the major econometric method of evaluation of such policies. It includes an overview of recent studies providing evidence on the effectiveness of several public policy instruments fostering R&D and innovation.

This chapter devoted to the literature review is structured as follows. The first section brings an overview of the economy of innovation. After discussing the definitions of innovation, it highlights the relationship between innovation and economic growth and innovation and firms' activities and competitiveness. It also stresses the measures of innovation and the geographical concentration of innovation activities. The second section presents the theoretical justification and rationales of public intervention to support private R&D and innovation. It presents the several main public intervention instruments supporting innovation but also their possible inefficiency and the risks of public intervention. The third section brings a large literature review on the econometric evaluation of innovation policies. Finally, the fourth section discusses the evidence of public R&D subsidies and their effects on innovation. The fifth section brings concluding remarks.

1.2 The economy of innovation

1.2.1 Definition of innovation

The concept of innovation has become a widely-debated subject and attract a raising interest, not only within firms but also at the regional and national levels. If the term of innovation is usually used, it is nevertheless a notion on which the authors do not have consensus regarding how to define it. Mostly inspired by the vision of [Schumpeter \(1934, 1942\)](#), the various definitions of the innovation hold the idea of a new combination of ways which lead to new or significantly improved products and services. According to the OECD Oslo Manual ([2005](#)), an innovation is “*the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organizational method in business practices, workplace organization or external relations*”. In other words, the minimum requirement for an innovation is that the product, process, marketing method or organizational method must be new (or significantly improved) to the firm. This definition is the most commonly used.

According to [Edison et al. \(2013\)](#) who review the literature on innovation and completed it with a study, there are more than 41 definitions with various aspects of innovation. [Edison et al. \(2013\)](#) define innovation as follows: “*production or adoption, assimilation, and exploitation of a value-added novelty in economic and social spheres; renewal and enlargement of products, services, and markets; development of new methods of production; and the establishment of new management systems. It is both a process and an outcome*”.

Depending on its impact on the market and the change in underlying technology, innovation can be qualified as *incremental* or *radical*. *Incremental innovation* make reference to relatively minor changes in technology based on existing platforms that deliver relatively low incremental customer benefits and *radical innovation* make reference to a disruptive innovation which introduces first-time features or exceptional performance ([Edison et al., 2013](#)). According to the degree of novelty, this innovation can be a novelty to the firm itself or to the industry, or to the market or to the world.

Based on the work of [Schumpeter \(1934\)](#), innovations are commonly classified into four types of innovation: *product innovation, process innovation, marketing innovation and organizational innovation*. This four types of innovation which can use new knowledge or technologies, or can be based on new uses or combinations of existing knowledge or technologies

are well explained in the OECD Oslo Manual (2005).

In economics, the two first types are the most used and are defined by the OECD Oslo Manual (2005) as follows. A *product innovation* is the introduction of a good or service that is new or significantly improved with respect to its characteristics or intended uses. This includes significant improvements in technical specifications, components, and materials, incorporated software, user-friendliness or other functional characteristics. A *process innovation* is the implementation of a new or significantly improved production or delivery method. This includes significant changes in techniques, equipment and/or software used to increase quality or to produce or deliver new or significantly improved products.

However, the two other types of innovation are also very important for a successful launch of products to market and for processes organization (Edison et al., 2013). A *marketing innovation* which is the implementation of a new marketing method involving significant changes in product design or packaging, product placement, product promotion or pricing, aims at better addressing customer needs, opening up new markets, or newly positioning a firm's product on the market, with the objective of increasing its sales. Finally, an *organizational innovation* corresponds to the implementation of a new organizational method in the firm's business practices, workplace organization or external relations. It can help to increase a firm's performance by reducing administrative costs or transaction costs, gaining access to non-tradable assets (e.g. non-codified external knowledge).

1.2.2 Innovation and growth

The relation between innovation and economic growth has attracted a great interest from researchers and was a well-debated topic in the economic literature. Economists writing about economic growth have recognized the key role of technological advance on the economic performance (Schumpeter, 1934).

In the 1950s many studies tried to measure the effect of technological change on the economy. The classical and neoclassical growth theories (exogenous growth theory) are based on the understanding that economic growth depends on the accumulation of capital within an economy. In other words, when the amount of capital increases due to technological progress, the productivity of labor rises and thus lead to economic growth (Solow, 1956; Denison, 1962 and Hansen and Prescott, 2002 for a review). In the view of this theory,

economic growth is seen as the outcome of resources accumulation and the constraints on growth and social change are due to the constraints on the resources accumulation. In this theory, only the traditional factors of production (natural resources, capital, labor) were considered as endogenous.

In contrast to this theory, since [Arrow \(1962\)](#) and later, the endogenous growth models including innovation process and its effects ([Romer, 1986](#); [Lucas, 1988](#)), the role of knowledge in the growth process has been highlighted. In the endogenous growth theory, as the investment in human capital, innovation, and knowledge are considered as significant contributors (inputs) to economic growth. Over the last few years, increasing attention has been paid to innovation and this has been accompanied by a change of views in what drives economic growth ([Grossman and Helpman, 1991](#); [Romer, 1994](#); [Barro and Sala-i Martin, 1995](#); [Aghion et al., 1998](#); [Encaoua et al., 1998](#); [Encaoua and Ulph, 2000](#); [Encaoua et al., 2004](#)). The endogenous growth theories have made it possible to bring new analytical methods and views on the forms of technical progress and on its impact in terms of economic growth by incorporating measures of R&D, education, and training.

Economists such as Romer and Grossman, in developing new growth theories, explained the forces which drive long-term economic growth and consider that knowledge investments, and thus innovation, are characterized by increasing returns and are the key factors of long-term economic growth. [Romer \(1986\)](#) makes endogenous the innovation by considering it as a function of the behavior, initiatives and development of the skills of the economic agents. He considers that innovation activities increase the stock of knowledge and the diffusion of this knowledge benefits to all firms instead of being limited to the innovative firm. Firms are then interdependent, and the research and innovation made by each firm benefit to other firms in the economy and pulls the economy towards growth. In following [Arrow \(1962\)](#), endogenous growth models emphasize that the private sector activities contribute to technological progress rather than public sector funding for research.

Since the industrial revolution, much of the rise in living standards is due to innovation. Innovation is a crucial factor in determining competitiveness and national progress and it is important for helping address global challenges, such as economic growth, living standard, health, pollution, climate change, sustainable development, etc. ([OECD, 2015b](#)). Investing in research in an efficient system of knowledge creation and diffusion is essential for innovation. Moreover, the improvements in the skill composition of labor play an important role in

productivity and growth. In the macroeconomic literature, the contribution of education and human capital accumulation to economic growth is well documented. States should increase the investment in education, training of researchers and highly skilled workers to promote scientific research and innovation. In its new report, the OECD suggests policymakers to build a competitive business environment that encourages investment in technology and in knowledge-based capital to improve innovation across the economy, to invest in research and knowledge infrastructure, to help in overcoming barriers to innovation and to ensure the ultimate contribution of innovation to growth and well-being (OECD, 2015b).

1.2.3 Innovation and firms

Innovation is considered as an increasingly essential factor of growth, competitiveness, and success for firms as for nations. For a firm, the innovation is the implementation of a new solution, for example, to improve its competitive position, its performance, or its know-how to acquire a competitive advantage (Schumpeter, 1934). In other words, a firm can find the necessity of acting or reacting with regard to its competitive environment to create new products or by developing existing products, but also, by optimizing its production system with the adoption of the last technologies stemming from the basic research. According to Arrow (1962) and Schumpeter (1934), the firms are incentivized to innovate because of the profit they get from. By innovating a firm may prevent the entry into the market (sector) of new firms (Arrow, 1962) while answering to market needs and keeping monopolistic position (Schumpeter, 1934).

The conditions of demand and the change of the level of technological opportunities depend on the firm's characteristics and market structures. Based on the work of Griliches and Schmookler (1963) and Schmookler (1966), and later Scherer (1982), economists distinguish two types of innovations as the origin of the impulse results from technology opportunities (*technology-push*) or from market opportunities (*demand-pull*).

The hypothesis of *technology-push* innovation is based on the idea that the firms make research and development or have new technologies breakthrough that drives the launch of a new product or process. Firms offer to potential customers as possible improvements in their performance without any previous demand. In a technology-push approach, firms focus on technical issues and trigger a search for scientific and technical knowledge both internal

and external knowledge sources to develop an innovative or technical solution to offer in the marketplace. In contrast with this, as well explained by [Schmookler \(1966\)](#), the hypothesis of *demand-pull* innovation is based on the idea that the firm's response to the market demand for a solution to a problem or a need in the marketplace leading to the development of a new innovative product. As firms are looking for profit-making opportunities and as the profitability of innovation increases with market size. In a market-pull approach, firms take ideas from the market, analyze technological solutions and design new innovative product to meet some demand based mainly on the expectations of customers.

Some authors such as [Geroski \(1994\)](#), [Nickell \(1996\)](#) and [Blundell et al. \(1999\)](#) has found in their empirical works that there is a positive relationship between market concentration or competition and innovation. [Scherer \(1965\)](#) suggest that a low intensity of competition facilitate innovation. [Aghion et al. \(2005\)](#) find that a low level of competition may increase the incremental profit from innovating; but on the other hand, a very high level of competition may also reduce innovation incentives for laggards. See next section for more details on the economic mechanism explaining the effect of concentration on innovation.

The fundamental characteristic of every new innovation need a new combination of existing ideas, capabilities, skills, resources, etc. ([Fagerberg, 2004](#)) and firms search widely for new ideas, inputs and sources of inspiration. Innovation requires high levels of resources in terms of new equipment, launching new productive processes in the firms. But the availability of knowledge and qualified human resources able to implement changes in the process of production is essential. All innovative firm, large or small, must develop the capacity for absorbing (outside) knowledge called *absorptive capacity* ([Cohen and Levinthal, 1990](#)). Absorptive capacity was defined by [Cohen and Levinthal \(1989\)](#) as a firm's ability to identify, assimilate and exploit knowledge from its environment. [Van Den Bosch et al. \(2003\)](#) define it as the ability to recognize the value of external knowledge, to assimilate it, and to apply it to commercial ends. Absorbing external knowledge is important for firms, and particularly for smaller firms which have to interact with others to compensate their small internal resources. These learning or absorptive capacity are essential assets for firms development. Innovation also requires financial means to undertake expenditures for research and development which improve absorptive capacities and generate new knowledge and innovations ([Cohen and Levinthal, 1989](#)).

Depending on their size, we can distinguish small firms (SMEs) with innovative activities and large firms, sometimes, characterized by the procurement of big laboratories devoted to research and development. In the literature, different authors such as [Schumpeter \(1942\)](#) and [Acs and Audretsch \(1987\)](#) argued that big firms have more advantage in term of innovation than small firms. This view was defended later by different authors arguing that, because of the availability of important resources ([Comanor, 1967](#); [Acs and Audretsch, 1988, 1990](#)), the market structure ([Kamien and Schwartz, 1975](#); [Cohen et al., 1987](#); [Cohen and Levin, 1989](#); [Cohen and Klepper, 1996](#); [Cohen and Klepper, 1992](#); and [Levin et al., 1985](#)), the economies of scale ([Scherer, 1991](#)) the diversification of the risks ([Schumpeter, 1942](#) and [Nelson, 1959](#)), the large firms can minimize risks and uncertainties and thus reduce market imperfections and optimize success when investing in research projects. In contrast with this view, some authors such as [Scherer \(1991\)](#); [Acs and Audretsch \(1988, 1990\)](#) suggest that small firms may have comparative advantage at least in certain industries because of the difference in management structure ([Rothwell, 1989](#)), the bureaucratic organization of large firms that does not conduct to undertake risky R&D ([Scherer, 1991](#); [Link and Bozeman, 1991](#)) and the spillovers ([Link and Rees, 1990](#); [Acs et al., 1994](#)). The innovative small company which knows success is accordingly going to increase its size. Small firms play an important role in research because they sometimes identify the domains of progress which are then exploited by the big firms ([Guellec, 1999](#)).

According to [Schmookler \(1966\)](#), [Levin et al. \(1985\)](#) and [Cohen et al. \(1987\)](#), innovation is determined by the level of knowledge and the complexity of the technology in the industry sector. Innovation processes differ greatly from sector to sector in terms of development, rate of technological change, linkages, and access to knowledge, organizational structures and institutional factors [Malerba \(2005\)](#). Within a sectoral system, innovative activities may be concentrated in few innovators or may be dispersed among a large group of firms ([Malerba, 2002](#)). Authors such as [Pavitt \(1984\)](#); [Breschi and Malerba \(1997\)](#); [Breschi et al. \(2000\)](#) have found in their research that the organization of innovative activities at the sectoral level could be concentrated in few large innovators or diffused among several new firms. [Acs and Audretsch \(1987, 1988, 1990\)](#) found that the relative innovative advantage of large firms tends to be promoted in industries with high capital-intensive, advertising intensive and concentrated. However, in the industries that are highly innovative and composed predominantly by large firms, the small firms have the relative innovative advantage.

1.2.4 Geography of innovation and knowledge spillovers

Over the last two decades, the spatial dimension of innovation has received much attention in the innovation literature. Innovation has a geographic dimension that explains the determinants of innovation (Audretsch and Feldman, 2004) and affects economic growth and technological change (Feldman and Kogler, 2010). As explained by Audretsch and Feldman (2004), the work of Krugman (1991) helped trigger a new literature (New Economic Geography) with the goal of understanding the spatial dimension of innovative activity and specifically the mechanisms that underlie the spatial clustering of innovative activities. Economic theory describes how factors external to the firm impact competitiveness and innovation and how geography provides a platform to organize innovation activities by providing socioeconomic interactions across spaces (Feldman and Kogler, 2010)³. As well documented by Feldman and Kogler (2010), there are several studies that demonstrate the spatial concentration of innovation and especially patents (Feldman and Florida, 1994; Audretsch and Feldman, 1996) and new product introductions (Jaffe, 1989; Acs et al., 1994).

Since the seminal work of Marshall (1890), economists and geographers have tried to demonstrate the local concentration and the clustering of economic activities and innovation. As explained by Krugman (1991), the works of Marshall (1890) and later of (Hoover, 1948) have explained there are three types of agglomeration economies. The first agglomeration economy is related to the concentration of firms near a high level of demand to reduce transportation costs (Porter, 1990). The second concerns the availability of a skilled labor market and inputs. The third reason of agglomeration is related to the presence of knowledge spillovers which allow an economic agent to benefit from knowledge-intensive activities conducted in the same area by other agents and therefore reduce its own production costs. This latter reason of agglomeration is the most popular used by economists and geographers to explain the concentration of innovation activities (Feldman and Kogler, 2010).

Previous literature (see Jaffe et al., 1993; Zucker et al., 1994) stresses the importance of localized knowledge spillovers. The type of activity concentrations that benefit most from spillovers, particularly technological, is the subject of considerable debates. Economists have identified two types of knowledge spillovers thought to be important for innovation and

³The literature on the spatial dimension of innovative activities and the determinants and mechanisms that underlie spatial clustering of innovative activities are well explained by (Feldman and Kogler, 2010).

growth: MAR⁴ spillovers (Glaeser et al., 1992) and Jacobs spillovers (Feldman and Audretsch, 1999; Carlino, 2001).

According to Marshall (1890), and later Arrow (1962) and Romer (1986) (MAR) knowledge spillovers is transmitted by the presence of a certain technological nearby corresponding to a strong specialization. This implies that the proximity of firms within a common industry affects how knowledge flows among firms facilitate innovation (Glaeser et al., 1992). The opportunity to exchange ideas from employee to employee is fertile in leading to innovation. This view is adopted by Porter (1990) who argued that knowledge spillovers stimulate innovation and are maximized in cities with specialized and geographically concentrated industries. In this view, the spillovers permitted are intra-sectoral (Porter, 2000) and intra-sectoral relationships will play on competition and promote competitiveness and firms performance.

In contrast to the MAR view, Jacobs spillovers (Jacobs, 1969) imply that proximity of firms from different industries affects how knowledge flows among firms to facilitate innovation. Jacobs believes that the most important knowledge spillovers result from a concentration of a variety of industries firms in one place. Here, the spillovers permitted are inter-sectoral (Jacobs, 1969). Inter-sectoral relationships are transversal and allow the development of complementarities and cross-fertilization (Delgado et al., 2012) to promote competitiveness and firms performance.

1.2.5 Indicators and measures of innovation

Measuring innovation is very difficult because of the complexity of innovation process and innovation activities and the perceptions of what could be considered as innovation (see Griliches, 1979). In their study, Edison et al. (2013) identified 244 determinants of innovation. Despite these difficulties, in the literature of the measurement of innovation, authors generally used resources devoted to research and development, patent statistics and new product announcements as measures of innovative inputs or outputs.

Some studies have focused on the effects of R&D expenditure on the innovation process. In other words, this corresponds to innovative efforts measured by expenditures on R&D or by personnel engaged in R&D. Authors used generally R&D expenditure (Griliches, 1979; David

⁴This form of externalities is sometimes called Marshall-Arrow-Romer (MAR), with reference to different authors behind this concept

et al., 2000; Berger and Diez, 2006; Czarnitzki et al., 2007), R&D intensity which is the ratio of R&D expenditure to total assets (Desyllas and Hughes, 2009), R&D personnel intensity or percentage of workforce time dedicated to innovation projects (Berger and Diez, 2006). It is worth noting that there are other innovation inputs such as design activities, technical development and experimentation, new market development for new product and training. The OECD has provided the definition of R&D and its components: *basic research*, *applied research* and *experimental development*. According to the OECD (2015a) in the Frascati Manual, “*research and experimental development (R&D) comprise creative and systematic work undertaken in order to increase the stock of knowledge and to devise new applications of available knowledge*”. According to the Frascati Manual, the first limitation of using R&D is that it is an input related to technological change and the second limitation is related to the fact that it does not encompass all the effort of firms and governments in this area.

Patent indicators are generally used as the proxies for innovation outcomes. A patent is a property right to a knowledge asset. The pioneers in using patent statistics are (Scherer, 1965; Schmookler, 1966; Grabowski, 1968) and were followed by different researchers such as (Comanor and Scherer, 1969; Griliches, 1984, 1998; Feldman and Audretsch, 1999; Griliches, 1990), and for a complete literature review, see Basberg (1987) and Hall and Rosenberg (2010). Patent counts have been used most frequently to approximate the innovative output of firms but there are significant problems with patent counts as a measure of innovation. The first problem when using patents is related to its economic value which is highly heterogeneous. The great majority of patents are never exploited commercially, and only a few of them bring major technological improvements (Cohen and Levin, 1989) and it may consist of several related claims which might be filed as separate patents (Hagedoorn and Cloudt, 2003). Authors such as Acs and Audretsch (1989), Basberg (1987), Pavitt (1988) and Griliches et al. (1986) have discussed the strengths and weaknesses of patents statistics as a measure of innovation. Despite the limitations of patent statistics, they represent a good innovation proxy for measuring the effect of R&D investments (Griliches, 1984; Griliches et al., 1986; Pavitt, 1988). Because of the limitations of patent counts which is quantitative, increasingly researchers are using patent citations which include a measure of quantity and quality of patents as an indicator of inventive performance of firms (see Narin et al., 1987; Pavitt, 1988; Trajtenberg, 1990; Jaffe et al., 1993; Nishimura and Okamuro, 2011a).

As documented in the Frascati Manual, these two basic families of innovation statistics are complemented by several others. There are the statistics on scientific publications (bibliometrics), the publications in trade and technical journals, the skilled human resources, the technology balance of payments, globalization indicators, and activity in high-technology sectors (OECD, 2015a). Moreover, some information on innovation and innovative activities can be drawn indirectly from many other sources, such as business surveys or education statistics. It is worth noting that as innovation may be a change in the process or in the organization of the production or an exploration of new markets for new products and it is very difficult to identify what could be qualified as innovation (Griliches, 1979). Therefore, it is not easy to have good innovation statistics for making econometric evaluations.

To measure innovation, several countries, and more especially the OECD countries, conduct innovation surveys. Innovation surveys exist in developed countries but also in many developing countries under different acronyms well documented in more details by Godin (2002) and Mytelka and Gachino (2004). In Europe, the Community Innovation Surveys (CIS) conducted every two years, are the main data source on firms' innovation. The CIS has become a major data source on innovation indicators and are commonly used for academic research on innovation. Even if they are mostly used to measure innovation in firms, regions and countries, the innovation survey statistics have several limits.

In addition to the difficulty of measuring innovation, there are limits related to the statistics from innovation surveys. Many papers (Holbrook and Hughes, 2001; Tomlinson et al., 2000; Tether et al., 2001; Bogliacino et al., 2012) have discussed the limitations of innovation surveys and have pointed out the inadequate coverage of innovation in services, the lack of focus on non-technological innovation and the lack of information on the dynamics of innovation from a systems viewpoint. Similarly, Bloch (2007) said that to have a complete understanding of how firms innovate, we need to go beyond technological innovation and examine the introduction of other (non-technological) innovations.

Salazar and Holbrook (2004) asserted that there is need of a shift from seeing and studying innovation as a result, to studying innovation as an activity. They explained further that to implement better public policy, we need to better understand what firms do to be innovative, the kinds of activity they undertake, the diffusion of knowledge and their innovative capabilities and therefore to collect adequate data for the analysis of innovation systems and for policy-making.

In discussing the limits of the data from innovation surveys, [Mairesse and Mohnen \(2010\)](#) have pointed out the qualitative, subjective and censored nature of data collected in innovation surveys. At first, there are a lot of qualitative variables less informative than quantitative because of the simple “yes/no” questions and there are many subjective variables based on the personal appreciation and judgment of the respondents and this subjectivity may affect the quality of variables and cause measurement errors. Moreover, the cross-sectional nature of data and censored variables are problematical when dealing with endogeneity and selection issues. Finally, [Smith \(2005\)](#), [OECD \(2009\)](#), [Dachs and Pyka \(2010\)](#) and [Bach et al. \(2014\)](#) pointed the lack of international comparability between indicators based on innovation surveys. All these limits of the data create specific difficulties and require much care for the construction of indicators and their analysis and interpretation ([Mairesse and Mohnen, 2010](#)).

1.3 Rationales and instruments for public innovation policies

The seminal argument for R&D subsidies rationale has been provided by [Arrow \(1962\)](#). In his work, [Nelson \(1959\)](#) argued that firms are likely to under-invest in research because the benefits and outcome from such investments are very hard to appropriate. Authors including [Martin and Scott \(2000\)](#); [Edler and Georghiou \(2007\)](#); [Edler et al. \(2013, 2016\)](#); [Georghiou et al. \(2014\)](#) have proposed reviews on the numerous rationales for public innovation policies. In general, the economic analysis theoretically justifies public support to R&D by the existence of market failures due to market imperfections. These imperfections of the market mechanisms sometimes are caused by knowledge spillovers and sometimes by other reasons ([Martin and Scott, 2000](#); [Cerulli et al., 2008](#); [Lallement, 2011](#); [Montmartin and Massard, 2015](#)). Neoclassical theory based on a positive externality argument suggests that market failures due to knowledge spillovers induce private R&D investments which may remain below the socially optimal level ([Arrow, 1962](#)). Therefore, the government is required to participate in R&D activities to address the market failures by providing several instruments supporting and encouraging firms to invest in R&D and innovate. According to [Falck et al. \(2008\)](#), by subsidizing firms, the government reduces market failures and R&D risk and stimulates

productivity-enhancing innovation process. However, public intervention can be subject to failures. In this section, we will present the rationales of innovation policies, thereafter we present the main instruments and we finish this section by discussing the main limitations of public intervention.

1.3.1 Rationales for public innovation policies

In the innovation economic literature, scholars have focused on analyzing the sources of market failures and their consequences on firms' innovation and their potential solutions. Various authors including [Sutton \(1991\)](#); [Martin and Scott \(2000\)](#); [Hall \(2002\)](#); [Daklia et al. \(2004\)](#); [Cerulli et al. \(2008\)](#); [Lallement \(2011\)](#); [Montmartin and Massard \(2015\)](#) and [Leibowicz \(2018\)](#) have discussed several sources of market failures inhibiting innovation (including mainly the knowledge externalities or spillovers, information asymmetry, imperfect competition, coordination problem).

1.3.1.1 Markets failures related to spillovers

The most commonly accepted explanation of market failures refers to the fact that knowledge has the characteristics of a public good, i.e. partial non-exclusivity and non-rivalry ([Lallement, 2011](#)). Knowledge is non-rival because an infinity of agents can benefit from and it is non-exclusive because whatever the expended amount on R&D, the knowledge diffuses among agents without any pecuniary compensation for the investor agent. R&D activities and thus innovation may incur important costs for the innovating firms. Research activities generate externalities or knowledge spillovers⁵ which make it difficult for the firms that incur R&D expenditures to appropriate the returns from these research and increase the uncertainties for success. Because of these spillovers, some firms adopt a free-rider behavior and innovate by imitating their competitors instead of investing themselves in R&D. Therefore, the decision to innovate is a risky process, because generally firms are not insured in advance that their efforts for innovation will be rewarded by commercial or technological successes. Due to the impossibility to observe and to control for the returns of research and the risk

⁵Economists have identified two types of knowledge spillovers thought to be important for innovation: MAR spillovers ([1890](#)), Jacobs spillovers ([1969](#)). Knowledge spillovers can be internal (positive impact between individuals within a production organization) or external (positive impact of knowledge is between individuals outside of a production organization).

of failing for the production of a new good or the development of a new process, firms have fewer individual incentives to undertake expenditure in research projects to innovate. When knowledge spillovers lead to incomplete appropriability of the R&D results, it causes a rise of market failures (Griliches, 1992). R&D involves three types of uncertainties related to technological success, commercial success, and competitor behavior (Malmberg et al., 1996) and if these uncertainties are high, firms tend to invest in R&D below the socially optimum level (Nishimura and Okamuro, 2011a).

However, as explained by Cerulli et al. (2008), the argument of positive spillovers to theoretically justify public intervention is criticized by authors such as Cohen and Levin (1989). Cohen and Levin (1989) argue that knowledge cannot be easily absorbed unless imitative firms, which need preexisting R&D, invest in their turn on a certain level of R&D. Therefore, when the level of spillovers is high, firms could have greater incentives to perform R&D, to enlarge their absorptive capacity and benefit more from the R&D efforts of others. Nadiri (1993) goes further and argues that R&D should not be taken as a pure public good because firms have tools to protect their inventive capacity, such as patents, secrecy, and so on.

1.3.1.2 Other specific markets failures

The second aspect of market failures is related to the imperfections (asymmetric information and moral hazard) in the capital market which tends to ration the financing of new products or processes (Hall, 2002). The high uncertainty about the returns to innovation investment (Holmstrom, 1989) and the absence of collateral linked to the intangible assets⁶ nature of innovation create strong information asymmetry problem between lenders and borrowers and then reduce high-risk investments in innovation and therefore reduce the financing for innovation.

The third aspect of market failure for R&D is related to the existence of imperfect competition⁷ in the market characterized by the existence of entry barriers (too high fixed costs) and/or exit barriers (sunk costs) (Sutton, 1991) which can lower the R&D spending level below the socially optimal level. If the monopoly firm raises the price of the good it sup-

⁶An intangible asset is defined as an identifiable, non-monetary asset without physical substance but which is not necessarily subject to market failures (i.e. patent, trademark).

⁷Excessive market power or, on the contrary, excessive fragmentation of market power

plies, the demand decreases and, therefore, the firm underestimate effects of innovation on consumers and thus the need of R&D investment ([Montmartin and Massard, 2015](#)).

The fourth aspect is related to the absence of coordination leading to the unnecessary duplication of certain R&D efforts targeting innovating projects with potentially high returns. When several firms independently invest in these R&D projects, social return eventually decreases as the number of firms increases ([Spence, 1984](#); [Daklia et al., 2004](#); [Cerulli et al., 2008](#)) because they become very costly.

Moreover, scholars have stressed other market failures related to the lack of technological infrastructure that actors need to operate (such as IT, telecom and roads); to the rent transfer problem; and to the localization of innovation activities due to firms' location choices in sub-optimal spatial structuring (see [Montmartin and Massard \(2015\)](#) for more details on location externalities)⁸ related to the New Economic Geography and Growth models.

1.3.1.3 Failures related to the innovation system

In addition the market failures, various other authors have emphasized other sources of failures related to the innovation system⁹ and especially to the systematic relationship between firms and both public and private institutions. There are various kinds of specific-failures in the economy ([Dobrinsky, 2009](#)) that can be caused by the agents because of the complex links and interactions among them. [Arnold and Thuriaux \(2003\)](#) explained several aspects of such specific-failures. They point out the failures in institutions (such as universities and research institutes, public regulatory and policy implementation offices, etc.) which are not able to perform efficiently their functions which affect negatively the agents or stakeholders. There are also the network failures which are caused by the poor linkages and the low degree of trust among the different agents interacting among them. Authors show also the capability failures of firms due to their inability to act in their own best interests because of their poor managerial or technological skills and their inability to absorb externally generated technologies. Finally, the authors point out the framework

⁸According to ([Montmartin and Massard, 2015](#)), the location choices of firms generate two main externalities leading to opposing incentives to invest in R&D for private firms: over-investment or under-investment in R&D depending respectively, on the concentration of firms in the market outcome is higher than the concentration in the optimal outcome or lower than the concentration in the optimal outcome.

⁹For further details on innovation system, see ([Nelson, 1993](#); [Geels, 2004](#); [Woolthuis et al., 2005](#)).

failures related to constraining regulations or poor business environment which have negative impacts on the economy and especially on R&D and innovation.

In this context, firms do not capture all benefits from their investments in R&D, meaning that the level of private investments in R&D is too low and sub-optimal. All these failures may be large enough to justify public policies aiming at correcting or reducing market failures and enhancing R&D investments. Therefore, public intervention should be not only funding of basic science, but more widely ensuring that the innovation system performs as a whole by taking into account all aspects of failures. The failures leading to private under-investment in innovation differ from a sector to another but also across the economy and policy designer should take into account these differences.

1.3.2 Innovation policies instruments

The risk of under-investment in technological advance and in R&D globally because of market failures, justify public intervention to promote private innovation activities ([Martin and Scott, 2000](#)). Public intervention for R&D can help to overcome issues faced by the private sector and thus foster technology breakthroughs and innovation. Although public supports can be more or less direct (direct/indirect support), [Edler and Georghiou \(2007\)](#) propose a classification of instruments for innovation policies and classify them into supply-side instruments (influencing innovation generation) and demand-side instruments (influencing those requesting, buying or applying innovation).

Public intervention can be done through supply-side instruments in the form of direct funding of firms' R&D; R&D award (Prizing); fiscal incentives for innovation activities; debt and risk sharing schemes and technology extension services ([Edler and Georghiou, 2007](#)). The supply-side instruments seek to address market failures related to lack of information; access to resources; but also system failures including the lack of connectivity and institutional rigidity ([Edler et al., 2013, 2016](#)).

Besides, public intervention can be done through demand-side instruments may include four main instruments such as legislation and regulations for markets; public procurement of innovative goods; supporting private demand by offering subsidies or tax incentives to consumers and systemic policies¹⁰ ([Edler and Georghiou, 2007](#); [OECD, 2011](#)). The demand-

¹⁰Systemic policies include more indirect support such as infrastructure; making accessible the education

side instruments may help to address market failures, institutional failures, capability failures, inefficiency in the ability or willingness of users to demand and apply innovation but also to improve the linkage and interaction between demand and supply (Edler et al., 2013, 2016).

Demand-side instruments may be linked to other demand-side instruments or be complementary with supply-side instruments and resulting in mixed policies and collaborative R&D and innovation instruments (including cluster policies, network policies and support for R&D cooperation) (Edler et al., 2013).

In this section, instead of presenting all these public instruments, we focus on the more popular instruments of public intervention for individual firms such as R&D subsidies, tax incentives, and collaborative innovation policies.

1.3.2.1 R&D direct subsidies (grants or funds)

In the presence of knowledge spillovers leading to incomplete appropriability of the R&D returns, public authorities have to intervene and support firms' R&D activities (Nelson, 1959; Arrow, 1962) to correct for these market failures. Here, the public support may be supposed to work as a form of compensation (Spence, 1984) for the firms undertaking R&D investments. Direct funding programs aim more generally at stimulating firms' private R&D through various instruments, including grants, subsidized loans, and venture capital (Guellec and Van Pottelsberghe De La Potterie, 1997, 2003; David et al., 2000; Geuna and Nesta, 2006; Avnimelech and Teubal, 2008; Cunningham et al., 2012; Becker, 2015a). R&D grants increase firm's chance of attracting venture capital (Gompers and Lerner, 2001). R&D subsidies may produce a signal effect that facilitates firms' access to external sources of finance because they reduce the information asymmetries and risk and uncertainties, leading to lower private costs of capital (Meuleman and De Maeseneire, 2012). Moreover, to certify firms to private financiers, many countries spend public funds on R&D grants to alleviate debt and equity gaps for firms' innovation projects (Meuleman and De Maeseneire, 2012).

system (creation of basic knowledge); protection intellectual property; financial reform; making available the R&D financing; standards; labeling; lowering real interest rates or providing stable macroeconomic conditions (For further details, see Wiczorek and Hekkert, 2012; Woiceshyn and Eriksson, 2014; Rullani et al., 2016). Public authorities need to establish a regulatory environment that reduces uncertainty for innovators and that reduces barriers to innovation.

David et al. (2000) show three mechanisms through which public R&D subsidies can help firms and stimulate private R&D. Firstly, public R&D support can increase the efficiency of the R&D of firms by lowering the common cost (cost sharing) and increasing the absorptive capacity. The second mechanism is that public R&D support may enable research facilities and allows firms' success in new projects by overcoming fixed R&D start-up costs. Finally, the public R&D support may represent signals for future demand for technologies, goods, and services leading to commercial success. By supporting research that further stimulates the innovation process, as well as providing services that leverage innovation, the government makes private R&D more effective. The government may tend to work toward avoiding the criticism of wasting public funds (Lach, 2002) and, therefore, selects projects with lower risks and higher expected returns that could be undertaken without public funds (pick-the-winner strategy).

1.3.2.2 R&D tax incentives

R&D tax incentives have become a major instrument used to correct the insufficient supply of R&D. In 2016 29 of the 35 OECD member states 22 of the 28 EU countries among other countries across the world provide tax credits on R&D expenditures of firms (OECD, 2017). Tax credits reduce marginal costs of R&D (Hall and Van Reenen, 2000) and encourage firms to spend more on innovative activities. Hall and Van Reenen (2000); Bloom et al. (2002); Mohnen and Lokshin (2010); Czarnitzki et al. (2011) have provided a large literature review on the effectiveness of R&D tax incentive policies.

Tax incentives may allow firms to decide which R&D projects to fund and it allows them to decide the timing and amount of investment (Klette et al., 2000). This may explain the analyze of Guellec and Van Pottelsberghe De La Potterie (2003) which state that even if R&D subsidies have a higher impact on increasing firms R&D expenditures, tax incentives affect the expenditures have a quicker effect rather than direct subsidies for R&D. Tax incentives are fiscal instruments which differ significantly in terms of their generosity, their design and the categories of firms or R&D areas they target (OECD, 2012). Tax incentives are different from a country to another and their effectiveness depends on these specificities of the individual schemes and on the operational (country, regional, etc.) contexts (Edler et al., 2013). The instrument of tax incentives is sometimes implemented in the framework of policy mix (combining R&D tax incentives with R&D direct subsidies).

1.3.2.3 Collaborative R&D and innovation policies

Public intervention instruments that connect actors in R&D and innovation aim at fostering innovation by overcoming market and systemic failures and more especially network failures (problems in the interaction among actors in the innovation system) inhibiting innovation. The collaborative R&D policy instruments aim at developing collaboration between firms, higher education and research institutions, and other public and private entities and may be implemented in several ways including networking policies, support for R&D cooperation policies and cluster policies (Edler et al., 2013). Both clusters and networks diffuse knowledge, facilitate cooperation between innovation actors and can also increase cooperative activities including training, skills and information sharing.

Networking policies are recognized as an important instrument for firm's innovativeness (Porter and Ketels, 2003). According to Fischer and Varga (2002), networking activities are more particularly based on vertical relationships (customer, manufacturer supplier and producer service provider networks) than on horizontal linkages (producer networks, industry-university linkages). In their work, Pittaway et al. (2004) have brought a large literature review of research linking the networking behavior of firms with their innovative capacity. They highlight among others several benefits of networking identified in the literature¹¹ including risk sharing, access to new markets and technologies, pooling complementary skills, access to external knowledge, diffusing innovations across and within sectors.

Support for R&D cooperation policies is a policy instrument which includes grants for collaborative R&D. Public authorities can promote collaborative R&D for internalizing knowledge spillovers and reducing uncertainties through collaboration and better coordination. Innovation is an interactive process characterized by technological interrelatedness between various subsystems (Teece, 1996) and it is possible to provide grants for collaborative R&D between knowledge exploiting entities (firms) (Mowery et al., 1996) and knowledge producing institutions (universities and research and training centers) (Etzkowitz and Leydesdorff, 2000) or between firms and their competitors (horizontal collaboration) (Hamel et al., 1989) and between suppliers and customers (vertical collaboration or supply chain collaboration) (Barratt, 2004). For further details, Edler et al. (2013) and Belderbos et al. (2015) have provided recently a deeper analysis and overview. Collaborative R&D grants can help solving

¹¹For more details, see Pittaway et al. (2004); Fischer and Varga (2002); Rothwell (1991).

issues through cost and risk sharing as well as getting access to complementary knowledge. Grants for collaborative R&D aim at reducing the costs of collaboration and create, thereby, incentives to create or maintain linkages for innovation.

According to [Falck et al. \(2008\)](#), public-private partnership is especially interested in creating connecting platforms which connect actors of similar industries and thus create new and productive ties that increase knowledge flows. Knowledge creation and innovation particularly gain from firm cooperation as the individual risk of failure decreases. When spillovers are high enough, collaborative R&D with rival firms can help internalizing knowledge spillovers and enhancing the incentive to invest in R&D. Cooperating firms internalizing these spillovers are more profitable compared to non-cooperating firms ([Kamien et al., 1992](#)). This collaboration promotes trust among the members and can improve R&D efficiency through better coordination and information sharing.

Moreover, firms attempt to increase incoming spillovers, not only directly through information sharing and cooperative arrangements, but also indirectly by investing in their own R&D. Moreover, firms should have absorptive capacity for optimally benefiting from R&D cooperation ([Veugelers and Cassiman, 2005](#)). The concept of absorptive capacity was primarily introduced by [Cohen and Levinthal \(1989\)](#) and further theoretically developed by [Kamien and Zang \(2000\)](#). This concept stresses the importance of a stock of prior knowledge to effectively absorb spillovers while cooperating. [Mowery and Rosenberg \(1991\)](#) stressed that collaborative research programs alone are not sufficient but the development of sufficient expertise within firms to use the results of externally performed research is needed.

Cluster policies are considered to be among the most significant strategies for public authorities to stimulate firms' innovation. [Porter \(1990, 2000\)](#) defined a cluster as "a geographically proximate group of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities" and asserted that cluster policies aim at removing obstacles, constraints, and inefficiencies that impede innovation. However, besides this geographical declination of clusters, there is another approach of clusters based on the target of specific sectors or industries because some economic activities do not need to clusters ([Porter and Ketels, 2003](#)) and for some industries, being close to the market served is more important than being geographically close to other companies ([Ketels and Memedovic, 2008](#)). Cluster policies have become an important tool for promoting technology and innovation in many countries because of its ability to bring together innovation

actors to facilitate collaboration on complementary economic activities and to strengthen scientific and industrial specialization patterns while encouraging the emergence of new domains of economic and technological activities (Martin and Sunley, 2003; Ketels and Memedovic, 2008).

Clusters policies include several programs and instruments to support collaboration between private and public actors for R&D and innovation Cunningham et al. (2012). To implement clusters, several tools have been adopted including the networking platforms and technology specialization. To increase the dynamism of local economies, several countries and regions have implemented cluster policies and developed networking platforms facilitating interactions between industries, research centers, and universities. Some countries and regions have made great efforts to foster cluster development by enabling industrial and technological specialization (Lundvall, 2010) to develop their economies. Cluster policies are varied and highly context-specific, but include fostering knowledge spillovers, innovation, regional development, supporting firms, increasing employment, etc. and often seek to foster dynamic regional economies (Edler et al., 2013). Cluster policies are a mix of several public intervention instruments.

1.3.3 Possible inefficiency and risks of public intervention

The previous section has shown the main arguments underlying the rationales of public intervention for supporting innovation policies. Public intervention devoted to enhance innovation may fail to achieve a socially efficient allocation of resources and may obviously be very costly. However, in addition to these costs, public intervention may miss their target and become inefficient, even detrimental.

Public subsidies for R&D can have harmful effects of various kinds and here are three of them. As described by Guellec and Van Pottelsberghe De La Potterie (2003) and Lallement (2011), the first negative effect is the classical crowding-out effect or substitution effect due to the opportunistic behavior of firms. It happens when the subsidized companies substitute public support for the R&D by the private expenditure they would have financed by themselves in the absence of public subsidies. The second negative effect corresponds to the fact that such public support to promote innovation can lead to higher prices of activities related to R&D (salaries of researchers for example) and this induces a rise of research or production

costs and therefore lead to a decrease of private investment and consumption (David et al., 2000). The third harmful effect is the distortive allocation effect¹² which happens when public subsidies are oriented to sectoral or technological opportunities less promising than those to which market forces alone would have led (Guellec and Van Pottelsberghe De La Potterie, 2003).

It is also possible that the public sector itself fails (government failure) when struggling to make the right choices because of information asymmetry. The public sector does not have often better information than innovation actors and is less informed about their needs and preferences. Moreover, there are many limits in the government attempt to provide cooperation among firms or public subsidies to promote innovation. Several researchers defend that government should not target particular technological fields, industries or regions for subsidization (Hospers et al., 2009). They argue that there are no reasons to believe that policymakers are better informed than managers of local firms in evaluating the future economic potentials of the targets. This discussion is consistent with the public choice theory which considers government failures to be as common as market failures because of massive information asymmetries and the arbitrary behavior of politicians and bureaucrats (Wolf, 1993). The government may fail because the political and administrative failings arise when self-interests override the public interest (James, 2000). These lobbying behaviors and corruption are the main issues with public procurement contracts for innovation.

In addition, network failure related to the collaboration between actors may exist. As well documented by Cassiman and Veugelers (2002), the other problem that cooperating firms may face is the fact that they can cooperate with a more direct competitor and thus lose information about their partners and the R&D spillovers are very low and then cooperation lead to lower R&D investment. However, if firms are not competitors but supply independent or complementary goods, cooperation leads to high R&D investment levels for any level of spillovers (De Bondt et al., 1992; Röller et al., 1997).

Because of all the issues enumerated above, it is necessary even mandatory for the public sector to know whether to intervene, and then, if necessary, exactly how to intervene. The public sector's success in keeping a good environment of the market is reflected in a prospering and dynamic environment that attracts firms (Falck et al., 2008). To promote innovation,

¹²This occurs also when aids are oriented to the less attractive firms for private R&D spending which would be excluded from the market.

the public sector must obtain good information and make a clear diagnosis and have to make deep cost-benefits analyses before any intervention. This is why there is a need to implement policies using a mix of several instruments to account for other potential constraints.

1.4 Econometric evaluation of innovation policies

The issues in the social and economic situation as well as the challenges of growth and sustainable development push public policymakers to support R&D and innovation. In struggling to improve the performance of innovation systems and particularly firms innovativeness, there is a strong desire for policymakers which spend a lot of public resources, to know about the effectiveness of the policies they implement. Evaluations aim at analyzing the economic impacts of a policy: impacts on the performance and behavior of firms, impacts on innovation, employment, etc. However, identifying the true effects of an R&D policy is a complex and challenging task because of the complexity of innovation systems and innovation process. The impact evaluation literature provides a comprehensive overview of assessing the effectiveness of public R&D policies. In this context of evaluation, several econometric methods have been used to evaluate public programs supporting firms' R&D and innovation.

There are two different quantitative approaches to deal with impact evaluations: *ex-ante* and *ex-post* evaluations (Blundell and Costa Dias, 2009). The *ex-ante* evaluation (before the program) consists in explaining a complete model including the economic agents' behaviors and is particularly useful to plan the results of a policy which has never been implemented previously. The *ex-post* evaluation (after the program) is empirical and consists in testing directly the effect of an implemented policy without necessarily attempting to specify complete models or even trying to understand all the mechanisms in the process.

In empirical studies, it is important to distinguish the controlled experiments from the natural experiments (Blundell and Costa Dias, 2009). The *controlled experiments* approach is the most convincing method of evaluation because in this kind of experiment, the group that benefits from the policy and the comparison group that does not benefit from it are determined randomly in the eligible population. The *natural experiments* are observational studies which are commonly a situation where the evaluator does not influence on assignment process and the data on outcomes of the population, as well as other social and economic factors are collected after the implementation of the policy. To assess the impact of a program,

this approach attempts to find a naturally occurring comparison group but it sometimes misses the mechanism underlying the program's impact on the population (Khandker et al., 2010) and is therefore subject to selection bias.

1.4.1 Evaluation challenges, counterfactual and selection bias

Evaluating the impact of the participation in a public R&D policy is generally a typical case of natural experiments where the assignment of treatments is typically not random. Non-random selection may be explained by at least two reasons. The first reason is related to the fact that firms decide to make R&D and decide to participate or not in a given public R&D policy (self-selection) (David et al., 2000; Klette et al., 2000). The firms' specific unobserved characteristics may influence their outcomes and therefore, the difference in outcomes after the intervention cannot be entirely attributed to the program itself. The second reason is related to the fact that public agencies choose the firms they subsidy and to what extent. In addition to selecting on the basis of the quality and feasibility of the proposals, the agencies may want to encourage R&D in small firms, or in some research fields where a higher gap between private and social returns is assumed to exist (Czarnitzki et al., 2007), or to select firms presenting experiences in R&D projects. Selection may depend on observable but also on unobserved characteristics. The non-random selection leads to sample selection bias or endogeneity problem and is, therefore, a key aspect that evaluators must take into account in order to get the true effect of a policy. If the selection bias is not corrected, the analysis of policies and treatments may bring up misleading results with bias and inconsistency (Busom, 2000; Czarnitzki et al., 2007).

The main challenge of the impact evaluation is to determine what would have happened to the beneficiaries if they did not participate in the program. Because of the impossibility of comparing how the same firm would have fared with and without the participation in the policy, one has to determine a comparison group that is sufficiently similar in their structure and innovation activity. The econometric challenge is to construct a convincing and reasonable comparison group for beneficiaries known also as counterfactual. The counterfactual framework was developed by Roy (1951) and Rubin (1974) and since adopted by many statisticians and econometricians including (Rosenbaum and Rubin, 1983; Heckman et al., 1997; Angrist, 1998; Imbens and Wooldridge, 2009).

For a theoretical formulation, we follow the standard evaluation framework of [Rubin \(1974\)](#) in which the firms, the treatment, and the potential outcomes are the main pillars. We have a binary treatment indicator D_i which take the value one if the firm i participates in the policy and zero otherwise. The potential outcomes are then defined as Y_i^T for participating and Y_i^C for non-participating firm i , where $i = 1, \dots, N$ and N denotes the total number of firms. The treatment effect Δ_i for a firm i can be easily measured by a simple subtraction of mean outcomes and can be written as follows:

$$\begin{aligned}\Delta_i &= Y_i^T - Y_i^C \\ &= E(Y_i^T | D = 1) - E(Y_i^C | D = 0)\end{aligned}\tag{1.1}$$

As Y_i^C is not observable at the same time with Y_i^T for each firm i , estimating the individual treatment effect Δ_i is not possible. The statistical solution is to estimate Average effects for the entire firms or for some interesting sub-groups. We have two main parameters to evaluate: ATET (Average treatment effects on the treated) and ATE (Average treatment effect on all the population). In the evaluation literature, the parameter that received the most attention is the Average treatment effect on the treated (ATET) because of the difficulty for policy evaluators to ensure external validity in addition to the internal validity of samples.

The ATET can be defined as:

$$\begin{aligned}\Delta_i^{ATET} &= (Y_i^T - Y_i^C | D = 1) \\ &= E[(Y_i^T | D = 1) - (Y_i^C | D = 1)] \\ &= E[(Y_i^T | D = 1) - (Y_i^C | D = 1)] + E[(Y_i^C | D = 1) - (Y_i^C | D = 0)] \\ &= ATET + SB\end{aligned}\tag{1.2}$$

where $SB = [(Y_i^C | D = 1) - (Y_i^C | D = 0)]$ is the selection bias due to the fact that the outcomes of firms from treatment and comparison group would differ even in the absence of treatment. The true parameter Δ_i^{ATET} is only identified if $[(Y_i^C | D = 1) - (Y_i^C | D = 0)] = 0$. If the characteristics of the firms benefiting from the policy are the same, or if the treated are randomly selected from the population, the selection bias equals zero ($SB = 0$) and Δ_i^{ATET} is a good estimation of the policy effect. The basic objective of the impact assessment is to find a way to get rid of the selection bias and determine the real impact of the intervention.

1.4.2 Econometric models

The econometric evaluations literature offers different estimation strategies to identify treatment effects when the available observations on firms are subject to a selection bias (Cochrane and Rubin, 1973; Heckman et al., 1999; Imbens and Wooldridge, 2009; Blundell and Costa Dias, 2009). These strategies include methods like Heckman’s selection models, instrumental variables (IV), control function (CF), regression discontinuity (RD), difference-in-difference (DID), matching models and conditional difference-in-difference (CDiD) among others. Each of these methods provides an alternative approach to deal with selection bias and is more or less efficient depending on the nature of data and characteristics of the R&D intervention process. Recently, Athey and Imbens (2017) have analyzed the new developments of econometric literature estimating causal effects of public programs. Cerulli (2010) has provided a critical review of the econometric models measuring the effect of public support to private R&D. He analyzed deeply the different econometric specifications (structural vs. reduced form), the type of data used (cross-sectional vs. longitudinal) and the type of policy variable (discrete vs. continuous).

Instrumental variables (IV) method is among the most used econometric approach addressing the endogeneity issues and particularly when controlled experiment is not feasible (Heckman et al., 1999). The method which has attracted considerable attention in the statistics literature relies on finding a variable (instrument) that is highly correlated with the program participation (good instrument) but that is not correlated with unobserved characteristics affecting outcomes (valid instrument). It overcomes both endogeneity caused by selection on observable and unobservable factors and endogeneity in individual participation and program placement (Khandker et al., 2010) within a system of equations. The IV estimator has been so well studied and there exist a large literature focusing on the binary as well as heterogeneous treatment effects but also as explained by Athey and Imbens (2017) on a key development of the notion of the local average treatment effect (Imbens, 2014 for a review) and on the weak instruments (Andrews et al., 2006 for a survey). The major concerns of IV estimator are related to the weakness of the instruments and the correlation with unobserved characteristics. The instrumental variable has been used many times to estimate the effect of public R&D subsidies for firms (Wallsten, 2000; Busom, 2000; Clausen, 2009).

Control function (CF) approaches (selection models) are statistical methods to correct for endogeneity problems by modeling the endogeneity in the error term (Heckman, 1977). When selection is on unmeasured confounding, the CF approach takes these unobservables into account when estimating the treatment effect. As the IV estimation, the CF approach tackles the endogeneity caused by selection on observable and unobservable factors as an omitted variable problem (Khandker et al., 2010). It represents a two-step procedure and considers a system composed of two equations in which it models the decision process before estimating the effect of the treatment on the outcome variable. The main critic on this kind of models is that it imposes a strong restrictive assumption on the distribution of the error terms. Control function approaches have been used by Busom (2000); Takalo et al. (2013); Hussinger (2008) in the framework of innovation policy evaluation.

Regression discontinuity (RD) approach has become increasingly common in the social sciences in the last years. It allows estimating the treatment effect by exploiting the situation where the probability participate in the policy changes discontinuously with some continuous variables (Blundell and Costa Dias, 2009). This approach relies on a discrete eligibility where firms which are on one side of the threshold benefit from the intervention and those on the other side do not benefit from. Recently, Imbens and Lemieux (2008), Lee and Lemieux (2010) and Skovron and Titiunik (2015) have provided a review of the literature and deep analyses on how to employ regression discontinuity design in empirical research. Regression discontinuity approach has been used to evaluate the impact of R&D subsidies on firm innovation by several authors including Benavente et al. (2012), Bronzini and Iachini (2014) and Bronzini and Piselli (2016).

The *Difference-in-difference (DID)* method estimates the treatment effect on a comparison of beneficiaries and non-beneficiaries before and after the intervention by assuming that the counterfactual outcome of a beneficiary firm can be approximated by its outcome in an earlier period preceding the intervention (Khandker et al., 2010). It controls for both common macroeconomic trends as well as firm-specific time-unvarying effects. The data are available for the two groups before and after the intervention, the DID method is very easy to implement but its main drawback is related to the assumption of time-invariant selection bias while firms are characterized by their unobserved time-varying heterogeneity. If the beneficiaries firms react differently to macroeconomic shocks, the estimates are biased (Aerts and Schmidt, 2008). When there is multiple time periods, one may use the *panel fixed-effects*

model which can help to control not only the unobserved time-invariant heterogeneity but also for heterogeneity in observed characteristics over a multiple period-setting (Khandker et al., 2010). DID method has been used many times to evaluate the impact of R&D subsidies on firm innovation (see Lach, 2002; Martin et al., 2011; Barbieri et al., 2012).

Matching method has become a popular approach to estimate causal effects of an intervention and is widely applied in very diverse fields of empirical study. Matching models attempt to reduce the bias due to confounding variables (Dehejia and Wahba, 1999) by mimicking randomization. Some estimators use matching methods by comparing beneficiary with non-beneficiary(ies) with similar observed characteristics, others rely on reweighting observations to get a similar group or calculate propensity score corresponding to the conditional probability of benefiting from the policy. This conceptual framework for evaluation has been used many times in non-experimental statistical evaluation (for recent reviews, see Abadie and Imbens, 2006; Heckman and Vytlacil, 2007; Garrido et al., 2014; Imbens, 2015). The main concerns of matching are that it deals with only observable characteristics and if there relevant unobserved characteristics the estimates are likely to be biased. The matching method has been used to analyze the effects of public R&D policy schemes on the innovation activities of firms (Almus and Czarnitzki, 2003; Hua and Xianping, 2006; Czarnitzki et al., 2007).

Conditional difference-in-difference (CDiD) method combines the advantages of matching method and difference-in-difference to evaluate the treatment effect. Heckman et al. (1997); Blundell et al. (1999); Dehejia and Wahba (2002); Abadie and Imbens (2006) have provided a further of this estimator and showed that it is a powerful tool which controls for selection on both observed and unobserved firms characteristics. The matching technique controls for potentially different reactions to macroeconomic changes in the treated and the non-treated group and the difference-in-difference controls for unobserved heterogeneity between treated and non-treated firms (Aerts and Schmidt, 2008). The main limitation of the CDiD method is related to the fact that it is impossible to remove eventual relevant time-varying unobserved characteristics. This method is becoming more and more popular and has been used many times to evaluate the impact of public R&D policies by authors including Dehejia and Wahba (2002); Bellégo and Dortet-Bernadet (2014); Dujardin et al. (2015) and Ben Hassine and Mathieu (2017).

1.5 Empirical evidence of public innovation policies

In this empirical literature review, we focus on three public intervention instruments. We focus at first, on the effectiveness of public R&D support from the viewpoint of the private R&D stimulation and innovation. And after that, we present some empirical evidence on the effectiveness of tax incentives instrument. And finally, we highlight the impact of cluster policies on firms innovation. We do not focus on the studies evaluating the impact of these instrument on collaborations, networking, spillovers and firms' behavior.

1.5.1 Impacts of R&D subsidies on private R&D and innovation

R&D subsidies for firms may stimulate private investment in R&D or innovation, but may also lead to a reduction of this private investment when public funds substitute for private R&D investments. In the empirical literature concerned the evaluation of R&D policies, empirical studies have examined the effectiveness of R&D subsidies by focusing on the input additionality (R&D expenditure and employment in R&D activities) and output additionality (R&D outputs like patents and new products) but also the impact on macroeconomic outcomes such as productivity, employment and growth. This section does not cover the studies focusing on behavioral additionality effect which is a little neglected in the literature but have recently received more attention.

There are numerous studies including several meta-analysis works. [David et al. \(2000\)](#) have provided a critical review of studies on the additionality inputs of public subsidies. This review of evaluation studies have been updated by recent meta-analysis studies including [García-Quevedo \(2004\)](#), [Correa et al. \(2013\)](#) and [Dimos and Pugh \(2016\)](#) and systemic reviews including [Edler et al. \(2013\)](#), [Zúñiga-Vicente et al. \(2014\)](#), [Becker \(2015a\)](#) and [Petrin \(2018\)](#).

In the literature, most of the studies focus on the input additionality by testing the crowding-in (complementarity) and crowding-out (substitution) hypothesis of public funding. The findings of earlier studies are very mixed because of the presence of additionality effects as well as crowding-out effects of public R&D on private R&D. However, the major criticism on these earlier studies in the literature is that it disregards the endogeneity of R&D subsidies and possible problem of sample selection bias ([David et al., 2000](#); [Cerulli, 2010](#)). The analysis of policies and treatments may bring up misleading results if the selection bias is not corrected ([Czarnitzki et al., 2007](#)). There are studies which exploit the new develop-

ment of econometric methods (see the previous section) overcoming database limitations in different ways to account for endogeneity and selection bias when evaluating the effects of R&D policies.

Some individual micro-level studies¹³ conclude that there is a crowding-out effect. These studies argued that public subsidies are not efficient in stimulating private R&D because firms tend to substitute the R&D subsidies with the R&D spending they would have funded by themselves. However, several recent micro-level studies¹⁴ reject the crowding-out hypothesis and find additionality in the sense that public subsidies increase private R&D spending. Recently, a study assessing the efficiency of public R&D in terms of stimulus of private R&D was done by [Cincera et al. \(2009\)](#) in the EU Member States and the other OECD countries. In this study, authors find a positive effect of public subsidies for R&D on the private R&D. However, the efficiency differs quite significantly from a country to another. It's rather high in the first group of countries, medium in the second group and rather weak in the third group. The authors conclude that these differences can be explained by the presence sometimes, of complementary effects and, sometimes, on the contrary of crowding-out effects between public subsidies for R&D and the private R&D expenditures, given the characteristics of the considered countries.

[David et al. \(2000\)](#) survey the body of available econometric evidence accumulated over the 1965-2000 period and analyze 33 studies. Their findings suggest the presence of complementarity in 16 studies and crowding-out effects of public R&D funding in 11 studies. They emphasize that in contrast to the studies based on data from other countries which generally find a complementary effect, most of the studies based on data from the United States conclude for a crowding-out effect. [David et al. \(2000\)](#) find that there are more substitution

¹³Including [Busom \(2000\)](#), [Gelabert et al. \(2009\)](#), [De Jorge and Suárez \(2011\)](#) in Spain; [Wallsten \(2000\)](#) in United States, [Suetens \(2002\)](#) in Belgium, [Hua and Xianping \(2006\)](#) in China; [Lach \(2002\)](#) in Israel; and [Catozzella and Vivarelli \(2011\)](#) in Italy

¹⁴Including [Carboni \(2011\)](#), [Cerulli and Potì \(2012\)](#), [Bronzini and Iachini \(2014\)](#) in Italy; [Duguet \(2004\)](#), [Mairesse et al. \(2004\)](#), [Marino et al. \(2016\)](#) in France; [Aerts and Schmidt \(2008\)](#), [Czarnitzki and Delanote \(2017\)](#) in Belgium; [Czarnitzki and Fier \(2002\)](#), [Czarnitzki and Hussinger \(2004\)](#), [Czarnitzki and Licht \(2006\)](#), [Hussinger \(2008\)](#) in Germany; [Huergo and Moreno \(2017\)](#) in Spain; [Einiö \(2009\)](#) in Finland; [Klette and Møen \(2012\)](#), [Henningesen et al. \(2012\)](#) in Norway; [Bloch and Graversen \(2012\)](#) in Denmark; [Özçelik and Taymaz \(2008\)](#) in Turkey; [Becker and Pain \(2008\)](#) in UK; [Guellec and Van Pottelsberghe De La Potterie \(2003\)](#) in 17 OECD countries; [Falk \(2006\)](#) in 21 OECD countries; and [Aristei et al. \(2017\)](#) for the largest EU Member States.

effects in micro-level studies than macro-level studies.

Moreover, there are three studies using meta-evaluation. [García-Quevedo \(2004\)](#) analyzes 74 studies of the pre-2002 period and find complementarity in 38 studies, no effect in 19 studies and crowding-out in 17 studies. And similarly to [David et al. \(2000\)](#), [García-Quevedo \(2004\)](#) finds that there are more substitution effects in the micro-level studies compared to the macro-level studies. [Correa et al. \(2013\)](#) apply meta-analysis techniques to a sample of 37 studies assessing the impact of direct subsidies on business R&D and published during the 2004-2011 period. Their results show that the effect of public investment on R&D is predominantly positive and significant. They conclude that public funds do not crowd-out but stimulate firms' R&D spending. More recently, [Dimos and Pugh \(2016\)](#) carry out a meta-analysis of 52 micro-level evaluation studies published after the year 2000. Their findings reject the crowding-out effect of private investment by public subsidy but reveal no evidence of substantial additionality.

Furthermore, there are systematic review papers that analyze the empirical studies. [Edler et al. \(2013\)](#) summarize 24 studies examining the relationship between public R&D subsidies and private R&D and report complementarity for twelve of them, mixed effect for seven, crowding-out for only two and no effect for three of them. [Zúñiga-Vicente et al. \(2014\)](#) analyze the empirical literature of 77 studies on the relationship between public R&D subsidies and private R&D investment over the past five decades. They emphasize a set of issues that are critical to understanding the potential effect of public R&D subsidies on private R&D spending and especially the dynamic aspects, the composition of firm R&D, the constraints faced by the firm and the amount and source of public subsidies. They assert that all these issues have not been investigated in depth and conclude that the empirical evidence on the effectiveness of public subsidies is mixed and inconclusive. [Becker \(2015a\)](#) analyses the empirical literature and concludes that results before 2000 are mixed and inconclusive but recent studies reject the crowding-out hypothesis and tend to find additionality effect.

Even if most of the studies evaluating the effectiveness of R&D subsidies focus on the input additionality, there are some studies that evaluate the effectiveness R&D policy in terms of R&D output additionality and especially innovation. [Almus and Czarnitzki \(2003\)](#) and [Czarnitzki and Hussinger \(2004\)](#) analyze the effects of public R&D funding on R&D expenditure and innovation activities of German firms and find positive impacts on the patenting

behavior of firms. Several studies¹⁵ report a positive output additionality¹⁶. However, some other studies including [Zemplinerová et al. \(2012\)](#) in Czech Republic and [Hong et al. \(2016\)](#) in China, among others¹⁷ report a negative effect on innovation output. [Petrin \(2018\)](#) analyses 15 micro-studies evaluating the impact of direct government support on a firm level including the most recent publications (2007-2017 period). She finds that out of the 15 studies evaluating additionality, eight find positive effects of government support of R&D on innovative activities of firms, three find a negative effect on innovation output, and four find mixed effects. In the literature, several studies find mixed effects, positive and negative, of government R&D funding on innovation output (see [Herrera and Sánchez-González \(2013\)](#) in Spain; [Radicic and Pugh \(2016\)](#) in 28 EU countries; and more recently [Szczygielski et al. \(2017\)](#) in Turkey and Poland).

[Petrin \(2018\)](#) bring a more complete report of the empirical literature. She reviews 98 articles and studies evaluating effectiveness and impact of government support for R&D on firms' R&D expenditure, innovation output, firms' behavioral changes and general welfare, covering the EU and OECD countries, and a few for China and Taiwan and covering the 1960-2017 period. She concludes for a complementarity of public and private R&D expenditures and a positive but modest impact on innovation at the firm level. She finds that the magnitude of the effect varies with firm size, generosity of support, size of the project supported, sectors, etc. and that there is heterogeneity in empirical studies with respect to the periods analyzed as well as the level of aggregation and data used. She suggests complementing the pure econometric estimations of the impact and effectiveness of government support through long-term ex-post evaluation studies and qualitative in-depth case studies.

In the literature, even if limited, there are studies¹⁸ focusing on the effectiveness of government innovation policy on output additionality more related to firms economic performance (i.e. aggregate productivity growth, employment, turnover, value added, etc.). In Germany,

¹⁵Including [Herrera and Bravo Ibarra \(2010\)](#) in Spain; [Almus and Czarnitzki \(2003\)](#), [Czarnitzki and Hussinger \(2004\)](#), [Czarnitzki and Licht \(2006\)](#), [Schneider and Veugelers \(2010\)](#), [Alecke et al. \(2012\)](#), [Czarnitzki and Lopes-Bento \(2014\)](#) in Germany; [Hottenrott and Lopes-Bento \(2014\)](#) in Belgium; [Duguet \(2004\)](#) in France; [Cerulli and Potì \(2012\)](#), [Bronzini and Piselli \(2016\)](#) in Italy; and [Arvanitis et al. \(2010\)](#) in Switzerland

¹⁶For an overview of relevant empirical studies, see [Albors-Garrigos and Barrera \(2011\)](#), [Czarnitzki and Lopes-Bento \(2013\)](#) and [Edler et al. \(2013\)](#).

¹⁷See [Edler et al. \(2013\)](#) and [Petrin \(2018\)](#) for a large overview of empirical studies.

¹⁸See [Brautzsch et al. \(2015\)](#); [Petrin \(2018\)](#) for a recent overview.

[Brautzsch et al. \(2015\)](#) analyze the macroeconomic effects of R&D subsidies on employment and production in the business cycle. Their findings suggest that R&D subsidies have stimulated a substantial leverage effect on output such as employment, added value, and production that amounts to at least twice the initial funding. [Becker \(2015b\)](#) analyzes data from the European CIS concerning the effectiveness of public support in 15 EU countries. Its results suggest a positive effect of public innovation support on labor productivity and a negative impact on turnover changes and a negative yet not significant influence on employment. The influences of R&D investment on innovative activities increase firms performance measured by the latter three indicators. [Karhunen and Huovari \(2015\)](#) examine the effect of R&D subsidies on labor productivity using firm-level data on Finnish SMEs from 2000 to 2012. They find no significant positive effects on labor productivity over the five-year period after a subsidy is granted. However, the results vary over time and indicate a positive effect on employment. In France, [Dortet-Bernadet and Sicsic \(2017\)](#) analyze the effect of the increase in R&D aids on the employment of small firms using data from 2004 to 2010 and using a method combining a matching technique and a labor demand model. They find that the effect of the public support on R&D employment is positive and increased during the studied period. Further, they conclude that only between 18 and 34% of the supplementary aid obtained by firms between 2008 and 2010 was used to finance new jobs for highly qualified workers.

In summary, the evidence presented on input and output additionality at the firm level suggests that R&D subsidies may mostly stimulate private R&D investment and may positively impact innovation outcomes measured by patents, sales of new products or introduction of new processes. These subsidies may also increase the productivity and therefore the competitiveness of beneficiary firms.

1.5.2 Impacts of R&D tax incentives on firms innovation

The R&D tax incentive policy aims at inciting firms to spend more on R&D. As explained by [Mohnen and Lokshin \(2010\)](#), the most common way to verify whether a tax incentive policy is effective is to test for additionality as opposed to crowding-out of R&D. A review of the econometric studies evaluating the effects of R&D tax credits on firms' performance has been provided by [Hall and Van Reenen \(2000\)](#) and more recently updated by [Parsons and Phillips](#)

(2007), Mohnen and Lokshin (2010) and Becker (2015a).

It is worth noting that in the literature of evaluation of the effect of tax incentives on private R&D investment, some authors use counterfactual approach and compare experimental and treatment firms before and after the introduction of a policy change, or comparing firms that are close to a discontinuity in the treatment design (Koga, 2003; Parisi and Sembenelli, 2003; Haegeland and Møen, 2007; Corchuelo and Martínez Ros, 2009; Czarnitzki et al., 2011; Duguet, 2012; Cappelen et al., 2012; Lokshin and Mohnen, 2013; Lhuillery et al., 2013; Bozio et al., 2014; Marino et al., 2016). There are also some authors which use the structural modeling approach that permits simulations of the effects of future tax incentives distinguishing between short-run and long-run effects of the user cost on R&D investment (Bloom et al., 2002; Mairesse et al., 2004; Baghana and Mohnen, 2009; Harris et al., 2009; Lokshin and Mohnen, 2012; Mulkey and Mairesse, 2013; Azcona et al., 2014).

Bloom et al. (2002) use a panel data study over the period 1979-1997 of nine OECD countries¹⁹ to examine the impact of fiscal incentives on the level of R&D. They find that tax incentives are effective in increasing R&D intensity. They find also that the effect is not large in the short run but is more substantial over the long-run. Applying a similar estimation in Northern Ireland for a panel of manufacturing plants covering the 1998-2003 period, Harris et al. (2009) find that fiscal incentives have positive on private R&D in the long-run. Parisi and Sembenelli (2003) apply a censored panel-data regression model with random effects to Italian firms over the 1992-97 period and find positive effects of tax credits on R&D spending. Koga (2003) examines the effectiveness of R&D tax credits using data on Japanese manufacturing firms over 1989-1998 period and find that R&D tax credit is effective in increasing R&D investment, especially in large firms.

Baghana and Mohnen (2009) evaluate the effectiveness of R&D tax incentives in the Canadian province Quebec, using manufacturing firm over the 1997-2003 period. They find a positive effect on R&D and this effect is larger in the long run and slightly higher for small firms than for large firms. Czarnitzki et al. (2011) have evaluated the effect of R&D tax credits on innovation activities of Canadian manufacturing firms using data over the 1997-1999 period and a non-parametric matching approach. They concluded that tax credits increase the R&D engagement at the firm level and that the R&D activities induced by fiscal incentives lead to additional innovation output.

¹⁹Australia, Canada, France, Germany, Italy, Japan, Spain, the United Kingdom and the United States.

In France, [Mairesse et al. \(2004\)](#) evaluate the effect of the French R&D tax credits policy on private R&D spending over the 1980-1997 period and find that the incremental R&D tax credits stimulate private R&D spending. They conclude that a permanent increase in the rate of the tax credit by 10% would lead to a development of R&D investment and capital of 3% to 5.5% at the medium term. More recently [Duguet \(2012\)](#) evaluates the effects of this same policy on the growth rates of the private funding of R&D by using a panel data over the period 1993-2003 and estimating a matching method. He finds that, overall, the tax credits stimulate private funding of R&D and one euro of tax credit would give slightly more than one euro of total R&D. He also finds that the incremental R&D tax credit increases the growth of the number of researchers. These results are confirmed by the recent studies²⁰ of [Lhuillery et al. \(2013\)](#), [Mulkay and Mairesse \(2013\)](#) and [Bozio et al. \(2014\)](#) which suggest also positive effect (additionality) of the tax credits.

In Spain, [Corchuelo and Martínez Ros \(2009\)](#) explores the effect of fiscal incentives for R&D on innovation by using both matching estimators and Heckman's two-step selection model with instrumental variables. They find that large firms, especially those that implement innovations are more likely to use the tax incentives and that the effect of the policy is positive, but significant only in large firms. They conclude that tax incentives increase innovative activities by large and high-tech sector firms. More recently, [Azcona et al. \(2014\)](#) evaluate the effectiveness of R&D tax incentives on knowledge capital accumulation in Spanish manufacturing firms and find that while large firms are more likely to use the program compared to small ones, the impact of the tax credits is smaller for large firms than for small and medium-sized enterprises.

In Norway, [Haegeland and Møen \(2007\)](#) use a difference-in-difference regression approach, comparing growth in R&D investments for firms above and below the 4 million tax credit cap. Their results suggest that the Norwegian R&D tax credit implemented in 2002 has a positive and significant impact on firm R&D investments. In evaluating the effect of the same policy on Norwegian firms, [Cappelen et al. \(2012\)](#) find that projects receiving tax credits result in the development of new production processes and to some extent the development of new products for the firm. However, the R&D tax credits do not contribute to innovations in the form of new products for the market or patenting.

[Lokshin and Mohnen \(2012\)](#) have recently analyzed the Netherlands' R&D incentive pro-

²⁰See [Guillou et al. \(2015\)](#) and [Salies \(2017\)](#) for a recent more complete review of the studies in France.

gram using a cost-benefit method over the period 1996-2004 and have found an additional effect suggesting that R&D incentives in the Netherlands are effective in stimulating firms' investment in R&D. They warned that the hypothesis of crowding-out effect can be rejected only for small firms. Moreover, the study of [Lokshin and Mohnen \(2013\)](#) for the period 1997-2004 using instrumental variables method shows a positive effect of the Dutch R&D tax incentive scheme on the wages of R&D workers. [Cappelen et al. \(2012\)](#) evaluate the effects of the Dutch R&D tax incentive scheme on patenting and innovations using panel data covering the three-year periods 1999-2001 and 2002-2004. Their findings suggest that the policy contributes to an increase in the rate of innovation by firms and contributes to the development of new production processes and to some extent to new products for the firms.

[Hall and Van Reenen \(2000\)](#) provide a survey of the econometric evidence on the effectiveness of fiscal incentives for R&D. They analyze and criticize the methodologies used to evaluate the effect of the tax system on R&D behavior and conclude that a dollar in tax credit for R&D stimulates a dollar of additional R&D. They add in their analysis that the effect of the tax credit on R&D spending is weak in the initial years but is more efficient in the long run. Overall, even if R&D tax incentives are subject to intense debate among economists, the studies which have focused on the evaluation of its effectiveness tend to conclude to a positive effect of research tax credits on R&D investment. The magnitude of the effects found in the literature varies depending on the data, estimation method and model specification.

1.5.3 Impacts of cluster policies on firms innovation

Even if cluster policies have been considered to be a good instrument for supporting firms and promoting innovation, there exist few empirical studies evaluating their effectiveness. Some studies have evaluated the effectiveness of cluster policies on innovation outcomes measured as the number of filed patents ([Branstetter and Sakakibara, 2002](#); [Falck et al., 2010](#); [Nishimura and Okamuro, 2011a,b](#); [Martin et al., 2011](#); [Engel et al., 2013](#); [Brossard et al., 2014](#); [Bellégo and Dortet-Bernadet, 2014](#); [Ben Hassine and Mathieu, 2017](#)) or R&D productivity ([Nishimura and Okamuro, 2011a](#)) or R&D investment ([Falck et al., 2010](#); [Bellégo and Dortet-Bernadet, 2014](#); [Ben Hassine and Mathieu, 2017](#)).

[Branstetter and Sakakibara \(2002\)](#) analyze the impact of the Japanese government-sponsored research consortia policy on the research productivity of participating firms using

data covering the 1980-1994 period and a difference-in-difference approach. Their results suggest positive effects on the patenting activity of firms involved in the policy. They go further and conclude that the policy is likely to have a stronger positive impact when it conducts relatively basic, rather than relatively applied, R&D.

[Falck et al. \(2010\)](#) evaluate the impact of a cluster-oriented policy (Bavarian High-Tech Offensive) implemented in 1999 in Germany using micro data and the difference-in-difference method. They find that the cluster-oriented policy increases the likelihood of innovation by a firm by 4.6-5.7 percentage points, depending on the innovation measure considered. They conclude that even if there is an increase of opportunity for obtaining access to external know-how, cooperating with public scientific institutes, and accessing suitable R&D personnel, there is a decrease of R&D spending in the target industries by 19.4% on average. [Engel et al. \(2013\)](#) analyze two German cluster initiatives in biotechnology using difference-in-difference and find a positive impact on regional R&D activities in the short-term.

[Nishimura and Okamuro \(2011a\)](#) evaluate the effects of the Japanese Industrial Cluster Project (ICP) policy implemented in 2001 using instrumental variables (IV) method. They focus on the effect of participation in the cluster project on patent applications and the role of collaboration with universities. They find that participation in the cluster project generally leads to higher R&D productivity only when firms collaborate with national universities within the same cluster area. [Nishimura and Okamuro \(2011b\)](#) examine the effects of the same policy using micro data covering the 2006-2008 period and combining the matching and difference-in-difference estimator. They focus on direct R&D support and indirect networking/coordination support and find that the effect of indirect support is significantly higher than that of direct R&D support on innovation outcomes. They conclude that participation in the ICP policy should be accompanied by the utilization of various support programs and firms should, therefore, select the program that is most aligned with their aims.

[Martin et al. \(2011\)](#) analyze the impact of a specific cluster policy that was implemented in 1999, by the French administration in charge of spatial planning and regional policy (DIACT, ex DATAR). By using micro data covering the 1996-2004 period, they use difference-in-difference method, and then the triple difference method and finally they combine these two preceding methods with a matching approach to improve the estimation. They find that the LPS policy had no effect on the innovation of firms involved in the LPS policy. They explain that cluster policies improve the performance of firms engaged in the clusters

and also accelerate the diffusion of externalities (input and labor market externalities and technological externalities).

In France, [Brossard et al. \(2014\)](#) use macro data and difference-in-differences method to estimate the impact of the competitiveness clusters policy. They show that the policy has a significant positive impact on regional patenting. They find that one supplementary competitiveness cluster label in a region increases its patenting average from 0.11 to 0.14% per capita. However, they find also that these effects are stronger in the world-class clusters and are weaker and non-significant for national clusters. They conclude that after three years, the cluster policy accumulates a rise of 0.76% in per capita patenting for regions that obtained one world-class cluster.

[Bellégo and Dortet-Bernadet \(2014\)](#) use micro data and difference-in-differences method and then combine it with matching techniques to evaluate the impacts of the French competitiveness clusters policy on firm's R&D spending and innovation. Their results suggest that the small and medium-sized enterprises and midsized firms engaged in the policy have realized on average an additional R&D expenditure compared to similar companies stayed outside the policy. Authors affirm that firms have significantly increased on average their total R&D at the same time, they would not have decreased their private R&D expenditure, indicating then the absence of crowding-out effect. For the effect on innovation, they find that the policy has no effect on firm's innovation in particular on filed patents. Moreover, their results suggest that the policy does not have significant effects on the sales of innovative products and on improvements of the innovation process.

By evaluating the effectiveness of this same French policy on firm's performance, [Ben Hasine and Mathieu \(2017\)](#) and use micro data and conditional difference-in-differences method, find that the effects on private R&D are similar than those found by [Bellégo and Dortet-Bernadet \(2014\)](#). The results highlight a leverage effect on private R&D from 2009. According to their results, being a member of a cluster increases the R&D activities of small and medium-sized enterprises from 2010. Moreover, authors highlight a substantial increase in R&D spending but especially the presence of a leverage for the foreign large companies investing in R&D. This effect is more mixed for the mid-tier companies. For the effect on innovation, they find that the competitiveness clusters policy has no effect on firm's innovation and particularly on filed patents.

Overall, the findings of studies evaluating the effect clusters policy on innovation are mixed and are not entirely conclusive. These results need to be used with much caution because of the difficulty related to the evaluation of clusters and subsidies. Further quantitative and qualitative analyses should be done to better understand the effectiveness of public clusters policy.

1.6 Concluding remarks

This chapter has surveyed the theoretical and empirical literature on the effects of public R&D policies on private R&D investment. It has addressed more comprehensively the theoretical and empirical issues related to public innovation policy and their evaluation. Following the complex definition of innovation, an overview was given on the different aspects of the relationship between innovation, economic growth and firms' development and its spatial concentration and the difficulties related to its measurement.

According to the economic theory, because of the market failures, the uncertain nature of R&D, the high costs of R&D activities, the lack of absorptive capacities and the systemic failures, firms may face several problems inhibiting innovation. These problems require public intervention which aims at correcting this issues and creating an enabling environment for private R&D and innovation. The rationales of public intervention to support private R&D investment has been discussed deeply in the chapter and several instruments of intervention used to support private R&D are presented. In the literature, there are many public instruments but in this chapter, we focus on three of them including the R&D subsidies, R&D tax incentives, promotion of networking through cluster policies. All these aspects have been discussed in the chapter.

After reviewing the main econometric models used in the literature to evaluate the effects of public R&D policy for private R&D investment, this chapter provides a significant body of literature on the evidence of these instruments at the firm level. It focuses at first, on the effectiveness of direct R&D subsidies in terms of input and output additionality. Although some crowding-out effects have been found in former studies and particularly in the USA, and even if there is an ongoing debate among economists, recent empirical evidence on input and output additionality at the firm level suggests that R&D subsidies generally stimulate private R&D investment and may positively impact innovation outcomes but also increase

the productivity and therefore the competitiveness of beneficiary firms. When focusing on research tax credits on R&D investment, the studies which have focused on the evaluation of its effectiveness tend to conclude for a positive effect. Finally, the findings of studies evaluating the effect clusters policy on input and output additionality are mixed and non-conclusive.

It is worth noting that there is a great heterogeneity of the results from the empirical studies that tried to evaluate the effects of public support for R&D and there is no consensus in the literature. The effects found in the literature and their magnitude vary depending on the geographical scope, the data used and their level of aggregation, the measurement and definition of variables, the estimation method and model specification (see [David et al. \(2000\)](#); [Cerulli and Potì \(2012\)](#) for more details).

As explained by [Cerulli and Potì \(2012\)](#), even if the majority of models focus on testing private R&D additionality, much attention should be devoted to the effects of R&D effort on firms' performance (productivity, profitability, and degree of innovativeness) to improve living standards, economic growth, and so on. In the following chapters, we use the new development of empirical models and particularly natural experiments studies approach for which we need to control for selection bias to evaluate the impacts of innovation policies. Our contribution to this on-going R&D and innovation policy evaluation consists of empirical analyses conducted in three studies.

In the second chapter, we use macro-data and evaluate the effect of the European Union (EU) Framework Programmes for Research and Development (FPs) policy on the regional innovation of the EU 27 countries. To evaluate the subsidies effectiveness at the regional level, we use panel model approaches which deal with unobservables and endogeneity and we focus on the output additionality measured by the aggregated number of patents filed at the regional level. The two other chapters (three and four) are devoted to the analysis of the French competitiveness clusters policy in terms of input additionality (incentives for private R&D investments) but also in terms of output additionality (innovation and other economic performance). The third chapter uses micro-data of French small and medium-sized enterprises (SMEs) and evaluate the effect of the policy in terms of on input and output additionality by using a quasi-experimental counterfactuals setting for subsidized (treated) and non-subsidized (non-treated) firms and by combining propensity score matching and difference-in-difference approaches also know as conditional difference-in-difference (CDiD).

The fourth chapter uses micro-data and evaluates the effects of this same French clusters policy on input and output additionality of midsized (ETIs) and Large firms (GE) using panel model approaches which deal with selection biases due to the presence of endogeneity and several unobservables. The choice of using two different methods to evaluate the effects of the competitiveness clusters policy on SMEs and large firms' innovation and economic performance is motivated by the methodological issues related to the lack of counterfactuals for large firms.

Chapter 2

Evidence on the impact of the 5th and 6th Framework Programmes on European regional innovation²¹

²¹An older version of this chapter is a paper co-authored with S. Charlot (Université Lumière Lyon 2). This work benefits from the support of ANR project (RENEWAL). The older version is put into ANR WP and has been presented at the 3rd Geography of Innovation Conference, at the 2nd International Conference on the Economics of Innovation by GAEL Lab (2016), at JMA Conference (2016), at Journée Doctorale d'Economie (2016), at Journée des Jeunes Chercheurs (Lyon, 2015).

Abstract

This chapter analyzes the impacts of the EU Fifth and Sixth FPs policy on the innovation of European regions. Using a panel data set covering the 1995-2012 period and macro-data of 218 regions of the entire EU-27, we estimate a regional knowledge production function including the FPs amounts spent in each region. We analyze the policy effects, by using a random-trend model that controls for the regions' unobserved heterogeneity (fixed and time-varying) that can affect innovation. This model permits that such unobserved regional heterogeneity is time-varying. We use a translog specification in order to take into account the complementarity and substitution effects between factors but also the threshold effects and the initial endowments of innovative factors.

Findings show that for the entire EU countries the FP5 expenditure has no impact on regional innovation but the FP6 spending impacts positively the European regional innovation. Moreover, for the EU-27, results reveal complementarity effects between human capital and FP6 and human capital and SumFP5-6 (the sum of FP5 and FP6 amounts) spending but also substitution between regional R&D spending and FP6 spending. No complementarity or substitution effect is detected between innovation factors and the FP5 spending. Moreover, when focusing on the more innovative countries (EU top 11), the FP5 spending is slightly significant and the sum of the two amounts of the policy (SumFP5-6) has a stronger impact on regional innovation in these countries. Similarly, results show complementarity between human capital and FP6 or SumFP5-6 spending but also substitution between regional R&D spending and FP6 spending. For the EU top 11, no complementarity or substitution effect is detected between innovation factors and the FP5 spending. Furthermore, when focusing on the less innovative countries (EU Low 16), findings show that the FP5 has no effect but the FP6 and the SumFP5-6 have significant effect on regional innovation. However, no complementarity or substitution effect is detected between factors. Finally, these results confirm the role of thresholds effects and that it is necessary to observe a certain level of innovative factors to make the policy efficient.

Keywords: EU Framework Programmes, Regional innovation, Knowledge production function, Panel data, Random trend Model.

JEL classification: O30, R11, C13, C23

2.1 Introduction

Due to its role on economic progress, industrial change and international competitiveness (Romer, 1986; Grossman and Helpman, 1991; Barro and Sala-i Martin, 1995; Aghion et al., 1998; Encaoua et al., 2004), the concept of innovation has become a widely-debated subject and attracted a raising interest, not only within firms, but also at the national levels. According to the (OECD, 2015b), innovation helps to drive economic growth and to address global challenges, such as living standard, health, pollution, climate change and sustainable development. Therefore, several countries in the world have started to implement various innovation policies. Most of the developed and developing countries have spent public resources to boost their innovation and economic system and increase the level of welfare.

In Europe, over the last three decades, the EU has developed its systems of innovation by funding, through the Framework Programmes (FPs) on Research and Technological Development (RTD), thousands of collaborative R&D projects to support transnational cooperation and mobility for training purposes. Based on the Maastricht treaty of the EU, the European FPs were implemented to realize two main objectives: First, to strengthen the scientific and technological bases of the industry to foster international competitiveness and, second, to promote research activities in support of other EU policies (CORDIS, 2002)²². The first FP (FP1) was implemented in 1984 and the eighth covers the 2014-2020 period. According to Roediger-Schluga and Barber (2006), although the promotion of collaborative R&D has remained the cornerstone of FPs policy, their priorities have changed a little over time from enhancing European abilities to produce new technologies (FP1-FP4) to enhancing the ability to use them effectively (FP5), to developing scientific and technical excellence in a European Research Area (FP6). Since their implementation, the FPs have known strong changes in their budgets from €3.75 billion for the first phase (FP1) to €80 billion for the Horizon 2020 program (FP8).

In this work, we focus on the FP5 (1998-2002) and the FP6 (2002-2006) programmes. These programmes represented, respectively, almost €14.96 billion and €17.5 billion funded by the European Union and partners (firms and national or regional governments)²³. Indeed,

²²Community Research and Development Information Service (CORDIS)

²³Associated countries include the 27 EU-membership (Bulgaria, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, and Slovenia) as well as Iceland, Israel, Liechtenstein, Norway and Switzerland. For more details, see CORDIS (2002).

the objective of this policy instruments is to promote collaboration among actors, by directly funding R&D projects, or dissemination of research results (Bach et al., 2014), projects must involve public and private actors to be funded.

The FP5 focused on a limited number of research areas combining technological, industrial, economic, social and cultural aspects. The FP5 comprises five main thematic programmes²⁴: Quality of Life and Management of Living Resources, User-friendly Information Society (IST), Competitive and Sustainable Growth, Energy, Environment and Sustainable Development, and Nuclear Energy.

The FP6 represented about 4 to 5% of the overall expenditure on RTD in the EU Member States (CORDIS, 2002). The main objective of FP6 was to contribute to the creation of the European Research Area (ERA) by improving integration and coordination of research in Europe which is so far largely fragmented. The framework programmes supported collaboration in research, promoted mobility and coordination and invested in mobilizing research in support of other EU policies. At the same time, it helped to target at strengthening the competitiveness of the European economy, solving major societal questions and supporting the formulation and implementation of other EU policies. Activities under FP6 was conducted in compliance with ethical principles, including those reflected in the Charter of Fundamental Rights of the European Union. Furthermore, they strived both to increase the role of women in research and to improve information for, and dialogue with, society.

Different studies assess the effects of FPs and especially the FP5 and FP6. They mainly focus on the characteristics and the impact of (interregional) collaborations on the innovation process. They use micro-level data providing information on the firms and the institutions involved in collaborations enhanced thanks to the FPs. These studies show that participating firms are more innovative than average (Dekker et al., 2008; Robin et al., 2011) and that projects funded are more explanatory, in terms of distance to the core competence of firms, and risky (Matt et al., 2012; Bach et al., 2014). This may explain why the previous studies

²⁴The thematic priorities the in FP5 are the following (Sub-programme name given in brackets): Quality of Life and management of living resources (Quality of Life); User-friendly information society (IST); Competitive and sustainable growth (GROWTH); Energy, environment and sustainable development (EESD); Confirming the international role of community research (INCO2); Promotion of innovation and encouragement of SME participation (Innovation/SMEs); Improving the human research potential and the socio-economic knowledge base (Improving) (CORDIS, 2002).

found low (or null) direct effects on economic performance of participants to FP5. [Dekker et al. \(2008\)](#) and [Robin et al. \(2011\)](#) find that participation seems to have no impact on sales of innovative products. [Barajas et al. \(2012\)](#) also conclude to poor direct effects on the economic results of participants. However, a recent analysis ([Aguiar and Gagnepain, 2014](#)) highlights a strong effect on firms' performance (labor productivity and profit margin), when focusing on firms that participate in the IST²⁵ Programme. [Fisher et al. \(2009\)](#) found that first-time participants and medium-sized companies to benefit the most from participation in the FP5 and FP6 in terms of innovation. They see participation in the IST programme as a way of obtaining access to new knowledge and resources which in turn positively affect economic performance.

One part of this strand of the literature focuses on the role of FPs in the regional dimension of collaborations and knowledge flows and emphasizes the fact that FPs have boosted the European integration process ([Constantelou et al., 2004](#)). [Maggioni et al. \(2007\)](#) show that geographical distance is also an important factor to assess the effect of FP5 on collaborations and network. The analysis of the role of spatial dimension is justified by the huge debate on whether geographical proximity is more relevant than technological proximity to innovate.

This chapter proposes a relevant methodology to assess the effect of the FP5 and FP6 spending on innovation at the aggregated regional level, controlling for main innovation inputs, i.e. human capital (HK) and R&D, as well as main unobserved factors that may affect the innovation process and may be correlated with these main inputs and the regional FPs spending. Using a panel data set covering the 1995-2012 period and macro-data of 218 regions of the entire EU-27, we estimate a regional knowledge production function including the FPs amounts spent in each region. We analyze the policy effects, by using a random-trend model that controls for the regions' unobserved heterogeneity (fixed and time-varying) that can affect innovation. This model permits that such unobserved regional heterogeneity is time-varying. This allows to properly accounting for the non-random selection of actors involved in collaborations and, compared with previous studies, this would better account for the endogeneity of FP5 and FP6 spending as well as R&D and HK, especially those linked to selection biases. We use a translog specification in order to take into account the complementarity and substitution effects between factors but also the threshold effects and the initial endowments of innovative factors.

²⁵User-friendly information society (IST) is a sub-programme of the FP5.

Findings show that for the entire EU countries the FP5 expenditure has no impact on regional innovation but the FP6 spending impacts positively the European regional innovation. Moreover, for the EU-27, results reveal complementarity effects between human capital and FP6 and human capital and SumFP5-6 (the sum of FP5 and FP6 amounts) spending but also substitution between regional R&D spending and FP6 spending. No complementarity or substitution effect is detected between innovation factors and the FP5 spending.

Moreover, when focusing on the more innovative countries (EU top 11), the FP5 spending is slightly significant and the sum of the two amounts of the policy (SumFP5-6) has a stronger impact on regional innovation in these countries. For the EU top 11, no complementarity or substitution effect is detected between innovation factors and the FP5 spending. Furthermore, when focusing on the less innovative countries (EU Low 16), findings show that the FP5 has no effect but the FP5 and the SumFP5-6 have significant effects on regional innovation. However, no complementarity or substitution effect is detected between factors.

Finally, these results confirm the role of thresholds effects and that it is necessary to observe a certain level of innovative factors to make the policy efficient in the long run. All these results highlight the importance of introducing a more flexible function to take into account the complementarity and substitution effects between factors but also the threshold effects and the initial endowments of innovative factors, to assess the impact of policies, especially collaborative policies such as FPs.

This chapter is organized as follows. Section 2 presents the literature review. Section 3 describes the empirical methodology and the used data. Section 4 presents the estimation results. Section 5 concludes.

2.2 The EU Framework Programmes policy

The competitiveness of companies, the productivity and the growth they provide is essential for the growth and competitiveness of countries. Innovation plays a great role in growth by supporting and strengthening advances in new technologies, and by focusing greater on knowledge creation and use [OECD \(2007\)](#). The individual and collective well-being of citizens depends on innovation and on the quality and relevance of Research and Technological Development.

As it's difficult for an individual research team (laboratory or company), a region, or a country to be active and play a leading role in the many important areas of scientific and technological progress, conducting an European research policy become necessary to cope with these challenges. Organizing international cooperation, coordination, and networking and increasing the mobility of individuals and ideas at different levels become necessary for the development of research and innovation in the global economy.

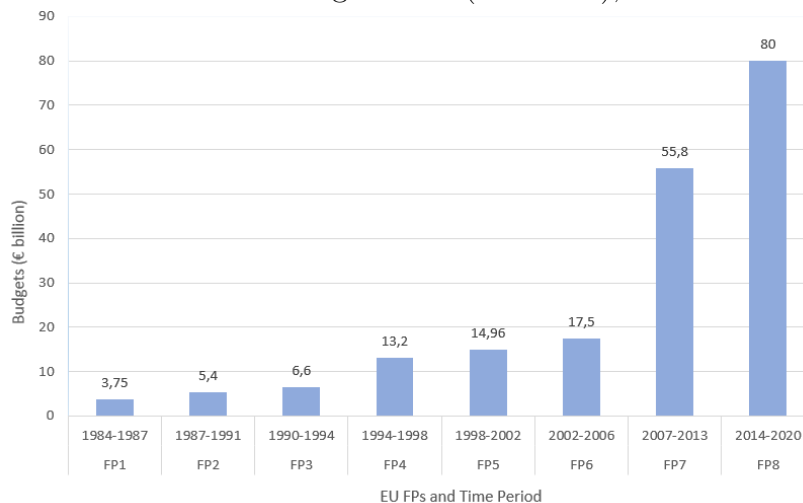
Based on the Maastricht Treaty and taking up this challenge the European Commission, the EU Member States and the scientific community and industry are committed to work jointly to promote research activities and to make the EU the most dynamic knowledge-based economy in the world.

The Framework Programmes are instruments used as tools of public policy to improve the activities of research in the EU member states through collaborations in projects of research and development. The main objective of these programs is to promote and to strengthen the development of regions as well as countries in the field of the science and technology and especially in innovation-oriented R&D. These projects are intended for educational organizations, universities, laboratories, research centers, firms and public and private organizations.

Started in 1984, the first FP (FP1) was implemented for the 1984-1988 period and the eighth (FP8 named also Horizon 2020), started in 2014, runs until 2020. [Figure 2.1](#) presents the different Framework Programmes phases, their time period and their budgets. Except the FP7 and the FP8 which are scheduled for a duration of seven years, the different phases of the policy were programmed between four and five years. The priorities of the policy have more or less changed a little over time. It goes from enhancing European abilities to produce new technologies (FP1-FP4), to enhancing the ability to use them effectively (FP5), to developing scientific and technical excellence in a European Research Area (FP6).

However, the promotion of collaborative R&D has remained the cornerstone of the policy.

Figure 2.1: The EU Framework Programmes (FP1-FP8), Time Period and Budgets



Source: CORDIS, Author's representation

Since the beginning of their existence, the Framework Programmes have known changes in their budgets which showed a constant rise from €3.75 billion (FP1), €5.4 billion (FP2), €6.6 billion (FP3), €13.2 billion (FP4), €14.96 billion (FP5), 17.5 billion (FP6), to 55.8 billion (FP7). The total budget of the current Horizon 2020 program (FP8) is expected to fund nearly €80 billion. These budgets are financed by the contributions of the EU member states and by the contributions given by the policy's associated countries.

The programmes and the budgets of the policy are directly managed by the European Commission which appeals skills and expertise of independent experts for the selection phases of the proposals and the evaluation of the projects. These programmes fix the main themes of research by thematic priorities and the budgets which are associated with them. The selection mode of the projects is based on the system of calls for tenders, published in the official journal of the European Union. The majority of the European projects is based on the network of a consortium of research including several teams from various countries.

In this study, we focus especially on the 5th and 6th Framework programmes and we present them with more details below.

2.2.1 The Fifth Framework Programme

The Fifth Framework Programme was implemented to help the EU countries to solve societal problems and to respond to major socio-economic challenges faced by their citizens. It focused on a number of objectives and different areas combining technological, industrial, economic, social and cultural aspects (CORDIS, 1999). The main strategy when conceiving this phase was the use of Key Action concept which allows to target the most important themes and to deal with concrete issues through multi-disciplinary approaches involving all the interested parties.

The FP5 has two distinct parts (see table 2.1). The first one is the European Community (EC) section which covered research, technological development, and demonstration activities. This part concentrated a budget of €13.7 billion (about 92% of the total budget). The second part is the Euratom programme which concerned the research and training activities in the nuclear sector. This section of the programme received a budget of €1.26 billion (about 8% of the total budget). Combining this two parts' budget brought the global budget for research in the period 1998-2002 to €14.96 billion which represent an increase of 4.61% compared to the previous phase (FP4).

The FP5 had a multi-theme structure, consisting of seven specific programmes in which four are Thematic Programmes and the three other are Horizontal Programmes. There are three latter programmes which are transverse and are complements for the thematic programmes and respond to common needs for all research areas (CORDIS, 1999).

The four Thematic Programmes are: Quality of Life and management of living resources (Quality of Life), User-friendly information society (IST), Competitive and sustainable growth (GROWTH) and Energy, environment and sustainable development (EESD). The Horizontal Programmes are: Confirming the international role of Community research (INCO 2), Promotion of innovation and encouragement of SMEs participation (Innovation) and Improving the human research potential and the socio-economic knowledge base.

The FP5 differs considerably from the previous Programmes because it focused on a limited number of research areas and the priorities were selected on the basis of a set of common criteria reflecting the major concerns of increasing industrial competitiveness and the quality of life for European citizens. It also enabled overcoming the barriers that exist, not only between disciplines but also between the programmes and the concerned partners.

Table 2.1: The FP5 Programme: Maximum Amounts and Breakdown (1998-2002)

FP5 - EC Programme: Maximum Amounts and Breakdown (1998-2002)	
Indirect Actions	€Million
First Activity	
Research, technological development and demonstration activities	10843
Indicative breakdown by theme (Million euro):	
1. Quality of life and management of living resources (2 413)	
2. User-friendly information society (3 600)	
3. Competitive and sustainable growth (2 705)	
4. Energy, environment and sustainable development (2 125)	
Second Activity	
Confirming the international role of Community Research	475
Third Activity	
Promotion of innovation and encouragement of SME participation	363
Fourth Activity	
Improving human research potential and the socio-economic knowledge base	1 280
Direct Actions	
Joint Research Centre (JRC)	739
Maximum Overall Amount	13 700
FP5 - Euratom Programme: Maximum Amounts and Breakdown (1998-2002)	
Indirect Actions	
Research and Training in the field of Nuclear Energy	979
Direct Actions	
Joint Research Centre (JRC)	281
Maximum Overall Amount	1 260
Maximum Overall FP5 Amount (13 700 + 1 260)	14 960

Source: CORDIS, <http://cordis.europa.eu/fp5/src/budget.htm>

2.2.2 The Sixth Framework Programme

As the FP5, the Sixth Framework Programme was implemented to reach two main objectives: strengthening the scientific and technological bases of industry and encouraging international competitiveness. It covered the Community activities in the field of science, research, technological development and innovation for the 2002-2006 period (CORDIS, 2002) and represents a budget of €17.5 billion (an increase of 17% compared to the FP5, see table 2.2). The FP6 also provided possibilities and funding for organizations in non-European countries. It promoted transnational collaboration, networking in the field of research and it promoted also mobility and coordination to improve innovation and to support the other EU policies. The FP6 has two main parts which are the focus on the Integrating Community research and the Structuring of the European Research Area (ERA).

The largest part of FP6 is the Integrating Research which is divided into seven priority thematic areas and some specific activities or cross-cutting activities covering a wider field of research (CORDIS, 2002). It accounted for more than 80% of the total FP6 budget. This integration is to be accomplished by carrying out research projects that have an integrating effect on the researchers and their organizations (countries, regions, firms, etc.). The seven priority thematic areas that are targeted by the the FP6 are: Life sciences, genomics and biotechnology for health; Information society technologies; Nanotechnologies, nano-sciences, knowledge-based functional materials, new production processes and devices; Aeronautics and space; Food quality and safety; Sustainable development, global change and ecosystems; and Citizens and governance in a knowledge-based society (CORDIS, 2002). These priority thematic areas receive more than 71% of the budget. The specific activities represent 13% of the total budget and is an additional open theme that is designed to discover any new and emerging areas of research that have not been foreseen in the seven priority themes.

The second main part of the FP6 is the contribution to the creation of the European Research Area (ERA) which is considered to be a vision for the future of research in Europe. It aims at bringing scientific excellence, improving competitiveness, and innovation through the promotion of cooperation, complementarity and coordination between relevant actors, at all levels. The Structuring of the ERA represented 16% of the FP6 budget which was the main financial instrument of the European Commission to implement the ERA.

Table 2.2: The FP6 Programme: Maximum Amounts and Breakdown (2002-2006)

FP6 - EC Programme: Maximum Amounts and Breakdown (2002-2006)	
Actions	€Million
1. Focusing and integrating Community research	14 682
Seven Thematic priorities	12 438
Indicative breakdown by theme (Million euro):	
1. Life sciences, genomics and biotechnology for health (2514)	
2. Information society technologies (3 984)	
3. Nanotechnologies and nano-sciences, knowledge-based multifunctional materials and new production processes and devices (1 429)	
4. Aeronautics and space (1 182)	
5. Food quality and safety (753)	
6. Sustainable development, global change and ecosystems (2 329)	
7. Citizens and governance in a knowledge-based society (247)	
Specific activities covering a wider field of research	2 244
a. Policy support and anticipating scientific and technological needs (590)	
b. Horizontal research activities involving SMEs (473)	
c. Specific measures in support of international cooperation (346)	
d. Non-nuclear activities of the Joint Research Centre (835)	
2. Structuring the European Research Area	2 854
a. Research and innovation (319)	
b. Human resources (1 732)	
c. Research infrastructures (715)	
d. Science and society (88)	
Maximum Overall FP6 Amount (14 682 + 2 854)	17 536

 Source: CORDIS, <https://cordis.europa.eu/fp6/budget.htm>

2.3 Related literature

There exist few empirical works evaluating the effects of the FPs and some of them focus on the Fifth. The results are quite mixed, depending on the output indicators, the methodology and the spatial scale at which the study is carried out. [Scherngell and Barber \(2009\)](#) analyze the cross-region collaborations in R&D and separate the geographical from the technological proximity as a determinant of collaborative R&D projects funded by the FP5. They mainly show that geographical factors are important determinants of cross-region collaboration intensities, but the effect of technological proximity is stronger. [Dekker et al. \(2008\)](#) use the 3rd and 4th waves of the Community Innovation Survey (CIS) data in France, Germany, and the Netherlands to assess the effects of FP4 and FP5 on the sale of innovative products of firms that participate to these programmes. Their results first show that participants to FP4 and FP5 are more innovative firms on average. They have also highlighted that the smaller firms increase their R&D capacity after participating in this kind of programmes. Finally, controlling for this selection bias by using a Heckman strategy, participation seems to have no impact on the sales of innovative products. Authors explain this result by the fact that projects funded by the FP are riskier and conclude that these projects would not exist without the European innovation policy. This is in line with the results of a more recent work that evaluates the effect of FP5 and FP6 ([Matt et al., 2012](#)) using data on the collaborative projects conducted by European firms.

[Aguiar and Gagnepain \(2014\)](#) use the data from the CORDIS that provides information on IST projects and on the other hand the Analyse Major Databases from European Sources (AMADEUS) that provides information on firms. They use a two-steps estimation strategy: first, they estimate the probability to participate in an IST programme, distinguishing small, medium or large projects, as a function of some firms' characteristics. In a second equation, the firms' performance depends on firms' characteristics as well as the estimated probability to participate in the FP5, calculated in the first step. Their results suggest that, on average, participation in a large IST FP5 programme raises labor productivity by at least 35% and the effect on profit margin is very limited.

For the evaluation of the FP6, by analyzing the effects of the policy on Spanish firms' economic performance, [Barajas et al. \(2012\)](#) find that R&D cooperation has a positive impact on the technological capacity of firms, captured through intangible fixed assets of participants.

Concerning the economic indicators, EBITDA²⁶, labor productivity and sales are positively influenced by the improvement of the technological capacity of firms. Assessing the effects of FP5 and FP6, Fisher et al. (2009) found that first-time participants and medium-sized companies benefited the most from participation in the FP5 and FP6 in terms of innovation. They highlight that participation in the IST programme is a way to obtain access to new knowledge and resources which, in turn, positively affect economic performance.

The estimated effects of the FPs on firms' performance are rather mixed, depending crucially on the part of the programme the studies are dedicated to. In this chapter, we take another way to assess this impact by estimating a knowledge production function (KPF) at the regional level. Our analysis of the determinants of innovation activity at the regional level is based on the estimation of a KPF model (Griliches, 1979), in which we include the traditional R&D expenditure and the human capital given its well-known effects on knowledge production and absorption at the local level. Also, after controlling unobserved factor, we introduce in the model the FP5 and FP6 spending amounts and assess their impacts on innovation.

2.4 Methodology

2.4.1 The knowledge production function

In this study, we want to investigate the effects of the European R&D policy on innovation by using a knowledge production function (KPF). The theoretical framework of the KPF was developed by Griliches (1979) in a firm-level study. This framework represents an important methodological approach to study the relationships between knowledge production and its inputs and outputs and, therefore, allows to study innovation and technical change. Although the KPF finds its foundations at the firm level, it was used in many studies implemented at a more aggregated level and particularly at the regional level (Feldman and Florida, 1994; Bode, 2004; Ponds et al., 2010; Marrocu et al., 2011; Usai et al., 2013; Marrocu et al., 2013).

In this empirical research, we attempt, through the KPF, to explain the effectiveness of regional innovation by examining the causal relationships between innovative inputs and out-

²⁶A company's earnings before interest, taxes, depreciation, and amortization (commonly abbreviated EBITDA).

puts, after controlling for other relevant factors. Here, innovation is proxied by the patenting activity (patents) at the regional level. Following the well-established literature on KPF, we consider the regional R&D expenditure as the first knowledge production factor. In their study, (Cohen and Levinthal, 1990) have emphasized the importance of absorptive capacity of territories to ensure the effectiveness of R&D spending. Human capital plays a relevant role because highly skilled workers can generate new ideas, support and enhance the innovative process. Therefore, besides R&D spending, we include human capital measured by the number of people with tertiary education (ISCED11, classification levels 5-8) as a knowledge production factor. In this study, we extend the KPF and include the FP5 and FP6 amounts spent in a region in the model as innovative inputs and assess their effectiveness.

The regional innovation process depends not only on the R&D spending and human capital observed in the region but also on numerous unobserved factors. For example, firms may locate their R&D activities in regions in which they can find factors that support innovation and in which they can benefit from localized spillovers resulting from the concentration of other innovative firms, skills, infrastructure, etc. Consequently, regional innovation depends also on a set of unobserved characteristics such as the governance, institutions, cultures, regional industrial structure, innovation system, intensity of collaborative R&D, networking among actors, infrastructure, agglomeration, several regional policies, etc., because they determine location decisions as further discussed by Charlot et al. (2014). Whereas some of these unobserved characteristics may affect innovation and are uncorrelated with innovation inputs, most of them are likely to affect both innovation and its inputs as well as other factors such as innovation policies.

The main innovation factors introduced in a regional knowledge production function are therefore subject to endogeneity, and assessing the effects of FP5 and FP6 by using a KPF requires tackling most of these issues, especially it requires controlling for the numerous effects of unobserved characteristics which may affect the innovation process. To this aim, we follow Papke (1994) and Wooldridge (2005) by using a random trend model. For applying the random trend model to estimate the KPF, we can use the log-log specification or the translog specification.

2.4.2 The Cobb-Douglas production function

The general form of the econometric model is as follows:

$$Y_{r,t} = F(R\&D_{r,t}, HK_{r,t}, FP5_{r,t}, FP6_{r,t}, \epsilon_{r,t}) \quad (2.1)$$

where $Y_{r,t}$ is the innovation output, $r = (1 \dots R)$ is an index of the regions, $t = (1 \dots T)$ indicates time, $R\&D$ is the regional spending amount in Research and Development, HK is the regional human capital, $FP5$ and $FP6$ are, respectively, the regional spending amount of the 5th and 6th Framework Programmes, and $\epsilon_{r,t}$ represents all unobservable factors that influence regional innovative performance. As F , we use the log-log specification better known as Cobb-Douglas function.

The Cobb-Douglas function is a function widely used in economy as a model of production function. It was proposed and tested econometrically by [Cobb and Douglas \(1928\)](#). It is used to represent the link which exists between the inputs and the output. To represent this function, we use this following log-linearized equation:

$$\ln(Y_{r,t}) = \beta_1 \ln(R\&D_{r,t}) + \beta_2 \ln(HK_{r,t}) + \beta_3 \ln(FP5_{r,t}) + \beta_4 \ln(FP6_{r,t}) + \epsilon_{r,t} \quad (2.2)$$

The elasticities of factors which measure the sensitivity of response of the production after a change in the input levels and the returns to scale are constant for a Cobb-Douglas function. This model is based on the hypothesis that there exists a homogeneity of the coefficients. The impact of the results can be limited by the Cobb-Douglas production function because it is based on restrictive hypotheses, in particular, unitarian substitution elasticity between factors. Therefore, it is possible to overcome these constraints and to resort to a more flexible production function (translog) allowing to approximate all the possible technology combinations.

The Cobb-Douglas specification is a particular case of the translog formulation, it can be interesting to check the contribution of a translog specification with regard to the Cobb-Douglas specification. While the estimation of a function Cobb-Douglas allows determining only the elasticities of factors, the estimation of a translog function allows determining also the substitution elasticities between factors.

2.4.3 The translog production function

The general form of the econometric model is as follows:

$$Y_{r,t} = F(R\&D_{r,t}, HK_{r,t}, FP5_{r,t}, FP6_{r,t}, \epsilon_{r,t}) \quad (2.3)$$

where $Y_{r,t}$ is the innovation output, $r = (1 \dots R)$ is an index of the regions, $t = (1 \dots T)$ indicates time, $R\&D$ is the regional spending amount in Research and Development, HK is the regional human capital, $FP5$ and $FP6$ are, respectively, the regional spending amount of the 5th and 6th Framework Programmes, and $\epsilon_{r,t}$ represents all unobservable factors that influence regional innovative performance. As F , we use the translog function which is a flexible form of the Cobb-Douglas function, most commonly used, and defined by [Christensen et al. \(1971\)](#) and [Christensen et al. \(1973\)](#).

As explained by [Pavelescu et al. \(2011\)](#), the translog production function proposed by Christiansen, Jorgensen and Lau is a flexible function that can be seen as a combination of the Cobb-Douglas function and the quadratic function and has both linear and quadratic terms with the ability to use more than two-factor inputs. To characterize the production function without using special structural assumptions, the specifications of the Cobb-Douglas must be abandoned in favor of flexible forms that impose no restriction on the structure of production. According to [Fuss et al. \(1978\)](#) and [Chambers \(1988\)](#), it can be regarded as second-order approximations, twice differentiable of any technology.

The concept of the translog production function allows to pass from a linear relationship between the output and the production factors which are taken into account, to a nonlinear one. The generalized form of the translog production function, which takes into account a number of n inputs (production factors), can be written as follows:

$$\ln(y_{r,t}) = \beta_0 + \sum_i^n \beta_i \ln(x_{r,t}^i) + \frac{1}{2} \sum_i^n \sum_j^n \beta_{ij} \ln(x_{r,t}^i) \ln(x_{r,t}^j) + \epsilon_{r,t} \quad (2.4)$$

with y , the innovation output and x^i , the input factors.

It is worth noting that the marginal product of a translog production function is formally a Cobb-Douglas production function. It is important to mention that [Ferguson \(1979\)](#) demonstrated that the marginal product is equal to the elasticity of scale. The elasticities of factors and the returns to scale are constant for a Cobb-Douglas function, while they depend on the level of the factors for a translog function. From a translog function, the interpretation

of coefficients is not straightforward as for a Cobb-Douglas function and the elasticities (E) of innovation factors are calculated as follows:

$$E_{(x_{r,t}^i)} = \frac{\partial(\ln(y_{r,t}))}{\partial(\ln(x_{r,t}^i))} = \beta_i + \sum_j \beta_{ij} \ln(x_{r,t}^i) \ln(x_{r,t}^j) \quad (2.5)$$

The elasticities can be calculated for each region at each time. At the point of approximation²⁷, the level of production of the translog specification is identical to that of the real technology which allows determining the characteristic parameters of the latter. As shown by [Fuss et al. \(1978\)](#), the point does not necessarily represent the average of the sample and among the point most commonly selected, the median is found or the geometric mean of variables (the arithmetic average of the logarithms of the variables). With the economic theory under the assumption of perfect competition, a production function must satisfy certain regularity conditions to result in compatible parameters (as discussed by [Heyer et al. \(2004\)](#), there are four hypothesis)²⁸. A translog function cannot satisfy regularity conditions globally without losing its flexible nature ([Fuss et al., 1978](#)). Indeed, imposing regularity conditions involves constraints on the gradient and the Hessian of the production function. Several researchers have developed different methods ([Gallant and Golub, 1984](#); [Lau, 1986](#); [Terrell, 1996](#); [Ryan and Wales, 2000](#)) and showed that the imposition of these conditions led to a significant change in the results.

If a flexible form has the advantage of being able to describe any technology, it still has some limitations. Most of these limitations arise when one wants to test a translog model under the assumption of perfect competition. The translog function describes the real technology at the point of approximation and its neighbors which limits the scope of the results. While the Cobb-Douglas function satisfies some regularity conditions, these latter cannot be globally satisfied for a flexible form.

²⁷Unfortunately, the point of approximation is not precisely known.

²⁸The positivity of marginal productivities of factors (H1) ensures that, all things equal elsewhere, an increase of a factor of production is accompanied by an increase in production. The diminishing returns (H2) means that the increase of a factor of production leads to an increase in production smaller and smaller. The convexity of isoquants (H3) means that for a given level of output, the substitution of one factor to another is accompanied by a decrease in the marginal productivity of the factor that increases and an increase in marginal productivity of the factor that decreases. The negativity of the own elasticities of factors (H4) means that the demand for a good falls when its price increases and the demand curve for a good is decreasing.

As explained above, the translog production function has potentially a series of advantages in the research of the economic activity from the theoretical point of view. But the great number of parameters that have to be estimated in order to make operational the translog function impose hard constraints on the result feasibility, because the occurrence of an extended collinearity is favored (Pavelescu et al., 2011). In fact, when the number of production factors increases, the number of the parameters to calculate explodes exponentially. As explained by Pavelescu et al. (2011), a solution used in order to surpass the difficulties generated by the collinearity is the limitation of the number of production factors.

As the Cobb-Douglas production function is nested in the translog production function, we can apply a Wald test or likelihood ratio test to check whether the Cobb-Douglas production function is rejected in favor of the translog production function. In our case, at the 5% significance level, the Cobb-Douglas production function is rejected by the Wald test in favor of the translog production function for all the models (see figure 2.4).

2.4.4 The econometric specification: a random trend model

In the applied econometric literature, many researchers have tackled the endogeneity issue by using panel data models (see Greunz, 2003; Moreno et al., 2005; Crescenzi et al., 2012; Marrocu et al., 2013). As documented by Charlot et al. (2014), Heckman and Hotz (1989), Wooldridge (2005) and Hsiao (2011) have shown that the two-way fixed effects approach has been used because it offers a solution to deal with the endogeneity problem related to selection bias (due to observable and unobserved characteristics). It accounts for the individual fixed effects and for time-invariant individual characteristics and all common factors that affect the outcomes of regions in the same way. Nevertheless, the main limit of the two-way fixed effect model is that the time trend is assumed to be common for all regions while, as explained above, several unobserved time-varying regional-specific characteristics such as governance, institutions, infrastructures, cultures, innovation system, intensity of collaborative R&D, networking among actors and several regional policies, are likely to affect heterogeneously the regions. These unobserved time-varying regional-specific characteristics are also related to the production of patents, R&D spending, human capital and also the amount of FP5 and FP6 spending in the regions.

To assess the effects of the FP5 and FP6 on regional innovation by accounting for the endogeneity issue, we adopt a random trend model proposed by Heckman and Hotz (1989). This model was empirically applied by Papke (1994) to examine the effects of enterprise zones on unemployment and more recently it was theoretically deeply studied by Wooldridge (2005). This model was recently applied by Charlot et al. (2014). The random trend model is an important extension of the standard linear model with an additive unobserved effect, where each region is allowed to have its own linear trend. It consists of introducing an individual time-varying component, in addition to the individual and time fixed effects. This model thus aims at controlling for all time-varying firm-specific unobserved factors, allowing, at the same time, that such factors are freely correlated with observable inputs. The specificity of the random trend model is that it allows the effect of the program to depend on the unobserved effects and as well for firm-specific slopes.

In this chapter, we extend the KPF by including the regional FP5 and FP6 spending amounts and assume that they may affect the innovation process. In a simple fixed-effects model:

$$\epsilon_{r,t} = \alpha_r + v_{r,t} \quad (2.6)$$

where α_r is the regional individual unobservable time-invariant effects and $v_{r,t}$ is the error term.

And in a two-way fixed effects model:

$$\epsilon_{r,t} = \alpha_r + \theta_t + v_{r,t} \quad (2.7)$$

where θ_t is the homogenous unobservable time fixed effects; α_r and $v_{r,t}$ are the same as in equation (2.10).

The individual fixed effects capture the impact of all unobserved characteristics. A two-way fixed effect model is, therefore, a relatively powerful model to evaluate the treatment effect when one can control for many individual time-varying characteristics. The main limitation of a two-way fixed effect model is that a “common trend assumption” is imposed, according to which unobservable characteristics affect trends in the same way for all the regions. In many cases, one can think on the contrary that unobserved factors are likely to affect not only the levels but also the trend followed by regions. So, with the random trend model we have the following:

$$\epsilon_{r,t} = \alpha_r + \theta_t + tg_r + v_{r,t} \quad (2.8)$$

where tg_r is the regional individual unobservable time-varying effects; α_r , θ_t and $v_{r,t}$ are the same as in equation (2.7).

By substituting (2.8) in (2.4), we get the four-input translog production function of innovation that can be written as follows, in a case of random trend model:

$$\ln(y_{r,t}) = \beta_0 + \sum_{i=1}^4 \beta_i \ln(x_{r,t}^i) + \frac{1}{2} \sum_{i=1}^4 \sum_{j=1}^4 \beta_{ij} \ln(x_{r,t}^i) \ln(x_{r,t}^j) + \alpha_r + \theta_t + tg_r + v_{r,t} \quad (2.9)$$

with y , the innovation output and x^i , the four input factors and g_r is the customary regional fixed-effect.

This model aims at controlling for all time-varying unobservable characteristics through individual-specific linear trends. Wooldridge (2010) demonstrates that the fixed effect estimator can be applied to estimate this model if the strict exogeneity assumption on the explanatory variables holds and if there is no serial correlation with the error term. In case of serial correlation, he demonstrates that the time-differentiating estimator is more relevant. This approach consists of first-differentiating the equation to eliminate the additive effect. The first-differentiated equation is as follows:

$$\Delta \ln(y_{r,t}) = \sum_{i=1}^4 \beta_i \Delta \ln(x_{r,t}^i) + \frac{1}{2} \sum_{i=1}^4 \sum_{j=1}^4 \beta_{ij} \Delta (\ln(x_{r,t}^i) \ln(x_{r,t}^j)) + \Delta \theta_t + g_r + \Delta v_{r,t} \quad (2.10)$$

In the general case, the fixed effect g_r in the first-differentiated model captures an individual trend reflecting the impact of unobserved heterogeneity. The random trend model can, therefore, be estimated by using a simple fixed effects model and all variables first-differentiated. In case of the translog function, the model is as follows:

$$\begin{aligned} y_{r,t} = & \beta_1 rd_{r,t} + \beta_2 hk_{r,t} + \beta_3 fp5_{r,t} + \beta_4 fp6_{r,t} + \frac{1}{2} \beta_{11} rd_{r,t}^2 + \frac{1}{2} \beta_{22} hk_{r,t}^2 + \frac{1}{2} \beta_{33} fp5_{r,t}^2 + \frac{1}{2} \beta_{44} fp6_{r,t}^2 \\ & + \beta_{12} rd_{r,t} * hk_{r,t} + \beta_{13} rd_{r,t} * fp5_{r,t} + \beta_{14} rd_{r,t} * fp6_{r,t} + \beta_{23} hk_{r,t} * fp5_{r,t} \\ & + \beta_{24} hk_{r,t} * fp6_{r,t} + \beta_{34} fp5_{r,t} * fp6_{r,t} + \theta_t + g_r + v_{r,t} \end{aligned} \quad (2.11)$$

where all variables are first-differentiated and in logarithm. $\beta_1, \beta_2, \beta_3$, and β_4 are first derivatives. $\beta_{11}, \beta_{22}, \beta_{33}$, and β_{44} are own second derivatives. $\beta_{12}, \beta_{13}, \beta_{14}, \beta_{23}, \beta_{24}$ and β_{34} , are cross second derivatives.

The elasticities of the different four factors (respectively, R&D, HK, FP5 and FP6) are calculated as follows:

$$E_{(RD)_{r,t}} = \beta_1 + \beta_{11}rd_{r,t} + \beta_{12}hk_{r,t} + \beta_{13}fp5_{r,t} + \beta_{14}fp6_{r,t} \quad (2.12)$$

$$E_{(HK)_{r,t}} = \beta_2 + \beta_{22}hk_{r,t} + \beta_{12}rd_{r,t} + \beta_{23}fp5_{r,t} + \beta_{24}fp6_{r,t} \quad (2.13)$$

$$E_{(FP5)_{r,t}} = \beta_3 + \beta_{33}fp5_{r,t} + \beta_{13}rd_{r,t} + \beta_{23}hk_{r,t} + \beta_{34}fp6_{r,t} \quad (2.14)$$

$$E_{(FP6)_{r,t}} = \beta_4 + \beta_{44}fp6_{r,t} + \beta_{14}rd_{r,t} + \beta_{24}hk_{r,t} + \beta_{34}fp5_{r,t} \quad (2.15)$$

For calculating these elasticities, we use the median and the arithmetic average of the logarithms of the variables as the points of approximation. It is possible to calculate these elasticities by year and/or by region.

2.5 Data

2.5.1 Sources and variables

As for data (see table 2.3), we use patents and R&D spending data set, provided by Eurostat for EU-27 regions over the 1995-2012 period. The FP5 and FP6 spending amount data come from the French Ministry of Research and were kindly provided and localized by EuroLIO²⁹. This dataset provides information on all the FPs projects and their participants making possible to precisely localized budgets allocated to each institution (research centers, firms...) each year. Whereas the decisions to grant these budgets were made during the FPs period (1998-2002 for the fifth and 2002-2006 for the sixth), the expenditure may be incurred after this period. As we aim at assessing their effects on innovation, our dataset provides information on this effective expenditure, for each region at each year.

The analysis is based on a combination of NUTS1³⁰ and NUTS2 regions that were selected to maximize homogeneity in terms of the relevant governance structure under the constraint of data availability. Consequently, the analysis is based on NUTS1 regions for Belgium, Denmark, Finland, Sweden, Slovenia and the United Kingdom and on NUTS2 regions for all other countries (i.e. Austria, Bulgaria, Cyprus, Czech Republic, Germany, Estonia, Greece, Spain, France, Hungary, Ireland, Italy, Lithuania, Luxembourg, Latvia, Malta, Netherlands,

²⁹EuroLIO (European Localized Innovation Observatory) (EuroLIO)

³⁰NUTS (Nomenclature des Unités Territoriales Statistiques) (NUTS 2010)

Poland, Portugal, Romania, and Slovakia). Our final data set covers 218 European regions and because of the missing data, the panel is unbalanced.

Table 2.3: Data sources and definitions of variables

Variable	Source	Definition
Patent	Eurostat	patent applications filed at the EPO classified by priority year and by inventor's region
R&D	Eurostat	total regional intramural R&D expenditure by public and private institutions, regardless of the sector
Human capital	Eurostat	number of population with tertiary education (ISCED11, classification levels 5-8)
FP5 amounts	MESR-EuroLIO	The amounts of 5 th Framework Programme in European regions
FP6 amounts	MESR-EuroLIO	The amounts of 6 th Framework Programme in European regions

All variables are available from 1995 to 2012 with some missing values

We measure the regional innovation output using the regional number of patents. The analysis is based on homogeneous comparable data for regions belonging to all EU countries and relies on European Patent Office (EPO) data as recorded by Eurostat in its regional database (patents application filed at the EPO classified by priority year and by inventor's region). This measure of innovation has many limitations, as extensively discussed by [Griliches \(1990\)](#). Patents account only for a small share of total innovation output. Unfortunately, because of the constraint of availability of other indicators, the regional patent is currently the most widely used indicator of regional innovation for the entire EU.

The innovation inputs are defined as follows. The regional research and development (R&D) variable, considered as the first innovation input, corresponds to the regional intramural R&D spending by public and private institutions, regardless of the sector. The amount of R&D expenditure at the regional level also includes the amounts of FP5 and FP6. To correct this endogeneity problem, we deducted the regional FPs expenditure amounts from R&D. For the other innovation input, expected to influence the process of knowledge production at the local level, we consider the availability of human capital. Following a well-established literature, we measure human capital as the size of the population with tertiary education (ISCED11, classification levels 5-8).

For identifying the direct effect of the policy, we use the amounts of FP5 and FP6. To include all the observations for the FP5 and FP6 variables, we follow [Battese \(1997\)](#) and set

$FP5 = (FP5 + X)$ where $X = 1$ if $FP5 = 0$, and $X = 0$ if $FP5 > 0$ as the $FP5$ expenditure amount and we do the same with the $FP6$ expenditure amount ($FP6 = (FP6 + X)$ where $X = 1$ if $FP6 = 0$, and $X = 0$ if $FP6 > 0$).

2.5.2 Descriptive statistics

As well established, the table 2.4 shows that the number of patent applications in European regions are very heterogeneous. Its standard deviation (404) represents twice its mean (205). Denmark, Sweden, Finland, and Germany are the countries where the mean number of patents are larger, at the regional level. When weighting by the labor force, Luxembourg and Austria join these countries and Germany overtakes Denmark (see figure 2.2).

When we closely examine carefully the analysis of the EU patents filers in order to understand more precisely and to improve the assessment of the policy, we see that the distribution of patents among countries is very heterogeneous. Table 2.7 shows the total patents, public R&D spending and human capital of the EU during the whole observed period (1995-2012). Germany-based inventors alone has generated 42% of all patent applications for the EU in this period, followed by France (15%) and UK (10%). During the last two decades, the top six performers in the EU countries were Germany, France, the UK, Italy, Netherlands, and Sweden accounting together for 86% of all priority patents application filed at the EPO classified by priority year and by EU-based region inventors. The most eleven patenting EU countries are the top six cited above completed by Austria, Belgium, Finland, Denmark and Spain. These top eleven accounted together for 97% of all priority patents application filed at the EPO. Among the sixteen other countries³¹ and particularly the eastern EU Member States, a very low number of filed patents is found and they shared together 3% of all filed patents.

The R&D shows the same heterogeneity among regions and countries as patent number with a standard deviation representing about twice the mean (1521.2). The R&D expenditure per capita is quite high in countries such as Luxembourg, Sweden, and Lithuania. Germany is the European leading country in making efforts for R&D with 29% of all European public R&D expenditure and it is followed by France and, to a lesser extent, the United Kingdom

³¹Bulgaria, Cyprus, Czech Republic, Estonia, Greece, Hungary, Ireland, Latvia, Lithuania, Luxembourg, Malta, Poland, Portugal, Romania, Slovakia, and Slovenia

with, respectively 16.9% and 14.85%. The R&D expenditure of the EU Top 6 performers countries together represents 78% of the total public R&D expenditure of the whole European Union. The EU Top 11 countries generated 93% of the EU R&D and the other 16 countries (EU Low 16) share the remaining 7%. Table 2.8 shows an evolution in the distribution of the R&D effort with an increasing share for less developed countries to the detriment of leading countries.

The human capital measured by the size of the population with tertiary education is more homogeneous and we can see that its standard deviation (283) is a little larger than its mean (246). Weighted by the labor force, the share of human capital is much more similar among countries than patents, even though it is larger in Belgium, Lithuania, Estonia, and Cyprus than in other countries. Here we see that the EU Top 6 performers represent 61%, the EU Top 11 performers represent 80% and the others share the remaining 20%. The table 2.9 suggests that the evolution of this distribution has remained fairly stable during the period.

The FP5 and FP6 amounts are very heterogeneous across time and among beneficiary regions and countries (see figure 2.3): at the regional level the standard deviation of their amounts is three times greater than the mean for FP5 (respectively 13 and 4 million euros) and more than twice for FP6 (respectively 19 and 7 million euros). Table 2.10 shows that Germany receives 18.98% of the total amount of the FP5 and 19.80% of the total FP6 amount. It is followed by the United Kingdom with about 15% for the two programs and France with about 14% of the FP5 and FP6 amounts. The EU Top 6 performers receive 70.69% of the FP5 amounts and 70.73% of the FP6 amounts. The 16 less performers countries receive only about 10% of the amounts while about 90% go to the Top eleven. It is worth noting that, as many FP projects were assigned to the Brussels Region, in Belgium, while they, in fact, are localized somewhere else, spending amounts of FPs in this country are overvalued. When we keep the Brussels region in our dataset as when removing it, the estimates do not change. Focusing on their changes over time (see figure 2.3 and tables 2.11 and 2.12), FP5 spending amounts were larger between 2001 and 2004 than before 2001, reaching a peak in 2002. The expenditure on FP6 shows the same time-lag and was mainly spent from 2005 to 2009, but was still not negligible in 2011, as the program officially stopped in 2006. The countries (except Belgium) that benefit most from the FP5 in term of per capita are also those that benefit most from the FP6: Denmark, Luxembourg, Sweden, the Netherlands and to a lesser extent the United-Kingdom.

Table 2.4: Descriptive statistics

	N	Min	Max	Median	Mean	Std.dev
Patents / M. pc	3,833	0	2,493.810	78.300	161.350	229
Patents	3,877	0	4,982.670	45.370	205.840	403.660
R&D / per capita	3,659	0.820	5,324.830	444.670	656.810	667.490
R&D Expenditure	3,678	0.160	15,524.910	345	890.500	1,521.200
Human Capital (%)	3,871	0.010	0.540	0.210	0.210	0.080
Human Capital	3,871	1.180	2,506.200	150.790	246.250	283.770
FP5 / per capita	3,044	0	170.880	0.070	2.970	7.930
FP5	3,052	0	246,151,440	45,806.04	3,903,745	12,976,553
FP6 / per capita	2,170	0	147.150	1.360	5.020	9.580
FP6	2,170	0	317,864,384	936,114.90	6,918,875	18,848,354
Sum FP5-6 /per capita	3,044	0	178.660	2.160	6.540	11.880
Sum FP5-6	3,052	0	331,145,440	1,393,060	8,823,129	21,687,758

Source: Author's computations; Patent /M. pc is the number of patent per million capita, R&D Expenditure in million euros, Human Capital in thousands and all the others variables are in units.

2.6 Results

2.6.1 Results with the Cobb-Douglas function

Table 2.5 shows the results of the Cobb-Douglas production function. In estimating the Cobb-Douglas function, we run several models and use the number of patents as the dependent variable. The results suggest that human capital has no effect on innovation but R&D has a positive effect on innovation with an elasticity comprised between 0.220 and 0.238 in the different models. In the model 1, we include only FP5 and it seems to have no effect on innovation. In column 2, we include the FP6 and find a positive effect on innovation with an elasticity of 0.028. When we include the two variables at the same time in the model 3, we see in column 3 that the results remain unchanged. Finally, when we include the sum of the FP5 and FP6, we see that the total effect is almost similar to the effect of the only FP6 (0.027). As explained above, the Cobb-Douglas production function is nested in the translog production function, so we apply a Wald test to check whether the Cobb-Douglas production function is rejected in favor of the translog production function. In our case, at the 5% significance level, the Cobb-Douglas production function is rejected by the Wald test in favor of the translog production function for all the models (see figure 2.4).

Table 2.5: Results with Cobb-Douglas function

	Number of patents			
	(1)	(2)	(3)	(6)
R&D	0.221*** (0.060)	0.237*** (0.059)	0.238*** (0.059)	0.220*** (0.059)
HK	0.169 (0.133)	0.036 (0.132)	0.035 (0.132)	0.158 (0.131)
FP5	0.003 (0.002)		0.003 (0.002)	
FP6		0.028*** (0.003)	0.028*** (0.003)	
Sum FP5-6				0.027*** (0.003)
Observations	3,386	3,386	3,386	3,386
Adjusted R ²	0.005	0.037	0.038	0.036

Note: The dependent variable is the number of patents and all variables are log-transformed and first-differenced.

We used the within estimation to run our model. The columns give the estimates and the Standard errors (in parentheses below coefficients). Significance levels: ***1%; **5%; *10%

2.6.2 Results with the translog function

We first introduce variables on FPs in a translog function, in a random growth model for the entire EU-27 regions. Table 2.14, therefore, shows these estimates, for log-log specification and first differentiated model with individual fixed-effects. First of all, the coefficients of HK and R&D are very stable whatever the way to introduce FPs' variables. The R&D coefficient always ranges between 0.55 (column 5) and 0.60 (column 1), its square is also always significant and equal to about -0.065 . The human capital coefficient ranges between 0.508 (column 8) and 0.90 (column 1) and its square is about -0.11 . The interaction term between human capital and R&D spending is never significant. This leads to an average elasticity of the number of patents to R&D spending between 0.184 and 0.236 (table 2.22), at the mean point³². The elasticity of human capital is also negative at the mean point between -0.472 and 0.388. These results are a little stronger when we calculate the elasticities at the median point.

When introducing the FPs' variable, the amount of FP5 spent in one region seems to have no effect alone on the number of patents in that region. However, the regional FP6 expenditure seems to have a positive impact; its elasticity is equal to 0.028 when it is introduced only in level (columns 3 and 4). When its square is also introduced as well as an interaction term with the FP5 (column 5), the elasticity of the FP6 expenditure on the number of regional patents follows a convex form and is equal to 0,029 at the mean point

³²Table 2.21 presents the mean and median of all variables in logarithm according to the considered sample

(table 2.22). Estimates (columns 5 and 6) also highlight a substitution effect between the FP5 and FP6, as the coefficient of the interacting term between these variables is equal to -0.002 (table 2.13). If the sum of the FP5 and FP6 regional amounts is included as policy variable (columns 7 and 8 of table 2.22), results are quite similar to those obtained for the FP6 variable alone: 0.027 when introduced alone, in column 7, and $0,026$ at the mean point (column 8).

In table 2.13, we include in the model the FPs amounts and all their interacting terms with human capital and R&D spending. In column 2, the FP5 regional spending is still never significant. Coefficients associated to the regional FP6 amounts are similar to those obtained previously and the R&D spending and the FP6 spending seems to be substitutes as the interacting coefficient is significant and equal to -0.006 . These complete translog estimates show that, for entire EU-27 regions, only the FP6 spending has a significant effect on regional innovation, on average (0.026). This result remains positive but stronger when FP6 amount is replaced by the sum of FP5 and FP6 spending. In these case, the elasticity of the regional number of patents to FPs is equal to 0.043 (table 2.23). We find also that the elasticity of substitution between FP5 and FP6 is negative. This relationship is related to the negative correlation between the variables due to the fact that the FPs spending spilled over the periods. The FP5 program start later than the official lunched period and when the FP6 program started, the FP5 was running but with decreasing expenditures. That's why during the first years of the lunch of the FP6, its amounts were increasing while the FP5 amounts were decreasing. This explanation is confirmed by the fact that the effect of the sum of FP5 and FP6 spending (SumFP5-6) is positive and significant.

Moreover, when we focus on the complementarity and substitution of factors for the EU-27 countries, results in table 2.13 (column 4) show that there is complementarity between the human capital and the sum of FP5 and FP6 spending (0.007). This means that the decisions to invest in R&D must be joined to the investment in education and human capital to increase the innovation of countries. However, we find substitution (column 3) between the regional R&D spending and the FP6 spending (-0.006), meaning that there is a possible lack of coordination between national and European instruments. This may be due to a substitution effect between regional R&D spending and the europeans subsidies for innovation policies. No complementarity or substitution effect is observed between innovation the factors and the FP5 spending. Therefore, when the EU decides to fund research activities and

innovation policies, it should think at national public R&D subsidies structure but also think at improving training and teaching quality in higher education institutions to strengthen skills and human capital.

As described in the previous section, European countries and therefore regions are very heterogeneous, regarding their economic and innovation system and regarding the amount of FPs spending they benefit from. In order to distinguish different effects of the Framework Programmes, the same econometric models were run on three samples: the top 6 EU, the top 11 EU countries, and the low 16 EU countries, in terms of innovation activities, as described in the previous section. The results are shown in tables 2.15 to 2.20 and the calculated elasticities are presented in tables 2.24 to 2.29.

For the top 6 EU countries, results (table 2.15) for R&D variables and human capital have a much more significant scope compared to those obtained for the entire EU-27. Moreover, in these countries, the results (table 2.24 column 7) on the FPs effects are slightly similar than to those of the top 11 countries for both FP5 and FP6 although the effect of the sum of FP5 and FP6 is slightly stronger. Further, when focusing on the more eleven innovative countries (EU top 11), results (table 2.17 and 2.26) for R&D variables are very similar to those obtained for the entire EU-27. The regional level of human capital shows a strong concave elasticity for the 11 more innovative European countries. About the FPs impacts, the FP6 spending has the same effect as in all european countries (about 0.026), but the FP5 spending becomes significant alone as for the top 6 countries and the effect of the sum of FP5 and FP6 spending (SumFP5-6) is stronger (0.048) on regional innovation, whatever the way they enter in the regressions. Results for less performer 16 EU countries (EU Low 16) in table 2.19 suggest that while the human capital seems to have no effect, the effects of the R&D spending is negative and those of FP6 are quite similar to the previous ones of the EU-27 (0.027) in the partial translog. However, in the complete translog, the effect of the FP5 is null and those of FP6 and the sum of FP5 and FP6 seem to be negative (respectively -0.022 and -0.001). FP5 spending alone never affects regional innovation in these lagged EU regions, in terms of patents.

For the results of the complete translog (see tables 2.16, 2.18 and 2.20), we compute the elasticities at the mean point of variables. These results confirm the previous ones and suggest that the impacts of the FPs policy are larger in the EU top 11 performers countries, in terms of R&D and human capital than in the EU low 16 (lagging countries).

For the EU top 6 performers, results show complementarity between human capital and FP6 or SumFP5-6 spending but also substitution between regional R&D spending and FP6 spending. However, for these countries, no complementarity or substitution effect is detected between innovation factors and the FP5 spending. Further, when focusing on the Top EU11 performer countries, results in table 2.27 show complementarity effects between human capital and FP6 (0.007) and between human capital and the sum of FP5 and FP6 spending (SumFP5-6) (0.008) but also substitution between regional R&D spending and FP6 or SumFP5-6 spending. However, for these countries, no complementarity or substitution effect is detected between innovation factors and the FP5 spending. Furthermore, when focusing on the less innovative countries (EU Low 16), findings show that the FP5 has no effect but the FP6 and the SumFP5-6 have significant effects on regional innovation. However, no complementarity or substitution effect is detected between factors. These results may be explained by the earlier introduction of the FPs policies in leading European countries, but also reveal that certainly due to threshold effects, regions must have reached a certain level in innovation abilities in terms of R&D spending and human capital to make these policies efficient (absorptive capacity).

The results of the EU Low 16 countries in table 2.19 reinforce that idea: R&D, HK and the squared of HK are never significant, only the squared R&D is significant and equal to about -0.100 . The elasticities at the mean point show that the effect of human capital is null and the effects of regional R&D spending are negative on innovation. The effects of FP6 are also similar than previous ones but slightly smaller, as well as for the sum of FP5 and FP6. FP5 spending alone never affects regional innovation in these lagged EU regions, in terms of innovative process.

All these previous results (elasticities) are calculated at the median point and they are a little stronger than those calculated at the mean point. As you can see, the estimates from the translog production function are more significant than those from the Cobb-Douglas.

Finally, these results confirm the role of thresholds effects and that it is necessary to observe a certain level of innovative factors to make the policy efficient in the long run. These findings are in line with the assertion of Fagerberg (2004) who explained that every innovation need a new combination of existing capabilities, skills, and resources. Innovation requires high levels of resources but the availability of knowledge and qualified human resources able to implement changes in the process of production is essential. According to (Cohen and

Levinthal, 1989), innovation requires financial means to undertake expenditures for research and development which improve absorptive capacities and generate new knowledge and innovations. All these results highlight the importance of introducing a more flexible function to take into account the complementarity and substitution effects between factors but also the threshold effects and the initial endowments of innovative factors, to assess the impact of policies, especially collaborative policies such as FPs.

2.7 Conclusion

In this chapter, we have evaluated the impact of the 5th and 6th FP on the innovation process in European regions. Using a panel data set covering 218 regions of the entire EU-27 and the period 1995-2012 on innovative output, we estimate a regional knowledge production function including the FPs amount spent in each region. We follow Papke (1994) and Wooldridge (2010), to analyze the policy effect, by using a random-trend model that controls for the unobserved heterogeneity of regions that can affect innovation. This model permits that such unobserved regional heterogeneity is time-varying.

In our study, we use patent counts at the regional level over time for measuring the innovation after controlling for unobserved differences across regions. Although there are limitations to the use of patent data because all innovation is not patented, they are among the most available data to measure innovation. The results of this aggregate-level study have profound implication on European public policy, and particularly on the decisions of governments to funds research activities and innovation policies.

Findings show that for the entire EU countries the FP5 expenditure has no impact on regional innovation but the FP6 spending impacts positively the European regional innovation. Moreover, for the EU-27, results reveal complementarity effects between human capital and FP6 or SumFP5-6 spending but also substitution between regional R&D spending and FP6 spending. This means that innovation requires high levels of resources but the availability of knowledge and qualified human resources able to implement changes in the process of production is essential. No complementarity or substitution effect is detected between innovation factors and the FP5 spending. Findings show that there is a possible conflict between national and European instruments, may be due to a substitution effect between regional R&D spending and the Europeans subsidies for innovation policies.

Moreover, when focusing on the more innovative countries (EU top 11), the FP5 spending is slightly significant and the sum of the two amounts of the policy (SumFP5-6) has a stronger impact on regional innovation in these countries. Similarly, results show complementarity between human capital and FP6 or SumFP5-6 spending but also substitution between regional R&D spending and FP6 spending. Furthermore, when focusing on the less innovative countries (EU Low 16), findings show that the FP5 has no effect but the FP6 and the SumFP5-6 have significant effects on regional innovation. However, no complementarity or substitution effect is detected between factors for these countries.

Finally, these results confirm the role of thresholds effects and that it is necessary to observe a certain level of innovative factors to make the policy efficient in the long run. All these results highlight the importance of introducing a more flexible function to take into account the complementarity and substitution effects between factors but also the threshold effects and the initial endowments of innovative factors, to assess the impact of policies, especially collaborative policies such as FPs.

All these results highlight the importance of introducing more flexible functions to assess the impact of policies, especially collaborative policies such as Framework Programmes. By considering the distribution of the FPs amounts between European regions, these results suggest that there is an opportunity here for the EU commission to reallocate the subsidies towards lagging regions and supports national efforts for R&D and innovation policies. The fact that the FP6 has positive effects on lagging regions and not the FP5 is perhaps due to the increase of subsidies, the orientation towards other sectors, but also to the change of the structural funds at this period.

While our empirical study enables us to assess the impacts of the 5th and 6th Framework Programmes on the European regional innovation, it does not provide insight on the knowledge spillovers mechanisms and on networking and collaboration. It may be interesting to take into account the structural funds oriented towards innovation since 2007 when evaluating the impacts of the FPs. But also, it may make sense also to assess the policy according to the activity sectors in which regions are specialized because the FPs are oriented towards strategic priorities which give more consideration to some sectors than others. Therefore, developing a sectoral analysis approach may help to understand if the difference of effects between the FP5 and FP6 is due to the sectoral orientations.

2.8 Appendices Chapter 2

2.8.1 Descriptive statistics by country

Table 2.6: Regions and NUTS levels

Code	Country name	NUTS level	Number of regions
AT	Austria	2	9
BE	Belgium	1	3
BG	Bulgaria	2	6
CY	Cyprus	2	1
CZ	Czech Republic	2	8
DE	Germany	2	38
DK	Denmark	1	1
EE	Estonia	2	1
EL	Greece	2	13
ES	Spain	2	17
FI	Finland	1	2
FR	France	2	22
HU	Hungary	2	7
IE	Ireland	2	2
IT	Italy	2	21
LT	Lithuania	2	1
LU	Luxembourg	2	1
LV	Latvia	2	1
MT	Malta	2	1
NL	Netherlands	2	12
PL	Poland	2	16
PT	Portugal	2	7
RO	Romania	2	8
SE	Sweden	1	3
SI	Slovenia	1	1
SK	Slovakia	2	4
UK	United Kingdom	1	12
Total		-	218

Table 2.7: Overview of EU patents, R&D expenditures and human capital by country from 1995-2012

Country	Total patents		Public R&D expenditure		Human capital		
	Amount	Share %	Amount	Share %	Amount	Share %	
Germany	339092	42%	953503	29.11%	173904	18.24%	
France	118794	15%	554724	16.94%	130072	13.65%	
United Kingdom	76012	10%	486486	14.85%	157565	16.53%	
Italy	65615	8%	265468	8.11%	58779	6.17%	
Netherlands	49084	6%	159225	4.86%	40654	4.26%	
Sweden	34978	4%	122697	3.75%	24074	2.53%	
EU Top 6	683575	86%	2542103	78%	585047	61%	
Austria	21176	3%	90242	2.76%	12289	1.29%	
Belgium	20990	3%	84198	2.57%	28117	2.95%	
Finland	19186	2%	75932	2.32%	15567	1.63%	
Denmark	15397	2%	64048	1.96%	14975	1.57%	
Spain	16121	2%	181517	5.54%	105890	11.11%	
EU Top 11	776444	97%	3038041	93%	761884	80%	
Bulgaria	280	0.04%	5469	0.17%	12086	1.27%	
Cyprus	123	0.02%	904	0.03%	1970	0.21%	
Czech Republic	1768	0.22%	37965	1.16%	12776	1.34%	
Estonia	213	0.03%	3216	0.10%	3914	0.41%	
Greece	1222	0.15%	12817	0.39%	19600	2.06%	
Hungary	1945	0.24%	20284	0.62%	14569	1.53%	
Ireland	3593	0.45%	24761	0.76%	10382	1.09%	
Latvia	164	0.02%	1971	0.06%	4347	0.46%	
Lithuania	125	0.02%	10153	0.31%	10380	1.09%	
Luxembourg	1231	0.15%	6798	0.21%	982	0.10%	
Malta	72	0.01%	537	0.02%	364	0.04%	
Poland	2250	0.28%	50919	1.55%	56877	5.97%	
Portugal	996	0.12%	31418	0.96%	11985	1.26%	
Romania	6056	0.76%	11983	0.37%	21237	2.23%	
Slovakia	405	0.05%	7270	0.22%	6332	0.66%	
Slovenia	1149	0.14%	10767	0.33%	3541	0.37%	
All other EU 16	21591	3%	237231	7%	191342	20%	
Total EU 27		798035	100%	3275272	100%	953226	100%

Source: Data from Eurostat, author's computations.

Patents are in units, R&D amounts are in million euros and human capital are in thousands

Table 2.8: Overview of the European R&D expenditures from 1995 to 2012

Year	EU27			Germany		EU Top 6		EU Top 11		Other EU 16	
	Amount	Amount	Share %	Amount	Share %	Amount	Share %	Amount	Share %	Amount	Share %
1995	124 834	41 229	33%	107 500	86%	120 220	96%	4 614	4%		
1996	131 548	42 120	32%	108 626	83%	122 229	93%	9 320	7%		
1997	139 138	43 014	31%	112 977	81%	127 449	92%	11 689	8%		
1998	151 111	44 884	30%	116 464	77%	138 236	91%	12 875	9%		
1999	162 789	47 153	29%	129 288	79%	152 060	93%	10 729	7%		
2000	167 329	48 094	29%	132 560	79%	156 588	94%	10 741	6%		
2001	171 046	49 191	29%	135 341	79%	159 997	94%	11 049	6%		
2002	175 428	50 271	29%	138 589	79%	164 433	94%	10 994	6%		
2003	179 260	52 317	29%	140 984	79%	168 012	94%	11 248	6%		
2004	181 443	51 324	28%	141 507	78%	169 450	93%	11 993	7%		
2005	187 310	52 403	28%	144 675	77%	174 353	93%	12 957	7%		
2006	194 381	54 398	28%	149 333	77%	181 239	93%	13 142	7%		
2007	203 294	56 504	28%	154 686	76%	188 886	93%	14 407	7%		
2008	209 438	58 508	28%	157 076	75%	193 373	92%	16 064	8%		
2009	213 386	60 606	28%	160 110	75%	196 649	92%	16 736	8%		
2010	220 805	63 915	29%	165 668	75%	203 056	92%	17 748	8%		
2011	229 379	67 111	29%	171 115	75%	208 873	91%	20 506	9%		
2012	233 355	70 459	30%	175 607	75%	212 936	91%	20 419	9%		
Total	3 275 272	953 503	29%	2 542 103	78%	3 038 041	93%	237 231	7%		

Source: Data from Eurostat, author's computations, amounts are in million euros

Table 2.9: The EU human capital from 1995-2012

Year	EU27			Germany		EU Top 6		EU Top 11		Other EU 16	
	All	Number	Share %	Number	Share %	Number	Share %	Number	Share %	Number	Share %
1995	39740	8057	20%	24429	61%	31036	78%	8704	22%		
1996	40425	8420	21%	25274	63%	32142	80%	8282	20%		
1997	41032	8503	21%	25889	63%	33053	81%	7979	19%		
1998	41937	8605	21%	26573	63%	34069	81%	7868	19%		
1999	43609	8725	20%	27332	63%	35198	81%	8411	19%		
2000	45053	8865	20%	28168	63%	36448	81%	8605	19%		
2001	46698	9305	20%	29491	63%	38080	82%	8618	18%		
2002	47884	8871	19%	29808	62%	38998	81%	8886	19%		
2003	50308	9469	19%	31366	62%	40875	81%	9433	19%		
2004	53155	9738	18%	32646	61%	42801	81%	10354	19%		
2005	55899	10046	18%	34054	61%	44885	80%	11014	20%		
2006	57514	9865	17%	34762	60%	45922	80%	11593	20%		
2007	59279	9997	17%	35812	60%	47226	80%	12053	20%		
2008	61627	10435	17%	37245	60%	48919	79%	12708	21%		
2009	64200	10914	17%	38814	60%	50797	79%	13402	21%		
2010	66005	11043	17%	39798	60%	52192	79%	13813	21%		
2011	68066	11361	17%	40913	60%	53585	79%	14481	21%		
2012	70795	11684	17%	42672	60%	55657	79%	15138	21%		
Total	953226	173904	18%	585047	61%	761884	80%	191342	20%		

Source: Data from Eurostat, author's computations, Human Capital is in thousands and is

equivalent to the number population with tertiary (ISCED11, classification levels 5-8).

Table 2.10: Total amounts of FP5, FP6 and Sum FP5-FP6 by country

Country	FP5 amounts		FP6 amounts		Sum FP5 and FP6	
	Amount	Share %	Amount	Share %	Amount	Share %
Germany	2261509945	18.98%	2972661801	19.80%	5234171062	19.44%
France	1693880796	14.22%	2137024820	14.23%	3830905220	14.23%
United Kingdom	2001286633	16.80%	2324487497	15.48%	4325773914	16.06%
Italy	1182738218	9.93%	1431053783	9.53%	2613791623	9.71%
Netherlands	808786433	6.79%	1085740342	7.23%	1894526559	7.04%
Sweden	473812800	3.98%	667932263	4.45%	1141745009	4.24%
EU Top 6	8422014825	70.69%	10618900506	70.73%	19040913387	70.71%
Austria	290246465	2.44%	415178996	2.77%	705425299	2.62%
Belgium	611519299	5.13%	739955671	4.93%	1351474916	5.02%
Finland	271587586	2.28%	339622085	2.26%	611209635	2.27%
Denmark	336167642	2.82%	382081006	2.54%	718248630	2.67%
Spain	795596113	6.68%	927917680	6.18%	1723513487	6.40%
EU Top 11	10727131930	90.04%	13423655944	89.41%	24150785354	89.69%
Bulgaria	22820372	0.19%	38852352	0.26%	61672616	0.23%
Cyprus	19907279	0.17%	26767168	0.18%	46674429	0.17%
Czech Republic	63987438	0.54%	127831640	0.85%	191818934	0.71%
Estonia	19826029	0.17%	33332774	0.22%	53158785	0.20%
Greece	447988090	3.76%	413973749	2.76%	861961605	3.20%
Hungary	63721583	0.53%	145734530	0.97%	209455987	0.78%
Ireland	142104908	1.19%	191262341	1.27%	333367213	1.24%
Latvia	12452387	0.10%	17615025	0.12%	30067394	0.11%
Lithuania	11236389	0.09%	26442425	0.18%	37678796	0.14%
Luxembourg	21920183	0.18%	21380937	0.14%	43301102	0.16%
Malta	3822776	0.03%	9909117	0.07%	13731875	0.05%
Poland	120106632	1.01%	210749954	1.40%	330856298	1.23%
Portugal	152456713	1.28%	163718516	1.09%	316175103	1.17%
Romania	23758783	0.20%	53223982	0.35%	76982621	0.29%
Slovakia	22958099	0.19%	35033645	0.23%	57991672	0.22%
Slovenia	38034134	0.32%	74478615	0.50%	112512731	0.42%
All other EU 16	1187101795	9.96%	1590306770	10.59%	2777407161	10.31%
Total EU 27	11 914 233 725	100%	15 013 962 714	100%	26 928 192 515	100%

Source: French Ministry of Research (MESR), author's computations, amounts are in units

Table 2.11: FP5 amounts over time

Year	EU27	Germany		EU Top 6		EU Top 11		Other EU 16	
	Amount	Amount	Share %	Amount	Share %	Amount	Share %	Amount	Share %
1998	0	0		0		0		0	
1999	81421938	31074643	38%	73331891	90%	79533493	98%	1888445	2%
2000	1211465909	241486115	20%	875778353	72%	1094891216	90%	116574694	10%
2001	2011189806	386304585	19%	1445871545	72%	1820820522	91%	190369284	9%
2002	2864035027	543133236	19%	2015369257	70%	2573570502	90%	290464526	10%
2003	2791196300	520286821	19%	1963240145	70%	2508000469	90%	283195831	10%
2004	1901191635	345521631	18%	1318254536	69%	1702487156	90%	198704479	10%
2005	846723451	157407533	19%	590734987	70%	763139974	90%	83583478	10%
2006	186954354	34060370	18%	128021147	68%	167529522	90%	19424832	10%
2007	15623248	1820744	12%	8850285	57%	13499514	86%	2123734	14%
2008	3607545	413585	11%	2013955	56%	2910478	81%	697067	19%
2009	773758	0	0%	499951	65%	699736	90%	74023	10%
2010	20290	0	0%	20290	100%	20290	100%	0	0%
2011	20290	0	0%	20290	100%	20290	100%	0	0%
2012	6250	0	0%	6250	100%	6250	100%	0	0%
Total	11914229801	2261509261	19%	8422012881	71%	10727129410	90%	1187100391	10%

Source: French Ministry of research (MESR), author's computations, amounts are in units.

Table 2.12: FP6 amounts over time

Year	EU27	Germany		EU Top 6		EU Top 11		Other EU 16	
	Amount	Amount	Share %	Amount	Share %	Amount	Share %	Amount	Share %
2002	0	0		0		0		0	
2003	240524497	43157836	18%	165354053	69%	218606451	91%	21918047	9%
2004	1222976692	245898063	20%	875382671	72%	1102129160	90%	120847531	10%
2005	2170334902	434877051	20%	1534497442	71%	1942672860	90%	227662036	10%
2006	3189263282	635202181	20%	2246790112	70%	2840716560	89%	348546721	11%
2007	3181901472	635767642	20%	2247062192	71%	2833938370	89%	347963094	11%
2008	2636079512	522314620	20%	1872786472	71%	2352860070	89%	283219441	11%
2009	1606332852	315183694	20%	1140452222	71%	1443521300	90%	162811549	10%
2010	599314330	112905768	19%	422392769	70%	540388776	90%	58925554	10%
2011	145982995	25427918	17%	101394156	69%	131506342	90%	14476654	10%
2012	21248239	1926345	9%	12786460	60%	17313498	81%	3934740	19%
Total	15013958773	2972661118	20%	10618898549	71%	13423653387	89%	1590305367	11%

Source: French Ministry of research (MESR), author's computations, amounts are in units.

Figure 2.2: Heterogeneity of patents, R&D effort and human capital across countries

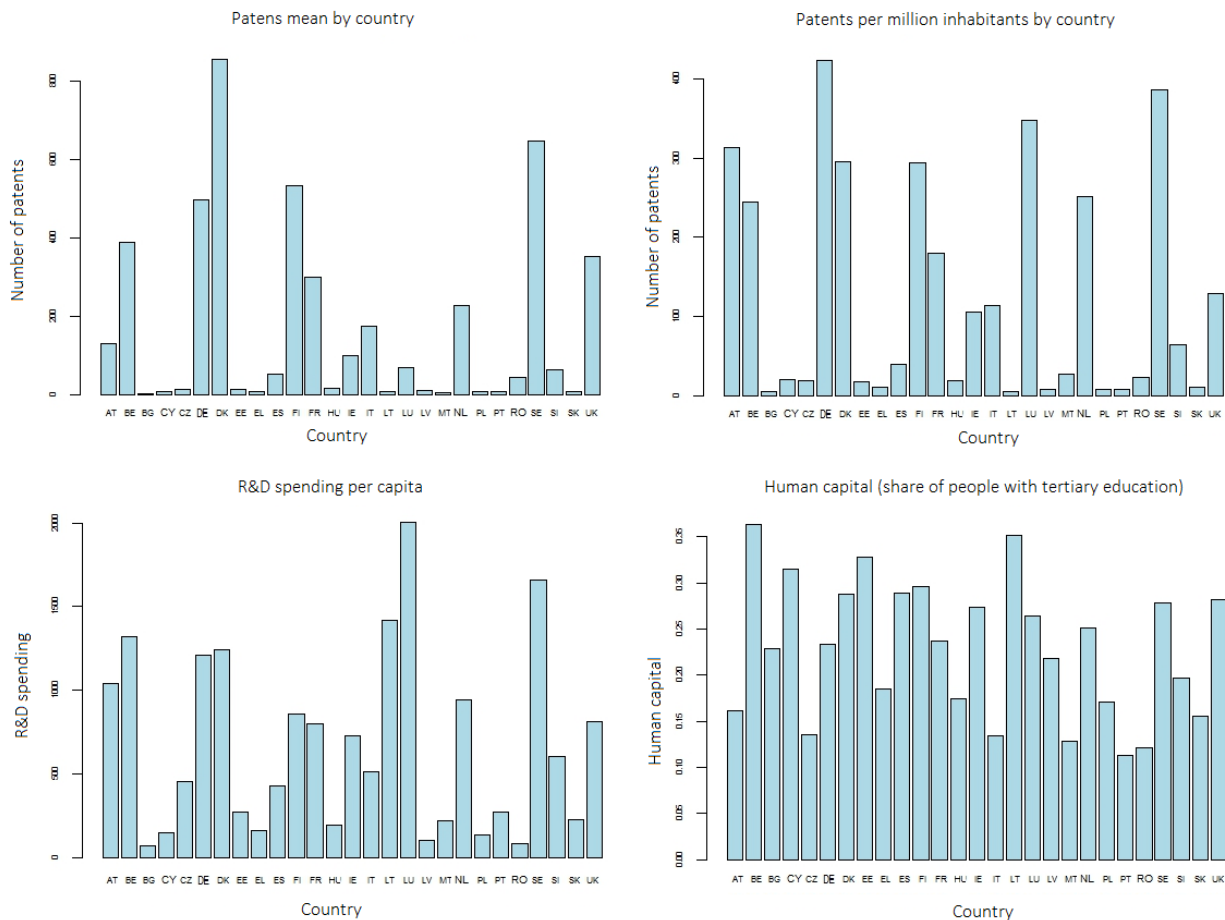
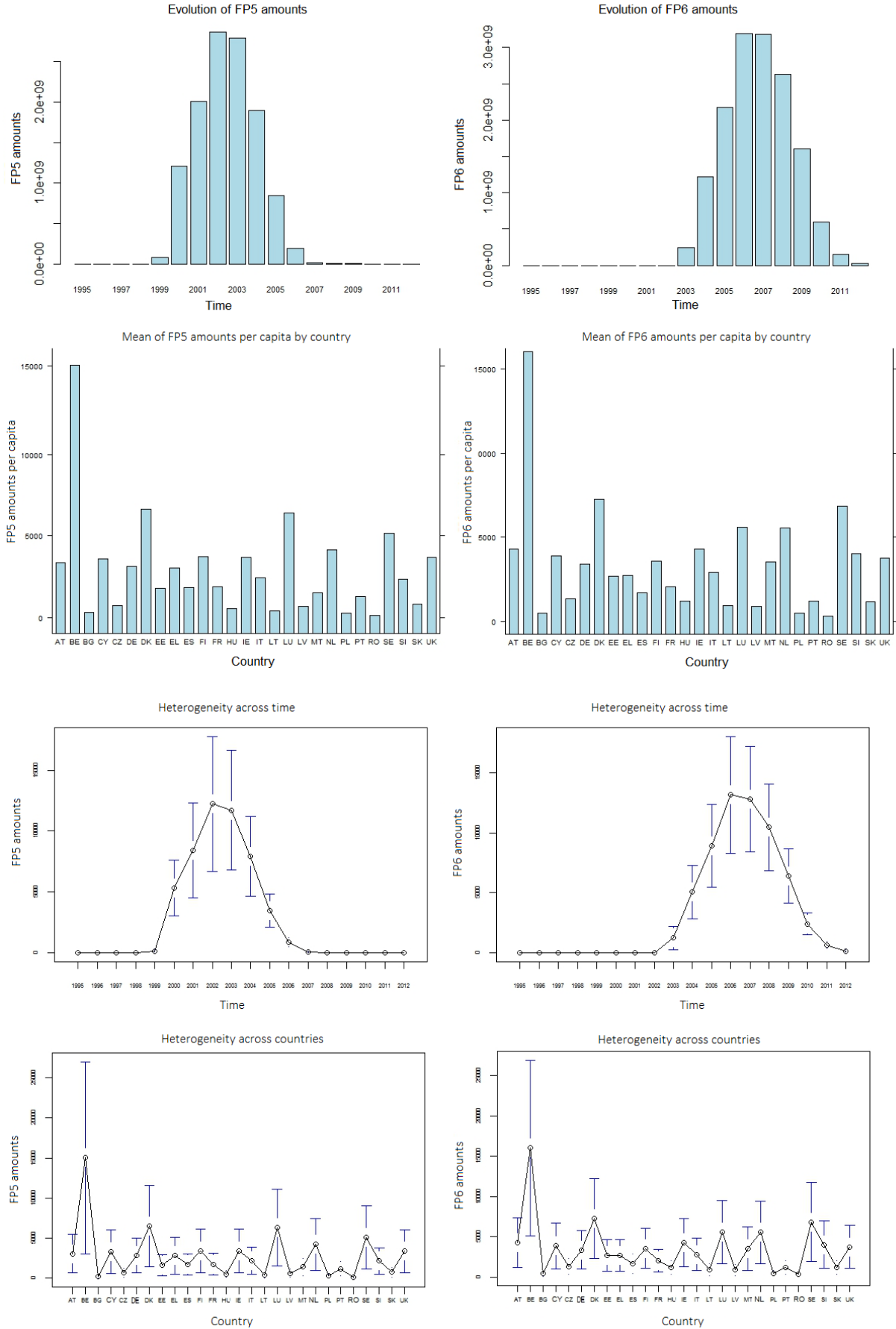


Figure 2.3: Distribution of FP5 and FP6 spending over time and between countries



2.8.2 Tables of estimation results

Figure 2.4: Implementation of the Wald test (Cob-Dougllass *vs.* Translog)

```

> # WALD TEST: H0: Cobb-Douglas function is rejected in favor of the translog function
>
> library(lmtest)
> #Equation 1: with R&D expenditure and humamn capital
> waldtest( eq1_RGM_CD, eq1_RGM_TL )
wald test

Model 1: diff(log(pat_tot), 1) ~ diff(log(dep_rd_allsect_ok), 1) + diff(log(nb_pop_activ_niv_5_8),
1)
Model 2: diff(log(pat_tot), 1) ~ diff(log(dep_rd_allsect_ok), 1) + diff(log(nb_pop_activ_niv_5_8),
1) + diff(log(dep_rd_allsect_ok) * log(dep_rd_allsect_ok),
1) + diff(log(nb_pop_activ_niv_5_8) * log(nb_pop_activ_niv_5_8),
1) + diff(log(nb_pop_activ_niv_5_8) * log(dep_rd_allsect_ok),
1)
Res.Df Df  chisq Pr(>Chisq)
1      3167
2      3164  3 15.711    0.0013 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
> #Equation 2: with R&D expenditure, humamn capital and FP5
> waldtest( eq2_RGM_CD, eq2_RGM_TL )
wald test

Model 1: diff(log(pat_tot), 1) ~ diff(log(dep_rd_allsect_ok), 1) + diff(log(nb_pop_activ_niv_5_8),
1) + diff(log(FP5_c), 1)
Model 2: diff(log(pat_tot), 1) ~ diff(log(dep_rd_allsect_ok), 1) + diff(log(nb_pop_activ_niv_5_8),
1) + diff(log(FP5_c), 1) + diff(log(dep_rd_allsect_ok) *
log(dep_rd_allsect_ok), 1) + diff(log(nb_pop_activ_niv_5_8) *
log(nb_pop_activ_niv_5_8), 1) + diff(log(FP5_c) * log(FP5_c),
1) + diff(log(nb_pop_activ_niv_5_8) * log(dep_rd_allsect_ok),
1) + diff(log(dep_rd_allsect_ok) * log(FP5_c), 1) + diff(log(nb_pop_activ_niv_5_8) *
log(FP5_c), 1)
Res.Df Df  chisq Pr(>Chisq)
1      3166
2      3160  6 19.611  0.003247 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
> #Equation 3: with R&D expenditure, humamn capital and FP6
> waldtest( eq3_RGM_CD, eq3_RGM_TL )
wald test

Model 1: diff(log(pat_tot), 1) ~ diff(log(dep_rd_allsect_ok), 1) + diff(log(nb_pop_activ_niv_5_8),
1) + diff(log(FP6_c), 1)
Model 2: diff(log(pat_tot), 1) ~ diff(log(dep_rd_allsect_ok), 1) + diff(log(nb_pop_activ_niv_5_8),
1) + diff(log(FP6_c), 1) + diff(log(dep_rd_allsect_ok) *
log(dep_rd_allsect_ok), 1) + diff(log(nb_pop_activ_niv_5_8) *
log(nb_pop_activ_niv_5_8), 1) + diff(log(FP6_c) * log(FP6_c),
1) + diff(log(nb_pop_activ_niv_5_8) * log(dep_rd_allsect_ok),
1) + diff(log(dep_rd_allsect_ok) * log(FP6_c), 1) + diff(log(nb_pop_activ_niv_5_8) *
log(FP6_c), 1)
Res.Df Df  chisq Pr(>Chisq)
1      3166
2      3160  6 181.57 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
> #Equation 4: with R&D expenditure, humamn capital, FP5 and FP6
> waldtest( eq4_RGM_CD, eq4_RGM_TL )
wald test

Model 1: diff(log(pat_tot), 1) ~ diff(log(dep_rd_allsect_ok), 1) + diff(log(nb_pop_activ_niv_5_8),
1) + diff(log(FP5_c), 1) + diff(log(FP6_c), 1)
Model 2: diff(log(pat_tot), 1) ~ diff(log(dep_rd_allsect_ok), 1) + diff(log(nb_pop_activ_niv_5_8),
1) + diff(log(FP5_c), 1) + diff(log(FP6_c), 1) + diff(log(dep_rd_allsect_ok) *
log(dep_rd_allsect_ok), 1) + diff(log(nb_pop_activ_niv_5_8) *
log(nb_pop_activ_niv_5_8), 1) + diff(log(FP5_c) * log(FP5_c),
1) + diff(log(FP6_c) * log(FP6_c), 1) + diff(log(nb_pop_activ_niv_5_8) *
log(dep_rd_allsect_ok), 1) + diff(log(dep_rd_allsect_ok) *
log(FP5_c), 1) + diff(log(dep_rd_allsect_ok) * log(FP6_c),
1) + diff(log(nb_pop_activ_niv_5_8) * log(FP5_c), 1) + diff(log(nb_pop_activ_niv_5_8) *
log(FP6_c), 1) + diff(log(FP5_c) * log(FP6_c), 1)
Res.Df Df  chisq Pr(>Chisq)
1      3165
2      3155 10 293.99 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Note: These tests are implemented by using the *waldtest* function in R

Table 2.13: Translog Random trend model - EU27

	Number of Patents				
	(1)	(2)	(3)	(4)	(5)
R&D	0.603*** (0.178)	0.622*** (0.178)	0.558*** (0.171)	0.594*** (0.172)	0.564*** (0.168)
HK	0.900** (0.450)	0.902** (0.451)	0.764* (0.433)	0.530 (0.437)	0.601 (0.427)
FP5		-0.011 (0.013)			-0.011 (0.012)
FP6			-0.078*** (0.015)		-0.071*** (0.014)
Sum FP5-6				-0.082*** (0.014)	
Squared R&D	-0.065*** (0.020)	-0.067*** (0.021)	-0.060*** (0.020)	-0.066*** (0.020)	-0.062*** (0.019)
Squared HK	-0.103* (0.057)	-0.105* (0.058)	-0.122** (0.055)	-0.075 (0.056)	-0.100* (0.055)
Squared FP5		-0.001 (0.001)			0.0001 (0.001)
Squared FP6			0.011*** (0.001)		0.011*** (0.001)
Squared Sum FP5-6				0.007*** (0.001)	
R&D * HK	0.033 (0.052)	0.030 (0.052)	0.044 (0.050)	0.043 (0.050)	0.041 (0.050)
R&D * FP5		0.0005 (0.002)			0.0002 (0.002)
HK * FP5		0.004 (0.004)			0.005 (0.003)
R&D * FP6			-0.006** (0.003)		-0.004 (0.002)
HK * FP6			0.0004 (0.004)		0.001 (0.004)
R&D * Sum FP5-6				-0.002 (0.003)	
HK * Sum FP5-6				0.007* (0.004)	
FP5 * FP6					-0.002*** (0.0002)
Observations	3,386	3,386	3,386	3,386	3,386
Adjusted R ²	0.009	0.011	0.086	0.070	0.114

Note: The dependent variable is the number of patents and all variables are log-transformed and first-differenced. We used the within estimation to run our model. The columns give the estimates and the Standard errors (columns Standard errors are in parentheses presented below coefficients). Significance levels: ***1%; **5%; *10%.

Table 2.16: Translog Random trend model - Top EU6

	Number of Patents				
	(1)	(2)	(3)	(4)	(5)
R&D	1.057*** (0.228)	1.071*** (0.229)	0.980*** (0.205)	1.043*** (0.211)	0.932*** (0.196)
HK	1.932*** (0.567)	1.943*** (0.571)	1.309** (0.511)	1.132** (0.525)	1.087** (0.490)
FP5		0.009 (0.013)			0.013 (0.011)
FP6			-0.067*** (0.013)		-0.066*** (0.012)
Sum FP5-6				-0.043*** (0.013)	
Squared R&D	-0.099** (0.039)	-0.096** (0.040)	-0.083** (0.035)	-0.070* (0.036)	-0.086** (0.034)
Squared HK	-0.183* (0.095)	-0.178* (0.095)	-0.167* (0.086)	-0.092 (0.087)	-0.143* (0.082)
Squared FP5		-0.001 (0.001)			0.00004 (0.0005)
Squared FP6			0.011*** (0.001)		0.010*** (0.001)
Squared Sum FP5-6				0.006*** (0.001)	
R&D * HK	0.023 (0.107)	0.012 (0.109)	0.030 (0.098)	-0.021 (0.099)	0.040 (0.095)
R&D * FP5		-0.0004 (0.004)			-0.002 (0.003)
HK * FP5		0.001 (0.005)			0.004 (0.004)
R&D * FP6			-0.015*** (0.004)		-0.010*** (0.003)
HK * FP6			0.008* (0.005)		0.008* (0.004)
R&D * Sum FP5-6				-0.013*** (0.004)	
HK * Sum FP5-6				0.014*** (0.005)	
FP5 * FP6					-0.002*** (0.0002)
Observations	1,757	1,757	1,757	1,757	1,757
Adjusted R ²	0.022	0.025	0.207	0.166	0.277

Note: The dependent variable is the number of patents and all variables are log-transformed and first-differenced. We used the within estimation to run our model. The columns give the estimates and the Standard errors (columns Standard errors are in parentheses presented below coefficients). Significance levels: ***1%; **5%; *10%.

Table 2.14: Translog Random Trend Model - EU27

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Number of Patents							
R&D	0.603*** (0.178)	0.599*** (0.178)	0.583*** (0.174)	0.579*** (0.175)	0.551*** (0.172)	0.555*** (0.168)	0.556*** (0.175)	0.568*** (0.172)
HK	0.900*** (0.450)	0.880* (0.450)	0.830* (0.442)	0.809* (0.442)	0.612 (0.438)	0.657 (0.426)	0.629 (0.443)	0.508 (0.436)
Squared R&D	-0.065*** (0.020)	-0.065*** (0.020)	-0.063*** (0.020)	-0.062*** (0.020)	-0.064*** (0.020)	-0.060*** (0.019)	-0.065*** (0.020)	-0.068*** (0.020)
Squared HK	-0.103* (0.057)	-0.102* (0.058)	-0.113** (0.056)	-0.111** (0.056)	-0.089 (0.056)	-0.095* (0.054)	-0.079 (0.057)	-0.068 (0.056)
R&D * HK	0.033 (0.052)	0.034 (0.052)	0.037 (0.051)	0.038 (0.051)	0.047 (0.050)	0.033 (0.049)	0.044 (0.051)	0.048 (0.050)
FP5		0.003 (0.002)		0.003 (0.002)	0.017*** (0.003)	0.013 (0.009)		
FP6					0.028*** (0.003)	-0.081*** (0.010)		
FP5 * FP6					0.050*** (0.004)	-0.002*** (0.0002)		
Squared FP5						0.0004 (0.001)		
Squared FP6						0.010*** (0.001)		
Sum FP5-6							0.027*** (0.003)	-0.064*** (0.009)
Squared Sum FP5-6								0.007*** (0.001)
Observations	3,386	3,386	3,386	3,386	3,386	3,386	3,386	3,386
Adjusted R ²	0.009	0.009	0.042	0.042	0.064	0.111	0.040	0.069

Note: The dependent variable is the number of patents and all variables are log-transformed and first-differenced. We used the within estimation to run our model. The columns give the estimates, and the Standard errors (columns Standard errors are in parentheses presented below coefficients). Significance levels: ***1%; **5%; *10%.

Table 2.15: Translog Random trend model - Top EU6

	Number of patents							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R&D	1.057*** (0.228)	1.062*** (0.228)	1.065*** (0.219)	1.070*** (0.219)	0.997*** (0.210)	0.951*** (0.195)	1.011*** (0.217)	1.032*** (0.210)
HK	1.932*** (0.567)	1.930*** (0.567)	1.820*** (0.545)	1.818*** (0.544)	1.508*** (0.523)	1.310*** (0.485)	1.622*** (0.540)	1.280** (0.524)
Squared R&D	-0.099** (0.039)	-0.098** (0.039)	-0.074** (0.037)	-0.073* (0.037)	-0.082** (0.036)	-0.082** (0.033)	-0.096*** (0.037)	-0.092** (0.036)
Squared HK	-0.183* (0.095)	-0.179* (0.095)	-0.161* (0.091)	-0.157* (0.091)	-0.137 (0.087)	-0.137* (0.081)	-0.147 (0.090)	-0.103 (0.087)
R&D * HK	0.023 (0.107)	0.018 (0.103)	-0.034 (0.103)	-0.039 (0.103)	-0.003 (0.099)	0.012 (0.091)	0.020 (0.102)	0.004 (0.099)
FP5		0.004* (0.002)		0.004* (0.002)	0.021*** (0.002)	0.022*** (0.007)		
FP6			0.028*** (0.002)	0.028*** (0.002)	0.054*** (0.003)	-0.080*** (0.009)		
FP5 * FP6					-0.002*** (0.0002)	-0.002*** (0.0002)		
Squared FP5						-0.00001 (0.0005)		
Squared FP6						0.010*** (0.001)		
Sum FP5-6							0.031*** (0.002)	-0.047*** (0.008)
Squared Sum FP5-6								0.006*** (0.001)
Observations	1,757	1,757	1,757	1,757	1,757	1,757	1,757	1,757
Adjusted R ²	0.022	0.024	0.094	0.096	0.163	0.273	0.110	0.161

Note: The dependent variable is the number of patents and all variables are log-transformed and first-differenced. We used the within estimation to run our model. The columns give the estimates, and the Standard errors (columns Standard errors are in parentheses presented below coefficients). Significance levels: ***1%; **5%; *10%.

Table 2.17: Translog Random Trend Model - Top EU11

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Number of patents							
R&D	0.631*** (0.178)	0.626*** (0.178)	0.693*** (0.173)	0.688*** (0.172)	0.654*** (0.168)	0.650*** (0.158)	0.594*** (0.172)	0.650*** (0.168)
HK	1.989*** (0.480)	1.986*** (0.479)	1.935*** (0.464)	1.932*** (0.464)	1.686*** (0.452)	1.639*** (0.427)	1.747*** (0.464)	1.536*** (0.452)
Squared R&D	-0.097*** (0.030)	-0.097*** (0.030)	-0.078*** (0.029)	-0.077*** (0.029)	-0.077*** (0.028)	-0.076*** (0.027)	-0.089*** (0.029)	-0.089*** (0.028)
Squared HK	-0.255*** (0.082)	-0.254*** (0.082)	-0.233*** (0.079)	-0.232*** (0.079)	-0.199*** (0.077)	-0.207*** (0.073)	-0.218*** (0.079)	-0.189*** (0.077)
R&D * HK	0.150 (0.093)	0.149 (0.093)	0.091 (0.090)	0.089 (0.090)	0.085 (0.087)	0.083 (0.082)	0.125 (0.089)	0.111 (0.087)
FP5		0.004* (0.002)		0.004* (0.002)	0.019*** (0.002)	0.020*** (0.007)		
FP6			0.028*** (0.002)	0.028*** (0.002)	0.051*** (0.003)	-0.084*** (0.009)		
FP5 * FP6					-0.002*** (0.0002)	-0.002*** (0.0002)		
Squared FP5						0.0001 (0.0005)		
Squared FP6						0.010*** (0.001)		
Sum FP5-6							0.029*** (0.002)	-0.052*** (0.008)
Squared Sum FP5-6								0.006*** (0.001)
Observations	2,292	2,292	2,292	2,292	2,292	2,292	2,292	2,292
Adjusted R ²	0.028	0.030	0.088	0.089	0.134	0.223	0.091	0.134

Note: The dependent variable is the number of patents and all variables are log-transformed and first-differenced. We used the within estimation to run our model. The columns give the estimates, and the Standard errors (columns Standard errors are in parentheses presented below coefficients). Significance levels: ***1%; **5%; *10%.

Table 2.18: RGM Results for complete translog - Top EU11

	Number of patents				
	(1)	(2)	(3)	(4)	(5)
R&D	0.631*** (0.178)	0.666*** (0.179)	0.668*** (0.163)	0.712*** (0.169)	0.673*** (0.158)
HK	1.989*** (0.480)	1.948*** (0.480)	1.683*** (0.440)	1.488*** (0.452)	1.425*** (0.426)
FP5		-0.010 (0.012)			-0.007 (0.011)
FP6			-0.061*** (0.012)		-0.061*** (0.012)
Sum FP5-6				-0.076*** (0.012)	
Squared R&D	-0.097*** (0.030)	-0.100*** (0.031)	-0.081*** (0.028)	-0.084*** (0.029)	-0.085*** (0.027)
Squared HK	-0.255*** (0.082)	-0.251*** (0.082)	-0.245*** (0.075)	-0.183** (0.077)	-0.210*** (0.073)
Squared FP5		-0.001 (0.001)			-0.0001 (0.001)
Squared FP6			0.011*** (0.001)		0.011*** (0.001)
Squared Sum FP5-6				0.006*** (0.001)	
R&D * HK	0.150 (0.093)	0.145 (0.093)	0.117 (0.085)	0.092 (0.088)	0.106 (0.083)
R&D * FP5		0.001 (0.003)			0.002 (0.003)
HK * FP5		0.003 (0.004)			0.003 (0.003)
R&D * FP6			-0.015*** (0.003)		-0.011*** (0.003)
HK * FP6			0.006 (0.004)		0.007* (0.004)
R&D * Sum FP5-6				-0.002 (0.003)	
HK * Sum FP5-6				0.008** (0.004)	
FP5 * FP6					-0.002*** (0.0002)
Observations	2,292	2,292	2,292	2,292	2,292
Adjusted R ²	0.028	0.033	0.181	0.137	0.232

Note: The dependent variable is the number of patents and all variables are log-transformed and first-differenced. We used the within estimation to run our model. The columns give the estimates and the Standard errors (columns Standard errors are in parentheses presented below coefficients). Significance levels: ***1%; **5%; *10%.

Table 2.19: Partial Translog Random trend model - Low EU16

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Number of patents							
R&D	0.675 (0.441)	0.677 (0.442)	0.545 (0.439)	0.544 (0.440)	0.517 (0.438)	0.422 (0.435)	0.566 (0.440)	0.411 (0.437)
HK	-0.045 (0.904)	-0.040 (0.908)	-0.234 (0.898)	-0.239 (0.902)	-0.337 (0.899)	-0.299 (0.889)	-0.321 (0.903)	-0.484 (0.894)
Squared R&D	-0.101** (0.048)	-0.101** (0.048)	-0.095** (0.047)	-0.095** (0.047)	-0.091* (0.047)	-0.081* (0.047)	-0.089* (0.047)	-0.081* (0.047)
Squared HK	-0.036 (0.107)	-0.037 (0.107)	-0.040 (0.106)	-0.039 (0.106)	-0.023 (0.106)	-0.033 (0.105)	-0.008 (0.107)	0.003 (0.106)
R&D * HK	0.043 (0.091)	0.043 (0.091)	0.072 (0.090)	0.072 (0.090)	0.073 (0.090)	0.077 (0.089)	0.056 (0.090)	0.086 (0.090)
FP5		-0.0004 (0.006)		0.0004 (0.006)	0.012* (0.007)	-0.002 (0.027)		
FP6			0.027*** (0.007)	0.027*** (0.007)	0.045*** (0.009)	-0.089*** (0.028)		
FP5 * FP6					-0.002*** (0.001)	-0.002*** (0.001)		
Squared FP5						0.001 (0.002)		
Squared FP6							0.011*** (0.002)	
Sum FP5-6							0.022*** (0.007)	-0.104*** (0.027)
Squared Sum FP5-6								0.010*** (0.002)
Observations	1,094	1,094	1,094	1,094	1,094	1,094	1,094	1,094
Adjusted R ²	0.006	0.006	0.021	0.021	0.028	0.050	0.016	0.036

Note: The dependent variable is the number of patents and all variables are log-transformed and first-differenced. We used the within estimation to run our model. The columns give the estimates, and the Standard errors (columns Standard errors are in parentheses presented below coefficients). Significance levels: ***1%; **5%; *10%.

Table 2.20: RGM Results for complete translog - Low EU16

	Number of patents				
	(1)	(2)	(3)	(4)	(5)
R&D	0.675 (0.441)	0.685 (0.446)	0.528 (0.436)	0.406 (0.437)	0.488 (0.439)
HK	-0.045 (0.904)	-0.012 (0.913)	-0.052 (0.896)	-0.450 (0.898)	-0.136 (0.902)
FP5		-0.006 (0.038)			-0.019 (0.037)
FP6			-0.115*** (0.044)		-0.096** (0.045)
Sum FP5-6				-0.116*** (0.039)	
Squared R&D	-0.101** (0.048)	-0.100** (0.048)	-0.089* (0.047)	-0.080* (0.047)	-0.080* (0.047)
Squared HK	-0.036 (0.107)	-0.041 (0.108)	-0.054 (0.106)	-0.003 (0.107)	-0.039 (0.107)
Squared FP5		-0.0002 (0.002)			0.001 (0.002)
Squared FP6			0.009*** (0.002)		0.010*** (0.002)
Squared Sum FP5-6				0.010*** (0.002)	
R&D * HK	0.043 (0.091)	0.041 (0.091)	0.052 (0.091)	0.086 (0.090)	0.051 (0.091)
R&D * FP5		-0.001 (0.005)			-0.002 (0.005)
HK * FP5		0.003 (0.008)			0.007 (0.008)
R&D * FP6			0.007 (0.006)		0.008 (0.006)
HK * FP6			-0.001 (0.011)		-0.003 (0.011)
R&D * Sum FP5-6				-0.0002 (0.006)	
HK * Sum FP5-6				0.003 (0.009)	
FP5 * FP6					-0.002*** (0.001)
Observations	1,094	1,094	1,094	1,094	1,094
Adjusted R ²	0.006	0.006	0.042	0.036	0.052

Note: The dependent variable is the number of patents and all variables are log-transformed and first-differenced. We used the within estimation to run our model. The columns give the estimates and the Standard errors (columns Standard errors are in parentheses presented below coefficients). Significance levels: ***1%; **5%; *10%.

2.8.3 Calculated Elasticities

Table 2.21: Mean and median of variables in logarithm used to compute the elasticities

EU27			
	N	Median	Mean
Log (R&D)	3678	5.64	5.84
Log (Human capital)	3871	4.97	5.02
Log (FP5)	3052	7.76	10.73
Log (FP6)	2180	12.57	13.73
Log (Sum_FP5-6)	3052	12.89	14.15
EU Top 6			
	N	Mean	Median
Log (R&D)	1879	6.48	6.49
Log (Human capital)	1919	5.28	5.39
Log (FP5)	1512	8.45	11.89
Log (FP6)	1080	13.48	14.59
Log (Sum_FP5-6)	1512	13.79	15.08
EU Top 11			
	N	Mean	Median
Log (R&D)	2446	6.31	6.39
Log (Human capital)	2495	5.22	5.32
Log (FP5)	1960	8.38	11.78
Log (FP6)	1400	13.33	14.46
Log (Sum_FP5-6)	1960	13.64	14.89
EU Low 16			
	N	Mean	Median
Log (R&D)	1232	4.31	4.28
Log (Human capital)	1376	4.51	4.55
Log (FP5)	1092	6.66	9.21
Log (FP6)	780	11.21	12.59
Log (Sum_FP5-6)	1092	11.54	12.89

Source: Author's computations. This value are used to calculate the elasticities.

Table 2.22: Elasticity for partial translog - EU 27

EU 27								
Elasticity at the mean values in constrained translog								
	1	2	3	4	5	6	7	8
R&D	0.236	0.232	0.228	0.229	0.190	0.217	0.189	0.184
HK	0.388	0.373	0.268	0.257	0.000	-0.472	0.000	0.000
FP5		0.000		0.000	-0.008	-0.025		
FP6			0.028	0.028	0.034	0.029		
Sum FP56							0.027	0.026

Table 2.23: Elasticity for complete translog - EU 27

EU 27					
Elasticity at the mean values in non-constrained translog					
	1	2	3	4	5
R&D	0.236	0.244	0.144	0.222	0.214
HK	0.388	0.380	0.158	0.090	-0.522
FP5		0.000			-0.025
FP6			0.026		0.052
Sum_FP5-6				0.043	

Table 2.24: Elasticity for partial translog - EU Top 6

EU Top 6								
Elasticity at the mean values in constrained translog								
	1	2	3	4	5	6	7	8
R&D	0.415	0.427	0.585	0.597	0.466	0.420	0.389	0.436
HK	0.966	0.985	0.970	0.989	1.508	0.587	1.622	1.280
FP5		0.000		0.004	-0.006	-0.005		
FP6			0.028	0.028	0.037	0.038		
Sum FP56							0.031	0.036

Table 2.25: Elasticity for complete translog - EU Top 6

UE Top 6					
Elasticity at the mean values in non-constrained translog					
	1	2	3	4	5
R&D	0.415	0.449	0.361	0.589	0.375
HK	0.966	1.003	0.427	1.325	0.305
FP5		0.000			-0.027
FP6			0.026		0.052
Sum_FP5-6				0.029	

Table 2.26: Elasticity for partial translog - EU Top 11

UE Top 11								
Elasticity at the mean values in constrained translog								
	1	2	3	4	5	6	7	8
R&D	0.019	0.014	0.201	0.202	0.168	0.170	0.032	0.088
HK	0.658	0.660	0.719	0.721	0.647	0.558	0.609	0.549
FP5		0.000		0.004	-0.008	-0.007		
FP6			0.028	0.028	0.034	0.033		
Sum FP56							0.029	0.030

Table 2.27: Elasticity for complete translog - EU Top 11

UE Top 11					
Elasticity at the mean values in non-constrained translog					
	1	2	3	4	5
R&D	0.019	0.035	0.077	0.182	0.137
HK	0.658	0.638	0.404	0.724	0.302
FP5		0.000			-0.027
FP6			-0.009		0.069
Sum_FP5-6				0.048	

Table 2.28: Elasticity for partial translog - EU Low 16

UE Low 16								
Elasticity at the mean values in constrained translog								
	1	2	3	4	5	6	7	8
R&D	-0.435	-0.435	-0.409	-0.409	-0.392	-0.349	-0.384	-0.349
HK	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
FP5		0.000		0.000	0.012	0.000		
FP6			0.027	0.027	0.045	0.034		
Sum FP56							0.000	0.000

Table 2.29: Elasticity for complete translog - EU Low 16

UE Low 16					
Elasticity at the mean values in non-constrained translog					
	1	2	3	4	5
R&D	-0.435	-0.431	-0.451	-0.345	-0.345
HK	0.000	0.000	0.000	0.000	-0.022
FP5		0.000			-0.022
FP6			-0.014		0.003
Sum_FP5-6				-0.001	

Chapter 3

Assessing the impacts of the French competitiveness clusters policy on SMEs' performance³³

³³I thank EuroLIO for the opportunity to participate in the study entitled "Impacts économiques et territoriaux des pôles de compétitivité selon les territoires" ordered by the CGET and France Stratégie.

Abstract

This chapter examines the effectiveness of the competitiveness clusters policy on participating small and medium-sized enterprises (SMEs) in terms of innovation input additionality and output additionality. We combine data from several sources to build a rich firm-level panel data set covering the 2005-2012 period and use an original strategy to construct different measures of treatment distinguishing cluster membership and participation in R&D projects. We first analyze the selection process before using the conditional difference-in-difference (CDiD) estimator to control for unobserved heterogeneity effects and to test the additionality hypothesis.

The findings suggest the rejection of any crowding-out effect, no matter what treatment option is used, and indicate substantial additionality effects on innovation inputs (R&D spending and employment related to R&D). With regard to output additionality, there are positive effects on employment, but the effects on other types of economic performance are generally weak or nonexistent. Moreover, when the different treatment options are compared, joint participation in clusters and projects induces a strong multiplier effect on privately financed R&D, and to a lesser extent, adhesion to clusters has a positive effect on privately financed R&D. However, participating in Unique Interministerial Fund (FUI) projects alone rarely has positive effects in terms of input additionality and therefore does not lead to a substantial increase in private R&D spending. Furthermore, with regard to output performance, the effects of joint treatments are strongly positive for total employment; to a lesser extent, this is also the case for SMEs only in being a member of a cluster. But the effects are very weak or nonexistent for SMEs that participate only in FUI projects. On the whole, the results suggest that the effects of the policy are stronger for SMEs that receive both treatments. The effects of only cluster adhesion are stronger than those of only participating in FUI projects.

Keywords: Clusters policy, R&D subsidies, SMEs, Policy Evaluation, Conditional Difference-in-Difference

JEL-Classification: C14, C21, O32, O38

3.1 Introduction

France is traditionally very centralized in its economic policy approach. However, the publication of the report of Blanc (2004) entitled “*Pour un écosystème de la croissance*” and another of DATAR (2004)³⁴ called “*La France, puissance industrielle, une nouvelle politique industrielle par les territoires*” constitutes a decisive turning point for the design of French economic policies. By emphasizing a certain lack of competitiveness and the risk of a deindustrialization process that France is facing, these two reports make reference, among others, to regional clusters policies implemented in certain European countries³⁵. They suggest that in a global economy characterized by permanent competition, French industry should be more reactive in building capacity to develop new technologies because, while technical progress has become a factor of production that is continuously involved in productivity gains, new technologies are the subjects of increasing complexity and an extremely high rate of evolution. Encouraged by the European Council’s objective³⁶ and following these two reports, the government decided to implement an ambitious industrial policy called the competitiveness clusters policy.

This newly implemented industrial policy aims to bring new dynamism and creativity to the way that France conducts innovation and its regional policy. A competitiveness cluster is therefore defined by the DATAR (2004) as a grouping of small and large companies, research laboratories and training establishments in a well-identified territory and with a targeted theme. A competitiveness cluster is defined by the 2005 finance law as a “*grouping on the same territory, of companies, higher education institutions, and public or private research centers which have to work together to implement innovation projects for economic development*”. This notion is close to the definition of a cluster by Porter (1990) as “*a group of companies and institutions sharing the same field of expertise, close geographically, connected between them and complementary*”. This policy aims to enhance innovation and competitiveness and develop economic growth by promoting collaboration among firms, laboratories, and training centers.

³⁴La Délégation interministérielle à l’Aménagement du Territoire et à l’Attractivité Régionale (DATAR).

³⁵In Germany, the United Kingdom, Spain, Italy, Netherlands and Ireland, for instance

³⁶In March 2000, the European Union implemented the Lisbon strategy, which aims to enhance the knowledge-based economy, advance economic development and make Europe a more attractive place to invest by raising overall R&D investment to 3% of gross domestic product (GDP) by 2010.

Each competitiveness cluster develops its own strategy to develop strategic partnerships between the various actors that have complementary skills and to develop strategic collaborative R&D projects. Through the policy, the government aims to stimulate privately financed R&D and to enable cross-fertilization between industry and science through collaboration. These collaborative R&D projects can bring public and private research closer together and promote a global environment that is favorable to innovation, jobs creation and improvement of firms' performance. This policy may be viewed as a mixture of policy instruments because, in addition to the development of connectivity among actors, the competitiveness clusters policy accumulates not only supply-side instruments (see chapter 1) in the form of direct funding of firms' R&D but also fiscal incentives for innovation. The government provides direct grants to R&D projects through the FUI, which is the main funding instrument, and other public agencies also support the funding of firms and innovative activities in parallel with the FUI.

As the policy leads to substantial costs for the government, it is, therefore, important to study its effects on the beneficiary companies in terms of both input additionality (R&D expenditure) and output additionality (innovation, employment and firms' performance related to the market). In the literature, there are few studies that assess the impact of the French competitiveness clusters policy. These studies include [Erdyn-Technopolis and Bearpoint \(2012\)](#); [Fontagné et al. \(2013\)](#); [Brossard et al. \(2014\)](#); [Bellégo and Dortet-Bernadet \(2014\)](#); [Ben Hassine and Mathieu \(2017\)](#) and [Chaudey and Dessertine \(2016\)](#). Globally, the findings of these studies reject the crowding-out hypothesis and suggest weak positive impacts on the input additionality (private R&D and employment in R&D) of SMEs. However, they find no substantial effects of the policy in terms of output additionality (innovation and market performance). This lack of conclusive results regarding the effectiveness of the policy is partly attributable to the lack of adequate data and methodology and also to the simultaneity of several instruments of innovation policies.

This chapter contributes to this growing literature on the evaluation of the competitiveness clusters policy by focusing on its impacts on SMEs in terms of input and output additionality. We can ask many questions about the policy impacts. What are the factors that determine the participation of firms in the clusters policy? What are the impacts of participation in the competitiveness clusters policy in terms of input and output additionality? To boost their performance, do firms need to belong to clusters, to participate in FUI projects or to partici-

pate jointly in clusters and projects? We try to answer all these questions in this chapter. To assess the impacts of the policy, we use the conditional difference-in-difference method, which consists of combining the difference-in-difference with matching techniques, and we consider two levels of treatment (adhesion in clusters and participation in FUI projects). Our sample is composed of unbalanced panel data of French SMEs over the period from 2005 to 2012.

Our results suggest that participation in the competitiveness clusters policy has positive effects on participating SMEs' innovation and performance. Whatever the type of participation, there is no crowding-out effect. However, the effects are heterogeneous and sometimes mixed when we take into account and compare the different types of participation. There are strong effects on employment and, to a lesser extent, on R&D spending. The effects on turnover, added value and export are generally weak or nonexistent. The effects of the policy are very strong for the SMEs that receive both treatments. The effects of being only a member of clusters are weaker than the effects of participating in both treatments but stronger than the effects of participating only in FUI projects.

The chapter is organized as follows: Section 2 presents the French competitiveness clusters policy. Section 3 presents the related literature review. Section 4 describes the data in detail and presents summary statistics for the main variables to highlight trends and stylized facts. Section 5 presents the econometric methodology used to assess the impact of the policy. Section 6 presents the results, and section 7 concludes.

3.2 The French competitiveness clusters policy

3.2.1 Definition and implementation of the policy

Created in 2004, the competitiveness clusters policy aims to make the economy more competitive, create jobs, bring private and public research together and develop certain areas that are experiencing difficulty while preventing companies from relocating ([DATAR, 2004](#)). The goal of the policy is to build on synergies and collaborative innovation projects to give partner firms the chance to become first in their markets, both in France and abroad. The interministerial committee in charge of the planning and development of the territory (CIADT) is in charge of attributing the label "Pôle de Compétitivité". A competitiveness cluster is an association that brings together, based on a targeted theme, companies, research laborato-

ries, training establishments and national and local public authorities. It aims to foster the development of collaborative research and development (R&D) projects and innovation.

The core activity of the clusters is to develop collaborative innovation projects while integrating the potential economic benefits as early as possible. According to the DATAR, clusters are supposed to have two main priorities (DATAR, 2004). The first consists of reinforcing the economic benefits of R&D projects and becoming manufacturers of the products of the future by transforming collaborative R&D efforts into innovative products, processes, and services to be released onto the market. The second consists of supporting firms by offering them collective and individual services to access funding, international markets, and industrial properties and also by addressing their needs in terms of skills and individual assistance.

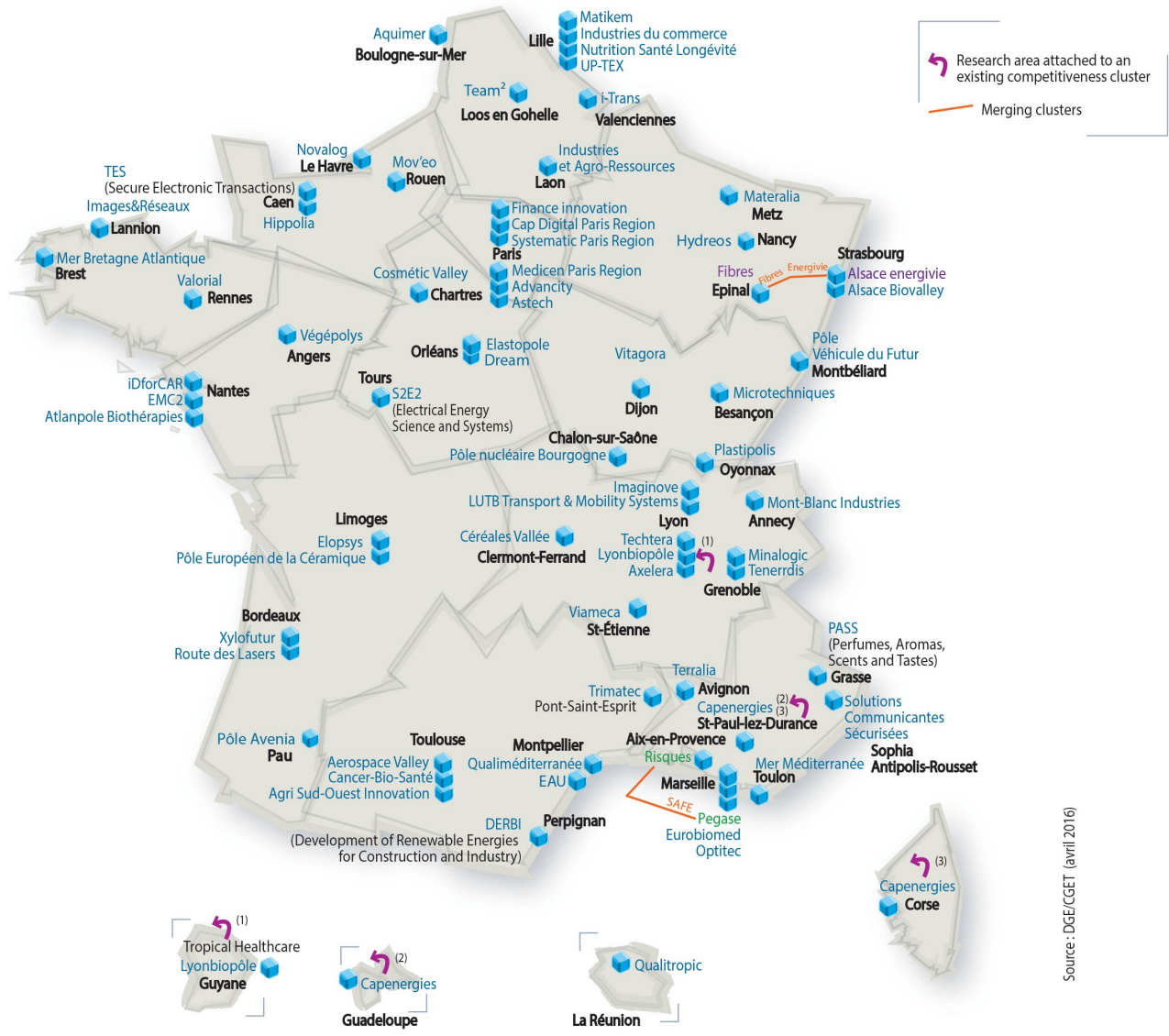
The competitiveness clusters policy is implemented in several phases, and in each phase, the authorities set the priority targets. The first phase (2006-2008) was implemented in 2004; it aimed to support firms in becoming more competitive and innovative and also to develop certain areas of difficulty and to prevent relocations. After a positive evaluation of the first phase of the policy, the government proceeded to the launch of the second phase (2009-2012), which is often called "Pôles 2.0". In addition to continuing the support of private R&D, a cornerstone of the dynamics of the clusters, the second phase has three priorities. First, it must strengthen the animation and strategic management of the clusters; in particular, it must make the implementation of "contracts of performance" more rigorous and also strengthen the roles of local and national authorities. Second, it must enable the development of structured projects, in particular platforms of innovation³⁷. Third, it must increase support for the development of innovation ecosystems (see appendix, figure 3.9) and the growth of firms. The current third phase (2013-2018) of the policy was launched in 2013 and is characterized by a more partnership-based approach between national and local authorities. This phase also aims to concentrate the action of clusters on products suitable for large-scale manufacturing and services for the purposes of increasing the impact of clusters on economic growth, competitiveness and job creation. Therefore, its purpose is to substantially increase the economic outputs from the R&D projects by increasing support

³⁷Platforms of innovation include infrastructures and mutualized equipment of R&D and innovation intended to offer services or resources (services, equipment rental, etc.) that allow agents to foster collaborative R&D and can even serve as laboratories or living labs for testing

for SMEs and mid-tier firms (ETIs).

After the disappearance of certain clusters that did not achieve their goals and the labeling of new clusters over time, 71 clusters are currently recognized by the national authorities. The different clusters and their locations are presented in the figure(3.1).

Figure 3.1: Map of the 71 Competitiveness clusters (Pôles)



Source: DGE/CGET (April 2016),

For more information about Competitiveness clusters, see: www.competitivite.gouv.fr/en

3.2.2 Funding and budgets of the French policy mix

In order to create a favorable environment for the development of companies and innovation, the state supports private R&D efforts through the clusters policy. The policy is implemented in the context of a policy mix. In addition to the FUI, which is the main direct funding instrument of the clusters, there are several other direct and indirect instruments for supporting R&D and innovation activities. Therefore, we distinguish direct subsidies from tax incentives.

3.2.2.1 Direct subsidies

The FUI is the main instrument of funding for the competitiveness clusters policy. It regroups government resources that come, in particular, from the ministries of economy, industry, equipment, agriculture, defense, and health and from the DIACT. The main objective of the FUI is to finance collaborative R&D projects involving enterprises, laboratories and public research centers. The FUI supports applied research projects concerning the development of products or services that are susceptible to being launched on the market in the short or middle term.

In 2005, the CIADT (French committee in charge of spatial planning and regional policy) decided to attribute €1.5 billion to the funding of the first phase of the policy. During the following two phases of the policy, the government spent €1.5 billion for each phase. It finances the projects retained after the calls for projects (AAP), which occur twice a year. To be eligible for public funding, a project must be labeled by a competitiveness cluster and piloted by a company and must be collaborative (involving at least two companies and a research or training establishment). During every call for projects, about a hundred projects are selected to benefit from the subsidies. Between 2006 and 2012, the FUI enabled the funding of 1187 projects for a total amount of more than €1.37 billion.

Moreover, additional public support exists in the form of direct subsidies, which fund firms' innovative activities in parallel with the FUI. The figures (3.2) and (3.3) show in detail the different funding instruments and the number of funded projects. Among the sources of funding are public agencies such as the National Agency of Research (ANR), the Public Investment Bank (Bpifrance), the Agency of Industrial Innovation (AII), the Industrial Strategic Innovation (ISI) and the Caisse des dépôts et consignations (CDC).

The ANR was created at the same time as the clusters policy. The ANR and the competitiveness clusters policy pursue three common objectives: strengthening the links between public and private research actors, creating value from research and building recognized scientific and technological communities at the national and international levels. To achieve its goals, the ANR designed and disseminated funding instruments to support the research and innovation public policy. This public agency launches regular calls for projects on different themes and enables the financing of some projects for laboratories and companies. From the creation of the agency in 2005 until 2012, the ANR financed 1872 collaborative projects at a total amount of €1.44 billion (see figure (3.2)). Since 2010, the ANR has been designated by the government as the manager of the Program of investments of future (PIA)³⁸, and it manages the selection, funding and impact evaluation of the projects.

The other sources of financial support for firms include the Bpifrance, charged with promoting and supporting innovation by SMEs, the AII, which supports large-scale industrial projects, and European Union funding³⁹, which supports research and innovation in Europe. However, it is worth noting that the funding of Bpifrance is of a different nature than the others because it includes repayable credits granted to the companies. Bpifrance supports regional and national policies by accompanying and supporting SMEs with advances, loans or guarantees during the most decisive phases of their life cycle (creation, innovation, and development). It facilitates the access of project holders and entrepreneurs to the funding partners and organisms of stockholders' equity. Between 2005 and 2012, Bpifrance financed 3080 projects for a total amount of more than €1.27 billion.

Furthermore, it is necessary to consider the role of local authorities supported by the FUI, which is very important and has enabled the funding of 1067 projects for a total amount of about €0.88 billion. At the local level, local and territorial authorities participate in the funding of the projects of clusters as structures of governance. Some projects of clusters are co-funded by the government and the local authorities. The government also finances part of the structures of governance of the clusters and the thematic collective actions of local authorities and companies through the DIRECCTE⁴⁰.

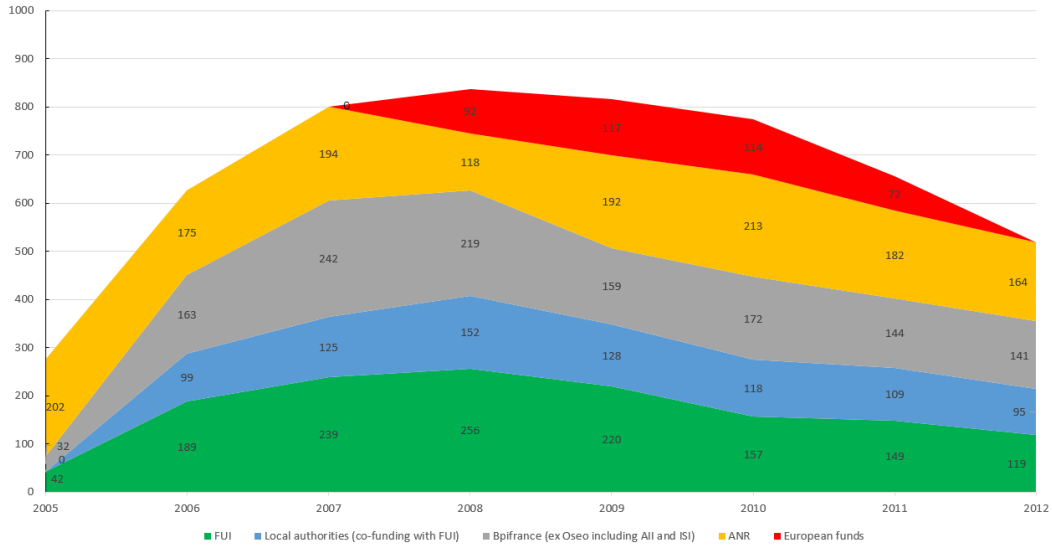
³⁸Programme des Investissements d'Avenir (PIA)

³⁹The EU has many funding opportunities to support research and innovation: the Research Framework Programme, the Competitiveness and Innovation Framework Programme, the Structural Funds and the Cohesion Fund within the cohesion policy and the European Agricultural Fund for Rural Development.

⁴⁰Directions régionales des entreprises, de la concurrence, de la consommation, du travail et de l'emploi

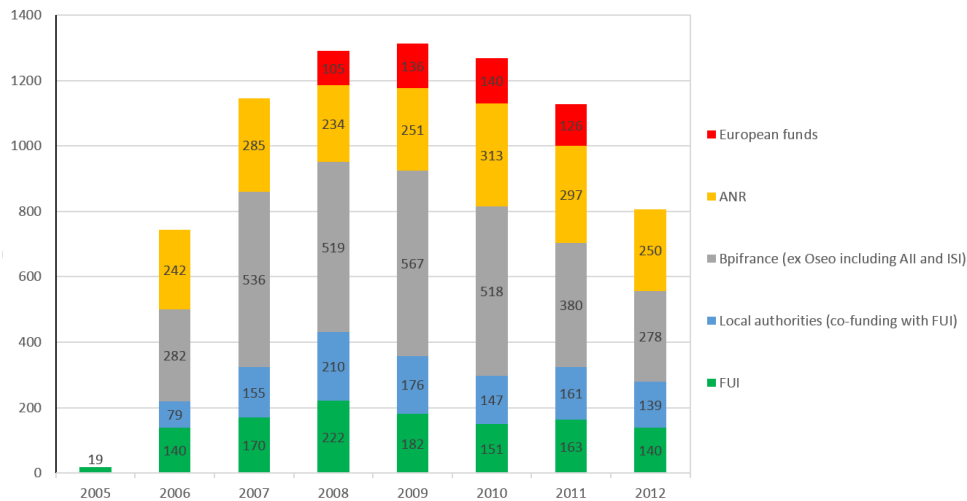
Globally, between 2005 and 2012, €5.3 billion were invested in R&D projects. However, a significant decrease of all these types of funding has been observed over the years, and as a result, the number of funded projects has also decreased.

Figure 3.2: Funding (€M) allocated to the competitiveness clusters policy (2005 to 2012)



Source: Data from the annual dashboards of the DGCIS, author's representation

Figure 3.3: Number of collaborative R&D projects by source of funding (2005 to 2012)



Source: Data from the annual dashboards of the DGCIS, author's representation

(DIRECCTE) are decentralized state administrative authorities belonging to the Ministry of Employment, Professional Training and Social Dialog and the Ministry of the Economy, Finance and Industry.

3.2.2.2 Indirect subsidies

The government encourages private R&D funding because one of the challenges of the policy consists of better mobilizing private funding in favor of firms to convert their collaborative R&D activities into commercial success. The government uses R&D tax incentives as an instrument to stimulate private R&D spending.

In addition to direct subsidies, the government uses research tax credit (Crédit Impôt Recherche, or CIR) as an instrument to stimulate private R&D investments. The credit consists of providing tax deductions, under certain conditions, to the companies that undertake R&D expenditures. The CIR aims to enhance firms' competitiveness, increase private research and encourage the hiring of personnel with training and scientific experience. The 2005 finance law (article 24) allows companies that undertake research expenditures to benefit from the CIR by deducting them from their taxes under certain conditions. The activities of fundamental research or applied research and the activities of experimental development, whatever the domain, can be taken into account within the framework of the CIR.

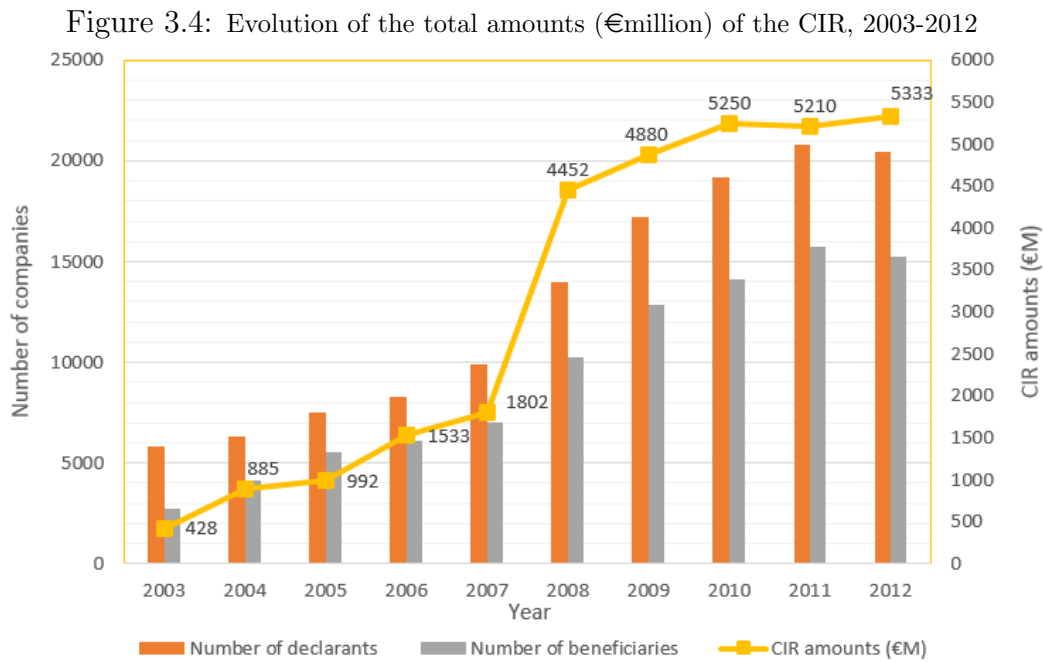
According to a report⁴¹ of the Ministry of Higher Education and Research (MESR), since the reforms of the CIR from 2004 until 2008, the number of declarant companies grew strongly, while during the previous decade, the appeal of the CIR was low. Since 2008, the CIR has been the primary source of public funding of R&D projects. The number of declarants increased substantially, and in 2011, approximately 20000 companies had deposited a statement (see table (3.1) and figure (3.4)).

The figure (3.4) indicates the evolution of the CIR amounts from 2003 to 2012⁴². It shows the important and successive increases of the amounts due to the modifications of the computation methods of the CIR in 2004 and again in 2008. Before 2004, the annual amount of the CIR was lower than €430 million. With the 2004 reform, the CIR became more attractive, and companies had more recourse to its use. This change resulted in a considerable increase of the amount, which doubled that year (€885 million) and reached €1.8 billion in 2007. In 2008, there was a new reform of the CIR, and the amount reached €4.5 billion that

⁴¹For a historical perspective, see the report "Développement et impact du CIR 1983-2011" of the MESR, available at: <http://www.enseignementsup-recherche.gouv.fr/cid80816/developpement-et-impact-du-credit-d-impot-recherche-1983-2011.html>

⁴²Data are definitive until 2009 and temporary for the 2010-2012 period. See <http://www.enseignementsup-recherche.gouv.fr/cid49931/cir-statistiques-rapports-et-etudes.html>.

year (meaning it more than doubled in four years). The amount of the CIR continued to rise further until reaching €5.25 billion in 2010 and €5.21 billion in 2011. According to the MESR, the slight reduction of the amounts observed for the year 2011 resulted in particular from the change in the computation methods of the costs of functioning. For 2012, the amount of the CIR was about €5.3 billion. The increase compared with 2011 was caused by the significant increase of the declared R&D expenditures; according to the MESR report, this increase resulted mainly from the dynamism of the R&D activities of companies in 2012.



Source: Data from Bilan-CIR 2014 of the MESR, author's representation

Table 3.1: Number of annual declarants, beneficiaries and the amounts of the CIR, 2003-2012

Year	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Number of declarants	5833	6287	7539	8261	9886	14012	17193	19214	20807	20441
Number of beneficiaries	2757	4169	5567	6095	6992	10290	12862	14115	15772	15281
CIR amounts (€M)	428	885	992	1533	1802	4452	4880	5250	5210	5333

Sources: Author's synthesis from the Report Bilan-CIR 2014 of the MESR

Moreover, in addition to the CIR, the government encourages private R&D funding by attracting venture capitalists as well as business angels to invest in firms through reductions of income tax (IR) or a solidarity tax on wealth (ISF) for investors who support SMEs.

3.3 Related literature

Clusters policies are considered a good public instrument to support private R&D activities and to improve firms' performance. Some studies assess the effectiveness of cluster policies (see [Criscuolo et al. \(2007\)](#) in the United Kingdom; [Branstetter and Sakakibara \(2002\)](#), [Nishimura and Okamuro \(2011a\)](#), [Nishimura and Okamuro \(2011b\)](#) in Japan; [Falck et al. \(2010\)](#), [Engel et al. \(2013\)](#) in Germany; [Dujardin et al. \(2015\)](#) in Belgium; and [Martin et al. \(2011\)](#), [Fontagné et al. \(2013\)](#), [Bellégo and Dortet-Bernadet \(2014\)](#), [Abdesslem et al. \(2016\)](#), [Chaudey and Dessertine \(2016\)](#), [Ben Hassine and Mathieu \(2017\)](#) in France).

Although there are rather few studies, two aspects of the effectiveness of cluster policies on firms' innovative activities and other performance have been investigated. The first aspect focuses on the effect on the beneficiary companies in terms of input additionality (R&D spending and employment in R&D), and the second aspect focuses on the effect in terms of output additionality (innovation, employment and firms' performance related to the market). These studies use empirical methods, including difference-in-difference ([Branstetter and Sakakibara, 2002](#); [Falck et al., 2010](#); [Martin et al., 2011](#); [Engel et al., 2013](#); [Nishimura and Okamuro, 2011b](#); [Dujardin et al., 2015](#); [Chaudey and Dessertine, 2016](#)) and conditional difference-in-difference ([Bellégo and Dortet-Bernadet, 2014](#); [Dujardin et al., 2015](#); [Abdesslem et al., 2016](#); [Ben Hassine and Mathieu, 2017](#)) (more details on these studies are provided in chapter 1).

A literature review on evaluations of the effectiveness of cluster policies has been provided in more detail in chapter 1. Here, we focus only on studies evaluating the French competitiveness clusters policy and present the effects first on input additionality and then on output additionality.

3.3.1 Effects of the clusters policy on input additionality

In the literature, studies focusing on the impact of clusters policies on input additionality are very limited. [Bellégo and Dortet-Bernadet \(2014\)](#) analyzes the impacts of the French cluster policy on the private R&D spending of SMEs and ETIs using microdata and the conditional difference-in-difference method. Their findings suggest that firms in clusters increase their private R&D spending. They reject the crowding-out hypothesis and conclude that an additional effect exists. By analyzing the effectiveness of the same policy on firm's perfor-

mance, [Ben Hassine and Mathieu \(2017\)](#) use the same econometric strategy with microdata for a longer period and find similar effects on private R&D. These two studies conclude that firms would not have decreased their private expenditure on R&D.

Moreover, [Bellégo and Dortet-Bernadet \(2014\)](#), [Chaudey and Dessertine \(2016\)](#) and, more recently, [Ben Hassine and Mathieu \(2017\)](#) find that the French competitiveness clusters policy has had positive effects on the employment of personnel devoted to R&D, especially in terms of engineering and technical and scientific staff.

3.3.2 Effects of the clusters policy on output additionality

Although cluster policies have been considered a good instrument for supporting local SMEs and promoting regional innovation, few empirical assessments exist.

Some studies show the effectiveness of cluster policies using the number of patents, and [Brossard et al. \(2014\)](#) find that the competitiveness clusters policy has had a significant positive impact on regional patenting. However, [Martin et al. \(2011\)](#) find that the local productive systems (LPS) policy has had no effect on the innovation of firms. Similarly, [Bellégo and Dortet-Bernadet \(2014\)](#) find that the competitiveness clusters policy has had no effect on firms' patents, on the sales of innovative products or on the improvement of innovation processes. These results are confirmed by a more recent study by [Ben Hassine and Mathieu \(2017\)](#), which analyzes the same policy and finds that it has had no effect on firms' innovation and especially on filed patents.

There is limited empirical evidence of other effects on the economic performance of firms. Although some findings suggest positive effects, other studies conclude that there is no significant effect on firms' economic performance.

[Martin et al. \(2011\)](#) find that the French LPS policy has had no significant effect on labor productivity and total employment. [Bellégo and Dortet-Bernadet \(2014\)](#) find that the competitiveness clusters policy has had no effect on firms' turnover. Moreover, ([Ben Hassine and Mathieu, 2017](#)) analyzes the competitiveness clusters policy and finds that the policy has had no significant effect on total employment, turnover, added value or export.

However, ([Chaudey and Dessertine, 2016](#)) analyze the effects of the competitiveness clusters policy on the employment of the companies participating in cluster R&D projects. Using firm-level data and difference-in-difference, they find a positive and significant effect of the

French competitiveness clusters on total employment. [Abdesslem et al. \(2016\)](#) analyzes the effects of the clusters policy on firms' performance in the French optic/photonic industry. They use microdata and find that the firms that have participated in the competitiveness clusters have become more productive (total factor and labor). They also found a positive and significant impact of the policy on exports, total fixed assets and total employment.

In sum, the findings of studies evaluating the effect of the competitiveness clusters policy on firms' innovative activities and economic performance are mixed and inconclusive. The evidence seems to show positive effects on input additionality (R&D spending and employment in R&D) by stimulating private R&D investment. However, the effects on output additionality (innovation and economic performance) are weak or generally nonexistent. These results should be used with much caution because of the difficulties, such as nonrandom selection and missing data, related to the evaluation of clusters and subsidies. Further analyses using adequate econometric techniques should be performed to better understand the effectiveness of public clusters policies.

3.4 Methodology

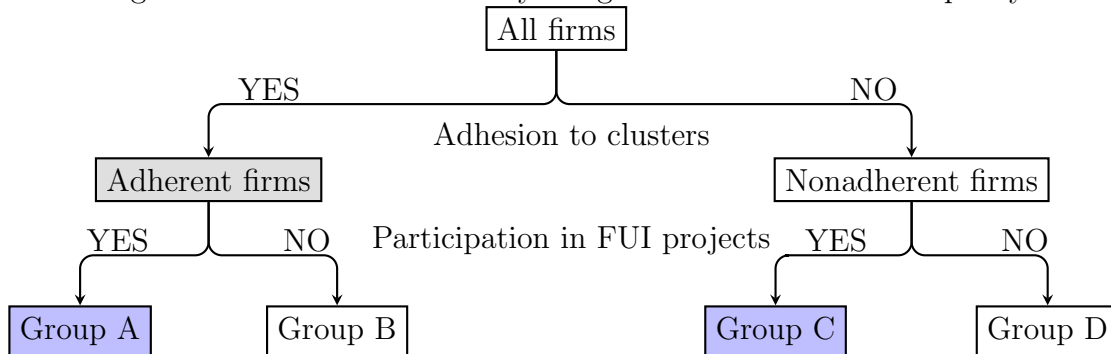
3.4.1 Quasi-experimental design

To evaluate the impacts of the competitiveness clusters policy, it is necessary to thoroughly understand the structure of participation and the characteristics of the participating firms. In this study, our strategy for identifying participating firms is different from those of [Bellégo and Dortet-Bernadet \(2014\)](#) and [Ben Hassine and Mathieu \(2017\)](#). In these studies, the authors consider firms that are members of clusters as participants and all other firms as controls. Here, we go further and consider two levels of treatment. Based on data sets from the DGE (being a member of clusters) and the FUI (projects), we present in the figure (3.5) the strategy of identification of firms' participation in the policy. On one hand, we have a group of firms that are members of at least one cluster, and among this group, some firms have participated in FUI projects, and others have not. On the other hand, we have a group of firms that are not members of a cluster, and among this group, some firms have participated in FUI projects, and others have not. Therefore, when evaluating the effect of the policy on firms' performance, by considering firms that are members of clusters as

participants and all other firms as nonparticipants, one may underestimate the effects by considering only the firms that belong to clusters and that do not participate in an FUI project as participants. Correspondingly, one can underestimate the effect on nonmember firms that participate in the policy by considering them controls. Therefore, by comparing adherents and nonadherents, one can underestimate the overall effect of the policy.

To deal with this problem and assess the impact of the competitiveness clusters policy, we distinguish two levels of treatment and measure and compare these different two treatment options. The first level of treatment is participation in clusters, and the second is participation in FUI projects. We aim to investigate the impact of each treatment separately and also to understand whether the combination of the two treatments is better than having just one of the two treatments. Consequently, benefiting from the competitiveness clusters policy is possible in three different forms: being only a member of a cluster, participating only in an FUI project, or a combination of the two. To evaluate the impacts of the policy, we created four groups (see figure 3.5) to identify an appropriate control group that has good overlap with the treated groups.

Figure 3.5: The crossover study design of the French clusters policy



- Group A adheres to clusters and participates in projects (both treatments).
- Group B adheres to clusters and does not participate in projects (treatment 1 only).
- Group C participates in projects and does not belong to clusters (treatment 2 only).
- Group D does not belong to clusters, does not participate in projects and constitutes the pure comparison group.

As explained above, the table 3.2 shows the crossover design and allows us to identify each treatment group and the appropriate control group. We can, therefore, estimate the impact of being a member of a cluster by comparing the outcome of Group B with the outcome of Group D, which is the pure comparison group. We can also estimate the impact of participation in an FUI project by comparing the outcome of Group C with the outcome of Group D. In addition, this design also makes it possible to compare the incremental impact of participating in a project when a firm has already adhered to a cluster (corresponding to the difference in outcomes between Group A and Group D).

Table 3.2: Treatment and comparison groups for the policy evaluation

		Treatment 1 (Cluster)	
		Treatment	Comparison
Treatment 2 (FUI project)	Treatment	Group A	Group C
	Comparison	Group B	Group D

3.4.2 Econometric strategy

The main challenge of the impact evaluation of the competitiveness clusters policy is to determine what would have happened to the participating firms if the policy had not existed. Therefore, we must determine the potential outcome of a participant in the absence of the policy. Let us consider Y_i^T and Y_i^C as two potential outcomes of firm i ; the causal effect of the treatment on the outcome would be defined as the difference between the two potential outcomes: ($\Delta = Y_i^T - Y_i^C$). Ideally, we wish to compare how the same firm would have fared with and without participation in the policy, but we cannot do so because at a given point in time, a firm cannot be both a participant and a nonparticipant in the policy. The challenge of the evaluation study is to construct a counterfactual framework that would represent a participant's outcome (not observed) in the absence of the policy. The counterfactual framework was developed by Roy (1951) and Rubin (1974) and has since been adopted by many statisticians and econometricians, including (Rosenbaum and Rubin, 1983; Heckman et al., 1997; Angrist, 1998; Imbens and Wooldridge, 2009).

For observational studies, the assignment of treatments is typically not random; especially for the competitiveness clusters policy, the selection process is not randomized because it is based on calls for projects. According to [Fontagné et al. \(2013\)](#), there are two selection problems: the first is related to the selection of the financed projects among others by public authorities, and the second is the self-selection of firms that decide to be a member of a cluster or to participate in a project. To deal with this bias and the potential bias that may arise due to the apparent difference in outcomes between the treated and untreated groups and the characteristics that influence firms' participation in the policy, we use the propensity score matching (PSM) method to assess the impact of the policy. PSM attempts to reduce the bias due to confounding variables ([Dehejia and Wahba, 1999](#)) by mimicking randomization and creating a treated sample of firms that is comparable in all observed characteristics to an untreated sample of firms. Matching estimators have recently been applied and discussed by ([Heckman et al., 1998](#); [Angrist, 1998](#); [Dehejia and Wahba, 1999, 2002](#); [Lechner, 2002](#) and [Garrido et al., 2014](#)).

PSM constructs a statistical comparison group that is based on a model of the probability of participating in the policy, using observed characteristics that are unaffected by the program. [Rosenbaum and Rubin \(1983\)](#) show that in PSM, each participant is matched to a nonparticipant on the basis of a single propensity score, reflecting the probability of participating conditional on their different observed characteristics. For a theoretical formulation, we assume a binary treatment D conditional to a set of observed characteristics X and the potential outcomes Y . Here, $D = 1$ if the firm participates in the policy, and $D = 0$ if it does not. The propensity score, defined as the conditional probability P of participation given the set of characteristics, is as follows:

$$P(X) = Pr(D = 1|X) \tag{3.1}$$

Here, we assign an estimated propensity score to every sampled firm⁴³. We define the common support and check the balancing test to be sure that the distributions of the two

⁴³It is worth noting that the validity of PSM depends on two conditions. The first condition, *conditional independence assumption (CIA)*, or *unconfoundedness* ($(Y^T, Y^C) \perp D|X$), implies that a set of observable characteristics X exists that is not affected by the treatment and potential outcomes Y and that is independent of the treatment assignment D . The second condition is the sizable *common support assumption (CSA)* ($0 < P(D = 1|X) < 1$), which implies that the observations of the participating firms have nearby comparison observations in the propensity score distribution ([Heckman et al., 1999](#)).

groups are similar. Formally, we check whether $P(X|D = 1) = P(X|D = 0)$. Then, we match participants to nonparticipants using a matching algorithm.

As explained by [Khandker et al. \(2010\)](#), if conditional independence holds, and if there is a sizable overlap in $P(X)$ across participants and nonparticipants, the PSM estimator for the effect of the treatment on the treated (ATT) can be specified as the mean difference in Y over the common support, weighting the comparison units by the propensity score distribution of participants. Then, outcomes of participating and nonparticipating firms with similar propensity scores are compared to obtain the policy effect. The ATT estimator based on the PSM can be written as follows:

$$\Delta^{ATT} = E_{P(X)|D=1} \{E[Y^T|D = 1, P(X)] - E[Y^C|D = 0, P(X)]\} \quad (3.2)$$

As the PSM take into account only firms' observed characteristics, bias may arise because the firms' unobserved characteristics may influence their decision to participate in the policy, and the effect may be a mix of the policy effect and the unobserved characteristics. To deal with this endogeneity bias due to selection based on unobserved characteristics, we combine the PSM with the difference-in-difference (DiD) method, also known as conditional difference-in-difference (CDiD) ([Heckman et al., 1997](#); [Abadie and Imbens, 2006](#); [Blundell and Costa Dias, 2009](#)). The advantage of the CDiD is that after controlling for selection based on observable characteristics, it removes firms' individual systematic effects and also eliminates the time effects, thus consistently estimating the treatment effect. The main limit of this method is that it does not take into account the eventual relevant unobserved time-varying factors. The CDiD can be implemented in a three-step procedure. First, it estimates the propensity score; second, it matches treated firms with control firms; and third, it exploits the longitudinal nature of the data by estimating a DiD estimator for each treated firm with its matched counterfactual(s).

With panel data over two time periods $t = \{1, 2\}$, the local linear DiD estimator for the mean difference in outcomes Y_{it} across participants i and nonparticipants j in the common support is given by

$$\Delta_{CDiD}^{ATT} = \frac{1}{N_T} \left[\sum_{i \in T} (Y_{i2}^T - Y_{i1}^T) - \sum_{i \in C} \omega(i, j) (Y_{j2}^C - Y_{j1}^C) \right] \quad (3.3)$$

where Y_{it}^T and Y_{jt}^C are, respectively, the outcomes for participant i and nonparticipant j in time period $t = \{1, 2\}$. $\omega(i, j)$ is the weight (using a PSM approach) given to the j^{th}

control firm matched to treatment firm i . The empirical model is as follows:

$$y_{i,t} = \alpha_i + \lambda t + \beta D_{i,t} + \text{control factors} + \epsilon_{i,t} \quad (3.4)$$

where α_i is the fixed effect that captures the time-invariant unobserved heterogeneity that was part of the selection bias. t is a set of dummies for every single year, more precise than just *pre*- and *post*-time period because we have many years of data and multiple treatments. $D_{i,t}$ is the indicator of treatment of firm i in year t , and β is the parameter of interest and corresponds to the *ATT* of a mixed method (DiD combined with PSM).

To calculate the propensity to participate in the policy, our calculations are based on the empirical evidence and the information available in our data set. Previous studies have identified firm characteristics that can influence a firm's decision to participate in cluster policies. Certain variables such as size, age, being a member of a group, experience in public subsidies, export, economic sector and geographical location are considered very important.

The propensity score model can be written as follows:

$$\begin{aligned} P_i(X) = & \theta_1 \log(\text{emp})_{i,\bar{t}} + \theta_2 \text{age}_{i,\bar{t}} + \theta_3 \text{appgroup}_{i,\bar{t}} + \theta_4 \text{dum_subven}_{i,\bar{t}} \\ & + \theta_5 \text{dum_sec_man}_{i,\bar{t}} + \theta_6 \text{dum_sec_hkis}_{i,\bar{t}} + \theta_7 \text{loc}_{i,\bar{t}} + u_{i,\bar{t}} \end{aligned} \quad (3.5)$$

where \bar{t} is the year preceding participation in the policy and is a requirement of an adequate balancing of pretreatment variables. As explained in the previous subsection, we create different treatment groups and then conduct several independent matches instead of one because each level of treatment has its own propensity score, and each propensity score is used individually to estimate the effect of that treatment.

We estimate the propensity score by using a logistic regression. To avoid matching on the predicted probabilities, which compress the propensity scores near zero and one, [Rubin and Thomas \(1992\)](#) and more recently [Sekhon \(2011\)](#) and [Diamond and Sekhon \(2013\)](#) recommended matching on the linear propensity score instead of the propensity score itself. The linear propensity score is computed as follows:

$$\log(P_i(X)) = \log\left(\frac{P_i(X)}{1 - P_i(X)}\right) \quad (3.6)$$

where $P_i(X)$ is the estimated propensity score.

We match each participant firm to the comparison firm with the closest propensity score using the *Nearest-neighbor (NN)* algorithm, which is one of the most frequently used matching

techniques. As in the NN matching technique, the difference of propensity scores for a participant and its closest comparison neighbor may be very high; thus, we tend to reduce the bias by combining it with a *caliper*⁴⁴ (Cochrane and Rubin, 1973; Rosenbaum and Rubin, 1985), which imposes a threshold for the maximum tolerated difference between matched firms. To limit the increase in bias and to increase the quality of matching and enforce common support, we perform one-to-one matching with replacement. To implement the matching and compute the ATT, we use the *matching* package (Sekhon, 2011) explained theoretically in the work of Diamond and Sekhon (2013).

To evaluate the impact of the policy, we first test the hypothesis of input additionality (R&D spending and employment related to R&D). Then, we test the hypothesis of output additionality (outcome variables related to firms' innovation and economic performance). All these variables are explained in more detail in the next section.

3.5 Data

3.5.1 Data sources and variables

We combine data from several sources and build a rich firm-level panel data set for French SMEs covering the 2005-2012 period, which is relevant to observe the impacts of the policy before and after the launch of the competitiveness clusters policy. In this work, we use several data sets from different sources, such as the DGE⁴⁵ and FUI data sets for the participation of firms, respectively, in clusters and FUI projects, the R&D survey for variables related to patents and R&D, the FICUS-FARE database for the economic and accounting variables, the LIFI database for the groups and nationality of firms and, finally, the declarations of social data (DADS) database for employment-related variables.

The DGE survey and the FUI data set provide information on participation in clusters and FUI projects. The DGE tracks the evolution of the cluster policy and updates the list of the adherent firms annually. This survey enables us not only to identify the firms that

⁴⁴A caliper of 0.25 standard deviations of each treated observation was used, as recommended in the literature (Cochrane and Rubin, 1973; Rosenbaum and Rubin, 1985 and more recently Stuart, 2010; Caliendo and Kopeinig, 2008). Rosenbaum and Rubin, 1985 explained that a caliper of 0.25 can reduce 90% of bias.

⁴⁵Direction générale des entreprises, ex-DGCIS (direction générale de la compétitivité, de l'industrie et des services)

belong to clusters and those that do not but provides information on their entry into and exit from clusters. The FUI has data on all projects in the framework of the clusters, and we can identify all firms that participate in the projects. By combining these two data sets, we are able to identify all adherent firms and nonadherent firms that participate in projects. In other words, we can identify the firms and assess the true effects of the policy. These two data sets provide information on the participation of firms in clusters and projects and therefore allow us to construct several variables characterizing participation. For every program (clusters or projects), there is a dummy variable that takes the value of one if an establishment or a firm participates in the program and zero otherwise. Data from the DGE cover the 2006-2012 period, and those from the FUI cover the 2007-2012 period.

In addition to information on the participation of firms in the program, the R&D survey conducted by the MESR is the main source of data and provides information about firms' R&D activities and innovation. This survey covers companies operating in French territory and performing work related to R&D. The variables from this data are classified into four main groups: variables related to R&D expenditure, variables related to the sources of R&D funding, variables providing information on R&D employment (scientists, engineers, researchers and other technical support staff for R&D) and variables related to filed patents and the involvement of firms in innovative products or processes. The latter variables allow us to evaluate the innovation level of a firm and particularly to calculate the number of patents it has filed⁴⁶.

Measuring the effects of the policy on firms' R&D-related variables using the econometric method presented in the next section implies knowing the evolution of participant firms' characteristics and comparing them with those of firms in the nonparticipant control group. The R&D survey is a nonexhaustive census for SMEs; therefore, it is impossible to obtain these firms' characteristics over years. However, the surveyed SMEs return systematically in the survey at least every five years. Because of this constraint, we do not choose a scope for the study as in the studies of [Bellégo and Dortet-Bernadet \(2014\)](#) and [Ben Hassine and Mathieu \(2017\)](#), in which only firms that have been surveyed for at least two consecutive years and spent less than €16 million in R&D are considered. With the objective of not losing many firms, we retain in our data, in addition to the SMEs that belong to clusters or

⁴⁶The main limit of these patents data is that the same patent may be filed more than once; therefore, it is possible to overestimate the number of patents.

participate in FUI projects, all the SMEs that appear at least twice in the data set, whatever the amount of their R&D expenditure. To avoid including bias in the estimates, we do not follow [Bellégo and Dortet-Bernadet \(2014\)](#), who used a weighting approach, but we follow [Ben Hassine and Mathieu \(2017\)](#) by applying linear interpolation and extrapolation⁴⁷ to retain SMEs and their characteristics related to R&D.

To complete the information on firm characteristics, we mainly use the FICUS-FARE data set, which is an annual firm-level data set that covers almost all French firms. It provides economic and accounting indicators (related to the balance sheet), such as turnover, added value, and export. This data set also provides variables on investment and exploitation subsidies that firms have received, firm age, and the economic sectors in which firms operate. To identify foreign companies, the scope of the groups and the position of a firm in its group, we use data on financial links (LIFI) provided by the French National Institute for Statistics (INSEE)⁴⁸. We use a dummy variable that takes the value of one if the firm is a member of a group and zero otherwise.

Finally, the DADS data set, available at the establishment level, provides information related to employment and geographical location. This data set allows us to better localize the activities of firms and to know the number of employees (and the structure of employment by type of qualification and activity sector)⁴⁹. We have aggregated the number of total employees and the employment of executives, managers and intellectual professionals at the firm level.

Table 3.3 shows all the variables classified into three groups. The first group of variables concerns input outcome variables (R&D spending and employment related to R&D). The second group of variables is related to output outcome variables (patents, total employment, and economic performance). The third group of variables is related to the determinants of

⁴⁷Linear interpolation allows us to estimate the missing values between two given points. The strategy for linear interpolation is to use the arithmetic mean to fill a gap or missing value between two data points. Linear extrapolation allows us to use the arithmetic mean to estimate values outside the interval between two points by using a subset of the data instead of the entire data set to estimate the missing values.

⁴⁸These are all French private sector companies with an equity portfolio exceeding €1.2 million, with a turnover above €60 million, or with more than 500 employees, whatever the sector.

⁴⁹The DADS data set contains only employer establishments; thus, not all employing establishments are included in the files. In addition, the data of special regimes provided by the DGFIP (Direction Générale des Finances Publiques) and of the Ministry of Defense are not included in the DADS data set.

firms' participation in the policy; they are used as controls to calculate the propensity score to control the selection bias.

To evaluate the impact of the policy, we first test the hypothesis of input additionality on several outcome variables. We use as outcome variables internal and external R&D spending (*derd* and *dird*), firms' total R&D budget (*budgetot*), subsidies (*financ_pub*) and firms' self-financed projects (*financ_pro*). We also use variables related to employment in R&D, such as R&D staff (*eff_rd*), employment of researchers (*researchemp*) and employment of executives, managers and intellectual professionals (*cs3*).

Moreover, we test the hypothesis of output additionality on several outcome variables related to firms' innovation and economic performance. For innovation, we use the total number of patents (*totbrev*) the firm has filed as an innovation proxy. To measure the effects of the policy in terms of performance related to employment, we use variables such as total average employees (*eff_moy_et*). For economic performance related to the market, we use indicators such as turnover (*turnover*), added value (*addedvalue*) and exports (*export*).

To explain the participation process and account for the selection problem, we use the empirical evidence and the information available in our data set to choose variables to calculate the propensity to participate in the policy. Previous studies identified certain firm characteristics that can influence the decision to participate in cluster policies. Certain firm characteristics such as size, age, being a member of a group, experience in public subsidies, export, economic sector and geographical location are considered very important.

In the literature, the size of a firm is considered an important characteristic that influences participation in clusters policy. We include the logarithm of the number of employees (*emp*). Older firms are expected to spend more on R&D, to have a greater accumulation of absorptive capacity and therefore to be more likely to participate in clusters. We calculate the firm's age as the number of years (*age*) that the firm has been operating in the market. Firms belonging to a group may be more likely to participate in clusters because they presumably have better access to information about governmental actions due to their network linkages. We include a dummy variable (*appgroup*) that takes the value of one if the firm is a member of a group and zero otherwise.

Firms that have already received public subsidies may better know the administrative procedures and be more likely to participate in public policies. We include a dummy variable (*dum_sub*) that takes the value of one if the firm has already benefited from a public subsidy

and zero otherwise. Firms that export are more exposed to international competition and are more likely to participate in the policy because the reduction of R&D costs is very important to them and enables them to continue to be competitive in the market. We include a dummy (*dum_export*) that takes the value of one if the firm exports and zero otherwise.

For the economic sector, firms that operate in high-technology manufacturing or in the highly knowledge-intensive sector may be more likely to participate in the clusters policy. Some previous studies suggest that public policies for firms mainly benefit companies in highly dynamic sectors. To control for the economic sector in which the firm operates, we include a dummy (*dum_sec_man*) that takes the value of one if the firm operates in the sector of manufacture of electrical, computer and electronic equipment and machinery. We also include another dummy variable (*dum_sec_hkis*) that takes the value of one if the firm operates in the sector of highly knowledge-intensive services.

Geographical location is a very important characteristic for a firm's decision to participate in the policy because of the proximity of potential partners, knowledge flows, and agglomeration economies. The geographical location (*loc*) of the firms in our study consists of eight dummy variables that correspond to the eight French metropolitan NUTS1 regions. We chose the NUTS1 regions instead of the NUTS3 regions (departments) because the clusters and the number of cluster member establishments are concentrated in certain NUTS1 regions, as shown, respectively, in figures (3.1) and (3.11).

After merging all these data sets, we obtain an unbalanced panel data set at the firm level that covers the 2005-2012 period. After filtering out the French SMEs on which we have information for no more than one year, we obtain a data set containing 41,449 observations, of which 7,697 are treated SMEs. To evaluate the effects of the policy using our econometric methodology and our quasi-experimental design, we need to create three different samples according to the three types of participation.

Table 3.3 shows all the variables classified into three groups. The first group is input outcome variables (R&D spending and employment related to R&D). The second group is output outcome variables (patents, total employment and economic performance). The third group is the determinants of firms' participation in the policy; these variables are used as controls to calculate the propensity score to control the selection bias.

Table 3.3: Description of variables

Variable	Source	Description
Input outcome variables		
derd	R&D	External R&D spending of the firm (subcontract with partners) (in k €)
dird	R&D	Internal R&D spending of the firm (for its own or for its partners) (in k €)
budgetot	R&D	Total Research and development budget (DIRD+DERD) of the firm (in k €)
financ_pro	R&D	R&D funding made by the firm itself (self-financed) (in k €)
financ_pub	R&D	Public funding for the firm's R&D (in k €)
cs3	DADS	Number of employees in executives, managers and high intellectual professions (CS3)
eff_rld	R&D	R&D staff in full-time equivalent
researchemp	R&D	Number of researcher employees (full-time equivalent)
Output outcome variables		
totbrev	R&D	Total number of patents filed by the firm
eff_moy_et	DADS	Firm's average employees in full-time equivalent
turnover	FICUS-FARE	Total turnover of the firm in euros (in k €)
addedvalue	FICUS-FARE	The firm's added value before taxes (in k €)
export	FICUS-FARE	Total export turnover of the firm (in k €)
Other control variables used to compute the propensity scores		
p_adh_ent	DGE	1 if the firm has adhered to at least one cluster for a given year, 0 otherwise
f_part_ent	FUI	1 if the firm has participated in at least one FUI project for a given year, 0 otherwise
log(emp)	DADS	Firm size measured by the logarithm of its total number of employees (full-time equivalent)
age	FICUS-FARE	The firm's age defined as the number of years the firm has been established
appgroup	LIFI	1 if the firm is membership of a group, 0 otherwise
dum_subven	FICUS-FARE	1 if the firm has received public subsidies, 0 otherwise
dum_sec_man	FICUS-FARE	1 if the firm operates in the high-technology manufacturing sector, 0 otherwise
dum_sec_hkis	FICUS-FARE	1 if the firm operates in high-knowledge intensive services, 0 otherwise
loc	DADS	Eight dummy variables corresponding to the eight French metropolitan NUTS1 regions

Sources: R&D survey, DGE, FUI, MENESR, INSEE, Ficus-Fare, DADS, Lifi.

3.5.2 Descriptive statistics

In this section, we present the descriptive statistics of our data. Table 1.10 displays mean values for the control and outcome variables before the matching procedure, aggregated by type of treatment. As explained in the previous section, we created three treatment groups (A, B and C) and a control group (D) according to the type of participation of firms in the policy and the study's quasi-experimental design.

In the pooled sample, 33,317 firms did not participate in the policy, 1,734 received both treatments (Group A), 5,963 adhered only to clusters (Group B), and 358 participated only in FUI projects (Group C). To avoid using treated firms in any year as a control, we created a pure control group (Group D) that is similar for the three groups and is composed of 27,354 observations before matching. We first present the descriptive statistics for each group

between treated and control firms for the entire period (see table 3.4); then, we present, for each year, the pre- and post-treatment characteristics of firms (see tables 3.17 to 3.20).

For input outcome variables, we observe in table 3.4 (column 2) that firms participating in the policy have a higher total R&D budget (€982 thousand) than nonparticipant firms (€576 thousand). This trend is similar for the firms' private expenditure (€742 compared with €453 thousand for pure controls) and other firm expenditures and also for received public subsidies (€108 compared with €36 thousand). Treated firms have more scientific employees and staff devoted to R&D.

For output outcome variables, we observe that firms participating in the policy file on average more patents than controls (1.5 compared with 0.8, respectively). They are larger than controls in terms of total employment (48 employees compared with 45). However, treated firms are on average smaller than controls in terms of economic performance variables related to the market, such as turnover (€10095 compared with €11276 thousand for controls), added value (€2972 compared with €3319 thousand) and export (€4055 compared with €4105 thousand).

For control variables, participating firms are younger than nonparticipating firms (23 compared to 27 years). We observe that 80% of treated firms have received subsidies, and only 50% of control firms have received subsidies. However, the numbers of exporting firms are similar between the treated and nontreated firms (70%).

Moreover, when comparing the three options of treatment, table 3.4 (columns 3 to 6) shows that firms' characteristics are heterogeneous across the three treatment options. Compared to other firms, the firms that participate only in FUI projects (Group C) are older and are on average larger for almost all input and output outcome variables. Row three shows that they have a total R&D budget that is slightly higher than that of firms receiving both treatments and almost twice as high as that of firms that only belong to clusters. These firms have on average more employees and higher economic performance. However, firms that receive both treatments (Group A) are younger, have on average higher CS3 employment and file more patents. In addition, the share of exporting firms and the share of firms receiving subsidies are higher in this group. The firms that belong to clusters and do not participate in FUI projects (Group B) are on average smaller in terms of all input and output outcomes.

Furthermore, if we look further into the descriptive statistics in the tables 3.17 to 3.20, we can see the firms' characteristics and their evolution between the pre- and post-treatment

periods. The characteristics of firms that participate in the policy differ from one year to another in the three groups.

In sum, the descriptive statistics show that participating firms perform better than non-participating firms in terms of input and output. All three treatment groups show higher average outcome variables than the controls. The firms in Group B are on average smaller in all types of outcomes. Group C is composed of older firms that are larger in terms of all types of economic performance.

Table 3.4: Average of firms characteristics across the different samples

	Global sample		Group A	Group B	Group C	Group D
	Treatment	Control	Treatment	Treatment	Treatment	Control
Input outcome variables						
derd	159.7	126.7	176.6	154.8	220.1	128.3
dird	826.4	496.9	1193.4	719.7	1271.8	447.6
budgetot	981.8	622.1	1370.1	869.0	1449.9	575.9
financ_pub	107.8	35.4	196.4	82.0	197.0	26.2
financ_pro	741.9	487.8	996.7	667.8	1044.4	453.0
eff_rd	9.1	5.8	13.1	8.0	13.6	5.3
researchemp	5.8	3.4	8.8	4.9	9.0	3.0
cs3	15.7	11.6	21.9	13.9	20.7	11.3
Output outcome variables						
totbrev	1.5	0.9	2.1	1.3	1.3	0.8
eff_moy_et	47.7	45.2	50.0	47.1	54.4	44.6
turnover	10094.9	11062.9	11206.8	9771.6	12095.0	11275.7
export	4054.6	4044.1	5306.1	3690.7	5628.2	4105.3
addedvalue	2971.9	3267.1	3235.3	2895.3	3824.5	3318.5
Other control variables						
emp	49.0	41.1	57.8	46.5	55.5	40.5
age	22.7	26.0	21.4	23.1	23.6	26.6
dum_export	0.7	0.7	0.8	0.7	0.7	0.7
dum_subven	0.8	0.5	0.9	0.7	0.8	0.5
Observations	7697	33752	1734	5963	358	27354

Note: Patents are in unit, R&D and salary variables are in thousand €, employment-related variables are in unit, and market-related variables are in thousand €.

Sources: R&D survey, DGE, FUI, MENESR, INSEE, Ficus-Fare, DADS, Lifi

3.6 Results

In this section, we first explain the drivers of firms' participation in the policy and then present our strategy of constructing an adequate counterfactual framework for participant firms. Finally, we present the estimated effects of the policy on participant firms' performance, discuss our results by group and compare them.

3.6.1 Estimated propensities to participate in the policy

We use the PSM approach to compute the probability of the participation of a firm in the policy based on its observable characteristics. This approach consists of estimating a logistic regression to predict the probability of participation conditional to the observed covariates. To evaluate the impacts of the competitiveness clusters policy, we must determine an adequate sampling to precisely estimate differences in outcomes between the treatment groups and the comparison group. As explained previously, we create three treatment groups to identify an appropriate control group with good overlap. We conduct several independent matchings instead of one because each treatment has its own propensity score, and each propensity score is used individually to estimate the effect of that treatment.

Following [Ben Hassine and Mathieu \(2017\)](#), we estimate the logistic model for each year to first take into account the entry and exit of firms from the policy, assuming that the determinant of participation in the policy may evolve over time. Therefore, in our study, the participation of a firm in the policy means that the firm participated for the first time or had participated before and remained a participant. All firms that were treated at least one time were excluded from the control group. Therefore, we estimate the model six times for Group A (2007-2012), seven times for Group B (2006-2012) and six times for Group C (2007-2012). As explained in the previous section, to calculate propensity scores, we control some firm characteristics, such as size, age, being a member of a group, experience in public subsidies, economic sector, export and geographical location. All the control variables used are measured for the year 2005, which is the pretreatment reference year. When a firm departs from (exits) the policy, it may continue to benefit from the network and cooperative linkages that it established while it was participating in the policy, both from information acquired through its participation in previous years and from its high exposure to spillovers. As we estimate the effect for each year in our study, we take into account the new entry/exit

issue.

The results for Group A (both treatments) presented in table 3.5 show that the firm size measured by the logarithm of total employees (*emp*) plays an important role and is positive and significant, as expected. Larger firms in terms of employment are more likely to be members of clusters and to participate in projects at the same time. The results suggest that an increase of 1% in employment increases the probability of participating in the policy by 40 percentage points until 2008 and declines slightly to approximately 30 percentage points from 2009. Younger firms are more likely to participate in the policy because the estimates of the firm age are negative and significant. The probability of participation decreases with firm age. The dummy variable (*pubsub*) is positive and very significant, meaning that if a firm has already benefited from public subsidies, it better knows the administrative procedures to benefit from another subsidy and therefore has an increased probability of participating in the public policy. For the economic sector, as expected, the results suggest that, in contrast to firms operating in high-technology manufacturing sectors, firms operating in the highly knowledge-intensive skills sector (*kis*) are more likely to participate in the clusters policy. The coefficient is positive and very significant. Firms with an export status are more likely to participate in the policy. Although their probability of participation in the policy seems to be nonsignificant between 2008 and 2010, it increased by between 40 percentage points in 2007 and 30 percentage points in 2011 and 2012.

For Group B, in which the firms belong to clusters and do not participate in projects (treatment 1 only), the results are presented in table 3.6. The results for this group show that the estimates are consistent with those of Group A but with a smaller magnitude for variables such as employment, experience in public subsidies, economic sector and export. Being a young firm has a positive effect on the probability of participation in the clusters, but the magnitude of the effect is slightly stronger than that of Group A. Firms operating in the highly knowledge-intensive skills sector are more likely to participate in the clusters policy. It is worth noting that the dummy variable indicating that the firm operates in a high-technology manufacturing sector, in contrast to that of the highly knowledge-intensive skills sector, has a negative and significant effect. Firms with an export status in 2005 are more likely to participate in the policy for the entire period.

The results for Group C, in which firms participate in projects and do not belong to clusters (treatment 2 only), are presented in table 3.7. For employment, the estimates are

quite similar to those for Group A. The firm age becomes nonsignificant and has no effect on the probability of participation in FUI projects. Being a member of a group seems to reduce the probability of participation in FUI projects in 2006 and to have no effect from 2007. Having experience in public subsidies significantly increases the probability of participation but with a lesser magnitude than that of Group A. Being in a knowledge-intensive skills sector increases the probability of participation in FUI projects in Group C from 2008 on, but with a decreasing trend over time and with a smaller magnitude than that of Group A.

All these results are consistent with those of previous studies evaluating the effects of public clusters policies. It is worth noting that our analysis shows that the firms that performed better before the policy are those that participated in the policy. A comparison of the magnitude of the effects of the control variables on firms' probability of participation in the policy shows that the results for the three groups reveal considerable heterogeneity of the effects across the three groups.

Table 3.5: Group A participation by year (2007-2012)

	Participation in competitiveness clusters and in FUI projects					
	(2007)	(2008)	(2009)	(2010)	(2011)	(2012)
log(emp05)	0.5*** (0.1)	0.5*** (0.1)	0.4*** (0.1)	0.4*** (0.1)	0.3*** (0.1)	0.3*** (0.1)
age05	-0.01*** (0.01)	-0.01*** (0.004)	-0.01*** (0.003)	-0.01*** (0.003)	-0.01*** (0.003)	-0.01*** (0.003)
appgroup05	0.5** (0.2)	0.2 (0.2)	0.1 (0.1)	0.2 (0.1)	0.02 (0.1)	-0.1 (0.1)
dum_subven05	1.3*** (0.2)	1.3*** (0.2)	1.3*** (0.1)	1.2*** (0.1)	1.1*** (0.1)	1.1*** (0.1)
dum_sec_man_electro05	-1.0 (1.0)	-1.4 (1.0)	-1.0 (0.7)	-0.6 (0.6)	0.4 (0.4)	0.3 (0.4)
dum_sec_hkis05	1.1*** (0.2)	0.8*** (0.2)	0.8*** (0.1)	0.8*** (0.1)	0.9*** (0.1)	0.8*** (0.1)
dum_export05	0.4* (0.2)	0.1 (0.2)	0.1 (0.1)	0.1 (0.1)	0.3* (0.1)	0.3** (0.1)
Constant	-18.7 (406.2)	-17.1 (271.8)	-16.9 (270.1)	-16.8 (248.8)	-16.9 (247.3)	-16.7 (247.5)
Location dummies	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Observations	8,143	7,410	7,729	7,687	7,598	7,463

Note: The columns give the estimates corresponding to the marginal effect of the considered variable on the firm's probability to participate in the policy. All the control variables used between 2007 and 2012 are measured for the year 2005 which is the pre-treatment reference year. The location dummies consist of eight dummy variables corresponding to the eight French metropolitan NUTS1 regions. Standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 3.7: Group C participation by year (2007-2012)

	Participation in FUI projects					
	(2007)	(2008)	(2009)	(2010)	(2011)	(2012)
log(emp05)	0.5*	0.3*	0.4***	0.4***	0.4***	0.5***
	(0.3)	(0.2)	(0.1)	(0.1)	(0.1)	(0.1)
age05	-0.001	-0.01	-0.01*	-0.01	-0.01**	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
appgroup05	-1.3**	0.2	0.1	-0.2	0.4	0.2
	(0.6)	(0.4)	(0.3)	(0.3)	(0.3)	(0.3)
dum_subven05	1.6**	1.0***	0.9***	0.8***	1.1***	0.9***
	(0.7)	(0.3)	(0.3)	(0.3)	(0.3)	(0.2)
dum_sec_man_electro05	-16.0	0.5	-0.2	1.0	-0.5	-0.5
	(3, 128.5)	(1.0)	(1.0)	(0.6)	(1.0)	(1.0)
dum_sec_hkis05	0.1	1.0***	1.0***	0.9***	0.6**	0.6**
	(0.6)	(0.4)	(0.3)	(0.3)	(0.3)	(0.3)
dum_export05	-0.1	0.3	0.4	0.3	0.1	-0.1
	(0.6)	(0.4)	(0.3)	(0.3)	(0.3)	(0.3)
Constant	-24.8	-23.8	-18.0	-18.0	-17.7	-17.8
	(13, 669.4)	(8, 994.0)	(445.8)	(410.5)	(413.1)	(415.6)
Location dummies	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Observations	8,025	7,231	7,497	7,437	7,324	7,190

Note: The columns give the estimates corresponding to the marginal effect of the considered variable on the firm's probability to participate in the policy. All the control variables used between 2007 and 2012 are measured for the year 2005 which is the pre-treatment reference year. The location dummies consist of eight dummy variables corresponding to the eight French metropolitan NUTS1 regions. Standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

3.6.2 Balancing firms' characteristics before/after matching

Before estimating the effect of the policy, we first compare some firm characteristics between participants (treatment group) and nonparticipants (control group) to control endogeneity and the factors determining participation. To compare the firms' characteristics before and after matching, we consider 2005 as the reference year (pretreatment year) and create treatment and control groups for each year. We create several subgroups within each of the three different samples, Group A, Group B, and Group C. The control groups across these subsamples are similar and vary between 8060 and 7108 observations before matching.

To account for the selection problem, we calculate the propensity to participate in the policy using certain firm characteristics such as size measured by the logarithm of employees, age, being a member of a group, experience in public subsidies, having exporter status,

Table 3.6: Group B participation by year (2006-2012)

	Participation in competitiveness clusters						
	(2006)	(2007)	(2008)	(2009)	(2010)	(2011)	(2012)
log(emp05)	0.3*** (0.04)	0.2*** (0.04)	0.2*** (0.04)	0.1*** (0.04)	0.1*** (0.04)	0.1** (0.04)	0.1* (0.04)
age05	-0.01*** (0.002)	-0.01*** (0.002)	-0.01*** (0.002)	-0.004*** (0.002)	-0.003* (0.002)	-0.004*** (0.002)	-0.004*** (0.002)
appgroup05	0.2* (0.1)	0.1 (0.1)	0.1 (0.1)	0.1 (0.1)	0.1 (0.1)	0.1* (0.1)	0.2*** (0.1)
dum_subven05	1.2*** (0.1)	1.0*** (0.1)	1.0*** (0.1)	0.9*** (0.1)	0.9*** (0.1)	0.9*** (0.1)	0.9*** (0.1)
dum_sec_man_electro05	-0.2 (0.3)	0.1 (0.2)	-0.3 (0.3)	0.1 (0.3)	0.3 (0.2)	0.1 (0.2)	0.1 (0.2)
dum_sec_hkis05	0.7*** (0.1)	0.5*** (0.1)	0.6*** (0.1)	0.7*** (0.1)	0.7*** (0.1)	0.6*** (0.1)	0.7*** (0.1)
dum_expport05	0.4*** (0.1)	0.2** (0.1)	0.2** (0.1)	0.3*** (0.1)	0.2*** (0.1)	0.2*** (0.1)	0.2** (0.1)
Constant	-4.1*** (0.8)	-3.5*** (0.8)	-4.0*** (1.1)	-3.8*** (1.1)	-4.0*** (1.1)	-3.9*** (1.1)	-3.9*** (1.1)
Location dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,859	8,938	8,011	8,303	8,278	8,275	8,070

Note: The columns give the estimates corresponding to the marginal effect of the considered variable on the firm's probability to participate in the policy. All the control variables used between 2007 and 2012 are measured for the year 2005 which is the pre-treatment reference year. The location dummies consist of eight dummy variables corresponding to the eight French metropolitan NUTS1 regions. Standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

economic sector and geographical location. The prematching differences between the treated and control groups for these characteristics are in general relatively high and may bias our estimates if we do not reduce them.

Tables 3.21, 3.22 and 3.23 present the before-and-after-matching differences in the characteristics of firms. As shown in these tables, the distances between the treatment and control groups are very high before matching. After applying the matching between the treated and control firms, each participant firm is matched with one nonparticipant firm. We obtain good improvement in the balance of characteristics between the two groups for each year, and the distances between the treated and control firms are exactly the same. Despite all the restrictions applied, there are very few firms that have no similar controls and are dropped from the data sets (see the last lines of the three tables).

The figures 3.6, 3.7 and 3.8 show, respectively, the distribution of the propensity score before and after matching for Group A, Group B and Group C. Figure 3.6 shows the distribution in Group A in 2007, figure 3.7 shows the distribution in Group B in 2006, and figure 3.8 shows the distribution in Group C in 2008. We present these years because after checking the other years, we found little difference in the results.

The figures show that our matching on the conditional probability of participation in the policy given a set of covariates produces samples with similar distributions of linear propensity scores between participant and control SMEs in the three different groups. We therefore consider that our quasi-experimental design to mimic a randomized experiment enables us to obtain data similar to those of a true control experiment and therefore respect the CIA and the common support assumptions. This finding indicates the adequacy of the common support and the validity of the propensity score, which enables a more precise policy impact evaluation.

Figure 3.6: Propensity score density before and after matching for Group A (year 2007)

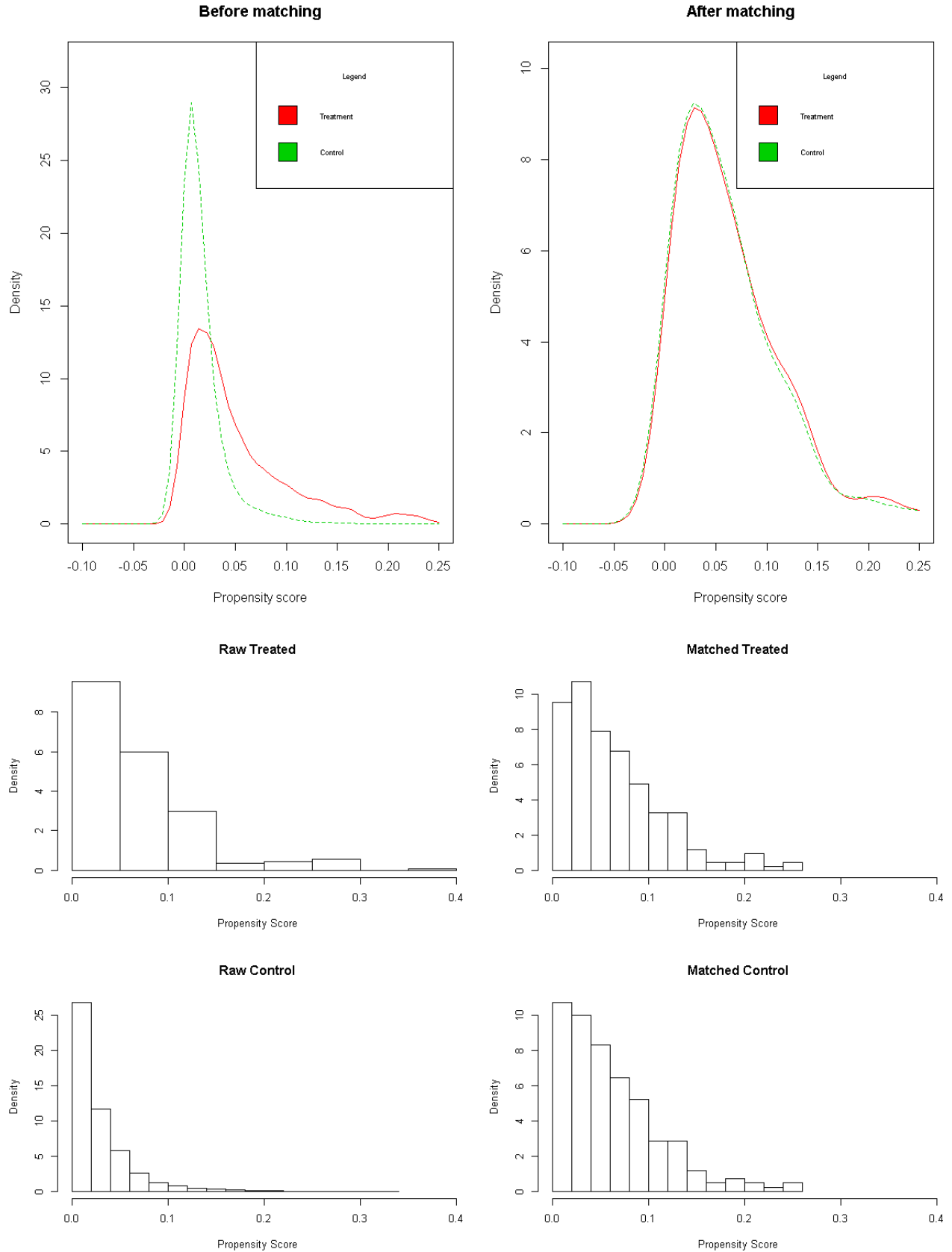


Figure 3.7: Propensity score density before and after matching for Group B (year 2006)

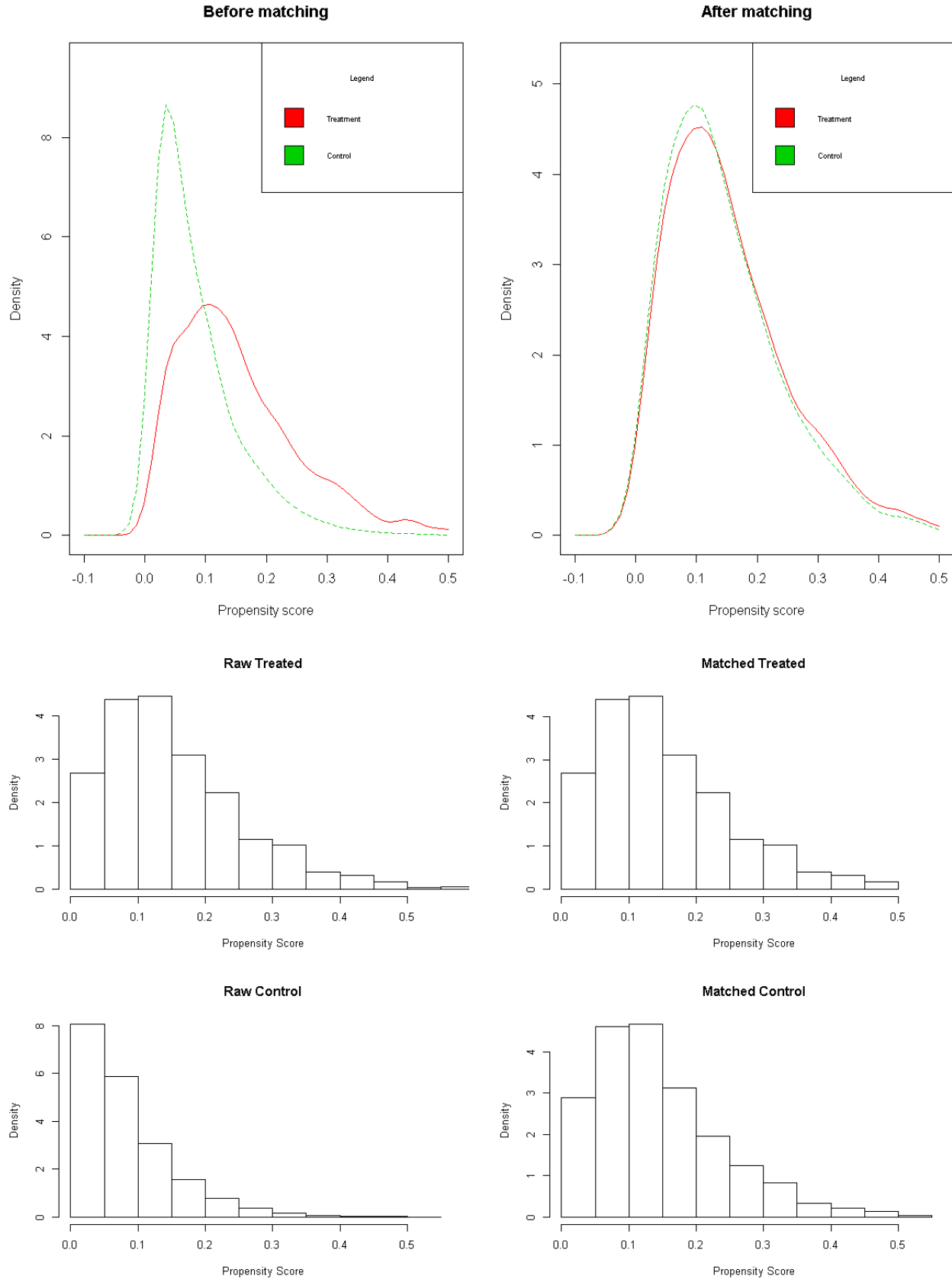
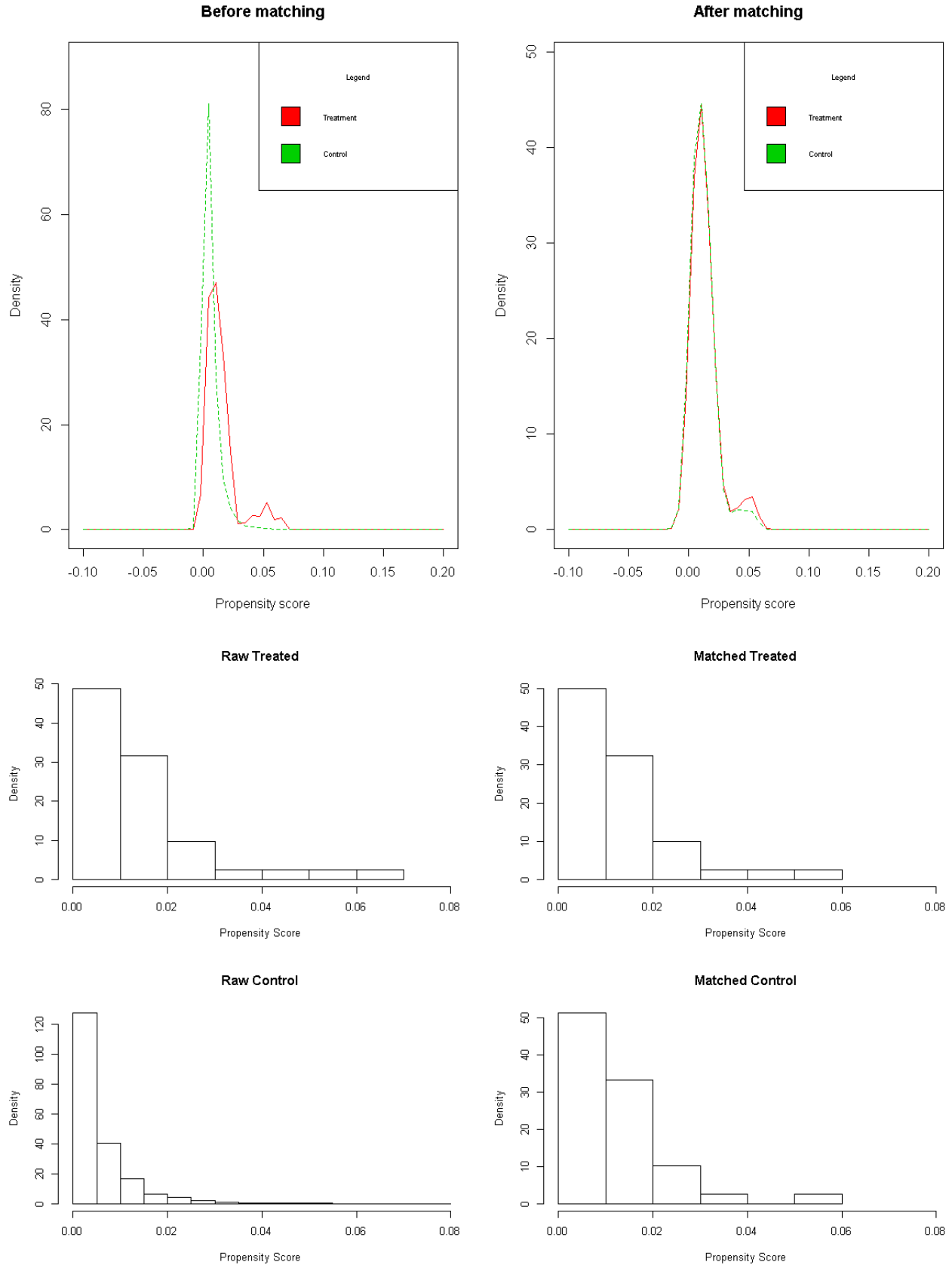


Figure 3.8: Propensity score density before and after matching for Group C (year 2008)



3.6.3 Average treatment effects of the policy on firms' outcomes

We use the propensity score to construct a good counterfactual framework and to reduce the selection bias to better measure the policy impacts. We have shown in the previous section that the procedure results in a proper balance between the treatment and counterfactual groups; therefore, the method allows computation of the ATT. Estimates of the matching estimators and standard errors estimated with the [Abadie and Imbens \(2006\)](#) method are provided by the *Matching* packages ([Sekhon, 2011](#)).

As noted in the previous sections, the estimations are based on three different treatment options and are classified in two types of outcome variables: input outcome variables (R&D spending and employment related to R&D) and output outcome variables (patents, total employment, and economic performance). First, we analyze the effects of the policy on the SMEs that belong to clusters and participate in FUI projects at the same time (Group A). Second, we analyze the effects on the SMEs that adhere only to clusters (Group B). Finally, we analyze the effects on the SMEs that participate only in FUI projects (Group C). The results of the treatment effects are reported in tables [3.8](#) to [3.13](#).

3.6.3.1 Effects on innovation input additionality

The results for the SMEs that both belong to clusters and participate in FUI projects (Group A) with regard to input additionality are summarized in table [3.8](#). The results suggest the rejection of the crowding-out hypothesis and conclude in favor of input additionality effects. We find that compared to nonparticipating firms, participating firms spent more in total R&D between 2008 and 2011 (plus €209,410 to 420,960, depending on the year). This difference is due especially to the increase in their internal R&D spending. It is worth noting that for private R&D spending, there is a discontinuity in the effects for 2009, which is the year of the implementation of the second phase of the policy. The participating SMEs saw a significant increase in the average public subsidies they received between 2008 and 2012 (plus €68,310 to 142,430, depending on the year). We find significant positive effects on SMEs' private R&D spending in 2008, 2010 and 2011 (plus €263,870 to 386,860, depending on the year). Moreover, when focusing on employment related to R&D, the effects of the policy on CS3 employment were strongly positive between 2007 and 2011 (plus 2.3 to 4.1 employees, depending on the year), and the effects were also positive between 2007 and 2012

on R&D staff (plus 1.5 to 2.5 employees, depending on the year) and researchers (plus 1.5 to 2.5 employees, depending on the year).

Table 3.8: Innovation input additionality effects for Group A

	(2007)	(2008)	(2009)	(2010)	(2011)	(2012)
External R&D Expenditure						
Estimate	66.68 (77.78)	74.98*** (44.14)	65.20*** (29.55)	-20.20 (36.40)	104.62 (74.71)	-821.22** (430.80)
Internal R&D Expenditure						
Estimate	-228.58 (356.94)	167.18 (110.25)	286.89*** (110.09)	305.87*** (99.09)	284.65*** (93.68)	326.79*** (95.49)
Total Budget in R&D						
Estimate	-249.36 (660.39)	376.07*** (120.13)	209.41** (101.11)	379.52*** (136.02)	424.96*** (127.90)	-477.48 (428.30)
Private funding						
Estimate	-287.01 (657.54)	358.29*** (119.83)	204.21 (140.14)	263.87** (116.48)	386.86*** (141.38)	-527.16 (424.90)
Public funding						
Estimate	20.95 (18.96)	68.31** (30.25)	89.67*** (29.52)	78.60*** (24.62)	72.47*** (20.06)	142.43*** (40.19)
R&D Staff						
Estimate	0.98 (0.67)	2.40*** (0.75)	1.50*** (0.60)	2.25*** (0.74)	2.47*** (0.68)	2.49*** (0.67)
Researchers						
Estimate	0.62 (0.41)	1.75*** (0.56)	1.49*** (0.45)	1.88*** (0.46)	1.85*** (0.46)	2.52*** (0.51)
CS3 employment						
Estimate	2.33*** (1.07)	3.35*** (1.12)	2.69*** (1.17)	4.10*** (1.28)	2.80*** (1.30)	1.67 (1.32)
Nb. Obs	270	440	610	650	700	710

Note: The ATT estimates are the mean difference between treatment group and corresponding control groups. One-to-one matching with replacement was implemented to decrease bias. Bootstrap with 1000 replications was used to estimate standard errors for the propensity score matching. The columns give the estimates and robust standard errors are below the estimates. Significance levels: ***1%; **5%; *10%.

The results with regard to input additionality for SMEs that adhere only to clusters (Group B) are summarized in table 3.9. The results favor the rejection of the crowding-out hypothesis but show rather weak input additionality effects. We find that compared to nonparticipating firms, participating firms spent more in total R&D between 2008 and 2012 (plus €154,480 to 160,420, depending on the year). For Group A, this increase is especially due to the increase in internal R&D spending. We find that public funding received by these SMEs increased between 2009 and 2012 (plus €26,690 to 37,930, depending on the year).

Compared to nonadherents, adherent SMEs spent more private R&D funds between 2007 and 2012 (plus €114,370 to 195,070, depending on the year). Moreover, when we focus on employment related to R&D, the effects of adhesion were positive between 2007 and 2012 on R&D staff (plus 0.6 to 1.3 employees, depending on the year) and researchers (plus 0.5 to 0.9 employees, depending on the year), but for CS3 employment, there were significant positive effects only in 2007 (plus 1.3 employees) and 2008 (plus 0.9 employees) compared to nonadherent SMEs.

Table 3.9: Innovation input additionality effects for Group B

	(2006)	(2007)	(2008)	(2009)	(2010)	(2011)	(2012)
External R&D Expenditure							
Estimate	2.41	14.81	-111.12	-199.32	32.64	58.02**	43.05
	(11.46)	(41.47)	(204.68)	(192.87)	(31.66)	(28.92)	(37.51)
Internal R&D Expenditure							
Estimate	29.77	7.72	75.25*	65.59	120.64**	145.61***	143.62**
	(26.92)	(86.33)	(44.58)	(52.89)	(53.43)	(51.56)	(65.22)
Total Budget in R&D							
Estimate	11.38	48.54	154.48*	90.67	151.03**	160.42***	155.88**
	(26.91)	(98.26)	(81.30)	(154.12)	(73.31)	(58.20)	(77.96)
Private funding							
Estimate	18.70	114.37*	150.04*	126.43*	149.26**	188.07***	195.07***
	(33.22)	(65.17)	(78.62)	(69.02)	(71.12)	(67.35)	(71.09)
Public funding							
Estimate	6.31	6.00	5.86	26.69**	39.60**	29.77*	37.93**
	(4.56)	(5.90)	(9.02)	(11.00)	(17.32)	(17.25)	(16.30)
R&D Staff							
Estimate	0.20	0.59***	0.97***	0.68***	1.07***	0.86***	1.32***
	(0.12)	(0.16)	(0.23)	(0.22)	(0.27)	(0.26)	(0.32)
Researchers							
Estimate	0.15	0.61***	0.89***	0.79***	0.48**	0.60***	0.59***
	(0.10)	(0.13)	(0.17)	(0.16)	(0.21)	(0.19)	(0.21)
CS3 employment							
Estimate	0.26	1.25***	0.85**	0.01	0.59	0.02	1.08
	(0.27)	(0.30)	(0.36)	(0.55)	(0.55)	(0.67)	(0.69)
Nb. Obs	1594	1858	1642	1758	1832	2054	1924

Note: The ATT estimates are the mean difference between treatment group and corresponding control groups. One-to-one matching with replacement was implemented to decrease bias. Bootstrap with 1000 replications was used to estimate standard errors for the propensity score matching. The columns give the estimates and robust standard errors are below the estimates. Significance levels: ***1%; **5%; *10%.

The results with regard to input additionality for SMEs that participate only in FUI projects (Group C) are summarized in table 3.10. The results suggest the rejection of the crowding-out effect but do not favor the substantial additionality of effects on the R&D of

participant SMEs. The results show that in this group, the policy rarely has positive effects in terms of input additionality. Participation only in projects seemed to increase the SMEs' total and privately financed R&D budget only in 2007 and 2012, but for the other years, this effect becomes nonsignificant. Regarding employment related to R&D, the results show a nonexistent effect. In sum, participating only in projects does not generally stimulate innovation input for participating SMEs.

Table 3.10: Innovation input additionality effects for Group C

	(2007)	(2008)	(2009)	(2010)	(2011)	(2012)
External R&D Expenditure						
Estimate	63.35**	183.08	-67.55	-1678.50	6.81	28.31
	(28.90)	(129.40)	(48.82)	(1756.90)	(52.30)	(41.70)
Internal R&D Expenditure						
Estimate	348.47***	81.32	-143.83	232.05	548.44*	215.73*
	(140.20)	(96.82)	(169.38)	(204.37)	(319.15)	(126.41)
Total Budget in R&D						
Estimate	278.59*	262.94	-153.72	388.84	190.02	79.94
	(155.99)	(228.11)	(176.15)	(326.63)	(133.91)	(167.73)
Private funding						
Estimate	329.59**	29.61	177.09	376.56	-165.99	253.38**
	(147.47)	(90.98)	(226.33)	(243.83)	(156.15)	(126.43)
Public funding						
Estimate	-3.47	51.64	-0.99	98.10***	186.65**	70.04
	(16.41)	(49.55)	(46.50)	(39.32)	(86.39)	(66.42)
R&D Staff						
Estimate	2.64**	-0.62	-0.65	1.66	-1.56	2.50*
	(1.13)	(0.89)	(1.77)	(1.62)	(1.62)	(1.45)
Researchers						
Estimate	1.31	0.08	-1.04	1.05	0.34	1.39*
	(1.01)	(0.46)	(1.30)	(1.11)	(0.68)	(0.84)
CS3 employment						
Estimate	-3.18*	0.37	1.45	-0.71	5.04**	1.34
	(1.95)	(1.49)	(3.45)	(2.69)	(2.45)	(3.43)
Nb. Obs	34	82	146	150	152	164

Note: The ATT estimates are the mean difference between treatment group and corresponding control groups. One-to-one matching with replacement was implemented to decrease bias. Bootstrap with 1000 replications was used to estimate standard errors for the propensity score matching. The columns give the estimates and robust standard errors are below the estimates. Significance levels: ***1%; **5%; *10%.

The comparison of the different treatment options reveals that the policy associated with both treatments (Group A) outperforms both cluster adhesion and FUI project participation considered separately. Moreover, being a member of a cluster seems to be more effective than participating in FUI projects with regard to input additionality. There is no crowding-out

effect, whatever the treatment option, and there are substantial positive effects on input additionality for SMEs in Group A and to a lesser extent for SMEs in Group B.

3.6.3.2 Effects on output additionality

The results for SMEs that both belong to clusters and participate in FUI projects (Group A) with regard to output additionality are summarized in table 3.11. The results suggest that the policy had positive effects on SMEs' number of patents filed in 2008 (0.9 patent) and 2009 (1.4 patents). The findings show that the effects of the policy on SMEs' total employment were significant and positive between 2007 and 2012 (plus 3 to 6.7 employees depending on the year). However, no significant effect was observed on SMEs' turnover, added value, and export, whatever the year.

The results for SMEs which adhere only in the clusters (Group B) with regard to output additionality are summarized in table 3.12. Results show that the impacts of the competitiveness clusters policy on SMEs' filed patents are negative in 2006 and 2012 (respectively -0.6 and -0.5 patents). The effects on total employment are positive between 2007 and 2012 (plus 1.2 to 5.8 employees depending on the year) but much weaker than for Group A. Results suggest that the competitiveness clusters seem to have significant positive effects on the turnover, added value and export of adherent SMEs only in 2011.

The results for SMEs which participate only in the FUI projects (Group C) with regard to output additionality are summarized in table 3.13. Results show that participating only in the FUI projects does not increase SMEs' patenting. We observe a positive effect of participation on the average number of employees in 2009 (6.6 employees) but no effect is observed for the other years. The policy has no effect on the participating SMEs' turnover and export. However, it seems to have positive impacts on added value in 2009 and 2011. It is worth noting that for this Group C, the relatively small number of observations used in the estimates may induce limitations of the analysis.

The comparison of different treatment options reveals that, for total employment, the policy associating both treatments (Group A) outperforms both clusters adhesion and FUI projects participation that are used separately. Moreover, although the effects are quite weak, or non-existent, being a member of clusters seems to be more effective than participating in FUI projects with regard to output additionality.

Table 3.11: Effects of participation on output additionality in Group A

	(2007)	(2008)	(2009)	(2010)	(2011)	(2012)
Total Patents						
Estimate	-0.39 (0.41)	0.93*** (0.42)	1.36*** (0.62)	0.90 (0.57)	0.37 (0.51)	0.04 (0.33)
Average number of employees (full-time equivalent)						
Estimate	2.98* (1.79)	6.06*** (1.62)	6.19*** (1.63)	6.56*** (2.05)	6.27*** (2.18)	5.91*** (1.79)
Turnover						
Estimate	-4542.00 (3006.30)	-2682.60 (2355.20)	-1947.30 (1867.70)	-644.42 (1847.50)	88.64 (1517.90)	2075.40 (1378.00)
Added Value						
Estimate	-133.57 (243.96)	-389.44 (618.89)	-665.45 (498.38)	-442.94 (466.80)	-134.54 (526.94)	-71.56 (365.85)
Export						
Estimate	62.93 (558.38)	-546.26 (695.78)	-508.47 (761.50)	-161.77 (724.98)	521.26 (703.27)	268.50 (519.24)
Nb. Obs	270	440	610	650	700	710

Note: The ATT estimates are the mean difference between treatment group and corresponding control groups. One-to-one matching with replacement was implemented to decrease bias. Bootstrap with 1000 replications was used to estimate standard errors for the propensity score matching. The columns give the estimates and robust standard errors are below the estimates. Significance levels: ***1%; **5%; *10%.

Table 3.12: Effects of participation on output additionality in Group B

	(2006)	(2007)	(2008)	(2009)	(2010)	(2011)	(2012)
Total Patents							
Estimate	-0.58** (0.25)	0.00 (0.23)	0.01 (0.31)	0.13 (0.23)	-0.25 (0.30)	-0.50** (0.25)	-0.48 (0.32)
Average number of employees (full-time equivalent)							
Estimate	1.23** (0.52)	1.39 (0.92)	2.50*** (0.85)	1.14 (1.04)	3.20*** (1.12)	5.80*** (1.40)	5.34*** (1.22)
Turnover							
Estimate	-603.77 (577.33)	-1368.40* (730.69)	-662.55 (584.95)	1525.70 (1715.00)	90.32 (453.97)	1238.30* (669.33)	66.10 (694.39)
Added Value							
Estimate	-140.12 (169.58)	57.65 (177.06)	-121.08 (243.01)	-88.51 (246.89)	36.08 (233.48)	302.41* (179.73)	349.42 (252.97)
Export							
Estimate	-222.87 (304.58)	41.67 (854.73)	-2.72 (248.44)	-412.86 (381.66)	96.44 (286.39)	896.83*** (288.93)	395.60 (374.68)
Nb. Obs	1594	1858	1642	1758	1832	2054	1924

Note: The ATT estimates are the mean difference between treatment group and corresponding control groups. One-to-one matching with replacement was implemented to decrease bias. Bootstrap with 1000 replications was used to estimate standard errors for the propensity score matching. The columns give the estimates and robust standard errors are below the estimates. Significance levels: ***1%; **5%; *10%.

Table 3.13: Effects of participation on output additionality in Group C

	(2007)	(2008)	(2009)	(2010)	(2011)	(2012)
Total Patents						
Estimate	1.15	-0.53	-0.80	-0.87	-2.50	-2.35
	(1.24)	(1.13)	(1.06)	(0.92)	(1.81)	(1.65)
Average number of employees (full-time equivalent)						
Estimate	-1.38	2.86	6.63*	-4.64	-0.92	1.43
	(2.01)	(3.44)	(3.57)	(4.32)	(4.30)	(5.33)
Turnover						
Estimate	659.35	-1379.80	1301.00	1548.90	1551.20	845.17
	(2807.00)	(1741.30)	(1224.40)	(1435.20)	(1920.00)	(1207.10)
Added Value						
Estimate	-160.06	662.61	2167.40**	1132.30	1457.10*	148.18
	(413.65)	(947.68)	(1019.40)	(1031.80)	(799.27)	(820.03)
Export						
Estimate	570.24	402.71	971.75	736.00	529.03	-615.79
	(1513.90)	(1616.80)	(830.72)	(1125.00)	(694.10)	(1437.00)
Nb. Obs	34	82	146	150	152	164

Note: The ATT estimates are the mean difference between treatment group and corresponding control groups. One-to-one matching with replacement was implemented to decrease bias. Bootstrap with 1000 replications was used to estimate standard errors for the propensity score matching. The columns give the estimates and robust standard errors are below the estimates. Significance levels: ***1%; **5%; *10%.

3.6.4 Sensitivity analysis

Our analysis assumes that matching is performed based on all relevant characteristics and that there is no unobserved confounder that may account for the differences across the treatment and control groups. The sensitivity analysis proposed by [Rosenbaum \(2002\)](#) enables us to examine how reasonable this assumption is. We performed sensitivity tests using the *psens* R function to examine what magnitude of a hidden bias due to an unobserved confounder would change the significance of the treatment effects. Here, to calculate Rosenbaum bounds for both the p-value and the estimated treatment effect, as in the literature, I set the maximum value for gamma at 2.0 with increments of 0.1. The results (see table [3.14](#)) show that gamma does not have to attain a very high value for the inferences to change because a gamma value equal to 1.2 or more could lead to a significant p-value. This finding suggests that even a small unobserved difference in a covariate would change our inference. We, therefore, conclude that although the competitiveness clusters policy has positive effects on SMEs' innovation input and output performance, the findings are sensitive to possible hidden bias due to an unobserved confounder.

Table 3.14: Sensitivity Analysis using Rosenbaum Sensitivity Test

Group A 2007			Group B 2006			Group C 2008					
Rosenbaum Sensitivity Test for Wilcoxon Signed Rank P-Value											
Unconfounded estimate			0.1525	Unconfounded estimate			0.1768	Unconfounded estimate			0.0724
Gamma	Lower bound	Upper bound	Gamma	Lower bound	Upper bound	Gamma	Lower bound	Upper bound			
1.0	0.1525	0.1525	1.0	0.1768	0.1768	1.0	0.0724	0.0724			
1.1	0.0659	0.2925	1.1	0.0184	0.5912	1.1	0.0422	0.1163			
1.2	0.0256	0.4563	1.2	0.0008	0.9012	1.2	0.0242	0.1699			
1.3	0.0091	0.6148	1.3	0.0000	0.9882	1.3	0.0138	0.2307			
1.4	0.0030	0.7466	1.4	0.0000	0.9992	1.4	0.0077	0.2961			
1.5	0.0010	0.8440	1.5	0.0000	1.0000	1.5	0.0043	0.3635			
1.6	0.0003	0.9094	1.6	0.0000	1.0000	1.6	0.0024	0.4305			
1.7	0.0001	0.9499	1.7	0.0000	1.0000	1.7	0.0013	0.4952			
1.8	0.0000	0.9735	1.8	0.0000	1.0000	1.8	0.0007	0.5565			
1.9	0.0000	0.9865	1.9	0.0000	1.0000	1.9	0.0004	0.6132			
2.0	0.0000	0.9934	2.0	0.0000	1.0000	2.0	0.0002	0.6650			

Note: Gamma is Odds of Differential Assignment To Treatment Due to Unobserved Factors

3.7 Conclusion

This chapter examines the effectiveness of the competitiveness clusters policy on participating SMEs' innovation input and output performance. We combine data from several sources to build a rich firm-level panel data set covering the 2005-2012 period and use an original strategy to identify participating firms to determine the structure of participation. We consider two levels of treatment (cluster adhesion and FUI project participation). Therefore, we distinguish three groups of treatment: receiving both treatments, receiving only the first treatment and receiving only the second treatment. We use the CDiD estimator, which is a combination of PSM with the DiD method, to account for the selection bias due to observable and unobserved characteristics when creating a counterfactual framework. We determine an adequate sampling, precisely estimate differences in outcomes between the treatment and control groups and conduct several independent matchings for each type of treatment at each time period.

Our results suggest that participation in the competitiveness clusters policy has strong positive effects on participating SMEs' innovation input. Joint participation in clusters and projects brings a strong multiplier effect to privately financed R&D, and to a lesser extent, only belonging to a cluster also has a positive effect on privately financed R&D. However, only participating in FUI projects rarely has positive effects in terms of input additionality and therefore does not lead to a leveraging effect on private R&D spending. Moreover, it is worth noting that no crowding-out effect is observed, whatever the treatment option.

With regard to output performance, the effects are strongly positive for total employment for SMEs that receive both treatments and to a lesser extent for SMEs that only belong to clusters. But the effects on employment are very weak or nonexistent for SMEs that only participate in FUI projects. The policy effects on other types of output performance (patents, turnover, added value, and export) are generally weak or nonexistent.

In sum, when we compare the effects of the policy through the three treatment options, we see that the effects are heterogeneous. Our results suggest that the effects of the policy are stronger for SMEs that receive both treatments. The effects of only cluster adhesion are stronger than those of only participating in FUI projects.

Like previous studies evaluating the effects of the competitiveness clusters policy on SMEs' performance, this study concludes that positive effects exist in terms of private R&D spending and employment related to R&D. These findings are in line with the results of previous studies regarding the absence of impacts on output performance related to the market. However, this study brings new evidence regarding the impact of the competitiveness clusters policy on total employment. It, therefore, contributes to the literature with new findings on two points. First, the results show that the policy has positive effects on total employment. Second, a comparison of the two policy instruments reveals that the effects are stronger for SMEs that receive both treatments, slightly weaker for those that are only a member of a cluster and very weak or nonexistent for those that participate only in FUI projects. These findings highlight the importance of strengthening the animation and strategic management of the clusters and also of providing services for firms in clusters. The development of structuring projects, such as platforms of innovation intended to offer services or resources, and the development of innovation ecosystems have a greater impact on firms' performance than financing R&D projects.

Finally, despite the robustness checks, these results should be interpreted with much caution. The weakness or absence of significant effects on output performance may be due to the fact that the policy is unsuccessful or was highly successful and generated large positive spillovers for nonparticipant firms. It may be interesting to complement this econometric evaluation with studies measuring the indirect effects of this policy through spillovers and externalities. We believe that not only should the limitations of the data be emphasized but several instruments of policy supporting firms, such as the CIR, should be controlled to improve these results.

3.8 Appendices Chapter 3

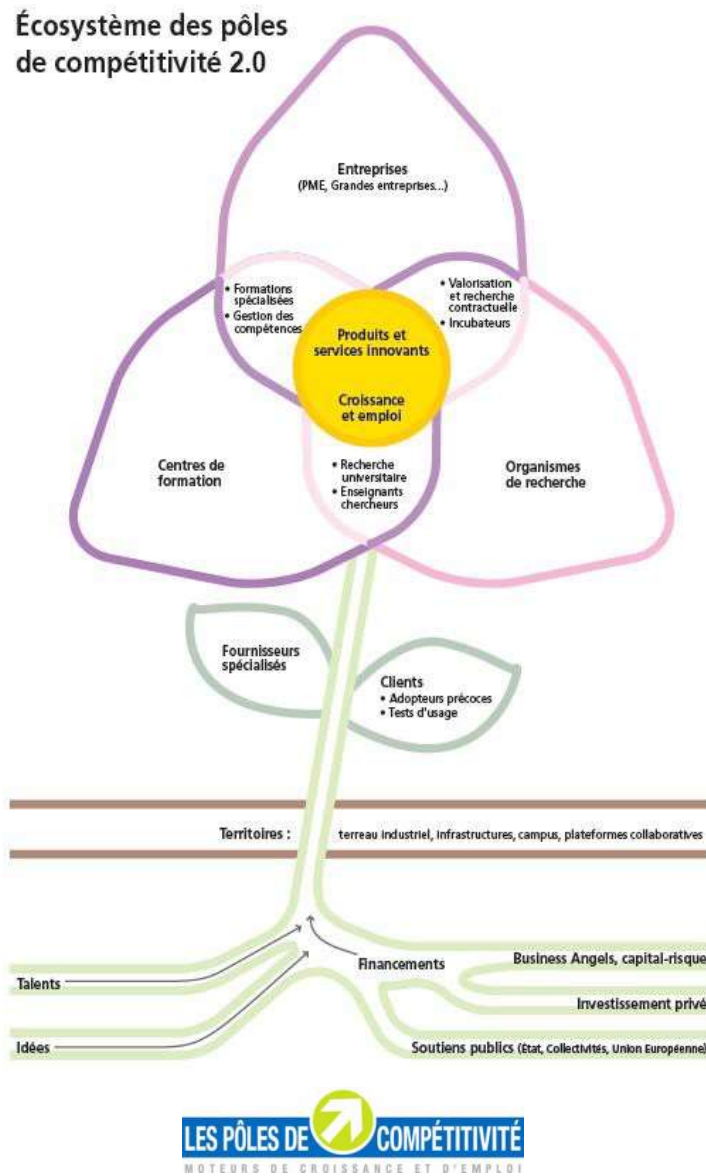
3.8.1 Literature review

Figure 3.10: Map of the Competitiveness clusters by type



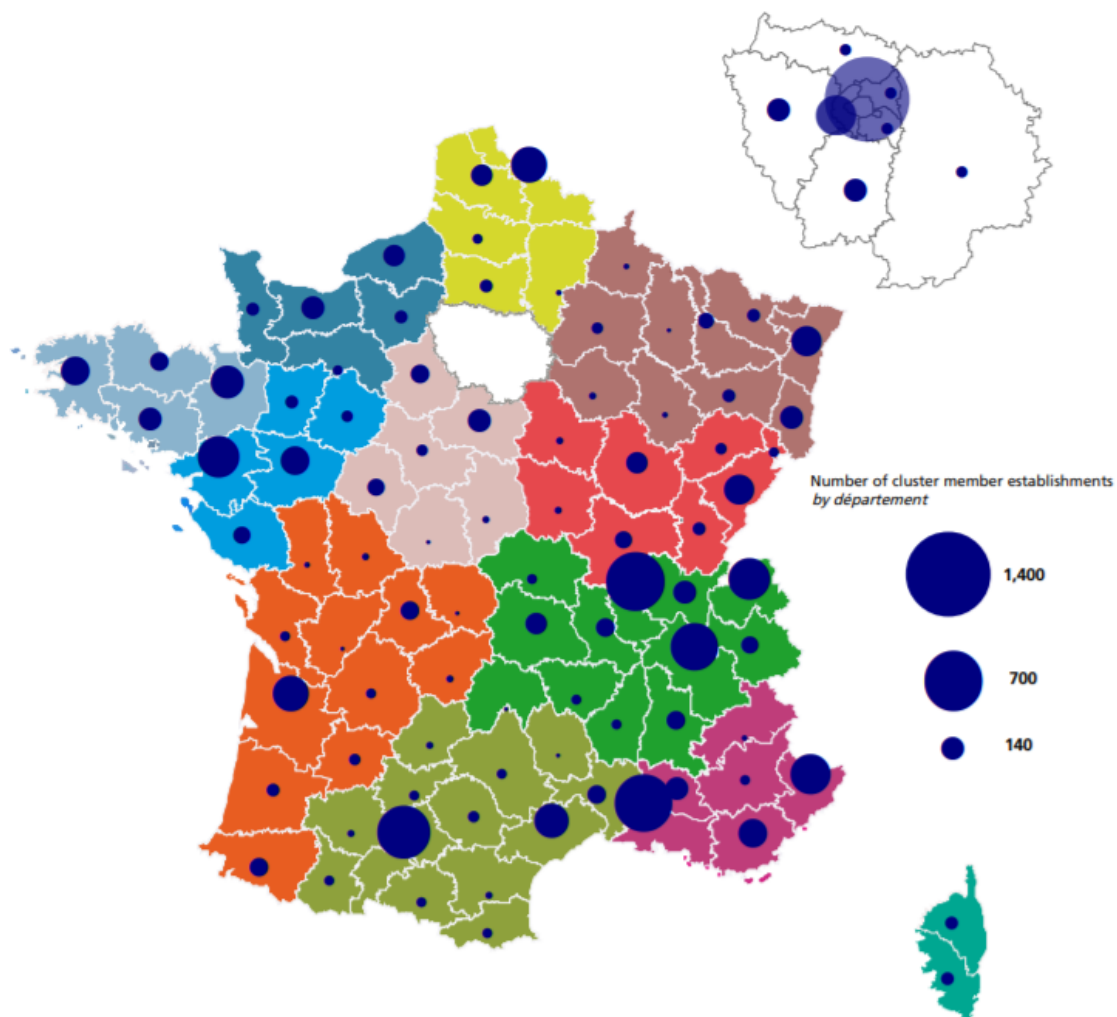
Source: DGE/CGET, 2016: Modified and adapted by the author

Figure 3.9: Ecosystem of the competitiveness clusters



Source: http://competitivite.gouv.fr/documents/commun/Ecosysteme_des_poles/ecosysteme-2.pdf.

Figure 3.11: Geographic distribution of cluster member establishments (2004)



Source: DGE

Geographical location of firms

- **If an enterprise with only one establishment**

We assign to the enterprise the location of its single establishment.

entloc = etabloc

- **If an enterprise with several establishments**

We first assign to the enterprise the location of its biggest establishment in terms of employees in CS3 category. If there are several establishments which have the same size in terms of employees in CS3 category, we assign to the enterprise the location of its biggest establishment in terms of total employees (all categories). If there are several establishments which have the same size in terms of total employees (all categories), we assign to the enterprise the location of its biggest establishment in terms of total paid salaries.

Table 3.15: The effects of cluster policies on innovation and firms' performance

Author Country	Evaluation	Data Time Period	Methodology	Aim of the policy	Findings
Falck et al. (2010), Germany	Analyzing the Cluster Initiative introduced in Bavaria. Presenting empirical evidence for it's economic success	Firm-level data Ifo Innovation Survey (1996-2001)	- DiD method - Triple DiD method (Using patents, sales, R&D)	The aim was to create a Bavarian-wide innovation network in support of state-wide knowledge flows	- cluster policy had a positive impact on innovation and the magnitude of the effects is economically meaningful - the cluster policy increased the likelihood of an innovation by a firm in the targeted industry by 4 to 7 % points - results confirm that the cluster policy is especially supportive of large firms; positive impact on turnover
Nishimura and Okamuro (2011a), Japan	Evaluate the effects of the "Industrial Cluster Project" (ICP) in Japan on the R&D productivity of participants	Firm-level data A database of 229 small firms Three data sources: lists of cluster participants, and patent data: (2003-2005)	- Poisson Tobit Model - 2SLS (IV) estimation following Wooldridge (2002) and treatment effect (TE) models (same results for the two model)	Industrial Cluster Policy (ICP) aiming to promote industry-university partnership within the same cluster	- large firms among SMEs benefit more from ICP - local firms collaborating with partners outside the cluster show higher R&D productivity, - the participation alone has no significant effect on the R&D productivity of firms - participants that collaborate with national, universities in the same cluster region significantly improve the R&D productivity - to improve their R&D productivity through the support programs of the ICP by collaborating with national universities in the same clusters
Nishimura and Okamuro (2011b), Japan	Which kind of support program contributes to firm performance? Evaluating the differences between direct and indirect R&D support	Firm-level data from an original survey conducted in 2009 (2006 2008)	- Probit regression DID estimation based on propensity score - Heckman's two-step procedure	Industrial Cluster Policy (ICP) aiming to promote industry-university partnership within the same cluster	- participants may obtain valuable information on potential partners through the support of the cluster projects - only cluster participants that actively exploit in the ICP support programs improve their performance. They expand the industry-university - government network after participating in the ICP - not every support program contributes to firms' performance - indirect support programs have an extensive and strong impact on output whereas direct R&D support has only a weak effect

Source: Author's synthesis

Table 3.16: The effects of cluster policies on innovation and firms' performance

Author Country	Evaluation	Data Time Period	Methodology	Aim of the policy	Findings
Martin et al. (2011), France	Assessing the impact of public support to LPS on firms' performance (TFP, employment, exports)	- Firm-level data - INSEE: employment - DIACT (DATAR): information about firm characteristics (1996-2004)	- Did method -Triple DID method - matching	The policy provided support to groups of firms located in the same area and belonging to the same industry called LPS	- not succeed in reversing the relative decline in productivity for the targeted firms - no effect on the employment and exports of firms involved in the LPS policy, - apparent failure of the LPS policy to improve the performance of targeted firms through better cooperation and to increase the attractiveness of existing clusters.
Brossard and Moussa (2014) France	Evaluating the effects of the competitiveness cluster policy in term of patents increasing.	Macro data (NUTS) Institute (INPI) - R&D survey - DGCI: Info on clusters (2005-2008)	- Did method 1997-2004: pre 2005-2008: post	Increasing innovation and competitiveness (by promoting public-private collaborations)	- the average impact of the French cluster policy is positive - produced a significant positive impact on regional patenting - strong effects in world-class clusters - weak and non-significant effects for the national clusters. - after three years the policy accumulates a rise of 0.76% in patenting for regions that have one world class cluster.
Bellégo et al. (2014), France	Evaluating the impact of the French competitiveness clusters policy on firms' performance	Firm-level data - R&D survey - DGCI: survey - FICUS-FARE - DADS, LFI CIR and JEI (2006-2009)	- Probit model - Matching - Unbalanced panel of the R&D survey - PME-ETIs	Increasing innovation and competitiveness (by promoting public-private collaborations)	- an additive effect on the R&D expenditure of firms (SMEs) - significant impacts on employment and in investment terms: employment of searchers and engineers - there are no effects on productivity, turnover, exports, sales of innovative products - more positive effects (in mean) for participants since 2006: this means that the policy can have a positive effect in the long run - the policy becomes more effective with time.
Dujardin et al. (2015), Belgium	Evaluating the impact of the Wallon's cluster policy on firms' economic performance	Firm-level data - DBRIS repertory (DGS) -BNB (Banque) - ONSS - BC Enterprise (2003-2011)	- Did method -Triple DID method - matching	Implementing the conditions of a shared prosperity through a structural recovery and a convergence towards the European averages	- the policy selected the firms that were initially larger firms in term of employment and more productive - there is no impact on productivity, - no impact in terms of export values, - however, there is a slight increase in the number of employees - there is a positive effect on the number of exported products.

Source: Author's synthesis

Assignment of a firm to a main cluster

In our sample, several firms belong to several clusters. It was thus necessary to define a criterion allowing to assign a main cluster to these firms. This assignment was mainly made on the basis of a criterion of localization and by an iterative process. The multi-establishment firms are located at the region (NUTS 3) of the location of their biggest establishment, in terms of the number of employees of managers, executives and high intellectual professionals (CS3 category in DADS database, for the INSEE).

Every cluster was located in the region (NUTS 3) of its headquarters. When a firm adheres to several clusters, that located in the same region is considered as the main cluster. If several clusters to which the firm adheres are located at the region, the main cluster is the one having most establishments members. If according to this last criterion there are still several main clusters, the hierarchy between worldwide cluster, worldwide track cluster and national cluster is used to determine the only main cluster.

If the firm is located in a region where are located none of the clusters to which it adheres, the same process as previously is applied by taking into account the same location at the regional scale (old regions). If the firm is not located in the same region where is located one of the clusters to which it adheres, the main cluster is the one to which the largest number of its establishments adheres. When the main cluster of the firm cannot be always identified according to this criterion, again the hierarchy between worldwide cluster, worldwide track cluster and national cluster is used to determine the main cluster.

3.8.2 Descriptive statistics

Table 3.17: Firms' pre-post participation characteristics by year in Group A

	Period 2005-2007				Period 2005-2008				Period 2005-2009			
	Pre-treatment		Post-treatment		Pre-treatment		Post-treatment		Pre-treatment		Post-treatment	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
	Input outcome variables											
derd	97.6	84.3	211.9	134.4	88.1	83.2	162.9	125.8	80.7	86.8	126.6	116.7
dird	1014.9	428.8	1224.5	438.8	867.3	402.8	1134.5	405.4	843.1	413.2	1077.2	410.9
budgetot	1112.5	513.2	1436.5	573.2	955.4	485.9	1297.4	531.2	916.1	500.0	1203.8	527.6
financ_pub	142.9	23.4	166.9	23.8	118.0	22.1	185.0	26.4	117.9	22.8	213.1	19.6
financ_pro	772.9	425.2	1057.4	434.4	663.2	400.8	975.8	385.7	661.0	409.7	863.4	400.0
eff_rd	12.3	5.1	13.6	5.2	11.4	4.8	13.6	4.9	10.8	5.0	12.2	5.0
researchemp	8.5	2.9	9.2	3.0	6.9	2.7	8.5	2.8	6.6	2.9	8.1	2.9
cs3	19.3	9.8	20.8	10.0	16.4	9.1	20.2	9.8	15.3	9.3	21.2	11.7
	Output outcome variables											
totbrev	2.4	0.7	2.0	0.9	1.2	0.7	2.0	0.7	1.2	0.7	2.5	0.9
eff_moy_et	54.3	46.0	60.0	48.1	46.2	39.6	54.4	42.5	42.2	39.4	51.1	41.8
turnover	12550.8	10778.2	14566.8	12018.6	12451.4	9435.0	11286.5	10818.6	10487.1	9359.1	9470.7	10035.2
addedvalue	3423.8	3233.4	3753.6	3611.7	3471.9	2928.1	3195.4	3314.1	3190.7	2873.7	2826.6	3162.4
export	6154.1	3722.3	7212.9	4379.6	4956.7	3238.7	5306.2	3604.2	4448.9	3220.2	4505.4	3503.9
	Other control variables											
emp	56.5	34.5	61.3	36.2	49.2	31.5	60.4	34.4	45.4	31.8	58.3	45.0
age	23.7	29.4	23.7	29.4	24.4	29.4	24.4	29.4	23.2	29.3	23.2	29.3
dum_export	0.8	0.7	0.8	0.7	0.7	0.7	0.9	0.8	0.7	0.7	0.8	0.7
dum_subven	0.8	0.5	0.8	0.5	0.8	0.5	0.9	0.5	0.8	0.5	0.9	0.5
Observations	135	8008	135	8008	220	7190	220	7190	305	7424	305	7424
	Period 2005-2010											
	Pre-treatment		Post-treatment		Pre-treatment		Post-treatment		Pre-treatment		Post-treatment	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
	Input outcome variables											
derd	113.0	82.8	145.5	144.1	108.1	81.4	164.7	79.2	96.5	82.0	145.0	118.3
dird	902.3	407.9	1211.2	418.3	811.3	389.5	1179.6	405.5	767.9	390.0	1164.5	410.1
budgetot	1015.3	490.8	1356.6	562.3	919.4	471.0	1344.3	484.4	864.4	472.0	1309.5	528.3
financ_pub	117.4	23.3	202.0	20.1	101.4	24.2	176.2	24.7	104.2	23.7	197.8	18.4
financ_pro	706.8	402.7	1029.6	453.9	649.2	379.4	1063.4	382.0	606.1	381.6	968.7	422.1
eff_rd	10.9	4.9	13.1	5.0	10.0	4.8	12.7	4.9	9.7	4.8	12.5	4.8
researchemp	6.8	2.8	8.7	2.9	6.3	2.7	8.5	2.8	6.0	2.7	8.5	2.7
cs3	15.4	9.3	23.7	12.7	14.2	9.0	22.0	13.1	13.6	9.0	21.5	13.3
	Output outcome variables											
totbrev	1.5	0.7	2.3	0.8	1.5	0.7	1.5	0.6	1.7	0.7	1.6	0.6
eff_moy_et	41.2	39.5	50.8	41.9	37.6	38.1	47.8	41.5	37.6	38.0	48.8	41.6
turnover	9952.3	9371.3	10290.3	10566.3	8781.6	9107.2	11461.3	10876.5	7394.7	9149.4	10538.5	11088.6
addedvalue	3049.8	2862.6	3037.1	3331.4	2816.0	2767.7	3557.7	3347.9	2563.2	2794.4	3246.8	3403.8
export	4237.5	3250.5	5061.6	3954.9	3639.0	3114.6	5102.2	3950.7	2710.2	3141.7	4033.3	4207.4
	Other control variables											
emp	45.3	31.8	59.7	46.0	41.4	30.9	57.4	46.7	39.5	30.8	58.5	47.1
age	23.3	29.1	23.3	29.1	24.4	29.2	24.4	29.2	24.4	29.4	24.4	29.4
dum_export	0.7	0.7	0.7	0.7	0.7	0.7	0.8	0.7	0.7	0.7	0.8	0.7
dum_subven	0.7	0.5	0.9	0.5	0.7	0.5	0.9	0.5	0.7	0.5	0.9	0.5
Observations	325	7362	325	7362	350	7248	350	7248	355	7108	355	7108

Note: Patents are in unit, R&D variables are in thousand, employment-related variables are in unit, and market-related variables are in thousand.

Sources: R&D survey, DGE, FUI, MENESR, INSEE, Ficus-Fare, DADS, Lifi, and the author's calculations.

Table 3.18: Firms' pre-post participation characteristics by year in Group B (1/2)

	Period 2005-2006				Period 2005-2007				Period 2005-2008				Period 2005-2009			
	Pre-treatment		Post-treatment		Pre-treatment		Post-treatment		Pre-treatment		Post-treatment		Pre-treatment		Post-treatment	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
	Input outcome variables															
derd	93.3	86.2	102.9	92.9	109.6	84.3	160.7	134.4	105.1	83.2	199.8	125.8	96.5	86.8	145.0	116.7
dird	768.6	436.2	780.1	441.0	714.7	428.8	766.8	438.8	638.1	402.8	712.6	405.4	767.9	413.2	1164.5	410.9
budgetot	858.9	522.4	883.0	534.0	824.4	513.2	923.7	573.2	743.2	485.9	912.4	531.2	864.4	500.0	1309.5	527.6
financ.pub	84.3	24.4	92.4	24.4	75.8	23.4	79.6	23.8	67.8	22.1	77.4	26.4	104.2	22.8	197.8	19.6
financ.pro	630.1	429.4	654.7	420.5	608.9	425.2	685.9	434.4	556.3	400.8	697.8	385.7	606.1	409.7	968.7	400.0
eff_rd	8.9	5.2	9.1	5.3	8.4	5.1	9.0	5.2	7.3	4.8	8.1	4.9	9.7	5.0	12.5	5.0
researchemp	5.3	3.0	5.5	3.0	4.8	2.9	5.4	3.0	4.3	2.7	5.0	2.8	6.0	2.9	8.5	2.9
cs3	14.5	9.9	14.4	9.5	12.8	9.8	13.8	10.0	11.8	9.1	13.2	9.8	13.6	9.3	21.5	11.7
	Output outcome variables															
totbrev	1.6	0.7	1.5	0.7	1.6	0.7	1.6	0.9	1.5	0.7	1.8	0.7	1.7	0.7	1.6	0.9
eff_moy_et	56.1	45.9	57.9	47.1	51.7	46.0	55.3	48.1	44.4	39.6	49.4	42.5	37.6	39.4	48.8	41.8
turnover	12180.6	10741.6	12976.7	11502.6	10886.8	10778.2	11684.7	12018.6	8500.5	9435.0	9940.2	10818.6	7394.7	9359.1	10538.5	10035.2
addedvalue	3601.6	3219.0	3811.4	3410.3	3273.4	3233.4	3530.3	3611.7	2676.9	2928.1	2940.8	3314.1	2563.2	2873.7	3246.8	3162.4
export	4556.6	3714.0	5017.5	4130.7	3767.1	3722.3	4300.8	4379.6	2935.1	3238.7	3345.0	3604.2	2710.2	3220.2	4033.3	3503.9
	Other control variables															
emp	46.8	34.7	48.0	35.1	41.9	34.5	46.6	36.2	38.1	31.5	43.5	34.4	39.5	31.8	58.5	45.0
age	27.0	29.3	27.0	29.3	26.7	29.4	26.7	29.4	26.3	29.4	26.3	29.4	24.4	29.3	24.4	29.3
dum_export	0.8	0.7	0.8	0.7	0.7	0.7	0.8	0.7	0.7	0.7	0.8	0.8	0.7	0.7	0.8	0.7
dum_subven	0.8	0.5	0.8	0.5	0.7	0.5	0.8	0.5	0.7	0.5	0.8	0.5	0.7	0.5	0.9	0.5
Observations	799	8060	799	8060	8008	8008	930	8008	821	8008	821	7190	355	7424	355	7424

Note: Patents are in unit, R&D variables are in thousand, employment-related variables are in unit, and market-related variables are in thousand.
 Sources: R&D survey, DGE, FUJ, MENESR, INSEE, Ficus-Fare, DADS, Lift, and the author's calculations.

Table 3.19: Firms' pre-post participation characteristics by year in Group B (2/2)

	Period 2005-2010				Period 2005-2011							
	Pre-treatment		Post-treatment		Pre-treatment		Post-treatment					
	Treated	Control	Treated	Control	Treated	Control	Treated	Control				
	Input outcome variables											
derd	96.9	82.8	144.7	144.1	91.6	81.4	160.3	79.2	91.6	82.0	160.3	118.3
dird	605.9	407.9	676.5	418.3	648.5	389.5	784.9	405.5	648.5	390.0	784.9	410.1
budgetot	702.7	490.8	821.2	562.3	737.8	471.0	931.9	484.4	737.8	472.0	931.9	528.3
financ-pub	66.9	23.3	93.4	20.1	71.6	24.2	106.1	24.7	71.6	23.7	106.1	18.4
financ-pro	545.8	402.7	640.3	453.9	574.0	379.4	726.7	382.0	574.0	381.6	726.7	422.1
effrd	7.0	4.9	7.7	5.0	7.2	4.8	8.2	4.9	7.2	4.8	8.2	4.8
researchemp	4.3	2.8	4.9	2.9	4.4	2.7	5.1	2.8	4.4	2.7	5.1	2.7
cs3	11.1	9.3	14.8	12.7	11.2	9.0	15.6	13.1	11.2	9.0	15.6	13.3
	Output outcome variables											
totbrev	1.2	0.7	1.3	0.8	1.2	0.7	0.9	0.6	1.2	0.7	0.9	0.6
effmoy-et	39.8	39.5	44.8	41.9	38.6	38.1	45.1	41.5	38.6	38.0	45.1	41.6
turnover	7519.1	9371.3	8743.2	10566.3	7793.6	9107.2	9854.6	10876.5	7793.6	9149.4	9854.6	11088.6
addedvalue	2419.3	2862.6	2824.5	3331.4	2393.8	2767.7	2973.1	3347.9	2393.8	2794.4	2973.1	3403.8
export	2632.4	3250.5	3331.5	3954.9	2815.4	3114.6	4068.4	3950.7	2815.4	3141.7	4068.4	4207.4
	Other control variables											
emp	35.1	31.8	50.8	46.0	34.8	30.9	51.8	46.7	34.8	30.8	51.8	47.1
age	26.7	29.1	26.7	29.1	26.3	29.2	26.3	29.2	26.3	29.4	26.3	29.4
dum-export	0.7	0.7	0.8	0.7	0.7	0.7	0.8	0.7	0.7	0.7	0.8	0.7
dum-silvben	0.7	0.5	0.8	0.5	0.7	0.5	0.7	0.5	0.7	0.5	0.7	0.5
Observations	916	7362	916	7362	1027	7248	1027	7248	1027	7108	1027	7108

Note: Patents are in unit, R&D variables are in thousand, employment-related variables are in unit, and market-related variables are in thousand.
Sources: R&D survey, DGE, FUJ, MENESR, INSEE, Ficus-Fare, DADS, Lifo, and the author's calculations.

Table 3.20: Firms' pre-post participation characteristics by year in Group C

	Period 2005-2007				Period 2005-2008				Period 2005-2009			
	Pre-treatment		Post-treatment		Pre-treatment		Post-treatment		Pre-treatment		Post-treatment	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
	Input outcome variables											
derd	44.1	84.3	94.4	134.4	99.6	83.2	136.5	125.8	91.6	86.8	160.3	116.7
dird	728.0	428.8	1007.3	438.8	924.6	402.8	1002.0	405.4	648.5	413.2	784.9	410.9
budgetot	772.1	513.2	1101.7	573.2	1024.3	485.9	1138.5	531.2	737.8	500.0	931.9	527.6
financ_pub	78.2	23.4	71.5	23.8	128.7	22.1	184.8	26.4	71.6	22.8	106.1	19.6
financ_pro	666.9	425.2	1028.1	434.4	744.9	400.8	751.7	385.7	574.0	409.7	726.7	400.0
eff_rd	9.7	5.1	11.1	5.2	11.0	4.8	10.4	4.9	7.2	5.0	8.2	5.0
researchemp	5.7	2.9	7.7	3.0	8.0	2.7	8.0	2.8	4.4	2.9	5.1	2.9
cs3	15.7	9.8	14.1	10.0	12.1	9.1	12.9	9.8	11.2	9.3	15.6	11.7
	Output outcome variables											
totbrev	0.8	0.7	2.0	0.9	1.5	0.7	1.1	0.7	1.2	0.7	0.9	0.9
eff_moy_et	42.8	46.0	43.4	48.1	32.9	39.6	35.3	42.5	38.6	39.4	45.1	41.8
turnover	6248.0	10778.2	5671.1	12018.6	15577.6	9435.0	17134.9	10818.6	7793.6	9359.1	9854.6	10035.2
addedvalue	1895.9	3233.4	1946.3	3611.7	2557.6	2928.1	3713.0	3314.1	2393.8	2873.7	2973.1	3162.4
export	2940.5	3722.3	2751.2	4379.6	9231.1	3238.7	10631.0	3604.2	2815.4	3220.2	4068.4	3503.9
	Other control variables											
emp	48.8	34.5	50.2	36.2	36.0	31.5	39.3	34.4	34.8	31.8	51.8	45.0
age	28.7	29.4	28.7	29.4	25.3	29.4	25.3	29.4	26.3	29.3	26.3	29.3
dum_export	0.7	0.7	0.9	0.7	0.8	0.7	0.9	0.8	0.7	0.7	0.8	0.7
dum_subven	0.8	0.5	0.8	0.5	0.7	0.5	0.8	0.5	0.7	0.5	0.7	0.5
Observations	17	8008	17	8008	41	7190	41	7190	1027	7424	1027	7424
	Period 2005-2010											
	Pre-treatment		Post-treatment		Pre-treatment		Post-treatment		Pre-treatment		Post-treatment	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
	Input outcome variables											
derd	112.3	82.8	246.9	144.1	109.1	81.4	142.1	79.2	109.1	82.0	142.1	118.3
dird	861.3	407.9	1095.4	418.3	835.2	389.5	1196.5	405.5	835.2	390.0	1196.5	410.1
budgetot	942.2	490.8	1342.3	562.3	944.3	471.0	1140.8	484.4	944.3	472.0	1140.8	528.3
financ_pub	67.5	23.3	162.8	20.1	93.1	24.2	264.8	24.7	93.1	23.7	264.8	18.4
financ_pro	748.9	402.7	1014.0	453.9	693.3	379.4	731.5	382.0	693.3	381.6	731.5	422.1
eff_rd	10.9	4.9	12.3	5.0	11.1	4.8	10.2	4.9	11.1	4.8	10.2	4.8
researchemp	7.1	2.8	7.8	2.9	7.1	2.7	6.8	2.8	7.1	2.7	6.8	2.7
cs3	13.0	9.3	18.0	12.7	13.9	9.0	20.4	13.1	13.9	9.0	20.4	13.3
	Output outcome variables											
totbrev	2.5	0.7	1.6	0.8	3.3	0.7	0.9	0.6	3.3	0.7	0.9	0.6
eff_moy_et	48.1	39.5	49.8	41.9	56.1	38.1	60.2	41.5	56.1	38.0	60.2	41.6
turnover	14766.5	9371.3	16816.2	10566.3	8889.8	9107.2	10676.4	10876.5	8889.8	9149.4	10676.4	11088.6
addedvalue	3047.8	2862.6	4700.6	3331.4	2884.4	2767.7	3950.6	3347.9	2884.4	2794.4	3950.6	3403.8
export	7578.5	3250.5	8730.2	3954.9	3813.9	3114.6	5002.6	3950.7	3813.9	3141.7	5002.6	4207.4
	Other control variables											
emp	41.3	31.8	51.6	46.0	45.4	30.9	58.9	46.7	45.4	30.8	58.9	47.1
age	26.4	29.1	26.4	29.1	24.3	29.2	24.3	29.2	24.3	29.4	24.3	29.4
dum_export	0.8	0.7	0.7	0.7	0.8	0.7	0.8	0.7	0.8	0.7	0.8	0.7
dum_subven	0.7	0.5	0.8	0.5	0.7	0.5	0.9	0.5	0.7	0.5	0.9	0.5
Observations	75	7362	75	7362	76	7248	76	7248	76	7108	76	7108

Note: Patents are in unit, R&D variables are in thousand, employment-related variables are in unit, and market-related variables are in thousand.

Sources: R&D survey, DGE, FUI, MENESR, INSEE, Ficus-Fare, DADS, Lifi, and the author's calculations.

Table 3.21: Firms' before-after matching characteristics by year in treatment and control groups (Group A)

	Period 2005-2007				Period 2005-2008				Period 2005-2009			
	Before matching		After matching		Before matching		After matching		Before matching		After matching	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
distance	0.0548	0.0159	0.0516	0.0512	0.0694	0.0285	0.0641	0.0626	0.0866	0.0375	0.0807	0.0803
log(emp)	3.5609	2.9463	3.3338	3.4960	3.3826	2.8872	3.3336	3.2704	3.2697	2.8719	3.2444	3.2203
age	23.7185	29.4038	23.7970	24.2782	24.4182	29.3794	24.6372	25.7023	23.1770	29.2945	23.4732	25.0705
agegroup	0.7333	0.5714	0.7293	0.6842	0.6545	0.5569	0.6465	0.6000	0.6262	0.5539	0.6174	0.6577
dum_subven	0.7704	0.4925	0.7669	0.6992	0.7545	0.4871	0.7488	0.7302	0.7574	0.4849	0.7517	0.7517
dum_sec_man_electro	0.0074	0.0227	0.0075	0.0075	0.0045	0.0223	0.0047	0.0140	0.0066	0.0216	0.0067	0.0067
dum_sec_hkhs	0.5481	0.3749	0.5414	0.5414	0.5182	0.3755	0.5070	0.5209	0.5508	0.3839	0.5403	0.5168
dum_export	0.7852	0.6941	0.7820	0.7970	0.7273	0.6960	0.7209	0.6605	0.7082	0.6905	0.7013	0.7383
Sample sizes:	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated
All	8008	135			7190	220			7424	305		
Matched	128	133			207	215			284	298		
Unmatched	7880	2			6983	5			7140	7		
	Period 2005-2010				Period 2005-2011				Period 2005-2012			
	Before matching		After matching		Before matching		After matching		Before matching		After matching	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
distance	0.0887	0.0402	0.0830	0.0822	0.0875	0.0441	0.0875	0.0866	0.0865	0.0456	0.0865	0.0869
log(emp)	3.2508	2.8701	3.2240	3.2591	3.1831	2.8451	3.1831	3.0962	3.1409	2.8452	3.1409	3.1819
age	23.2862	29.0554	23.5472	22.1950	24.3943	29.1738	24.3943	25.3371	24.3775	29.3545	24.3775	25.2451
agegroup	0.6246	0.5531	0.6164	0.5723	0.5829	0.5455	0.5829	0.5086	0.5577	0.5467	0.5577	0.5549
dum_subven	0.7231	0.4822	0.7170	0.7075	0.7057	0.4823	0.7057	0.6943	0.7155	0.4842	0.7155	0.6873
dum_sec_man_electro	0.0092	0.0217	0.0094	0.0126	0.0229	0.0221	0.0229	0.0286	0.0225	0.0219	0.0225	0.0169
dum_sec_hkhs	0.5569	0.3858	0.5472	0.5943	0.5686	0.3902	0.5686	0.5686	0.5380	0.3900	0.5380	0.5662
dum_export	0.7046	0.6898	0.6981	0.6887	0.7257	0.6852	0.7257	0.7086	0.7324	0.6871	0.7324	0.7099
Sample sizes:	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated
All	7362	325			7248	350			7108	355		
Matched	307	318			329	350			334	355		
Unmatched	7055	7			6919	0			6774	0		

Note: All the variables in this table, plus a set of dummy variables indicating the activity sectors and the geographical location of firms, have been used in the estimation of the propensity score. Patents are in unit, R&D variables are in thousand, employment-related variables are in unit, and market-related variables are in thousand.

Sources: R&D survey, DGE, FUJ, MENESR, INSEE, Ficus-Fare, DADS, Lifa, and the author's calculations.

Table 3.22: Firms' before-after matching characteristics by year in treatment and control groups (Group B)

	Period 2005-2006				Period 2005-2007				Period 2005-2008				Period 2005-2009			
	Before matching		After matching		Before matching		After matching		Before matching		After matching		Before matching		After matching	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
distance	0.1533	0.0839	0.1518	0.1500	0.1569	0.1560	0.1496	0.1487	0.1485	0.1008	0.1481	0.1468	0.1481	0.1008	0.1481	0.1468
log(emp)	3.3352	2.9464	3.3286	3.3147	3.2000	3.1855	3.0945	3.0965	3.0197	2.8719	3.0172	2.9961	3.0172	2.8719	3.0172	2.9961
age	27.0225	29.2630	27.0842	26.8693	26.7705	27.8966	26.3521	26.4792	26.8214	29.2945	26.8383	27.1788	26.8383	29.2945	26.8383	27.1788
appgroup	0.6671	0.5697	0.6658	0.6533	0.6250	0.6196	0.6041	0.5569	0.5791	0.5539	0.5786	0.5672	0.5786	0.5539	0.5786	0.5672
dum_subven	0.7672	0.4948	0.7663	0.7538	0.7220	0.7123	0.7125	0.4871	0.7054	0.4849	0.6856	0.6936	0.6856	0.4849	0.6856	0.6936
dum_sec_man_electro	0.0175	0.0218	0.0176	0.0201	0.0237	0.0227	0.0158	0.0223	0.0205	0.0183	0.0205	0.0205	0.0205	0.0216	0.0205	0.0205
dum_sec_hkis	0.4431	0.3787	0.4410	0.4472	0.4366	0.3749	0.4568	0.3755	0.4645	0.4835	0.4829	0.4692	0.4835	0.3839	0.4829	0.4692
dum_export	0.7760	0.6918	0.7751	0.7889	0.7446	0.6941	0.7369	0.6960	0.7359	0.7494	0.7289	0.7255	0.7359	0.6905	0.7289	0.7255
Sample sizes:	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated
All	8060	799			8008	930	7190	821	7424	879	7424	879	7424	879	7424	879
Matched	735	796			839	928	747	818	801	878	801	878	801	878	801	878
Unmatched	7325	3			7169	2	6443	3	6623	1	6623	1	6623	1	6623	1

	Period 2005-2010				Period 2005-2011				Period 2005-2012			
	Before matching		After matching		Before matching		After matching		Before matching		After matching	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
distance	0.1503	0.1057	0.1499	0.1490	0.1663	0.1654	0.1602	0.1597	0.1609	0.1136	0.1602	0.1597
log(emp)	3.0051	2.8701	3.0026	3.0290	2.9710	2.8451	2.9718	2.8452	2.9718	2.8452	2.9670	3.0110
age	26.6648	29.0554	26.6809	26.2645	26.2814	29.1738	26.4491	29.3545	26.4491	29.3545	26.4792	25.2542
appgroup	0.5753	0.5531	0.5749	0.6087	0.5764	0.5455	0.5946	0.5467	0.5946	0.5467	0.5938	0.6188
dum_subven	0.6714	0.4822	0.6710	0.6634	0.6845	0.4823	0.6788	0.4842	0.6788	0.4842	0.6781	0.6667
dum_sec_man_electro	0.0240	0.0217	0.0240	0.0219	0.0204	0.0221	0.0218	0.0219	0.0218	0.0219	0.0219	0.0323
dum_sec_hkis	0.4978	0.3858	0.4973	0.4973	0.4956	0.3902	0.4969	0.3900	0.4969	0.3900	0.4958	0.4781
dum_export	0.7194	0.6898	0.7191	0.7475	0.7128	0.6852	0.7110	0.6871	0.7110	0.6871	0.7104	0.7115
Sample sizes:	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated
All	7362	916			7248	1027	7108	962	7108	962	7108	962
Matched	831	915			917	1025	860	960	860	960	860	960
Unmatched	6531	1			6331	2	6248	2	6248	2	6248	2

Note: All the variables in this table, plus a set of dummy variables indicating the activity sectors and the geographical location of firms, have been used in the estimation of the propensity score. Patents are in unit, R&D variables are in thousand, employment-related variables are in unit, and market-related variables are in thousand. Sources: R&D survey, DGE, FUI, MENESR, INSEE, Ficus-Fare, DADS, Lifi, and the author's calculations.

Table 3.23: Firms' before-after matching characteristics by year in treatment and control groups (Group C)

	Period 2005-2007				Period 2005-2008				Period 2005-2009			
	Before matching		After matching		Before matching		After matching		Before matching		After matching	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
distance	0.0082	0.0021	0.0082	0.0081	0.0145	0.0056	0.0133	0.0134	0.0271	0.0096	0.0235	0.0232
log(emp)	3.1476	2.9463	3.1476	3.1651	3.2178	2.8872	3.2015	3.1757	3.2669	2.8719	3.2322	3.2841
age	28.7059	29.4038	28.7059	35.2941	25.3171	29.3794	25.4730	30.5750	23.7534	29.2945	23.9296	21.6479
appgroup	0.3529	0.5714	0.3529	0.4706	0.6098	0.5569	0.6000	0.7250	0.6164	0.5539	0.6056	0.5775
dum_subven	0.8235	0.4925	0.8235	0.8235	0.6829	0.4871	0.6750	0.6250	0.6986	0.4849	0.6901	0.6338
dum_sec_man-electro	0.0000	0.0227	0.0000	0.0000	0.0244	0.0223	0.0250	0.0250	0.0137	0.0216	0.0141	0.0141
dum_sec_lhhs	0.4118	0.3749	0.4118	0.4706	0.5610	0.3755	0.5500	0.5000	0.5616	0.3839	0.5493	0.5493
dum_export	0.7059	0.6941	0.7059	0.7059	0.7561	0.6960	0.7500	0.8000	0.7671	0.6905	0.7606	0.7465
Sample sizes:	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated
All	8008	17	8008	17	7190	41	7190	41	7424	73	7424	73
Matched	17	17	17	17	40	40	40	40	71	71	71	71
Unmatched	7991	0	7991	0	7150	1	7150	1	7353	2	7353	2
	Period 2005-2010				Period 2005-2011				Period 2005-2012			
	Before matching		After matching		Before matching		After matching		Before matching		After matching	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
log(emp)	0.0249	0.0099	0.0220	0.0220	0.0280	0.0102	0.0258	0.0254	0.0263	0.0112	0.0245	0.0245
age	3.2730	2.8701	3.2394	3.1496	3.3511	2.8451	3.3274	3.4496	3.3794	2.8452	3.3578	3.4532
appgroup	26.4000	29.0554	26.6438	28.6712	24.3289	29.1738	24.4400	27.3600	26.0244	29.3545	26.1481	25.4568
dum_subven	0.5733	0.5531	0.5616	0.4795	0.6974	0.5455	0.6933	0.7200	0.6585	0.5467	0.6543	0.7284
dum_sec_man-electro	0.6667	0.4822	0.6575	0.6575	0.7237	0.4823	0.7200	0.6400	0.6951	0.4842	0.6914	0.6914
dum_sec_lhhs	0.0400	0.0217	0.0411	0.0411	0.0132	0.0221	0.0133	0.0000	0.0122	0.0219	0.0123	0.0123
dum_export	0.5467	0.3858	0.5342	0.5753	0.4737	0.3902	0.4667	0.4800	0.5000	0.3900	0.4938	0.4444
Sample sizes:	0.7600	0.6898	0.7534	0.7123	0.7500	0.6852	0.7467	0.6800	0.7073	0.6871	0.7037	0.7160
All	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated
Matched	7362	75	7248	76	7248	76	7108	82	7108	82	7108	82
Unmatched	70	73	74	75	74	75	80	81	80	81	80	81
	7292	2	7174	1	7174	1	7028	1	7028	1	7028	1

Note: All the variables in this table, plus a set of dummy variables indicating the activity sectors and the geographical location of firms, have been used in the estimation of the propensity score. Patents are in unit, R&D variables are in thousand, employment-related variables are in unit, and market-related variables are in thousand.

Sources: R&D survey, DGE, FUJ, MENESR, INSEE, Ficus-Fare, DADS, Lifa, and the author's calculations.

Chapter 4

The impacts of the competitiveness clusters policy on the innovation and economic performance of French mid-sized and large firms⁵⁰

⁵⁰I thank EuroLIO for the opportunity to participate in the study entitled "Impacts économiques et territoriaux des pôles de compétitivité selon les territoires" ordered by the CGET and France Stratégie.

Abstract

This chapter analyzes the effectiveness of the French clusters policy on mid-sized and large firms' performance. Using firm-level data over the 2004-2012 period, we adopt a two-way fixed effects model to overcome selection bias by controlling not only for the unobserved time-invariant heterogeneity but also for heterogeneity in firms' observed characteristics over multiple periods. The results show that adherence to clusters has no impact on total R&D budgets and privately financed R&D, but participating in FUI projects leads to strong crowding-out effects. Moreover, the findings show that the policy has positive effects on innovation, CS3 employment and total employment. For the variables related to market performance, such as turnover, added value, and exports, the results are more mixed. Globally, clusters adhesion has positive effects on turnover, added value, and exports. However, the effects of participation in FUI projects are negative for turnover and added value and null for exports. Furthermore, the findings show that the impacts are very heterogeneous depending on the type of cluster and the number of years that a firm participates in the policy. We conclude that the effects of worldwide clusters are strongest on employment, the effects on economic performance are stronger for national clusters and the effects of worldwide track clusters are moderate for all economic performance indicators but strongest for innovation and privately funded R&D. All these results highlight the importance of clusters activities other than FUI projects, such as the animation and strategic management of clusters, and also the development of structuring projects such as platforms of innovation and innovation ecosystems. Finally, we find that the magnitude of the policy effects (positive or negative) increases slightly with the duration of participation in the program (number of years a firm participates in the program), whatever the performance indicator. The findings suggest that participation in the policy may have positive effects in the short run or in the long run, depending on the instrument and also on the considered performance indicator.

Keywords: Clusters policy, R&D subsidies, Policy Evaluation, Two-way fixed effects

JEL-Classification: C23, O32, O38

4.1 Introduction

The competitiveness clusters policy in France has been described in the previous chapters, as has the existing literature providing evaluations of these policies. The starting point of this chapter is the lack of evaluation of large firms.

The literature review presented earlier shows that almost all previous studies assessing the effects of cluster policies on firms' performance partly disregard or systematically remove large firms from their evaluations. These studies focus on the cluster policies' impacts on small and medium-sized enterprises (SMEs)⁵¹ and mid-sized firms (ETIs)⁵². In evaluating the impacts of the French competitiveness clusters policy, [Bellégo and Dortet-Bernadet \(2014\)](#) partly disregard large firms, and [Ben Hassine and Mathieu \(2017\)](#) systematically exclude firms belonging to a group and large firms. Therefore, the effects of this policy on large firms have never been evaluated econometrically. The explanation for this disregard is mainly related to the constraints of the counterfactual methods that are generally used. Most large firms spend large amounts on R&D, participate in the clusters and participate in the FUI projects; thus, it is very difficult if not impossible to find counterfactuals for them. A significant amount of money is spent on the policy to stimulate innovative activities. The large firms are not numerous (less than 1% of cluster members); however, they undertake a large share of national R&D investment (48.5% of total R&D spending in 2012) and represent the main beneficiaries of subsidies. Therefore, evaluating the impacts of the competitiveness clusters on large firms is a major concern for public authorities, researchers and policy evaluators.

The main goal of the current study is to fill this methodological gap by evaluating the effects of the competitiveness clusters policy on large firms' performance. The aim is therefore twofold. First, this study proposes to use an adequate econometric approach to evaluate the impacts of the competitiveness clusters policy on large firms by considering two policy instruments (being a member of clusters and participating in FUI projects) and their simultaneity. Second, the study analyzes in-depth the heterogeneity of the policy effects depending on the instrument used and the type of cluster.

⁵¹A mid-sized firm is defined by the INSEE as a firm with between 250 and 4999 workers with a turnover not exceeding €1.5 billion or a total balance sheet not exceeding €2 billion.

⁵²A large firm is defined by the INSEE as a firm with at least 5000 employees and with a turnover exceeding €1.5 billion and a total balance sheet exceeding €2 billion.

In particular, focusing on the effects of participation in the competitiveness clusters policy on innovation and economic performance of ETIs and large firms, one can ask many questions about the policy's impacts. What are the impacts on input additionality of participation in the competitiveness clusters policy? Do firms substitute the public subsidies from which they benefit for R&D spending? What are the impacts on innovation and economic performance of participation in the competitiveness clusters policy? To boost their performance, do firms need to belong to clusters or participate in FUI projects? Are the impacts of the policy homogeneous according to the type of cluster? Are the impacts of the policy homogeneous depending on the duration of participation in the policy? We will try to answer these questions in this work.

To tackle this evaluation issue, we use the two-way fixed effects model ([Baltagi, 2013](#); [Wooldridge, 2010, 2015](#)). This model can help to overcome the problem of bias due to selection on observable and unobserved firm characteristics without using counterfactuals. This method consists of introducing firm-specific unobserved effects and time fixed effects and therefore controls for all time-invariant firm-specific unobserved factors. Our sample is composed of unbalanced panel data covering the period 2004-2012 and focusing on French mid-sized and large firms. For the scope of the study, in addition to the firms in the R&D survey, we include all firms that participated in clusters or participated in FUI projects. After defining the scope of the study, the size of the data set is large, and we define three samples according to the availability of data. Sample 1 is composed of 4447 observations, sample 2 is composed of 7655 observations, and sample 3 is composed of 22756 observations.

Our results suggest that being a member of a cluster has no significant effect on private R&D. However, the results regarding the effect of FUI projects show the presence of the crowding-out effect and an eviction effect for R&D investment. In contrast with evidence from previous studies on SMEs, the findings concerning participation in FUI projects are in line with the results of [Ben Hassine and Mathieu \(2017\)](#) which indicate that participation in clusters has caused crowding-out effects on the R&D spending of ETIs and large firms. For innovation, both being a member of a cluster and participation in FUI significantly increases innovation output. For employment, the impacts of both instruments are strongly positive. Moreover, when the effects are statistically significant for employment, they are slightly stronger for participation in FUI projects than for being a member of a cluster. Notably, contrary to what one might expect, the effects on firms' R&D staff and researchers are

surprisingly very low or even nonexistent. For market-related performance, being a member of a cluster has positive effects on turnover and exports but no effect on added value.

Going further in the analysis, we show that the effects are heterogeneous depending on the type of cluster⁵³. We find that being a member of a worldwide-track cluster stimulates private R&D and has positive effects on firms' patenting, employment, turnover, and exports. Being a member of a national cluster has no effect on R&D and mixed effects on employment but strong positive effects on firms' patenting and on the three economic performance indicators. Finally, the results suggest that although being a member of a worldwide cluster seems to have positive effects on employment, it has no effect on private R&D, patenting and added value and negative effects on firms' turnover and exports. We conclude that the effects of worldwide clusters are the strongest on employment, the effects of national clusters are stronger on economic performance and the effects of worldwide-track clusters are moderate for all economic performance indicators but strongest for innovation and private R&D.

Furthermore, we find that the effects of the policy on firms' performance are heterogeneous, and the magnitude of all these effects (positive or negative) increases slightly with the duration of participation in the program (number of years a firm participates in the program), whatever the performance indicator. The findings suggest that participation in the policy may have positive effects in the short run or in the long run depending on the instrument but also on the considered performance indicator.

The chapter is organized as follows: section 2 describes the data and presents summary statistics for the main variables. Section 3 lays out the econometric strategy used in the study. Section 4 summarizes the results, and section 5 concludes.

⁵³The clusters are classified into three categories by the FUI committee (worldwide, worldwide-track and national). Since their implementation, the competitiveness clusters have not had the same status. We can therefore distinguish 71 poles in three types of cluster: the worldwide clusters (7 clusters), which compete at the international level; the worldwide-track clusters (11 clusters), which compete at the national level and eventually at the international level; and the national clusters (53 clusters), which are very important but do not need to compete at the international level. This distinction, which no longer exists (but did exist during the period of this study), had no predetermined implication regarding the resource allocation process, and the rules for participation were the same.

4.2 Data

4.2.1 Data sources and variables

In this work, we build a rich firm-level panel data set concerning French firms and covering the 2004-2012 period, which is relevant to observe the impacts of the policy. We use several data sets from different sources, such as the R&D survey for variables related to patents and R&D, the FICUS-FARE database for the accounting variables, the DADS database for employment-related variables, the LIFI database for the groups of firms and finally the DGE⁵⁴ and FUI data sets for the participation of firms, respectively, in clusters and FUI projects.

Table 4.1 shows all the variables classified into four main groups, three of which are related to performance indicators. The first group concerns patents and R&D expenditure-related variables. The second group is related to employment indicators, and the third group focuses on the more economic and market-related variables. The fourth group is related to firms' participation in the policy and to some control variables.

The variables related to patents and R&D expenditure are provided by the R&D survey conducted by the MESR, which is the main source of data on firms' R&D activities and innovation. This survey covers companies operating in French territory and performing work related to R&D. The variables from this data are classified into four main groups: variables related to R&D expenditure, variables related to the sources of R&D funding, variables providing information on R&D employment (scientists, engineers, researchers and other technical support staff for R&D) and finally, variables related to filed patents⁵⁵ and to the involvement of firms in an innovation product or process. The latter variables enable us to evaluate the impacts of the policy in terms of input (R&D investment) and output (number of patents) additionality. To assess the impact in terms of input additionality, we use as outcome variables internal and external R&D spending (*derd* and *dird*), total R&D budget (*budgetot*) and self-financed R&D (*financ_pro*). To evaluate the impact of the policy on R&D output additionality, we use the total number of filed patents (*totbrev*) as an innovation proxy.

⁵⁴The DGE (Direction Générale des Entreprises) is the ex-DGCIS (Direction Générale de la Compétitivité, de l'Industrie et des Services)

⁵⁵The main limit of these patents data is that the same patent may be filed more than once; therefore, it is possible to overestimate the number of patents.

The variables related to employment indicators are provided by the annual declarations of social data (DADS). This data set provides information on firms' employment and the structure of employment by type of qualification and by activity sector⁵⁶. The DADS data are available at the establishment level, and we have aggregated all variables at the firm level. For the control variables used in our model, we have computed two new variables: share of managers, which is the share of company executives, managers and intellectual professionals in the total employment of a firm (*sharehip*), and the number of establishments of every firm. To measure the effects of the policy in terms of performance related to employment, we use variables such as average number of full-time equivalent employees (*eff_moy_et*) and employment of executives, managers and intellectual professionals (*cs3*). Moreover, we use two other variables for employment related to R&D activities, which are provided by the R&D survey data set. These two variables (R&D staff (*eff_rd*) and researchers (*researchemp*)), are provided as full-time equivalents.

The economic variables related to the market are provided by the FICUS-FARE data set which is an annual firm-level data set covering almost all French firms. It provides economic and accounting indicators (related to the balance sheet) such as turnover and export turnover. This data set also enables us to know the economic sectors in which firms operate to identify the nationality of firms. For the economic performance variables related to the market, we use indicators such as turnover (*turnover*), added value (*addedvalue*) and exports (*export*).

To complete the information on firm characteristics, we use the data of financial links (LIFI) provided by the French National Institute for Statistics (INSEE)⁵⁷. It provides information on the scope of groups and the position of a firm in its group and firms' nationality. For the control variable, we have created a dummy variable that takes the value of one if the firm is a member of a group and zero otherwise.

Finally, the fourth group of variables provides information on the participation of firms in the policy. The data of the DGE survey and the FUI data set provide information on participation in clusters and projects. The DGE tracks the evolution of the cluster policy and updates the list of adherent firms annually. This survey enables us not only to identify

⁵⁶The DADS data set contains only employer establishments; thus, not all employing establishments are included in the files. In addition, the data of special regimes provided by the DGFIP (Direction Générale des Finances Publiques) and the data of the Ministry of Defense are not included in the DADS data set.

⁵⁷These are all the French companies of the private sector with an equity portfolio exceeding €1.2 million, with a turnover above €60 million, or with more than 500 employees, whatever the sector.

the firms that belong to clusters and those that do not but provides information on their entry into and exit from clusters. The FUI has data on all projects in the framework of the clusters, and we can identify all the firms that participate in the projects. By combining these two data sets, we are able to identify all adherent firms that participate in projects and nonadherent firms that participate in projects to better evaluate the real effects of the policy. The DGE and FUI data are available at the establishment level, and we have aggregated them at the firm level. These two data sets provide information on the participation of firms in clusters and projects and therefore enable us to construct several variables that characterize such participation. For each program (cluster or project), there is a dummy variable that takes the value of one if an establishment or a firm participates in the program and zero otherwise. For each program, there is also a variable that counts the number of establishments participating in the program for each participating firm. To take into account the heterogeneity of clusters, we have also created three dummy variables according to the type of cluster (worldwide, worldwide-track and national). Data from the DGE cover the 2006-2012 period, and those from the FUI cover the 2007-2012 period.

All these data are merged and finally result in an unbalanced panel data set at the firm level covering the 2004-2012 period. After defining the bounds of the ETIs and large firms, the size of the data set is still large, and we define three samples according to the availability of data. Sample 1 is composed of 4447 observations to estimate the effect on patents. Sample 2, composed of 7655 observations, does not contain the patent variable and allows us to estimate the effect on R&D spending and employment related to R&D. Finally, sample 3, composed of 22756 observations, does not contain patent or R&D variables and is used to estimate the effect of the policy on the economic variables that are less related to patents, such as employment, turnover, added value, and export. Table 4.2 shows the three samples according to firm size (ETIs or GE) and the distribution of firms according to the cluster type to which they adhere. The distribution of firms shows clearly that there are more ETIs than large firms in the samples.

Table 4.1: Description of variables

Variable name	Source	Description
Patent and R&D expenditure related variables (2004-2012)		
totbrev	R&D	Total number of patents filed by the firm
derd	R&D	External R&D spending of the firm (subcontract with partners) (in k €)
dird	R&D	Internal R&D spending of the firm (for its own or for its partners) (in k €)
budgetot	R&D	Total Research and development budget (DIRD+DERD) of the firm (in k €)
financ_pro	R&D	R&D funding made by the firm itself (self-financed) (in k €)
employment-related variables (2004-2012)		
eff_moy_et	DADS	Firm's average employees in full-time equivalent
emp	DADS	Total number of physical employees of the firm (all categories)
cs3	DADS	Number of employees in executives, managers and high intellectual professions (CS3)
eff_rld	R&D	R&D staff in full-time equivalent
researchemp	R&D	Number of researcher employees (full-time equivalent)
market-related variables (2004-2012)		
turnover	FICUS-FARE	Total turnover of the firm in euros (in k €)
addedvalue	FICUS-FARE	The firm's added value before taxes (in k €)
export	FICUS-FARE	Total export turnover of the firm (in k €)
Control variables used in the estimates (2004-2012)		
sharhip	DADS	Share of company executives, managers, and high intellectual professions
nbetb	DADS	Number of establishments of the firm
appgroup	LIFI	1 if the firm is a membership of a group, 0 otherwise
Clusters membership (2006-2012)		
p_adh_ent	DGE	1 if the firm has adhered to at least one cluster for a given year, 0 otherwise
nbetabcluster	DGE	Number of establishments of the firm belonging to at least one cluster
clustertype	DGE	Typology of cluster used to create three dummies (worldwide, worldwide track and national)
nbyearcluster	DGE	The number of years that the firm has adhered to a cluster at time t (D1-D8)
FUI projects participation (2007-2012)		
f_part_ent	FUI	1 if the firm has participated in at least one FUI project for a given year, 0 otherwise
nbetabproject	FUI	Number of establishments of the firm participating in at least one FUI project
nbyearproject	FUI	The number of years that the firm has participated in a FUI project at time t (F1-F6)

Sources: R&D survey, DGE, FUI, MENESR, INSEE, Ficus-Fare, DADS, Lifi.

4.2.2 Descriptive statistics

The descriptive statistics are organized by sample. In sample 1, the most restricted sample, the information on both firms' R&D spending and number of filed patents is jointly available. Sample 2 is larger than sample 1 because it excludes information on patents. Finally, sample 3 is the largest because it is used for the regressions that do not involve either the R&D or patent variables.

4.2.2.1 Sample structure: ETIs and large firms

In table 4.2, we distinguish the midsized firms (ETIs) from the large firms (GEs) in each sample. The table shows that there are more midsized firms than large firms in the samples: ETIs represent 98% of sample 1 and 96% of samples 2 and 3. In 2013, ETIs represented 0.14% of all French firms, and GEs represented 0.01%. Therefore, our samples are rather

representative of the overall structure of the French economy⁵⁸. Of the ETIs in sample 1, 32% participate in the policy. This rate is 28% for sample 2 and 24% for sample 3. For the GEs in samples 1, 2 and 3, the rates of participation in the policy are higher and stand, respectively, at 60%, 64%, and 42%.

Table 4.2: Structure of samples by type of cluster and by firm size

	Sample 1				Sample 2				Sample 3			
N	4447				7655				22756			
Cluster type	ETIs		GE		ETIs		GE		ETIs		GE	
Sub-samples	4358	98%	89	2%	7355	96%	300	4%	21790	96%	966	4%
Non-treated group	2959	67.9%	36	40.4%	5266	71.6%	108	36.0%	16581	76.1%	565	58.5%
Worldwide clusters	367	8.4%	28	31.5%	513	7.0%	75	25.0%	1246	5.7%	157	16.3%
National clusters	760	17.4%	9	10.1%	1180	16.0%	56	18.7%	2960	13.6%	136	14.1%
Worldwide-track clusters	272	6.2%	16	18.0%	396	5.4%	61	20.3%	1003	4.6%	108	11.2%

Sources: DGE, Ficus-Fare, DADS and the author's calculations.

Table 4.3: Number of clusters to which firms have adhered

	Sample 1				Sample 2				Sample 3			
Nb. Obs	1452				2281				5610			
Number of clusters	ETIs		GE		ETIs		GE		ETIs		GE	
Total Treated firms	1399	100%	53	100%	2089	100%	192	100%	5209	100%	401	100%
1 cluster	912	65,19%	5	9,43%	1340	64,15%	27	14,06%	3779	72,55%	122	30,42%
2 clusters	283	20,23%	7	13,21%	433	20,73%	26	13,54%	889	17,07%	78	19,45%
3 clusters	101	7,22%	11	20,75%	145	6,94%	31	16,15%	278	5,34%	52	12,97%
4 clusters or more	103	7,36%	30	56,60%	171	8,19%	108	56,25%	263	5,05%	149	37,16%

Sources: DGE, Ficus-Fare, DADS and the author's calculations.

Table 4.4: Number of projects to which firms have participated

	Sample 1				Sample 2				Sample 3			
Nb. Obs	657				993				2601			
Number of projects	ETIs		GE		ETIs		GE		ETIs		GE	
Total Treated firms	608	100%	49	100%	857	100%	136	100%	2191	100%	410	100%
1 project	335	55,10%	5	10,20%	463	54,03%	20	14,71%	1241	56,64%	111	27,07%
2 projects	126	20,72%	14	28,57%	178	20,77%	27	19,85%	390	17,80%	66	16,10%
3 projects	47	7,73%	4	8,16%	73	8,52%	8	5,88%	171	7,80%	31	7,56%
4 project or more	100	16,45%	26	53,06%	143	16,69%	81	59,56%	389	17,75%	202	49,27%

Sources: DGE, Ficus-Fare, DADS and the author's calculations.

⁵⁸According to the INSEE, in 2013, there were 3.75 million enterprises in France composed of 274 GEs (0.01%), 5300 ETIs (0.14%), 138000 SMEs (3.68%) and 3.61 million microenterprises (96.27%).

Table 4.5: Number of establishments of a firm that belong to clusters at the same time

	Sample 1				Sample 2				Sample 3			
Nb. Obs	1452				2281				5610			
Number of estab.	ETIs		GE		ETIs		GE		ETIs		GE	
Total Treated firms	1399	100%	53	100%	2089	100%	192	100%	5209	100%	401	100%
1 estab.	1094	78,20%	6	11,32%	1580	75,63%	45	23,44%	4250	81,59%	159	39,65%
2 estab.	202	14,44%	25	47,17%	335	16,04%	46	23,96%	655	12,57%	93	23,19%
3 estab.	60	4,29%	2	3,77%	89	4,26%	24	12,50%	161	3,09%	48	11,97%
4 estab. or more	43	3,07%	20	37,74%	85	4,07%	77	40,10%	143	2,75%	101	25,19%

Sources: DGE, Ficus-Fare, DADS and the author's calculations.

Table 4.6: Number of establishments of a firm that participate in projects at the same time

	Sample 1				Sample 2				Sample 3			
Nb. Obs	657				993				2601			
Number of estab.	ETIs		GE		ETIs		GE		ETIs		GE	
Total Treated firms	608	100%	49	100%	857	100%	136	100%	2191	100%	410	100%
1 estab.	487	80,10%	23	46,94%	674	78,65%	50	36,76%	1786	81,52%	224	54,63%
2 estab.	84	13,82%	9	18,37%	130	15,17%	33	24,26%	269	12,28%	86	20,98%
3 estab.	20	3,29%	12	24,49%	33	3,85%	24	17,65%	75	3,42%	34	8,29%
4 estab. or more	17	2,80%	5	10,20%	20	2,33%	29	21,32%	61	2,78%	66	16,10%

Sources: DGE, Ficus-Fare, DADS and the author's calculations.

Table 4.3 shows that many firms belong to several clusters. Some ETIs and large firms are members of more than 10 clusters. Among firms that are members of clusters, more than 35% of the ETIs in samples 1 and 2 and about 28% in sample 3 have joined at least two clusters at the same time. This rate is higher for large firms and stands at more than 90% for GEs in sample 1, 85% in sample 2 and 70% in sample 3. Notably, a majority of large firms belong to at least four clusters at the same time (53% in sample 1, 59% in sample 2 and 49% in sample 3). Similarly, table 4.4 shows that many firms have participated in several FUI projects. Among firms that have participated in FUI projects, about 17% of ETIs and between 49 and 60% of GEs have participated in at least four FUI projects at the same time.

Tables 4.5 and 4.6 show that many firms have several establishments that are members of several clusters and participate in several FUI projects. For large firms, the share with more than four establishments that are members of several clusters at the same time may attain 40% (sample 2), and the share with more than four establishments that participate in several FUI projects at the same time may attain 21% (sample 3). The structure of the samples, the heterogeneity of the firms and the multiple participation in clusters and projects may

increase the selection biases. Therefore, it makes sense to evaluate the effects of the policy in terms of the intensity of participation by controlling the number of establishments of a firm that belong to clusters at the same time and the number of establishments of a firm that participate in FUI projects at the same time.

4.2.2.2 Differences between treated and nontreated firms

Table 4.7 presents the descriptive statistics of the three samples by treated and nontreated firms. Sample 2 shows that treated firms invest more in total R&D expenditures (total budget including DIRD and DERD, €121066.8 compared to €41951.9 thousand for nontreated firms). This difference between the two groups has the same trend when total R&D expenditures are separated into internal and external R&D. Moreover, it is worth noting that private, self-financed R&D amounts are on average higher for treated firms (€80427.3 thousand) than for nontreated one (€24973.3 thousand). Treated firms have more ability to find other channels to fund their R&D and innovation activities. Sample 2 shows that firms that belong to clusters have received almost five and a half times more public subsidies (€22564 thousand on average) than nontreated firms (€4170 thousand on average). The trends observed for R&D spending variables in sample 2 are still valid for sample 1.

Moreover, sample 1 shows that compared to firms outside clusters, firms in clusters file more patents on average (17.4 patents compared to 9.7 patents).

Regarding employment, sample 2 shows statistics for R&D staff and researchers. Compared to nontreated firms, the treated firms have on average more R&D staff (141.5 compared to 68.9 for nontreated firms) and more researchers (129 compared to 39.2 for nontreated firms). Moreover, sample 3 shows that compared to nontreated firms, treated firms perform better on average in terms of average number of employees (1451.3 compared to 925.9 for nontreated firms), total employment (2756.9 compared to 1206 for nontreated firms) and CS3 employment (593.8 compared to 1206 for nontreated firms).

Furthermore, sample 3 shows that treated firms are larger in terms of economic performance variables related to the market such as turnover (€755178.7 thousand compared to €327596.9 thousand for nontreated firms), added value (€256822.7 thousand compared to €97475.3 thousand for nontreated firms) and exports (€225613.8 thousand compared to €86447.1 thousand for nontreated firms).

Table 4.7: Descriptive statistics of the treated and non-treated groups for the samples

Sample 1						
	Treated			Non-treated		
	Nb. Obs	Median	Mean	Nb. Obs	Median	Mean
totbrev	1452	0	17.4	2995	0	9.7
derd	1452	250	11509.8	2973	70	5056.5
dird	1452	7327.5	47844.4	2973	4245	20746.2
budgetot	1452	8731.5	59370.8	2973	5066	25806.7
financ_pro	1452	5698	30513.4	2972	3646.5	16613.6
financ_pub	1452	0	14121.1	2973	0	1998.8
eff_moy_et	1039	563.3	1009.4	2077	432	673.8
emp	1452	615.5	1241.6	2995	461	772.7
cs3	1452	160	376.7	2995	105	217.8
eff_rd	663	55	140.1	1385	21	68.1
researchemp	1451	26.1	102.6	2973	12	40.1
turnover	1428	162791	558945.6	2890	116151	329874.8
addedvalue	1428	52422.1	178868	2890	37028.5	91928.4
export	1338	57273	226891.2	2734	35200	133805.8
Sample 2						
	Treated			Non-treated		
	Nb. Obs	Median	Mean	Nb. Obs	Median	Mean
derd	2281	348	36114.3	5374	105	9144.1
dird	2281	11877	130736.1	5374	6915	44149.9
budgetot	2067	12077	121066.8	4693	7443	41951.9
financ_pro	2067	8909	80427.3	4692	6040	24973.3
financ_pub	2281	0	22564.7	5374	0	4170.5
eff_moy_et	1076	556.4	1005	2152	428	671.5
emp	2281	853	3783.1	5374	553	1082.7
cs3	2281	174	764.9	5374	97	225
eff_rd	686	55	141.5	1446	21	68.1
researchemp	2278	27	129	5358	10	39.2
turnover	2251	220165	864562.6	5252	124332	342399.8
addedvalue	2251	71376	348113.7	5252	39116	112470.8
export	2158	61651	278095.8	5091	34018	121768.7
Sample 3						
	Treated			Non-treated		
	Nb. Obs	Median	Mean	Nb. Obs	Median	Mean
eff_moy_et	3068	517	1451.3	8851	413	925.9
emp	5610	691	2756.9	17146	514	1206
cs3	5610	149	593.8	17146	99	292.4
turnover	5256	162530	755178.7	15682	101444	327596.9
addedvalue	5256	51161.9	256822.7	15682	32416	97475.3
export	5036	29078	225613.8	15135	11694	86447.1

Note: Patents are in unit, R&D variables are in thousand, employment-related variables are in unit, and market-related variables are in thousand.

Sources: R&D survey, DGE, FUI, MENESR, INSEE, Ficus-Fare, DADS, Lifi.

4.2.2.3 Heterogeneity according to type of cluster

Furthermore, as we want to check the heterogeneity of the policy effects according to the type of cluster, it is interesting to analyze the statistics by type of cluster. The clusters are classified into three categories by the FUI committee. Since their implementation, the competitiveness clusters have not had the same status. We can therefore distinguish 71 poles in three types of cluster: the worldwide clusters (7), which compete at the international level; the worldwide-track clusters (11), which compete at the national level and eventually at the international level; and the national clusters (53), which are very important but do not need to compete at the international level. This distinction, which no longer exists (but did exist during the period of this study), had no predetermined implications regarding the resource allocation process, and the rules for participation were the same.

Regarding the funding of the clusters, tables 4.8 and 4.9 show that the funding is very different according to the cluster type. Public funding is concentrated in certain clusters: the worldwide clusters, of which there are only seven, receive 42% of FUI funding. The FUI funding amounts over the 2006-2010 period totaled €1061 million for 865 projects. Of these funds, 42% were concentrated in the 7 worldwide clusters, as opposed to 25% for the 11 worldwide-track clusters and 33% for the 54 national clusters. We see that in total, 18 worldwide or worldwide-track clusters received 67% of the FUI funding and implemented 57% of the collaborative R&D projects funded by this institution. This represents an average ratio of €1.23 million for a funded project. This ratio differs according to the type of cluster and stands at €1.58 million for the worldwide clusters, €1.25 million for the worldwide-track clusters and €0.95 million for the national clusters. The amounts of funding decreased depending on the duration of participation in the policy.

Furthermore, local authorities spent more than €622 million to co-fund 767 projects. Similar to the FUI, the local funding is concentrated on the worldwide or worldwide-track clusters, with a rate of 68%. Local authorities assign 40% of their funding to the worldwide clusters and 28% to the worldwide-track clusters. However, in terms of the number of projects, it is important to note that 42% of the R&D projects funded by local authorities are implemented by the national clusters, as opposed to 34% and 24%, respectively, for the worldwide clusters and the worldwide-track clusters. The local authorities finance projects with a ratio of €0.81 million by project. This ratio varies according to the type of cluster

and stands at €0.96 million for both the worldwide clusters and the worldwide-track clusters and €0.61 million for the national clusters. Local authorities orient more of their funding towards the worldwide or worldwide-track clusters, but they fund many projects with moderate amounts for the national clusters.

Table 4.10 shows that firms that are members of worldwide clusters on average hold more patents, spend more on R&D and perform better in terms of all types of employment, turnover, and exports. They are followed by the firms that are members of worldwide-track clusters. These trends are similar in sample 2 and sample 3.

Table 4.8: Public funding (€Million) and collaborative projects funded between 2006 and 2010.

Funding of collaborative R&D projects by the FUI and the Local authorities by type of clusters							
		Worldwide clusters		Worldwide-track clusters		National clusters	
Number of clusters		7		10		53	
	All	Amount	Share in %	Amount	Share in %	Amount	Share in %
FUI	1061	445	42%	262	25%	354	33%
Local authorities (LA)	622	246	40%	177	28%	199	32%
Number of collaborative R&D projects funded by the FUI and the Local authorities by type of clusters							
		Worldwide clusters		Worldwide-track clusters		National clusters	
	All	Number	Share in %	Number	Share in %	Number	Share in %
FUI	865	282	33%	210	24%	373	43%
Local authorities (LA)	767	257	34%	184	24%	326	42%
The ratio of funding (€Million) by project and by type of clusters							
	All	Worldwide clusters	Worldwide-track clusters	National clusters			
Ratio for FUI projects	1.23	1.58	1.25	0.95			
Ratio for LA projects	0.81	0.96	0.96	0.61			

Source: Author's computations from the annual dashboards of the DGE

Table 4.9: The Funding (€Million) and the number of FUI projects by type of clusters

Year	2006	2007	2008	2009	2010
Worldwide clusters					
FUI Funding	94	119	88	84	60
Number of FUI projects	43	63	67	61	48
Worldwide-track clusters					
FUI Funding	39	57	69	60	37
Number of FUI projects	32	36	55	48	39
National clusters					
FUI Funding	56	63	99	76	60
Number of FUI projects	65	71	100	73	64

Sources: The annual dashboards of the DGE; author's synthesis

4.2.2.4 Differences in the number of years a firm participated

Tables 4.11 and 4.35 present information on the number of years a firm was a member of a cluster or participated in FUI projects. These tables seem to show that in 2012, a few firms had been members of clusters for seven years and, to a lesser extent, eight years, and a few firms had participated in FUI projects for six years.

In sum, the descriptive statistics show that, compared to nonparticipating firms, the participating firms on average have more patents, R&D activities (R&D spending and employment in R&D), employment and economic performance such as turnover, added value and exports. These averages are very heterogeneous across type of cluster.

Table 4.11: Number of years a firm has been in the policy clusters by size

	Sample 1				Sample 2				Sample 3			
Nb. Obs	1452				2281				5610			
Number of years	ETIs		GE		ETIs		GE		ETIs		GE	
Total Treated firms	1399	100%	53	100%	2089	100%	192	100%	5209	100%	401	100%
1 year	234	16,73%	8	15,09%	405	19,39%	29	15,10%	1112	21,35%	69	17,21%
2 years	251	17,94%	8	15,09%	386	18,48%	29	15,10%	984	18,89%	66	16,46%
3 years	234	16,73%	7	13,21%	344	16,47%	26	13,54%	848	16,28%	59	14,71%
4 years	233	16,65%	8	15,09%	320	15,32%	26	13,54%	727	13,96%	55	13,72%
5 years	206	14,72%	8	15,09%	274	13,12%	26	13,54%	589	11,31%	48	11,97%
6 years	170	12,15%	7	13,21%	227	10,87%	25	13,02%	502	9,64%	45	11,22%
7 years	60	4,29%	6	11,32%	114	5,46%	22	11,46%	381	7,31%	39	9,73%
8 years	11	0,79%	1	1,89%	19	0,91%	9	4,69%	66	1,27%	20	4,99%

Sources: DGE, Ficus-Fare, DADS and the author's calculations.

Table 4.12: Number of years a firm has been in the FUI projects by size

	Sample 1				Sample 2				Sample 3			
Nb. Obs	730				1093				2962			
Number of years	ETIs		GE		ETIs		GE		ETIs		GE	
Total Treated firms	680	100%	50	100%	955	100%	138	100%	2524	100%	438	100%
1 year	168	24,71%	9	18,00%	235	24,61%	25	18,12%	538	21,32%	70	15,98%
2 years	191	28,09%	9	18,00%	259	27,12%	25	18,12%	599	23,73%	75	17,12%
3 years	158	23,24%	11	22,00%	226	23,66%	27	19,57%	641	25,40%	95	21,69%
4 years	100	14,71%	9	18,00%	141	14,76%	25	18,12%	415	16,44%	82	18,72%
5 years	49	7,21%	9	18,00%	68	7,12%	24	17,39%	207	8,20%	68	15,53%
6 years	14	2,06%	3	6,00%	26	2,72%	12	8,70%	124	4,91%	48	10,96%

Sources: DGE, Ficus-Fare, DADS and the author's calculations.

Table 4.10: Descriptive statistics of variables by cluster type for the samples

		Sample 1																										
		totbrev			derrd			dird			budgetot			financ-pro			eff-rd			researchtemp								
	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean						
Non-treated group	2995	9.7	2973	5056.5	2973	20746.2	2973	25806.7	2972	16613.6	1385	68.1	2973	40.1	Worldwide	395	28.2	395	32788.9	395	111362.4	395	144212.1	395	68392.9	184	235.7	
Worldwide track	288	17.5	288	2134.5	288	28660.3	288	30794.9	288	23066.9	134	92.3	288	70.2	National	769	11.8	769	4090.9	769	22402.9	769	26493.8	769	13845.2	345	109.7	
National	769	11.8	769	4090.9	769	22402.9	769	26493.8	769	13845.2	345	109.7	768	46.3														
		Sample 2																										
		derrd			dird			budgetot			financ-pro			eff-moy-ct			eff-rd											
	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean										
Non-treated group	5374	9144.1	5374	44149.9	4693	41951.9	4692	24973.3	2152	671.5	1446	68.1	Worldwide	588	61096.4	588	240659.9	533	261803.3	533	165255.7	302	1272.1	193	236.3			
Worldwide track	457	56127.0	457	175012.0	390	86406.9	390	66970.8	228	922.0	139	94.3	National	1236	16830.0	1236	62071.7	1144	67312.2	1144	45492.4	546	891.9	354	108.3			
National	1236	16830.0	1236	62071.7	1144	67312.2	1144	45492.4	546	891.9	354	108.3																
		Sample 3																										
		researchtemp			emp			cs3			turnover			addevalue			export											
	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean										
Non-treated group	5358	39.2	5374	1082.7	5374	225.0	5252	342399.8	5252	112470.8	5091	121768.7	Worldwide	586	261.7	588	6570.5	588	1298422.5	584	497432.1	555	463203.4					
Worldwide track	457	156.4	457	6265.2	457	1444.6	446	1463960.4	446	743419.0	425	275201.9	National	1235	55.9	1236	1539.3	1236	246.6	1221	438104.3	1221	132300.4	1178	191928.7			
National	1235	55.9	1236	1539.3	1236	246.6	1221	438104.3	1221	132300.4	1178	191928.7																
		Sample 3																										
		eff-moy-ct			emp			cs3			turnover			addevalue			export											
	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean	Nb. Obs	Mean										
Non-treated group	8851	925.9	17146	1206.0	17146	292.4	15682	327596.9	15682	97475.3	15135	86447.1	Worldwide	858	1934.0	1403	4733.0	1403	1089.7	1298	1296586.3	1298	382068.2	1231	481088.3			
Worldwide track	665	1494.7	1111	3921.0	1111	994.9	1033	913627.4	1033	455854.1	982	182300.7	National	1545	1164.5	3096	1443.7	3096	225.1	2925	458965.2	2925	130953.3	2823	129278.2			
National	1545	1164.5	3096	1443.7	3096	225.1	2925	458965.2	2925	130953.3	2823	129278.2																

Note: Patents are in unit, R&D variables are in thousand, employment-related variables are in unit, and market-related variables are in thousand.

Sources: R&D survey, DGE, FUI, MENESR, INSEE, Ficus-Fare, DADS, Lifo, and the author's calculations.

4.3 Econometric strategy

The primary concern of an analysis of the effects of the French competitiveness clusters policy on large firms' outcomes is that firms choose whether to participate in the policy. Therefore, participation is likely to be correlated with unobserved characteristics of the firms that could affect their performance, such as governance, staff management, innovation system, experience in collaborative R&D projects, networking with other firms, participation in parallel policies, etc. In this case, the selection process leads to an endogeneity problem. The selection process is not randomized because it is based on calls for projects. According to [Fontagné et al. \(2013\)](#), there are two selection problems: one related to the selection of the financed projects by public authorities and the other to the self-selection of firms that decide to be members of a cluster or to participate in a project. Thus, a simple ordinary least squares (OLS) regression that compares participating and nonparticipating firms to evaluate the effects of the policy will likely be biased and inconsistent.

The literature on the microeconomic evaluation offers different estimation strategies to correct for selection bias (see [Cochrane and Rubin, 1973](#); [Heckman et al., 1999](#); [Imbens and Wooldridge, 2009](#); [Athey and Imbens, 2017](#) for a survey). In many studies, evaluators use counterfactual methods to assess policy effects by using different microeconomic methods. But a limits of this approach are that it sometimes ignores the unobserved characteristics of firms and also cannot be applied to firms that do not have similar counterfactuals, especially large firms. In the recent applied econometric literature, many researchers have dealt with the endogeneity issue by using panel data models (see e.g. [Baltagi, 2005, 2013](#); [Wooldridge, 2005, 2010, 2015](#); [Aghion et al., 2013](#); [Bell and Jones, 2015](#); [Wagner, 2016](#); [Moral-Benito, 2016](#)). As shown by [Heckman and Hotz \(1989\)](#), [Wooldridge \(2005\)](#) and [Hsiao \(2011\)](#), the two-way fixed effects approach has been used because it offers a solution to deal with the endogeneity problem related to selection bias (due to observable and unobserved characteristics).

4.3.1 The two-way fixed effects model

To assess the effects of participation in the policy on mid-sized enterprises and large firms' performance by accounting for the endogeneity issue, we adopt a two-way fixed effects model (unobserved effects model) ([Baltagi, 2005, 2013](#); [Wooldridge, 2010, 2015](#)). The two-way fixed effects model is a linear model that controls for common shocks affecting firms and also for

firms' unobserved heterogeneity, which may influence their choice of whether to participate in the policy (also called the self-selection problem (Wooldridge, 2010)).

The standard linear unobserved effects model can be written, for a firm i at time t , as

$$y_{i,t} = \beta X_{i,t} + u_{i,t} \quad (4.1)$$

where the dependent variable $y_{i,t}$ is the considered output of firm i at time t . $i = (1, 2, \dots, I)$ indicates firms, and $t = (1, 2, \dots, T)$ indicates time. The vector $X_{i,t}$ contains the independent variables, and $u_{i,t}$ is an error term. For a two-way fixed effects model, in addition to the firm-specific effects, we add common time effects θ_t that are supposed to influence a firm's performance; thus, we have $u_{i,t} = c_i + \theta_t + v_{i,t}$ (Wooldridge, 2010). c_i is a firm's unobserved heterogeneity (self-selection problem and unobserved characteristics), which accounts for permanent differences across firms that are likely to influence their performance; θ_t denotes the time fixed effects, and $v_{i,t}$ are idiosyncratic errors.

In this study, the two-way fixed effects model can be written as

$$y_{i,t} = \beta_1 sharhip_{i,t} + \beta_2 emp_{i,t} + \beta_3 rdspond_{i,t} + \beta_4 nbetb_{i,t} + \beta_5 appgroup_{i,t} + \delta_1 D_{i,t} + c_i + \theta_t + v_{i,t} \quad (4.2)$$

where we include the dummy variable $D_{i,t}$, which takes the value of one if the firm i belongs to a competitiveness cluster at time t and zero otherwise. Based on empirical evidence and information available in our data set, we include in the model explanatory variables (firms' characteristics), such as firm size (emp), share of managers, executives and intellectual professionals ($sharhip$), R&D expenditures ($rdspond$), the firm's number of establishments ($nbetb$) and the fact that the firm is a member of a group ($appgroup$), that affect firm performance and may also be correlated with program participation.

We include in the model the number of employees (emp). In the literature, the size of a firm is considered an important characteristic that influences its participation in the clusters policy. It may also be easier for larger firms to obtain more and better information on external resources in the clusters policy because they tend to be the core participants in the projects. Firms with a greater investment capacity and important R&D staff are more likely to participate in the clusters. Therefore, we include the share of managers, executives and intellectual professionals ($sharhip$) and the R&D expenditures ($rdspond$) of the firm in our model. We include in our model the number of establishments of the firm ($nbetb$) because

the structure of a firm can also be a determinant of its decision to participate in the cluster policy. Firms with multiple establishments may be more exposed to the policy and therefore more likely to participate in it because larger firms are generally those that have several establishments, and their R&D level is higher than that of firms with a single establishment. Finally, we include a dummy variable (*appgroup*) that takes the value of one if the firm is a member of a group and zero otherwise. The firms that belong to a group may be more likely to participate in the clusters because large firms are generally those that have several establishments, which may increase their probability of participating in the policy.

To evaluate the effect of participation in FUI projects, we replace $D_{i,t}$ with $F_{i,t}$ which is a dummy variable that takes the value of one if the firm i participates in an FUI project at time t and zero otherwise, and we obtain

$$y_{i,t} = \beta_1 \text{sharhip}_{i,t} + \beta_2 \text{emp}_{i,t} + \beta_3 \text{rdspend}_{i,t} + \beta_4 \text{nbetb}_{i,t} + \beta_5 \text{appgroup}_{i,t} \\ + \lambda_1 F_{i,t} + c_i + \theta_t + v_{i,t} \quad (4.3)$$

To control the simultaneity of the two treatments (being a member of a cluster and participating in an FUI project), we include the two variables in the model simultaneously and obtain

$$y_{i,t} = \beta_1 \text{sharhip}_{i,t} + \beta_2 \text{emp}_{i,t} + \beta_3 \text{rdspend}_{i,t} + \beta_4 \text{nbetb}_{i,t} + \beta_5 \text{appgroup}_{i,t} \\ + \delta_1 D_{i,t} + \lambda_1 F_{i,t} + c_i + \theta_t + v_{i,t} \quad (4.4)$$

We go further and check the effects of the intensity of a firm's activity level in the policy by including the number of establishments belonging to clusters and the number of establishments participating in FUI projects at the same time. We first include the two variables in the model separately, and then we include them together to control simultaneity. Thus, we obtain this following equation:

$$y_{i,t} = \beta_1 \text{sharhip}_{i,t} + \beta_2 \text{emp}_{i,t} + \beta_3 \text{rdspend}_{i,t} + \beta_4 \text{nbetb}_{i,t} + \beta_5 \text{appgroup}_{i,t} \\ + \delta_1 \text{nbetabcluster}_{i,t} + \delta_2 \text{nbetabproj}_{i,t} + c_i + \theta_t + v_{i,t} \quad (4.5)$$

where $\text{nbetabcluster}_{i,t}$ is the number of establishments of a firm i that belong to clusters at time t and $\text{nbetabproj}_{i,t}$ is the number of establishments of a firm i that participate in FUI projects at time t .

4.3.2 Modeling the heterogeneity of the policy effects

To account for heterogeneity according to the type of cluster, we categorize the typology of the competitiveness clusters in three types. To measure the impacts of the policy according to cluster type, we replace the dummy of participation in equation (4.2) by a series of three dummy variables according to the type of cluster (worldwide, worldwide-track and national) to which a firm belongs, and we obtain

$$y_{i,t} = \beta_1 sharhip_{i,t} + \beta_2 emp_{i,t} + \beta_3 rdspond_{i,t} + \beta_4 nbetb_{i,t} + \beta_5 appgroup_{i,t} \\ + \delta_1 worldwide_{i,t} + \delta_2 worldwidetrack_{i,t} + \delta_3 national_{i,t} + c_i + \theta_t + v_{i,t} \quad (4.6)$$

The specification is restrictive because participation has the same effect in each year after the participation begins. As the effect of participation in the clusters policy may take a long time to emerge, it is important to include the number of years that a firm has participated in the policy. We use a more flexible specification that consists of replacing $D_{i,t}$ with a series of program indicators, $D1_{i,t}, \dots, DM_{i,t}$, where $Dj_{i,t}$ is one if firm i at time t has been in the program exactly j years, and M is the maximum number of years the program has existed, $m=(1, \dots, M)$. In our study, the policy had existed for 8 years (2005-2012), so we have $M=8$. For FUI projects, we replace the series of program indicators $D1_{i,t}, \dots, DM_{i,t}$ with $F1_{i,t}, \dots, FN_{i,t}$, where $Fj_{i,t}$ is one if firm i at time t had been in an FUI project exactly j years, and N is the maximum number of years the project has existed $n=(1, \dots, N)$. Here, the FUI had existed for 6 years (2007-2012), so we have $N=6$.

By applying this proposition for the dummies of cluster participation, we obtain the following equation:

$$y_{i,t} = \beta_1 sharhip_{i,t} + \beta_2 emp_{i,t} + \beta_3 rdspond_{i,t} + \beta_4 nbetb_{i,t} + \beta_5 appgroup_{i,t} + \delta_1 D1_{i,t} \\ + \delta_2 D2_{i,t} + \delta_3 D3_{i,t} + \delta_4 D4_{i,t} + \delta_5 D5_{i,t} + \delta_6 D6_{i,t} + \delta_7 D7_{i,t} + \delta_8 D8_{i,t} + c_i + \theta_t + v_{i,t} \quad (4.7)$$

This is an extension of the model that allows the effect of participation in the policy to vary over time. The participation dummy is replaced by a series of dummy variables for each year of the policy. For example, $D2_{i,t}$ takes the value of one if firm i had participated for two years at year t and zero otherwise.

By applying this proposition for the dummies of FUI project participation, we obtain the following equation:

$$y_{i,t} = \beta_1 sharhip_{i,t} + \beta_2 emp_{i,t} + \beta_3 rdspond_{i,t} + \beta_4 nbetb_{i,t} + \beta_5 appgroup_{i,t} \\ + \lambda_1 F1_{i,t} + \lambda_2 F2_{i,t} + \lambda_3 F3_{i,t} + \lambda_4 F4_{i,t} + \lambda_5 F5_{i,t} + \lambda_6 F6_{i,t} + c_i + \theta_t + v_{i,t} \quad (4.8)$$

4.3.3 Testing the validity of the model

The fixed effects model is a linear model that controls for firms' unobserved heterogeneity (fixed and time-invariant factors). To implement the fixed effects model and obtain an efficient estimator, we must perform, in addition to specification tests, tests for the presence of individual and time unobserved effects and for correlation between these and the regressors. We also perform heteroskedasticity tests and serial correlation tests to choose the best estimator. As we have several types of dependent (outcome) variables, we implement the tests by considering variables such as patents, R&D spending, employment and turnover as dependent; the results of these tests are presented in table 4.13.

Tests for individual and time effects: The unobserved effects test is a semiparametric test with a null hypothesis assuming that there are no unobserved effects in the residuals. Wooldridge's test (Wooldridge, 2010) for unobserved individual effects has a p-value less than a significance level of 0.05, suggesting a rejection of the null hypothesis and confirming the presence of an individual unobserved effect, whatever the dependent variable. The results of the Lagrange Multiplier Test proposed by Breusch and Pagan (1980) also have a p-value less than a significance level of 0.05, suggesting a rejection of the null hypothesis, indicating that there are time effects in the data and suggesting the use of a two-way fixed effects model to consistently estimate the effects for all the dependent variables.

Specification test: Hausman's specification test (Hausman, 1978) allows us to choose between the random effects and the fixed effects estimators. The test determines whether there is a correlation between the unique errors and the regressors in the model. The null hypothesis is that there is no correlation between the two. The results of this test have a p-value less than a significance level of 0.05, suggesting a rejection of the null hypothesis and the adoption of the fixed effects estimator as a better choice, whatever the dependent variable.

Testing for *heteroskedasticity*: Heteroskedasticity occurs when the variance of the unobservable error, conditional on the independent variables, is not constant. When the scatter of the errors differs depending on the value of one or more of the independent variables, the error terms are said to be heteroskedastic (nonconstant variance) (Wooldridge, 2015). For more detail on heteroskedasticity, see White (1980); MacKinnon and White (1985); Long and Ervin (2000); Cribari-Neto (2004). According to (Baltagi, 2013), assuming homoskedastic distur-

bances when heteroskedasticity is present will result in consistent but inefficient estimates of the regression coefficients, making it necessary to compute robust standard errors to correct for the possible presence of heteroskedasticity. The Breusch-Pagan test (Breusch and Pagan, 1979) for heteroskedasticity (BP test) results in a p-value less than a significance level of 0.05; therefore, we can reject the null hypothesis that the variance of the residuals is constant and infer that heteroskedasticity is indeed present, whatever the dependent variable.

Testing for *serial correlation*: Serial correlation is present when the errors in two different time periods are correlated (Wooldridge, 2015). Errors suffer from serial correlation when they are correlated with residuals in previous periods. For further detail on the serial correlation problem, see (Durbin and Watson, 1951; Drukker et al., 2003; Baltagi, 2013; Wooldridge, 2015). When the idiosyncratic errors are serially correlated, Bertrand et al. (2004) show that the usual standard errors of the fixed effects estimator are understated or overstated. In our estimates, both Wooldridge's test and the Breusch-Godfrey/Wooldridge test for serial correlation have a p-value less than a significance level of 0.05; therefore, we can reject the null hypothesis that there is no serial correlation and confirm the presence of serial correlation in idiosyncratic errors, whatever the dependent variable. According to Baltagi (2013), ignoring serial correlation when it is present results in consistent but inefficient estimates of the regression coefficients and biased standard errors.

In this context, the econometric literature recommends the use of cluster-robust standard errors for the fixed effects estimator. The idea behind clustering is that each cross-sectional unit is defined as a cluster of observations over time, and arbitrary correlation and changing variances are allowed within each cluster (Wooldridge, 2015). In this study, we control for both heteroskedasticity and serial correlation to consistently and efficiently estimate the estimator by using the cluster-robust covariance matrix estimator proposed by (Arellano, 1987) which allows individual correlation and clusterization at the firm level.

In the two-way fixed effects model, the time effect is assumed to be common for all firms. However, several unobserved time-varying firm-specific characteristics, such as governance, staff management, innovation system, experience in collaborative R&D projects, networking with other firms and participation in parallel policies, are likely to affect heterogeneity in the firms but cannot be quantitatively measured; thus, they enter the panel regressions as unobserved common factors. To account for possible cross-sectional dependency due to such unobserved time-varying firm-specific characteristics, we also cluster by time period (Cameron

et al., 2011; Millo, 2017).

Table 4.13: Testing the validity of the models

	Dependent variable			
	Patents	R&D spending	Employment	Turnover
1/ Tests for unobserved individual effects				
Wooldridge's test - H0: There are no unobserved effects in the residuals.				
p-value	0.016	0.040	0.038	<0.001
2/ Specification test: Fixed effects vs random effects				
Hausman Test - H0: The appropriate model is Random effects				
p-value	<0.001	<0.001	<0.001	<0.001
3/ Tests for individual and time effects				
Lagrange Multiplier test ** - H0: There is no presence of individual and time effects				
p-value	<0.001	<0.001	<0.001	<0.001
4/ Testing for heteroscedasticity				
Studentized Breusch-Pagan test - H0: Homoscedasticity (residuals have constant variance)				
p-value	<0.001	<0.001	<0.001	<0.001
5/ Testing for serial correlation				
Wooldridge's test in FE panels*** - H0: There is no serial correlation				
p-value	<0.001	<0.001	<0.001	<0.001

Note: Tests and results are produced by the R *plm* and *lmtest* packages. All these tests have a p-value less than a significance level of 0.05, therefore we can reject the null hypothesis in each test.

** Lagrange Multiplier Test - two-ways effects (Breusch-Pagan) for unbalanced panels.

*** Similar results are found when using a more general test for serial correlation in panel models (Breusch-Godfrey/Wooldridge test).

4.4 Results

This section presents the econometric evidence of the effect of the competitiveness clusters policy on firms' performance. To assess the impacts of the policy on firms' performance, we have retained several variables on which the policy may have an effect: patents and R&D-related variables, employment-related variables and economic variables related to the market (turnover, added value, and export). For all results, we include control variables such as firm size, the share of managers, executives and intellectual professionals in all employment, the number of establishments, and the fact of being a member of a group. To estimate the effects

on patents, we also add R&D expenditures as a control. Whether or not we add the control variables, the results are robust and do not change much. All the tables of estimates without control variables are presented in detail in the appendix [4.6.3](#).

4.4.1 Effects on innovation and economic performance

In the various tables ([4.14](#) to [4.25](#)) that follow, the results for each variable are presented in a single table, and the treatment variables are successively introduced afterward. We first include as a treatment variable a dummy variable (column 1) indicating whether the firm is a member of clusters, and then we replace it by the number of establishments of the firm that belong to clusters (whatever the cluster class - column 2) to measure the effect of the activity intensity. For the effect of participation in FUI projects, we proceed in the same way described above by first including a dummy variable (column 3) indicating whether the firm has participated in FUI projects and then the number of establishments of the firm that participate in FUI projects (column 4) to measure the effect of the intensity of participating in a project. To make a robustness check and control the eventual simultaneity bias of the two treatments (being a member of clusters and participating in FUI projects), we first simultaneously include both the dummy of being a member of clusters and the dummy of participation in FUI projects (column 5). Further, we simultaneously include (column 6) both the number of establishments of the firm that belong to clusters and the number of establishments of the firm that participate in FUI projects.

4.4.1.1 Mixed effects on innovation input and output additionality

To assess the impact in terms of research and innovation efforts undertaken by firms and in terms of private R&D incentives and firms' expenditure, we use as outcome variables the firm's total R&D budget (*budgetot*), internal and external R&D spending (*derd* and *dird*) and self-financed R&D (*financ_pro*). Table [4.14](#) presents the policy effects on firms' total private R&D, tables [4.16](#) and [4.15](#) present, respectively, the effects on firms' internal and external R&D and table [4.17](#) presents the effects on private self-financed R&D.

Columns 1, 2 and 4 of the latter tables show that belonging to clusters seems to have no effect on firms' R&D spending. This finding means that on average, being a member of clusters does not stimulate firms' private R&D investments but does not lead to crowding-out

effects. The results suggest the rejection of the crowding-out effect but do not conclude in favor of the substantial additionality of effects on R&D.

However, when we include the dummy of participation in FUI projects or when we include the number of establishments of the firm that participate in FUI projects, the effect on R&D spending is negative and significant. The results suggest that participating in FUI projects leads to a decrease in private R&D spending, corresponding to a crowding-out effect on private self-financed R&D (between €-11374 and -13739 thousand (table 4.17)). These results are confirmed when we use other R&D spending variables: there is a reduction of internal R&D spending (between €-7842 and -21632 thousand (table 4.16)). Furthermore, the effect on firms' total R&D budgets seems to be negative (between €-14770 and -31522 thousand (table 4.14)), corresponding to an eviction effect: the firms that belong to clusters would have diminished their private R&D investment by more than the amount of the subsidies they received. These results are confirmed when we include in the model the number of establishments that participate in FUI projects.

When focusing on the impact of the policy on innovation output, we use the total number of patents the firm has filed as the outcome variable. Table 4.18, based on sample 1, provides estimates of the effects of the policy on ETIs' and large firms' total number of filed patents. Columns 1 and 4 show that being a member of clusters increases the number of filed patents (about 3.6 patents) even when we control for simultaneity with participation in FUI projects. Columns 3 and 4 show that participating in FUI projects has no effect on patents, but having several establishments that participate in FUI projects has a positive effect on patents (1.9 patents).

In sum, we find that belonging to competitiveness clusters seems to have no significant effect on private R&D spending but seems to increase firms' patenting and therefore innovation output. However, our estimates suggest that participation in FUI projects has a negative effect on private R&D investment. The results for the effect of FUI projects indicate the presence of the crowding-out effect and eviction effect. It is worth noting that although participation in FUI projects seems to have a negative effect on private R&D, the results suggest positive effects on innovation output. The results do not change much when we control for simultaneity of being a member of clusters and participation in FUI projects.

Table 4.14: Estimates on total budget in R&D

	Total Budget in R&D					
	(1)	(2)	(3)	(4)	(5)	(6)
Share of managers	30,240.7 (46,096.7)	30,508.4 (46,268.2)	34,540.5 (47,180.6)	34,706.9 (47,146.3)	34,124.2 (46,879.0)	34,685.5 (46,884.4)
Employment	-64.0*** (11.1)	-64.1*** (11.0)	-61.8*** (10.6)	-61.8*** (10.6)	-61.1*** (10.7)	-61.3*** (10.7)
Number of establishments	-1,505.8*** (157.1)	-1,505.8*** (156.4)	-1,502.4*** (158.7)	-1,502.5*** (158.7)	-1,483.3*** (162.6)	-1,480.3*** (162.0)
Membership of a group	9,422.8*** (2,101.7)	9,655.9*** (2,204.4)	11,030.2*** (3,544.3)	11,120.1*** (3,655.8)	9,629.5*** (2,968.2)	10,313.0*** (3,382.5)
Cluster membership	-2,861.7 (4,948.6)			1,559.7 (4,186.6)		
Nb. Estab. in clusters		481.3 (3,352.0)				3,413.1 (3,220.8)
FUI participation			-31,205.9*** (8,001.5)	-31,521.7*** (8,252.4)		
Nb. Estab. in FUI					-14,770.0*** (3,899.7)	-15,951.5*** (4,233.3)
Observations	8,031	8,031	8,031	8,031	8,031	8,031

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.15: Estimates on External R&D Expenditure

	External R&D Expenditure					
	(1)	(2)	(3)	(4)	(5)	(6)
Share of managers	-9,120.7 (5,602.6)	-9,134.3 (5,673.4)	-8,382.4 (5,611.4)	-8,382.1 (5,595.8)	-8,678.1 (5,625.3)	-8,623.9 (5,684.4)
Employment	-10.0*** (2.9)	-10.2*** (3.0)	-9.6*** (2.8)	-9.6*** (2.8)	-9.6*** (2.9)	-9.8*** (2.9)
Number of establishments	-342.7*** (29.4)	-345.0*** (29.0)	-341.2*** (30.0)	-341.2*** (30.0)	-335.7*** (31.3)	-339.0*** (29.2)
Membership of a group	1,970.8** (888.8)	2,120.9** (937.0)	2,367.0** (1,011.3)	2,367.4** (1,015.8)	2,071.7** (969.6)	2,368.8** (1,099.7)
Cluster membership	-766.3 (601.6)			6.4 (468.7)		
Nb. Estab. in clusters		543.4 (666.3)				1,318.8* (717.9)
FUI participation			-5,172.9*** (1,279.9)	-5,174.3*** (1,311.5)		
Nb. Estab. in FUI					-2,698.6** (1,052.4)	-3,462.0*** (1,150.5)
Observations	8,994	8,994	8,994	8,994	8,994	8,994

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.16: Estimates on Internal R&D Expenditure

	Internal R&D Expenditure					
	(1)	(2)	(3)	(4)	(5)	(6)
Share of managers	37,782.1 (42,343.1)	37,765.4 (42,553.6)	40,858.8 (43,051.0)	40,870.0 (43,031.6)	39,082.1 (42,566.6)	39,231.5 (42,828.8)
Employment	-50.1*** (7.2)	-50.6*** (7.4)	-48.6*** (7.0)	-48.6*** (7.0)	-49.0*** (7.2)	-49.5*** (7.5)
Number of establishments	-674.4*** (123.9)	-680.4*** (125.3)	-667.9*** (126.4)	-667.9*** (126.4)	-654.1*** (129.3)	-663.1*** (125.8)
Membership of a group	-15,132.5** (6,256.4)	-14,697.8** (6,115.0)	-13,488.6** (5,972.0)	-13,474.3** (6,000.7)	-14,803.8** (6,069.9)	-13,985.8** (5,892.9)
Cluster membership	-2,996.1 (4,128.7)			234.5 (3,567.0)		
Nb. Estab. in clusters		1,403.8 (2,098.6)				3,630.6* (2,011.4)
FUI participation			-21,582.1*** (5,891.6)	-21,632.0*** (6,110.9)		
Nb. Estab. in FUI					-7,841.5*** (3,009.6)	-9,943.3*** (2,743.1)
Observations	8,994	8,994	8,994	8,994	8,994	8,994

Note: Results are produced by the R *plm* and *lmtree* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.17: Estimates on private self-financed R&D

	Private funding					
	(1)	(2)	(3)	(4)	(5)	(6)
Share of managers	-12,524.0 (20,812.4)	-12,550.8 (20,747.2)	-10,972.8 (21,192.7)	-10,892.6 (21,190.0)	-9,170.4	-8,956.3
Employment	-35.6*** (8.6)	-35.5*** (8.7)	-34.8*** (8.6)	-34.8*** (8.6)	-33.0*** (9.0)	-33.1*** (9.1)
Number of establishments	-1,605.8*** (50.2)	-1,606.2*** (49.8)	-1,604.5*** (50.8)	-1,604.5*** (50.8)	-1,585.4*** (52.7)	-1,584.3*** (51.5)
Membership of a group	5,697.1*** (1,792.5)	5,495.9*** (1,586.8)	6,274.1*** (2,224.1)	6,317.5*** (2,238.2)	5,800.3** (2,416.4)	6,061.4** (2,383.2)
Cluster membership	-865.7 (1,498.5)			754.6 (1,009.9)		
Nb. Estab. in clusters		-1,222.4 (2,709.6)				1,304.2 (2,198.2)
FUI participation			-11,374.0*** (3,199.3)	-11,527.1*** (3,201.0)		
Nb. Estab. in FUI					-13,287.3*** (2,524.8)	-13,739.0*** (2,168.9)
Observations	8,030	8,030	8,030	8,030	8,030	8,030

Note: Results are produced by the R *plm* and *lmtree* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.18: Estimates on total patents

	Total Patents					
	(1)	(2)	(3)	(4)	(5)	(6)
Share of managers	19.0*** (6.0)	18.7*** (6.0)	18.5*** (6.0)	18.8*** (6.0)	18.3*** (6.0)	18.3*** (6.0)
Employment	0.01*** (0.002)	0.01*** (0.002)	0.01*** (0.002)	0.01*** (0.002)	0.01*** (0.002)	0.01*** (0.002)
dird	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Number of establishments	0.3** (0.1)	0.3** (0.1)	0.3** (0.1)	0.3* (0.1)	0.3* (0.1)	0.3* (0.1)
Membership of a group	-0.9 (7.6)	-1.2 (7.6)	-1.5 (7.6)	-1.1 (7.6)	-1.1 (7.6)	-1.1 (7.6)
Cluster membership	3.6*** (1.2)			3.5*** (1.2)		
Nb. Estab. in clusters		0.3 (0.7)				-0.01 (0.7)
FUI participation			1.9 (1.4)	1.3 (1.4)		
Nb. Estab. in FUI					1.9** (0.9)	1.9** (0.9)
Observations	5,656	5,656	5,656	5,656	5,656	5,656

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

4.4.1.2 Strong positive effects on employment

To measure the effects of the policy in terms of employment performance, we use variables such as average number of full-time equivalent employees (*eff_moy_et*), executives, managers, and intellectual professionals (*cs3*), full-time equivalent R&D staff (*eff_rd*) and full-time equivalent researchers (*researchemp*). The results are presented in tables 4.19 to 4.22.

Tables 4.19 and 4.20 (columns 1 and 4) show that being a member of a cluster has positive effects on average number of employees (between 36 and 39 full-time equivalent employees) and number of executives, managers and intellectual professionals (between 10 and 15 employees). Moreover, when we include the number of establishments that belong to clusters (columns 2 and 6), the effects trend the same way but are weaker (about 21 full-time equivalent employees and between 6 and 8 executives, managers, and intellectual professionals).

Similarly, participating in an FUI project (columns 3 and 4) also has positive effects on average number of employees (34 to 40 employees) and number of executives, managers and intellectual professionals (between 39 and 41 employees). When we include the number of

establishments that participates in FUI projects (columns 5 and 6), the policy impact on average number of employees is null, but the effect is positive for employment of executives, managers and intellectual professionals (about 35 employees).

Tables 4.21 and 4.22 (columns 1 to 6) show that being a member of a cluster or participating in FUI projects has no significant effect on firms' R&D staff and number of researchers. It is worth noting that contrary to what one might expect, the effects on firms' R&D staff and researchers are surprisingly very low or even nonexistent. The results do not change much when we control for simultaneity of the two instruments. These results are confirmed when we include the number of establishments that belong to clusters and the number of establishments that participate in FUI projects. These results are consistent with the impacts on R&D expenditure because a large share of expenditures is spent for the remuneration of researcher staff. As there is no negative effect of FUI projects on research staff, the crowding-out effect on R&D is due to other expenditure, probably to capital expenditure.

Globally, the impacts of the policy on firms' employment are significantly positive. Moreover, when the effects on employment are statistically significant, they are slightly stronger for participation in FUI projects than for participation in clusters.

Table 4.19: Estimates on Average number of employees (full-time equivalent)

	Average number of employees (full-time equivalent)					
	(1)	(2)	(3)	(4)	(5)	(6)
Share of managers	278.1*** (64.0)	280.0*** (64.2)	275.9*** (61.8)	276.7*** (62.7)	278.1*** (63.3)	280.5*** (64.2)
Number of establishments	25.1*** (5.8)	25.1*** (5.8)	25.1*** (5.8)	25.1*** (5.8)	25.1*** (5.8)	25.1*** (5.8)
Membership of a group	148.1*** (21.8)	147.0*** (21.5)	145.2*** (20.9)	147.2*** (21.6)	146.2*** (21.0)	147.2*** (21.5)
Cluster membership	38.9*** (9.8)			36.0*** (8.7)		
Nb. Estab. in clusters		21.9*** (7.1)				20.9*** (6.9)
FUI participation			39.5** (19.1)	35.1* (18.0)		
Nb. Estab. in FUI					13.7 (8.6)	12.0 (8.0)
Observations	11,919	11,919	11,919	11,919	11,919	11,919

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.20: Estimates on CS3 employment

	CS3 employment					
	(1)	(2)	(3)	(4)	(5)	(6)
Number of establishments	5.3*** (0.6)	5.2*** (0.6)	5.3*** (0.6)	5.3*** (0.6)	5.2*** (0.6)	5.2*** (0.6)
Membership of a group	123.3*** (16.5)	123.4*** (16.6)	123.2*** (16.6)	123.5*** (16.6)	123.9*** (16.5)	124.2*** (16.6)
Cluster membership	14.9*** (5.6)			10.6** (4.8)		
Nb. Estab. in clusters		7.8*** (2.6)				5.9** (2.4)
FUI participation			41.0** (16.4)	39.0** (16.0)		
Nb. Estab. in FUI					12.8*** (4.3)	11.6*** (3.9)
Observations	22,757	22,757	22,757	22,757	22,757	22,757

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.21: Estimates on R&D staff

	R&D staff					
	(1)	(2)	(3)	(4)	(5)	(6)
Share of managers	64.5*** (14.1)	64.4*** (14.1)	64.3*** (14.2)	64.3*** (14.2)	63.9*** (14.3)	63.9*** (14.3)
Number of establishments	5.7*** (1.1)	5.8*** (1.1)	5.7*** (1.2)	5.7*** (1.2)	5.6*** (1.2)	5.6*** (1.2)
Membership of a group	31.6** (13.3)	31.5** (13.5)	31.3** (13.0)	31.5** (13.1)	30.9** (12.6)	30.9** (12.9)
Cluster membership	1.0 (2.0)			0.8 (2.1)		
Nb. Estab. in clusters		-0.1 (1.7)				-0.4 (1.7)
FUI participation			1.0 (2.8)	0.9 (3.0)		
Nb. Estab. in FUI					4.3 (3.4)	4.3 (3.4)
Observations	2,777	2,777	2,777	2,777	2,777	2,777

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.22: Estimates on researchers

	Researchers					
	(1)	(2)	(3)	(4)	(5)	(6)
Share of managers	148.3*** (41.2)	147.9*** (41.4)	148.0*** (41.1)	148.2*** (41.3)	148.7*** (41.5)	147.9*** (41.6)
Number of establishments	0.5*** (0.1)	0.5*** (0.1)	0.5*** (0.1)	0.5*** (0.1)	0.5*** (0.1)	0.5*** (0.1)
Membership of a group	13.6*** (5.0)	13.4*** (5.1)	13.4*** (4.8)	13.5*** (4.9)	13.3*** (4.5)	12.6*** (4.6)
Cluster membership	2.4 (2.8)			2.2 (3.0)		
Nb. Estab. in clusters		-0.6 (1.8)				-3.1** (1.6)
FUI participation			2.1 (6.2)	1.7 (6.4)		
Nb. Estab. in FUI					9.0** (3.8)	10.8*** (4.0)
Observations	8,954	8,954	8,954	8,954	8,954	8,954

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

4.4.1.3 Mixed effects on economic performance

For the economic performance variables related to the market, we use indicators such as turnover (*turnover*), added value (*addedvalue*) and exports (*export*). The results related to these economic variables, based on sample 3, are presented in tables 4.23, 4.24 and 4.25.

Table 4.23 presents the results on turnover. Column 1 shows that being a member of a cluster seems to have no effect on turnover, but when we simultaneously include the dummies of being a member of clusters and participating in projects (column 4), the effects become significant and positive (about €21890 thousand). Having several establishments that belong to clusters seems to have no effects on turnover. However, participating in FUI projects has significant negative effects on turnover (between €-89733 and -94360 thousand). To a lesser extent, these results are confirmed when we include the number of establishments that participate in FUI projects (between €-59462 and -64152 thousand).

In table 4.24, the results suggest that being a member of clusters or the number of establishments that belong to clusters seem to have no effect on added value. However, participating in FUI projects or the number of establishments that participate in FUI projects seem to decrease added value (between €-20558 and -32462 thousand).

Table 4.25 shows that belonging to a cluster has significant positive effects on exports (between €16302 and 18285 thousand). Participation in FUI projects has no effect on exports, even when we include the number of establishments that participate in FUI projects (statistically nonsignificant).

Notably, for the economic variables, the approach used can be misleading in terms of effects. The policy can take time to have an effect on the market-related variables, especially on turnover and added value. This finding is consistent with what researchers and animators of very innovative clusters have asserted; therefore, it make sense to analyze the heterogeneity of effects according to the type of cluster and over years.

Table 4.23: Estimates on turnover

	Turnover					
	(1)	(2)	(3)	(4)	(5)	(6)
Share of managers	75,860.2 (81,459.4)	76,457.6 (81,438.6)	76,447.8 (81,120.5)	76,564.4 (81,481.9)	71,944.4 (81,618.7)	73,429.2 (82,067.4)
Employment	132.8*** (15.7)	132.6*** (15.4)	135.0*** (15.5)	134.7*** (15.4)	134.7*** (15.2)	133.9*** (14.9)
Number of establishments	1,462.7* (862.3)	1,439.9* (862.1)	1,488.3* (872.2)	1,488.3* (872.0)	1,609.3* (872.4)	1,555.3* (850.7)
Membership of a group	-9,680.3 (27,011.9)	-9,452.2 (27,151.1)	-11,767.3 (26,918.7)	-11,559.6 (26,956.8)	-16,101.9 (26,028.5)	-15,540.1 (26,049.5)
Cluster membership	10,557.0 (8,508.2)			21,890.4** (8,675.7)		
Nb. Estab. in clusters		6,260.4 (13,406.7)				17,566.8 (11,578.7)
FUI participation			-89,732.7*** (21,331.4)	-94,360.2*** (23,018.3)		
Nb. Estab. in FUI					-59,462.2*** (18,036.2)	-64,151.8*** (18,196.5)
Observations	20,939	20,939	20,939	20,939	20,939	20,939

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.24: Estimates on added value

	Added value					
	(1)	(2)	(3)	(4)	(5)	(6)
Share of managers	30,898.9 (26,734.7)	30,821.0 (26,478.4)	31,125.3 (26,876.1)	31,141.2 (26,909.3)	29,562.6 (26,985.3)	29,813.1 (26,822.7)
Employment	62.0*** (5.6)	62.0*** (5.5)	62.7*** (5.4)	62.7*** (5.4)	62.6*** (5.4)	62.4*** (5.3)
Number of establishments	-348.5 (217.5)	-345.5 (222.5)	-339.6 (220.5)	-339.6 (220.5)	-298.0 (219.3)	-307.2 (217.7)
Membership of a group	2,770.8 (5,513.3)	2,735.5 (5,566.0)	2,095.9 (5,475.1)	2,124.2 (5,479.7)	614.6 (5,161.4)	709.4 (5,174.1)
Cluster membership	-908.9 (2,023.1)			2,990.1 (2,046.4)		
Nb. Estab. in clusters		-799.2 (4,870.7)				2,963.5 (4,333.8)
FUI participation			-31,830.2*** (7,987.9)	-32,462.3*** (8,356.9)		
Nb. Estab. in FUI					-20,558.3*** (5,904.8)	-21,349.5*** (5,921.3)
Observations	20,939	20,939	20,939	20,939	20,939	20,939

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.25: Estimates on exports

	Export					
	(1)	(2)	(3)	(4)	(5)	(6)
Share of managers	7,199.1 (29,130.8)	6,591.9 (29,572.5)	6,518.2 (29,298.0)	7,127.8 (29,015.6)	6,588.2 (29,431.3)	6,568.2 (29,608.9)
Employment	38.3*** (4.6)	38.7*** (4.5)	38.9*** (4.6)	38.7*** (4.6)	38.7*** (4.6)	38.7*** (4.5)
Number of establishments	-36.3 (65.6)	-34.6 (73.5)	-31.9 (66.0)	-31.8 (65.8)	-34.4 (62.7)	-33.9 (71.7)
Membership of a group	75.4 (4,402.0)	-90.5 (4,524.7)	-438.5 (4,444.2)	-381.7 (4,587.7)	-126.0 (4,734.1)	-131.2 (4,862.5)
Cluster membership	16,302.0*** (5,963.9)			18,284.6*** (5,814.3)		
Nb. Estab. in clusters		-222.6 (6,956.0)				-157.3 (6,564.7)
FUI participation			-12,569.3 (9,353.0)	-16,479.7* (9,550.9)		
Nb. Estab. in FUI					-407.8 (5,006.6)	-365.6 (3,836.0)
Observations	20,172	20,172	20,172	20,172	20,172	20,172

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

4.4.2 Heterogeneity of effects

In this subsection, we analyze the heterogeneity of the policy impacts on firms' innovation and economic performance according to the type of cluster but also across years.

4.4.2.1 Heterogeneity of effects according to type of cluster

To measure the heterogeneity of the policy impacts according to the type of cluster (worldwide, worldwide-track and national) we replace the dummy of treatment with three dummy variables characterizing the type of cluster to which a firm adheres. The results presented in tables 4.26, 4.27 and 4.28 show that there are a diversity of clusters, and considering their differences is important.

In these three tables, we see that being a member of a worldwide cluster has no effect on private R&D spending and patents. The results suggest the rejection of the crowding-out effect but do not indicate substantial additionality for R&D. For employment, the worldwide clusters seem to have significant positive effects on average number of full-time equivalent employees (about 62 employees) and on employment of executives, managers and intellectual professionals (about 62 employees). No effect is observed on R&D staff and researchers. The effects of belonging to worldwide clusters seem to be negative for turnover and added value but null for exports.

Being a member of a worldwide-track cluster seems to significantly increase firms' patenting (about 7 patents) and to significantly increase firms' external R&D spending (€1236 thousand) and total self-financed R&D (€3721 thousand). Except for researchers, the effects of being a member of a worldwide-track cluster are positive for all other types of employment. Compared to the worldwide clusters, the magnitude of the effects of worldwide-track clusters is weaker for average number of full-time equivalent employees (about 37 employees) and employment of executives, managers and intellectual professionals (about 33 employees). The effects of these types of cluster are strongly positive for turnover (about €26898 thousand) and exports (about €21279 thousand) but null for added value.

Being a member of a national cluster seems to have mixed effects on private R&D. Even though the effects of this type of cluster seem to be negative for firms' external R&D spending, it is interesting to note that there is no crowding-out effect for total private self-financed R&D and total private R&D budget. Being a member of a national cluster seems to increase the

number of filed patents (about 3 patents). The effect of being a member of a national cluster on employment are weak and mixed. The results suggest that the effects on average number of full-time equivalent employees (29 employees) and on researchers (3 employees) are positive. However, the effects of this type of cluster seem to be negative for employment of executives, managers and intellectual professionals (8 employees). Moreover, the effects of national clusters are strongly significant and positive for turnover, added value, and export. The magnitude of the effects of this type of cluster is higher than the effects of the other types.

In sum, the effects of the policy are heterogeneous across cluster types. We find that being a member of a worldwide-track cluster seems to stimulate R&D spending and firms' patenting. We also find significant effects on turnover and exports. For national clusters, the results show that there is no effect on private R&D. However, the effects of this type of cluster are mixed for employment, positive for firms' patenting and strongly positive for the three economic performance indicators. Finally, our finding concerning worldwide clusters is more questionable. Although being a member of a worldwide cluster seems to have significant positive effects on employment, it has no effect on private R&D, patenting and added value; moreover, it seems to decrease firms' turnover and exports. These results also highlight the heterogeneity of the policy effects according to the type of cluster and show that the clusters that receive more FUI funding do not have greater effects on firms' performance. Thus, the other activities of clusters such as the animation and management of clusters and the development of innovation platforms and innovation systems may be important and non-negligible in making the policy effective.

Table 4.26: Estimates by type of clusters (1/3)

	totbrev	derd	dird	budgetot	financ_pro
charhip	18.7* (10.7)	-9,323.0 (5,824.0)	39,345.2 (43,678.1)	31,920.4 (47,675.2)	-12,237.7 (20,841.5)
emp	0.01** (0.004)	-9.9*** (2.9)	-48.9*** (7.4)	-62.6*** (11.1)	-35.1*** (8.5)
dird	-0.000* (0.000)				
nbetb	0.3** (0.1)	-343.7*** (29.1)	-679.2*** (122.4)	-1,506.3*** (156.3)	-1,606.1*** (49.7)
appgroup	-0.9 (0.7)	1,892.5** (815.3)	-16,196.8** (7,235.5)	7,808.4*** (2,163.2)	5,059.6*** (1,700.3)
Worldwide clusters	1.9 (1.4)	-1,867.7 (3,520.6)	-18,713.3 (15,704.7)	-23,003.0 (21,799.8)	-8,501.5 (8,111.8)
Worldwide-track clusters	6.6*** (1.4)	1,235.6* (712.3)	2,229.9 (2,296.5)	4,271.1 (2,769.9)	3,721.2** (1,880.1)
National clusters	3.3* (1.7)	-1,091.6*** (382.5)	119.6 (2,522.3)	1,072.2 (3,012.0)	23.3 (1,256.4)
Observations	5,656	8,994	8,994	8,031	8,030

Note: Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.27: Estimates by type of clusters (2/3)

	eff_moy_et	emp	cs3	eff_rd	researchemp
charhip	275.3*** (61.9)	-901.1*** (97.0)		63.1*** (13.7)	148.3*** (41.2)
nbetb	25.1*** (5.8)	3.3 (3.0)	5.3*** (0.6)	5.8*** (1.1)	0.5*** (0.1)
appgroup	146.8*** (21.9)	265.7*** (46.9)	121.9*** (16.9)	31.5** (13.2)	13.5*** (5.2)
Worldwide clusters	61.8*** (23.8)	123.0*** (26.1)	61.6*** (16.5)	6.0 (9.6)	0.8 (9.7)
Worldwide-track clusters	36.7* (21.1)	56.7** (27.3)	33.0** (13.2)	8.8* (5.1)	2.8 (3.1)
National clusters	28.5*** (5.9)	-15.3* (9.3)	-7.5** (3.0)	-3.4 (4.2)	2.8* (1.7)
Observations	11,919	22,757	22,757	2,777	8,954

Note: Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.28: Estimates by type of clusters (3/3)

	Turnover	export	addedvalue
charhip	78,929.4 (82,837.8)	6,943.0 (29,306.7)	32,276.8 (27,210.1)
emp	134.9*** (15.7)	38.6*** (4.5)	62.8*** (5.5)
nbetb	1,438.8* (864.6)	-43.8 (66.5)	-355.1 (218.8)
appgroup	-5,842.0 (27,509.2)	1,022.6 (4,286.8)	3,991.9 (5,705.7)
Worldwide clusters	-87,686.6*** (30,546.8)	-1,261.0 (14,444.4)	-33,706.5*** (9,613.0)
Worldwide-track clusters	21,279.0* (12,242.6)	26,898.0*** (6,594.7)	-905.1 (5,098.9)
National clusters	39,474.7*** (11,405.5)	18,409.1*** (5,003.5)	9,987.0*** (3,230.8)
Observations	20,939	20,172	20,939

Note: Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

4.4.2.2 Heterogeneity of effects over years

To complete the analysis, we use a more flexible specification that consists (equation 4.7) of replacing the treatment dummy with a series of program indicators according to the number of years a firm has pursued cluster membership (8 years). Similarly, for FUI projects (equation 4.8), we replace the treatment dummy with a series of FUI project participation indicators counting the number of years a firm has participated in projects (6 years).

Tables 4.29, 4.30 and 4.31 show the results according to the number of years that a firm has been a member of at least a competitiveness cluster. Tables 4.32, 4.33 and 4.34 show the results according to the number of years that a firm has participated in FUI projects.

In table 4.29, columns 2 to 5 show that being a member of a cluster seems to have positive effects in the first year on total R&D budget and self-financed R&D but causes a crowding-out effect on total R&D budget from the third year of clusters participation and on self-financed R&D from the fifth year. Column 1 indicates that being a member of a cluster seems to increase patent filing from the second year of participation.

Table 4.30 shows significant positive effects on average number of employees from the first year and on employment of executives, managers and intellectual professionals from the second year. It is also interesting to note that participation in clusters has positive significant effects on R&D staff and researchers from the sixth year. This time lag of six years may, to a certain extent, explain our findings in the previous subsection, which suggest that the clusters have no effect on these two employment indicators.

Table 4.31 shows positive effects on turnover in the first year of participation but negative effects from the 7 years. For added value, even though the effects seem to be positive in the first year, they are significantly negative from the third year of participation in clusters. Finally, the results show a positive effect on export in the second year of participation and from the fifth year.

Columns 2 to 5 of table 4.32 show that participating in FUI projects seems to cause crowding-out effects for all types of R&D spending (including internal R&D, external R&D, and total R&D budget) from the first year of participation and private self-financed R&D from the third year. These crowding-out effects increase over time, whatever the R&D spending indicator. Column 1 shows that participating in FUI projects seems to increase patents from the fourth year. Interestingly, the fourth year of participation has a positive effect and can

be explained by the fact that the projects last three years on average.

The findings in table 4.33 show that participation in FUI projects has positive effects on employment of executives, managers and intellectual professionals from the first year and on average number of employees from the third year. The effects of FUI projects on firms' R&D staff and number of researchers are positive from the fourth year. Similarly, as for firms' patenting, this four-year lag may be due to the fact that the projects last three years on average.

Finally, the results in table 4.34 show that the effects of participation in FUI projects seem to be negative from the first year on the economic variables, such as turnover and added value. However, no significant effect of FUI project participation is observed for firms' exports. It is worth noting that the magnitude of almost all these effects of being a member of clusters or participating in FUI projects (positive or negative) increases slightly depending on the duration of participation in the policy, whatever the performance indicator.

In sum, we find that the effects of the policy on firms' innovation and economic performance are very heterogeneous across years. Indeed, the magnitude of the effects, whether positive or negative, increases slightly depending on the duration of participation in the policy, whatever the performance indicator. Our findings suggest that for total R&D budget, the effect of cluster membership seems to be positive in the first year but causes a crowding-out effect from the third year, while FUI project participation leads to a crowding-out effect from the first year. For patents, even if there is a positive effect, it seems that clusters need just a one-year lag to have positive effects, while FUI projects need a four-year lag. Similarly, for R&D staff and researchers, there is a positive effect of clusters with a six-year lag and a positive effect of FUI projects with a four-year lag. For average number of full-time equivalent employees, clusters are effective immediately, while FUI projects seem to need a four-year lag to be effective. Finally, for turnover and added value, the effects of clusters are very mixed, while the effects of FUI projects are immediately negative.

Table 4.29: Estimates by number of years a firm has been a member of clusters (1/3)

	totbrev	derd	dird	budgetot	financ_pro
charhip	20.2* (10.7)	-9,579.0* (5,566.9)	34,287.5 (41,394.1)	25,404.8 (45,080.2)	-13,692.3 (20,591.2)
emp	0.01** (0.004)	-9.9*** (2.9)	-49.5*** (7.2)	-63.3*** (11.0)	-35.2*** (8.8)
dird	-0.000 (0.000)				
nbetb	0.3** (0.1)	-340.6*** (29.7)	-660.0*** (124.8)	-1,493.1*** (158.5)	-1,596.2*** (48.5)
appgroup	-0.3 (0.6)	1,410.3 (955.1)	-18,949.1*** (6,774.4)	3,543.1*** (1,375.0)	3,588.9** (1,489.1)
D1	1.1 (1.5)	1,734.0*** (629.4)	9,895.0 (6,755.2)	13,808.5* (8,086.8)	3,387.3** (1,608.8)
D2	3.9** (1.8)	-1,612.5*** (538.5)	-2,507.1 (2,795.8)	-4,126.3 (3,578.6)	-1,881.4 (1,262.3)
D3	5.3** (2.6)	-1,374.0** (666.5)	-7,718.4* (4,574.6)	-9,847.6* (5,184.9)	-792.0 (1,315.7)
D4	3.3** (1.5)	-2,480.1** (991.0)	-14,628.4*** (5,092.1)	-17,929.1*** (6,348.9)	-4,530.2 (2,969.6)
D5	9.5*** (1.5)	-3,554.1*** (770.0)	-17,397.4*** (6,706.5)	-21,944.2*** (8,218.0)	-6,479.3** (2,872.5)
D6	7.5*** (1.8)	-2,527.5** (1,200.9)	-18,035.8*** (5,507.8)	-24,389.5** (9,623.4)	-5,054.8*** (1,791.4)
D7	5.0*** (1.2)	-5,146.0*** (528.8)	-36,876.9*** (7,887.7)	-45,240.9*** (9,292.2)	-21,251.7** (8,954.0)
D8	6.2*** (2.2)	-2,720.9*** (1,012.2)	-45,043.5*** (13,331.9)	-46,159.2** (19,318.5)	-42,608.5*** (4,840.2)
Observations	5,656	8,994	8,994	8,031	8,030

Note: We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.30: Estimates by number of years a firm has been a member of clusters (2/3)

	eff_moy_et	emp	cs3	eff_rd	researchemp
charhip	279.4*** (64.8)	-893.9*** (101.2)		63.2*** (14.0)	149.5*** (40.4)
nbetb	25.1*** (5.8)	3.3 (3.0)	5.3*** (0.6)	5.7*** (1.1)	0.5*** (0.1)
appgroup	149.2*** (22.0)	269.7*** (45.7)	124.3*** (16.3)	33.1** (13.5)	14.6*** (4.5)
D1	28.6*** (10.1)	14.7 (11.9)	8.7 (6.7)	2.3 (3.7)	5.4 (5.4)
D2	44.7*** (16.0)	41.3** (16.9)	21.0** (10.3)	-0.1 (3.0)	-3.1 (3.1)
D3	43.7*** (7.5)	29.5* (16.1)	14.8*** (5.0)	-2.6 (4.2)	-2.9 (3.1)
D4	50.1*** (17.9)	38.1* (23.1)	17.8** (7.4)	0.7 (1.5)	-0.3 (4.0)
D5	44.4*** (13.1)	28.9** (12.4)	12.0** (5.0)	6.6 (4.9)	11.2 (7.4)
D6	37.2*** (10.6)	26.0* (14.0)	20.2** (9.9)	12.6* (7.0)	12.5*** (4.1)
D7	65.8*** (21.9)	26.9 (32.7)	31.2*** (5.6)	19.1*** (2.4)	12.6*** (4.1)
D8	73.9*** (22.1)	179.2*** (23.4)	110.0*** (8.3)	19.8*** (3.9)	16.5* (8.6)
Observations	11,919	22,757	22,757	2,777	8,954

Note: We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.31: Estimates by number of years a firm has been a member of clusters (3/3)

	Turnover	export	addedvalue
charhip	68,503.8 (81,123.4)	6,012.5 (29,109.9)	28,235.1 (26,994.8)
emp	133.2*** (15.8)	38.5*** (4.6)	62.2*** (5.6)
nbtb	1,493.0* (864.9)	-37.8 (71.8)	-341.0 (218.6)
appgroup	-13,319.0 (28,160.7)	-242.8 (4,152.6)	1,482.0 (5,773.8)
D1	27,301.7** (13,623.5)	14,783.6 (13,355.0)	6,844.3** (3,258.0)
D2	24,951.8 (17,024.0)	27,097.9** (12,123.8)	3,043.7 (5,021.1)
D3	920.9 (10,075.5)	8,138.2 (6,018.8)	-5,484.2** (2,745.3)
D4	-17,549.9 (11,130.9)	8,322.8 (7,151.9)	-10,637.9*** (3,209.8)
D5	-4,859.3 (8,900.8)	16,077.1** (7,076.2)	-11,413.0*** (2,904.6)
D6	-21,626.8 (18,991.3)	23,319.4* (13,517.9)	-11,814.3* (6,078.1)
D7	-65,309.6*** (10,604.5)	12,770.0* (7,600.8)	-22,232.7*** (3,837.2)
D8	-102,696.5*** (19,460.9)	-21,094.3* (11,709.6)	-40,659.6*** (6,910.3)
Observations	20,939	20,172	20,939

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.32: Estimates by number of years a firm has participated in FUI projects (1/3)

	totbrev	derd	dird	budgetot	financ.pro
charhip	19.2* (11.2)	-8,826.6 (5,706.1)	38,642.3 (42,794.3)	31,717.3 (46,970.0)	-13,507.9 (20,516.5)
emp	0.01** (0.004)	-9.6*** (2.8)	-48.2*** (7.2)	-61.0*** (10.8)	-35.1*** (8.1)
dird	-0.000 (0.000)				
nbtb	0.2** (0.1)	-340.8*** (29.2)	-662.1*** (124.7)	-1,494.0*** (160.0)	-1,599.0*** (56.1)
appgroup	-1.7 (1.1)	2,357.5** (925.8)	-12,056.6* (6,411.5)	12,199.2*** (4,049.8)	6,721.1*** (2,471.5)
F1	-0.3 (1.1)	-4,290.5*** (1,518.4)	-16,927.1*** (5,771.9)	-25,116.1*** (8,255.3)	-5,916.8 (4,622.8)
F2	1.5 (2.0)	-4,759.2*** (1,710.1)	-17,577.1*** (6,613.5)	-26,225.9*** (8,879.3)	-5,844.0 (3,979.2)
F3	-0.1 (0.9)	-7,975.6*** (2,288.9)	-26,107.9*** (8,513.1)	-38,977.5*** (11,801.4)	-14,989.7** (5,988.0)
F4	8.0** (4.1)	-6,213.3*** (2,355.9)	-23,060.1*** (5,753.3)	-39,266.2*** (10,433.1)	-23,565.4*** (6,193.9)
F5	6.8*** (2.1)	-6,942.8*** (2,611.2)	-37,373.7*** (9,297.9)	-53,553.4*** (11,488.0)	-32,633.0** (15,718.9)
F6	8.1*** (0.8)	-9,177.5*** (1,386.9)	-54,310.7*** (9,114.8)	-72,217.3*** (12,537.8)	-9,181.2** (4,386.3)
Observations	5,656	8,994	8,994	8,031	8,030

Note: Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.33: Estimates by number of years a firm has participated in FUI projects (2/3)

	eff_moy_et	emp	cs3	eff_rd	researchemp
charhip	277.8*** (62.1)	-897.1*** (99.3)		67.0*** (13.1)	151.6*** (40.6)
nbetb	25.1*** (5.8)	3.3 (3.0)	5.3*** (0.6)	5.8*** (1.1)	0.5*** (0.1)
appgroup	144.5*** (20.4)	265.8*** (47.1)	122.1*** (16.8)	32.3** (13.1)	10.3* (5.4)
F1	53.0 (34.1)	87.8** (40.1)	54.5* (33.0)	-4.5 (4.4)	-6.3 (6.9)
F2	39.4 (24.9)	66.8*** (20.7)	37.2*** (11.0)	-3.4 (4.1)	-7.6 (6.2)
F3	31.9** (16.0)	56.8*** (16.0)	34.6*** (8.6)	1.2 (3.8)	-0.6 (4.4)
F4	41.3** (20.7)	90.8** (42.8)	50.2** (19.6)	16.1* (9.3)	26.1** (13.2)
F5	44.3** (20.3)	25.5 (34.3)	17.7 (19.4)	25.1* (13.4)	17.5* (9.1)
F6	54.2** (23.3)	140.0*** (28.5)	50.8*** (14.1)	37.2*** (8.2)	33.7*** (8.8)
Observations	11,919	22,757	22,757	2,777	8,954

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.34: Estimates by number of years a firm has participated in FUI projects (3/3)

	Turnover	export	addedvalue
charhip	72,981.9 (80,486.4)	7,648.2 (29,495.6)	29,456.6 (26,929.2)
emp	134.8*** (15.8)	38.8*** (4.6)	62.7*** (5.5)
nbetb	1,492.7* (862.0)	-43.4 (70.4)	-339.6 (217.6)
appgroup	-10,219.5 (25,742.0)	-390.2 (4,580.1)	2,726.3 (5,036.0)
F1	-41,528.9** (17,799.1)	-1,962.1 (6,980.4)	-16,881.9** (7,002.6)
F2	-100,597.9** (43,694.1)	-466.7 (5,730.1)	-34,755.2** (16,540.0)
F3	-97,596.0 (79,721.1)	22,205.2 (25,535.3)	-57,269.1*** (15,697.6)
F4	-38,555.9 (55,431.9)	10,757.1 (15,343.5)	-18,063.1 (20,443.3)
F5	-118,650.4** (59,493.7)	14,480.9 (12,112.1)	-43,428.9** (18,389.6)
F6	-240,114.4*** (53,976.5)	-21,389.7 (13,614.9)	-91,157.4*** (19,163.4)
Observations	20,939	20,172	20,939

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

4.5 Conclusion

In this chapter, we assess the effects of the competitiveness clusters policy on the innovation and economic performance of ETIs and large firms. We adopt a two-way fixed effects model to deal with the endogeneity problem (selection bias and unobserved characteristics of firms) and to consistently estimate the effects of the policy. This study contributes to the literature on clusters policy and R&D subsidy evaluations by estimating the effects of being a member of a cluster and the effects of participating in FUI projects on ETIs and large firms.

Our findings show that the policy has positive effects on the innovation of firms that are members of clusters. For firms' R&D spending, the results show that being a member of a cluster has no effect on total R&D budgets and private self-financed R&D, but participating in FUI projects seems to lead to strong crowding-out effects. For employment, the effects are globally strong, and when the effects are statistically significant, they are slightly stronger for participation in FUI projects than for membership in clusters. Contrary to what one might expect, the effects on firms' R&D staff and researchers are surprisingly very low or even nonexistent. For the market performance variables, such as turnover, added value, and export, the results are more mixed. Globally, membership in clusters has positive effects on turnover, added value, and export. The effects of participation in FUI projects are significantly negative for turnover and added value but null for export.

When we go further and analyze the effects according to the type of cluster, we find that the results are very heterogeneous. The results suggest that being a member of a worldwide cluster has no effect on patenting, leads to crowding-out effects and greatly increases employment but decreases turnover and added value. The crowding-out effect may be explained by the fact that this type of cluster, representing only seven clusters, is characterized by the concentration of 42% of all FUI funding in only 33% of R&D projects. The average ratio of funding by project is very high. Worldwide clusters are also characterized by a concentration of large firms, which generally belong to several clusters and participate in several FUI projects. For worldwide-track clusters, the effects are positive for patents, private R&D spending, employment, turnover, and export. As for worldwide clusters, this type of cluster is also characterized by the presence of relatively large firms that receive 25% of all the FUI funding and implement 24% of the R&D projects. This type of cluster is smaller than the worldwide type and has a more moderate ratio of funding by project. Being a member of

a national cluster has positive effects on patents, turnover, added value, and export. Even though it has no effect on private R&D spending, its effects on employment are weak and mixed. This type of cluster is characterized by the presence of a relatively small number of large firms and a concentration of ETIs. These clusters benefit from only 33% of the funding but implement 44% of all FUI projects. All these results highlight the importance of cluster activities other than FUI projects, such as the animation and strategic management of clusters, and also the development of structuring projects such as platforms of innovation and innovation ecosystems. These results also highlight the heterogeneity of the policy effects according to the type of cluster.

Finally, we find that the effects of the policy on firms' performance are heterogeneous, and the magnitude of all these effects (positive or negative) increases slightly with the duration of participation in the program (number of years a firm participates in the program), whatever the performance indicator. The findings suggest that for total R&D budget, the effects of being a member of clusters seem to be positive in the short run but would cause a crowding-out effect in the long run, while FUI projects always lead to a crowding-out effect. For R&D staff and researchers, there are positive effects of both clusters and FUI projects in the long run. For average number of employees, clusters have positive effects in the short run, while FUI projects are effective in the long run.

In contrast to previous studies evaluating the effects of the competitiveness clusters policy by focusing on SMEs and ETIs, this study focuses on ETIs and large firms. For employment and R&D spending, the results are in line with the previous findings but with stronger impacts. However, this study brings new evidence on the impacts of the competitiveness clusters policy on ETIs' and large firms' innovation outputs (patents) and economic performance related to the market, while previous studies do not consider these issues. It, therefore, contributes to the increasing literature of competitiveness clusters policy evaluations by showing positive effects on patenting and market-related performance. Further, the findings show that the impacts of the policy are very heterogeneous according to the type of cluster and also according to the duration of participation in the program.

Although the robustness checks show that these results are robust, they still should be interpreted with much caution. We believe that not only should the limitations of the data, due to the nonrandom selection, missing data and structure of the R&D survey, be emphasized but several policy instruments supporting firms, such as the R&D tax credit (CIR), should be

controlled to improve these results. This would allow us to better identify the real effects of the policy in the context of a policy mix. It also may be interesting to tackle this evaluation issue by considering the process of cooperation and networking between firms and also knowledge spillovers. The policy can have positive impacts on cooperation and networking between firms and therefore can increase knowledge spillovers. In particular, it is expected that large firms may develop networking and generate knowledge spillovers that strongly impact SMEs' absorptive capacities and performance.

4.6 Appendices Chapter 4

4.6.1 Descriptive statistics

Table 4.35: Descriptive statistics of the samples

Sample 1						
	Nb. Obs	Min	Max	Median	Mean	Std.dev
totbrev	4447	0	1349	0	12.2	60.6
derd	4425	0	1336970	117.7	7174	46168.4
dird	4425	0	2385471	5116	29638.1	118584.6
budgetot	4425	0	3722441	5873	36820.3	158485.9
financ_pro	4424	-73353	1866095	4469.5	21175.7	79240.6
eff_moy_et	3116	79	23171	469.6	785.7	1142
emp	4447	251	35459	507	925.8	1568.5
cs3	4447	0	10597	123	269.7	530.6
eff_rd	2048	0	3326	28	91.4	199.9
researchemp	4424	0	2885	15.4	60.6	163
turnover	4318	0	24265367	128456	405630.5	1115178.8
addedvalue	4318	-767733	10048030	41180.1	120680.1	403591.6
export	4072	0	9513869	41419.5	164392.3	427725.7
Sample 2						
	Nb. Obs	Min	Max	Median	Mean	Std.dev
derd	7655	0	2153451	162	17180.6	106200.7
dird	7655	0	5234859	7931	69950.4	305657.8
budgetot	6760	0	5381633	8259	66142.8	321231.2
financ_pro	6759	-73353	5246907	6609	41931.9	222135.7
eff_moy_et	3228	29	23171	469	782.7	1193.1
emp	7655	251	183889	623	1887.4	9982
cs3	7655	0	33146	117	385.9	1667.3
eff_rd	2132	0	3326	28	91.7	200
researchemp	7636	0	3596	13	66	198.7
turnover	7503	0	28744711	137589	499055.6	1736921.2
addedvalue	7503	-767733	18295033	44908	183166.8	947742
export	7249	0	15788346	40775	168306.7	556542.3
Sample 3						
	Nb. Obs	Min	Max	Median	Mean	Std.dev
eff_moy_et	11919	2	57443	435	1061.2	3044.1
emp	22756	251	183889	547	1588.3	6942.6
cs3	22756	0	33146	111	366.7	1324.5
turnover	20938	-35442	47997620	112199	434931.4	2011949.9
addedvalue	20938	-1447151	18295033	35955	137475.8	725929.2
export	20171	-238	29108221	14722	121192.2	775226.6

Note: Patents are in unit, R&D variables are in thousand, employment-related variables are in unit, and market-related variables are in thousand.

Sources: R&D survey, DGE, FUI, MENESR, INSEE, Ficus-Fare, DADS, Lifi, and the author's calculations.

4.6.3 Estimation tables without control variables

Table 4.36: Estimates on total patents

	Total Patents					
	(1)	(2)	(3)	(4)	(5)	(6)
Cluster membership	4.0*** (1.1)			3.7*** (1.1)		
Nb. Estab. in clusters		0.7 (0.8)				0.2 (0.8)
FUI participation			2.8 (1.8)	2.1 (1.7)		
Nb. Estab. in FUI					2.7** (1.1)	2.7** (1.1)
Observations	5,722	5,722	5,722	5,722	5,722	5,722

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.37: Estimates on total budget in R&D

	Total Budget in R&D					
	(1)	(2)	(3)	(4)	(5)	(6)
Cluster membership	-5,561.6 (5,328.7)			-390.9 (4,372.6)		
Nb. Estab. in clusters		-1,372.5 (4,094.0)				3,321.9 (3,592.4)
FUI participation			-36,460.1*** (9,244.0)	-36,380.2*** (9,404.3)		
Nb. Estab. in FUI					-23,700.9*** (3,187.2)	-24,863.7*** (3,531.4)
Observations	8,031	8,031	8,031	8,031	8,031	8,031

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.38: Estimates on External R&D Expenditure

	External R&D Expenditure					
	(1)	(2)	(3)	(4)	(5)	(6)
Cluster membership	-1,348.5* (703.2)			-333.7 (467.0)		
Nb. Estab. in clusters		-1,073.2 (1,109.4)				200.4 (949.7)
FUI participation			-6,759.6*** (1,404.5)	-6,687.8*** (1,430.9)		
Nb. Estab. in FUI					-5,326.7*** (1,320.3)	-5,447.6*** (1,099.3)
Observations	8,994	8,994	8,994	8,994	8,994	8,994

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.39: Estimates on Internal R&D Expenditure

	Internal R&D Expenditure					
	(1)	(2)	(3)	(4)	(5)	(6)
Cluster membership	-5,455.4 (4,597.0)			-1,393.1 (3,794.8)		
Nb. Estab. in clusters		-2,987.3 (2,676.5)				566.2 (2,225.6)
FUI participation			-27,071.0*** (6,880.1)	-26,771.4*** (7,024.3)		
Nb. Estab. in FUI					-14,857.4*** (3,666.2)	-15,199.0*** (2,999.7)
Observations	8,994	8,994	8,994	8,994	8,994	8,994

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.40: Estimates on private self-financed R&D

	Private self-financed R&D					
	(1)	(2)	(3)	(4)	(5)	(6)
Cluster membership	-2,309.2 (1,707.6)			-237.0 (1,109.2)		
Nb. Estab. in clusters		-1,864.6 (3,208.7)				2,037.4 (2,700.5)
FUI participation			-14,598.3*** (3,335.7)	-14,549.8*** (3,295.1)		
Nb. Estab. in FUI					-19,941.5*** (2,637.8)	-20,655.1*** (2,700.3)
Observations	8,030	8,030	8,030	8,030	8,030	8,030

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.41: Estimates on Average number of employees (full-time equivalent)

	Average number of employees (full-time equivalent)					
	(1)	(2)	(3)	(4)	(5)	(6)
Cluster membership	39.6*** (11.0)			36.3*** (10.0)		
Nb. Estab. in clusters		22.9** (9.5)				21.7** (9.4)
FUI participation			46.5** (22.9)	42.1* (21.8)		
Nb. Estab. in FUI					16.3* (9.0)	14.5* (8.3)
Observations	11,919	11,919	11,919	11,919	11,919	11,919
R ²	0.003	0.002	0.002	0.004	0.001	0.003

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.42: Estimates on CS3 employment

	CS3 employment					
	(1)	(2)	(3)	(4)	(5)	(6)
Cluster membership	15.8*** (5.9)			10.9** (5.0)		
Nb. Estab. in clusters		18.5*** (6.3)				15.5*** (5.6)
FUI participation			46.7*** (16.3)	44.6*** (15.9)		
Nb. Estab. in FUI					21.2*** (5.5)	18.0*** (4.6)
Observations	22,757	22,757	22,757	22,757	22,757	22,757

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.43: Estimates on R&D staff

	R&D staff					
	(1)	(2)	(3)	(4)	(5)	(6)
Cluster membership	0.9 (1.9)			0.4 (2.1)		
Nb. Estab. in clusters		0.1 (1.8)				-0.3 (1.8)
FUI participation			3.3 (3.0)	3.2 (3.2)		
Nb. Estab. in FUI					5.8 (3.7)	5.9 (3.7)
Observations	2,777	2,777	2,777	2,777	2,777	2,777

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.44: Estimates on researchers

	Researchers					
	(1)	(2)	(3)	(4)	(5)	(6)
Cluster membership	2.3 (2.8)			1.9 (3.0)		
Nb. Estab. in clusters		1.0 (2.3)				-2.1 (2.0)
FUI participation			3.6 (6.4)	3.2 (6.7)		
Nb. Estab. in FUI					11.8*** (4.0)	13.1*** (4.3)
Observations	8,954	8,954	8,954	8,954	8,954	8,954

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.45: Estimates on turnover

	Turnover					
	(1)	(2)	(3)	(4)	(5)	(6)
Cluster membership	15,303.3** (7,614.0)			25,423.4*** (7,539.9)		
Nb. Estab. in clusters		13,603.4 (13,245.4)				24,285.9** (11,619.0)
FUI participation			-78,312.9*** (20,469.9)	-83,714.8*** (22,035.9)		
Nb. Estab. in FUI					-52,333.7*** (17,510.0)	-59,016.2*** (17,879.0)
Observations	20,939	20,939	20,939	20,939	20,939	20,939

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.46: Estimates on added value

	Added value					
	(1)	(2)	(3)	(4)	(5)	(6)
Cluster membership	1,050.5 (2,078.5)			4,531.9*** (1,740.0)		
Nb. Estab. in clusters		418.3 (5,124.9)				4,159.9 (4,597.2)
FUI participation			-27,836.0*** (7,723.5)	-28,798.9*** (7,993.4)		
Nb. Estab. in FUI					-19,526.5*** (5,594.3)	-20,671.1*** (5,648.6)
Observations	20,939	20,939	20,939	20,939	20,939	20,939

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.47: Estimates on exports

	Exports					
	(1)	(2)	(3)	(4)	(5)	(6)
Cluster membership	17,572.6*** (5,850.2)			19,282.0*** (5,710.8)		
Nb. Estab. in clusters		952.5 (6,941.7)				902.4 (6,580.6)
FUI participation			-9,971.3 (8,717.0)	-14,116.6 (8,927.3)		
Nb. Estab. in FUI					522.9 (4,760.4)	273.2 (3,582.5)
Observations	20,172	20,172	20,172	20,172	20,172	20,172

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.48: Estimates by type of clusters (1/3)

	totbrev	derd	dird	budgetot	financ_pro
Worldwide clusters	3.5* (2.2)	-3,065.8 (4,129.9)	-26,561.5 (17,514.5)	-34,300.8 (23,413.0)	-14,478.6 (9,192.1)
Worldwide-track clusters	6.7*** (1.5)	-909.1 (1,408.1)	-2,003.0 (4,309.1)	3,723.7 (3,021.7)	2,626.4 (1,823.2)
National clusters	3.3* (1.7)	-956.8*** (362.0)	6.5 (2,681.8)	444.8 (3,113.2)	-95.3 (1,370.6)
Observations	5,722	8,994	8,994	8,031	8,030

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.49: Estimates by type of clusters (2/3)

	eff_moy_et	emp	cs3	eff_rd	researchemp
Worldwide clusters	65.9** (26.9)	121.1*** (24.8)	57.7*** (15.8)	6.1 (9.8)	-0.5 (9.5)
Worldwide-track clusters	51.8* (29.5)	56.2** (27.9)	45.4** (18.5)	10.3** (4.8)	6.9* (3.8)
National clusters	21.4*** (7.0)	-14.0 (9.4)	-9.0*** (3.3)	-4.0 (4.5)	1.7 (1.5)
Observations	11,919	22,757	22,757	2,777	8,954

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.50: Estimates by type of clusters (3/3)

	Turnover	export	addedvalue
Worldwide clusters	-71,445.1** (29,079.3)	4,009.4 (14,188.3)	-24,973.1*** (9,094.8)
Worldwide-track clusters	34,509.6*** (9,752.6)	29,235.3*** (6,623.8)	2,420.9 (5,586.6)
National clusters	37,536.3*** (10,442.1)	18,017.7*** (4,772.7)	9,248.9*** (2,751.6)
Observations	20,939	20,172	20,939

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.51: Estimates by number of years a firm has been a member of clusters (1/3)

	totbrev	derd	dird	budgetot	financ_pro
D1	1.3 (1.5)	1,590.3*** (525.4)	9,078.9 (7,104.1)	12,274.2 (8,455.5)	2,419.7 (1,582.5)
D2	4.4** (1.9)	-2,137.0*** (671.4)	-4,699.3 (2,879.9)	-6,323.6* (3,737.7)	-3,061.1** (1,444.4)
D3	5.9** (2.4)	-2,045.2** (911.4)	-10,857.2** (4,805.6)	-13,392.9** (5,894.2)	-2,608.1* (1,539.2)
D4	3.6** (1.5)	-3,220.4** (1,293.2)	-17,956.6*** (5,755.4)	-21,692.6*** (7,223.6)	-6,436.4** (3,150.0)
D5	9.7*** (1.6)	-4,459.6*** (1,098.8)	-21,501.4*** (7,340.1)	-26,876.6*** (9,252.2)	-9,145.9*** (3,407.1)
D6	7.8*** (1.7)	-3,679.1*** (1,110.6)	-22,724.5*** (6,633.4)	-25,325.3** (9,931.6)	-3,142.9* (1,708.0)
D7	5.5*** (0.9)	-8,910.6*** (2,417.6)	-45,694.6*** (11,815.1)	-55,620.4*** (13,980.6)	-30,352.3** (14,404.3)
D8	9.1*** (1.7)	-4,004.7*** (1,508.8)	-52,494.5*** (15,181.1)	-58,936.9*** (21,262.3)	-50,155.6*** (5,865.5)
Observations	5,722	8,994	8,994	8,031	8,030

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.52: Estimates by number of years a firm has been a member of clusters (2/3)

	eff_moy_et	emp	cs3	eff_rd	researchemp
D1	33.6*** (11.3)	13.0 (11.3)	8.4 (6.8)	2.6 (3.7)	5.6 (5.5)
D2	49.5** (19.7)	40.1** (17.1)	21.8** (10.6)	0.03 (2.9)	-2.9 (3.3)
D3	41.6*** (9.4)	27.9* (15.9)	15.0*** (5.6)	-3.4 (4.2)	-3.5 (3.3)
D4	44.8** (22.8)	40.7* (22.3)	18.6*** (7.0)	0.1 (1.5)	-1.0 (4.3)
D5	31.9** (14.4)	35.2*** (9.8)	12.8** (5.3)	6.4 (5.5)	10.1 (8.1)
D6	23.1* (13.0)	31.6** (12.3)	20.7*** (7.2)	12.1* (7.3)	11.9*** (4.4)
D7	43.6* (23.0)	47.3* (27.3)	56.3*** (17.1)	20.1*** (2.8)	16.7*** (4.0)
D8	50.4** (20.9)	186.9*** (19.8)	101.6*** (7.2)	19.5*** (3.7)	14.2 (9.3)
Observations	11,919	22,757	22,757	2,777	8,954

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.53: Estimates by number of years a firm has been a member of clusters (3/3)

	Turnover	export	addedvalue
D1	29,519.3** (13,353.9)	15,491.3 (13,307.4)	8,017.2** (3,392.3)
D2	31,342.0* (17,031.6)	28,901.1** (12,204.8)	5,822.7 (5,499.2)
D3	5,941.2 (9,125.6)	9,388.4 (5,901.5)	-3,320.0 (2,667.0)
D4	-12,191.9 (10,669.1)	9,737.1 (7,223.0)	-8,484.9*** (2,973.8)
D5	789.8 (8,858.2)	17,412.0** (7,094.5)	-9,166.2*** (2,981.1)
D6	-15,536.3 (18,544.5)	24,855.0* (13,259.5)	-9,580.5* (5,755.4)
D7	-50,018.5*** (9,550.4)	15,416.1* (8,023.9)	-20,678.0*** (5,097.3)
D8	-79,152.0*** (17,684.1)	-10,789.8 (11,836.2)	-28,703.4*** (6,159.3)
Observations	20,939	20,172	20,939

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.54: Estimates by number of years a firm has participated in FUI projects (1/3)

	totbrev	derd	dird	budgetot	financ_pro
F1	0.5 (1.1)	-5,280.4*** (1,358.3)	-20,627.0*** (5,623.2)	-28,945.0*** (8,649.1)	-8,266.2* (4,581.9)
F2	2.4 (1.9)	-5,780.2*** (1,735.6)	-20,796.0*** (6,873.7)	-29,673.8*** (9,645.9)	-8,159.2* (4,335.9)
F3	0.8 (1.1)	-9,362.5*** (2,254.3)	-31,606.9*** (9,467.6)	-45,003.9*** (13,763.5)	-18,556.5*** (6,395.1)
F4	9.1** (4.5)	-8,169.3*** (2,384.1)	-30,360.6*** (7,566.3)	-41,470.3*** (14,080.5)	-22,190.4*** (4,793.5)
F5	7.7*** (2.5)	-13,081.7*** (4,743.0)	-51,574.9*** (13,904.1)	-70,528.7*** (18,254.9)	-48,795.6*** (15,268.6)
F6	10.8*** (1.6)	-11,919.2*** (2,114.0)	-67,762.0*** (11,328.8)	-92,029.1*** (15,470.2)	-21,305.2*** (4,721.2)
Observations	5,722	8,994	8,994	8,031	8,030

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.55: Estimates by number of years a firm has participated in FUI projects (2/3)

	eff_moy_et	emp	cs3	eff_rd	researchemp
F1	62.2 (42.1)	87.2** (39.8)	58.4* (34.2)	-1.8 (4.4)	-5.7 (7.1)
F2	44.1 (28.6)	64.3*** (22.8)	40.6*** (11.5)	-0.5 (4.1)	-6.2 (6.3)
F3	33.7** (17.0)	59.6*** (18.2)	39.9*** (8.0)	3.1 (4.4)	-0.1 (4.5)
F4	53.7*** (20.4)	104.5** (42.8)	60.8*** (17.2)	17.4* (9.5)	26.8** (12.6)
F5	25.3 (17.4)	74.0*** (18.9)	58.6* (30.7)	24.9* (14.0)	25.0** (10.3)
F6	50.1** (22.3)	171.0*** (25.7)	59.9*** (12.6)	39.6*** (8.1)	33.4*** (9.1)
Observations	11,919	22,757	22,757	2,777	8,954

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 4.56: Estimates by number of years a firm has participated in FUI projects (3/3)

	Turnover	export	addedvalue
F1	-29,072.6 (19,744.9)	1,208.8 (7,453.2)	-11,863.4 (7,639.8)
F2	-92,943.0** (43,359.4)	1,276.1 (5,538.0)	-32,026.7** (16,199.5)
F3	-91,147.9 (77,752.7)	23,880.4 (25,035.3)	-54,991.0*** (14,753.1)
F4	-24,567.5 (56,041.6)	14,000.7 (16,177.1)	-13,216.9 (20,482.9)
F5	-94,488.9* (53,653.2)	18,769.3 (11,640.6)	-43,287.4** (19,155.8)
F6	-214,422.1*** (52,675.3)	-13,193.5 (13,845.7)	-79,204.0*** (18,742.5)
Observations	20,939	20,172	20,939

Note: Results are produced by the R *plm* and *lmtest* packages and the *vcovHC* method from the *sandwich* package for weighting schemes (type argument) (Zeileis, 2004). We use the cluster-robust covariance matrix estimator (Arellano, 1987) to control for both heteroskedasticity and serial correlation and consistently estimate the fixed effects estimator. Robust standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Conclusions and discussion

This thesis aims at bringing a further understanding of the effectiveness of public innovation policies by mobilizing new development of econometric techniques and controlling for several intervention instruments. We use the new development of a variety of empirical models and particularly natural experiments studies approach, in order to answer the different research questions. In order to evaluate the impacts of innovation policies, we focus on both macro-level (European regions) to answer the first set of main research questions and thereafter micro-level (French SMEs, ETIs, and large firms) to answer the second set of research questions. This thesis contributes to this literature in terms of methodological aspects but also in terms of new findings. The major contributions to the on-going R&D and innovation policy evaluations consist of empirical analyses conducted in three studies presented in chapters 2, 3 and 4.

This concluding section summarizes the main findings and the contributions of the thesis, discusses the implications in terms of public policies, provides specific recommendations for policymakers. In addition, it identifies the main limitations and suggests some directions for future research.

Summary of the main findings

Literature review of public innovation policies

Surveying the literature of innovation and public R&D policies has enabled us to address more comprehensively the theoretical and empirical issues related to public innovation policy and their evaluation. This allows understanding the complexity of innovation and its different aspects especially with regard to firms' development but also the difficulties related to its measurement. An overview of the main econometric models used in the literature and

the different impact evaluation reveals that, although some crowding-out effects have been found in former studies, recent empirical evidence suggests that R&D subsidies may mostly stimulate private R&D investment and may positively impact innovation outcomes but also the productivity and competitiveness of firms. Moreover, the literature reveals that studies focusing on R&D tax incentives, generally conclude for positive effects but for cluster policies, findings are mixed and non-conclusive. Furthermore, reviewing the empirical literature reveals a great heterogeneity and a lack of consensus in results depending on the geographical scope, type of data, estimation method and model specification. Indeed, in observational studies approach data are subject to bias and make it challenging to evaluate innovation policies. Finally, the literature highlights the concentration of evaluation on testing R&D input additionality and the lack of studies evaluating the effects on firms' output performance.

Evidence on the impacts of EU 5th and 6th FPs policy on regional innovation

The **chapter 2** analyzes the impacts of the 5th and 6th FPs on the innovation of European regions. This study contributes to the literature in terms of methodology and new findings but also to a further understanding of the role of the FPs policy. We use macro-data (regional panel) covering the 1995-2012 period and 218 regions of the entire EU-27 and adopt a Knowledge Production Function (KPF) including the FPs amounts spent in each region. We use a translog production function which is a flexible approach allowing inclusion of interaction terms between the input factors to better account for the complexity of the relationship between innovation and its inputs. We analyze the policy effects by using a random trend model specification that controls for many innovation inputs and for all the unobserved heterogeneity of regions (fixed and time-varying) that can affect innovation. In terms of methodology, differently from other studies which generally use firm-level data to evaluate the effects of the FPs policy, this is the first study in the literature estimating a macroeconomic relationship between the FP5 and FP6 amounts aggregated at the regional level. The use of the translog function specification enabled us to take into account the complementarity and substitution effects between factors but also the threshold effects and the initial endowments of innovative factors. We estimate several specific models.

In terms of findings, the results bring new evidence on the impacts of the FP5 and FP6 programmes on innovation output at the macro-level in the EU-27. The results show that for the entire EU countries the FP5 expenditure has no impact on regional innovation but the

FP6 spending impacts positively the European regional innovation. Moreover, a comparison of the impacts between leading countries and lagging countries shows that the effects of the policy are strong on leading countries but too weak or nonexistent for lagging countries. Indeed, when focusing on the more innovative countries (EU top 11), the FP5 spending is slightly significant and the sum of the two amounts of the policy (SumFP5-6) has a stronger impact on regional innovation. However, when focusing on the less innovative countries (EU Low 16), findings show that the FP5 has no effect but the FP6 and the SumFP5-6 have a significant effect on regional innovation. Moreover, results reveal complementarity effects between human capital and FP6 and human capital and the sum of FP5 and FP6 amounts (SumFP5-6) spending but, on the contrary, substitution between regional R&D spending and FP6 spending. No complementarity or substitution effect is detected between innovation factors and the FP5 spending.

Finally, these results confirm the role of thresholds effects and that it is necessary to observe a certain level of innovative factors to make the policy efficient in the long run. These results highlight the importance of introducing a more flexible function to take into account the complementarity and substitution effects between factors but also the threshold effects and the initial endowments of innovative factors, to assess the impact of policies, especially collaborative policies such as the FPs.

The impacts of French clusters policy on SMEs performance

The **chapter 3** examines the effectiveness of the French competitiveness clusters policy on participating small and medium-sized enterprises (SMEs)' innovation input and output performance. This study contributes to the literature in terms of methodological aspects but also in terms of new findings. We combine data from several sources and build a rich firm-level (micro-level) dataset covering the 2005-2012 period and use an original strategy to construct different measures of treatment distinguishing cluster adhesion and participation in FUI projects. We consider two levels of treatment and therefore, we distinguish three groups of treatment: receiving both treatments, receiving only the first treatment and receiving only the second treatment. We adopt a quasi-experiments design and, first analyze the selection process before combining difference-in-difference method with matching techniques also known as conditional difference-in-difference (CDiD) estimator to construct good counterfactuals and then we evaluate the effects of the French clusters policy on the SME's innovation

and performance. This study contributes to the literature in terms of methodological aspects because in France the studies analyzing the clusters policy impacts on firms control for one policy instrument at the same time. This methodology makes it possible to control for two policy instruments and compare them. We determine an adequate sampling and conduct several independent matchings for each type of treatment at each time period.

In terms of findings, results suggest the rejection of any crowding-out effect and conclude for substantial additionality effects on innovation inputs. These results are similar to those of previous studies evaluating the effects of the competitiveness clusters policy on SMEs' performance by concluding for positive effects in terms of private R&D spending and employment related to R&D. Moreover, these findings are slightly in line with the results of previous results regarding the absence of impacts on economic performance. However, this study contributes to the literature in terms of new findings for two points. First, the results show that the policy has positive effects on total employment. Second, a comparison of the two policy instruments reveals that the effects are stronger for SMEs that receive both treatments, slightly weaker for those that are only members of clusters and very weak or nonexistent for those that participate only in FUI projects.

Moreover, when comparing the different treatment options in terms of input additionality, the effects of joint participation in clusters and FUI projects are stronger than those of being only a member of a cluster and, participating only in FUI projects has rarely positive effects in terms of input additionality. With regard to the output performance (patents, total employment, turnover, added value, and export), the effects on total employment are stronger for SMEs that receive both treatments than those that only belong to clusters. However, the effects are very weak or nonexistent for SMEs that participate only in FUI projects. The policy effects on other types of output performance (patents, turnover, added value, and export) are generally weak or nonexistent. In summary, the comparison of the effects through the three treatment options shows heterogeneous effects and suggests that the effects of the policy are stronger for SMEs that receive both treatments. The effects of being only a member of a cluster are stronger than those of only participating in FUI projects.

The impacts of French clusters policy on midsized and large firms

The **chapter 4** analyzes the impacts of the French competitiveness clusters policy on the innovation and economic performance of midsized and large firms. It contributes greatly to the literature in terms of methodological aspects but also in terms of new findings. Using micro-level data covering the 2004-2012 period, we adopt a two-way fixed effects model to overcome selection bias by controlling not only for the unobserved time-invariant heterogeneity but also for heterogeneity in firms' observed characteristics over a multiple-periods. This study contributes greatly to the literature in terms of methodological aspects because, as explained previously, in France and generally at the international level, there is a lack of evaluation of the impacts of cluster policies on large firms using econometric techniques because of methodological issues related to the lack of counterfactuals. In terms of methodological aspects, the other studies disregard completely or partially large firms, and to our knowledge, this is the first econometric study evaluating the effects of the competitiveness clusters policy on all large firms performance. Moreover, as in the previous chapter, it analyzes the impacts by controlling for two instruments and comparing them.

In terms of findings, this study brings new evidence on the impacts of the clusters policy on midsized and large firms' innovation and economic performance. These results show that being a member of clusters has no incident on total R&D budgets and privately financed R&D but participating in FUI projects leads to strong crowding-out effects. Contrary to what one might expect, results show that the effects on firms' R&D staff and researchers are surprisingly very low or even nonexistent. Moreover, findings show that the policy has positive effects on the innovation of firms that participate in the policy. However, the effect of belonging to a cluster is stronger than that of the participation in FUI projects on innovation output. About CS3 employment and total employment, the effects of the two instruments are globally positive but those of the participation in FUI projects are stronger. For the other economic performance related to market such as turnover, added value, and exports, the results are more mixed. Globally, being a member of clusters has positive effects on turnover, added value, and exports. However, the effects of participation in FUI projects are negative on turnover and added value but null for export.

Furthermore, the findings show that the impacts of the policy are very heterogeneous depending on the type of cluster. The results suggest that being a member of a worldwide

cluster has no effect on patenting, leads to crowding-out effects, greatly increases employment but decreases turnover and added value. For worldwide-track clusters, the effects are positive on patents, private R&D spending, employment, turnover, and export. Belonging to a national cluster has positive effects on patents, turnover, added value, and export. Even if it does not have any effects on private R&D spending, its effects on employment are weak and mixed. Finally, the findings show that the effects of the policy on firms' performance are heterogeneous depending on the duration of the participation in the policy and the magnitude of all these effects (positive or negative) increases slightly depending on the duration of participation in the policy, whatever the performance indicator.

Policy implications and recommendations

The findings presented in the previous section yield various implications for practice and might enable improvements in the way these public innovation policies are working.

European 5th and 6th Framework Programmes policy

The results of this aggregate-level study have profound implications on European public policy, and particularly on the decisions to fund research activities and innovation policies. The results show that FP5 expenditure has no impact on EU-27 regional innovation but for the FP6 spending, positive impacts are observed. The fact that the FP6 has positive effects on lagging regions and not the FP5 is perhaps due to the increase of subsidies for the FP6, the orientation of subsidies towards other sectors, but also to the change of the structural funds at this period. Even if there is a need for public R&D subsidies to foster innovation, our findings suggest that there are some conditions required to make effective the European support for R&D. It may be interesting to focus the FPs spending and European subsidies towards some specific strategic sectors but also to account for the simultaneity with structural funds.

Moreover, we observe complementarity effects between human capital and FP6 spending. This complementarity means that innovation requires high levels of resources but the availability of knowledge and qualified human resources able to implement changes in the process of production are necessary. To make the policy more effective in the long run, the EU commission can encourage national and regional efforts developing absorptive capacities

by improving training and teaching quality in higher education institutions to strengthen skills and human capital, especially for lagging countries.

Further, the findings suggest the presence of substitution effects between regional R&D spending and the FP6 spending for the more innovative EU countries (EU top 11). These substitution effects mean that there is a possible conflict between national and European instruments which may be due to a substitution effect between regional R&D spending and the European R&D subsidies. It makes sense to increase the coordination between European and regional R&D policies to avoid duplication issues. Therefore, with respect to the distribution of the FPs amounts between European regions, these results suggest that there is an opportunity here for the EU commission to reallocate the subsidies towards the development of absorptive capacities able to make the EU policy more effective or to find other types of European intervention instruments for lagging regions before scientific policies. This may be done through the improvement of the European structural funds aiming at increasing the absorptive capacities of knowledge for lagging regions.

Impacts of the French clusters policy and firms' performance

The findings suggest that being a member of a cluster has strong stimulating effects on SMEs' innovation input (R&D spending and employment related to R&D). Moreover, participating in FUI projects has weak effects on input additionality. However, no crowding-out effect is observed, whatever the treatment option. The results show that for economic performance, the effects of adhesion to clusters are weak, but the effects of participation only in FUI projects are weaker. The government can consolidate and strengthen both instruments by giving more attention to the participation in clusters because they have much stronger effects than FUI projects and they are much less costly for public funding. There is a need to promote the participation of innovation actors and more especially SMEs by showing them evidence on the observed outcomes through the clusters framework. The findings highlight the importance of the strengthening of the animation and strategic management of the clusters but also providing services for firms in clusters. The development of structuring projects such as the platforms of innovation which intend to offer services or resources and the development of innovation ecosystems have more impacts than financed R&D projects on firms' performance.

Moreover, results suggest that the effects of the policy are much stronger for SMEs which

receive both treatments in terms of stimulus of innovation inputs, total employment but also on economic performance. These findings highlight the importance of combining the participation in the activities of clusters and in subsidized R&D projects on firms' performance. Therefore, the government can encourage the selection process of FUI projects towards joint participation (participating in clusters and FUI projects at the same time) to make the policy more effective by combining the participation in FUI projects and clusters.

The findings show that participating in FUI projects seems to lead to strong crowding-out effects for large firms which largely benefit from the policy, in particular in terms of R&D projects subsidies. Further, the results show that the effects on firms' R&D staff and researchers are surprisingly low or even nonexistent. Moreover, the effects of participation in FUI projects are negative on turnover and added value but null for export. As large firms do not face difficulties to finance their own R&D project and therefore do not plan their R&D investments with the subsidies they receive in the framework of the FUI projects, they may substitute the subsidies they receive with their private R&D expenditure. It is worth noting that the impacts of the FUI projects on large firms' total employment are positive and significant. Perhaps, the process of projects funding needs to be rethought by orienting the FUI funding towards SMEs because the large firms which receive the larger share of funding do not increase their private R&D investment and their R&D staff. One possible explanation of these results may rely on the hypothesis that R&D is made by SMEs who create technology that is thereafter bought by large firms which industrially develop it and therefore create jobs. It may be very interesting to develop the approach to confirm these results, and more especially using qualitative approaches to investigate firms strategies.

Furthermore, the clusters adhesion has positive effects on turnover, added value, and exports. The participation of large firms in clusters and their participation in activities conducted outside the R&D project funded should be encouraged because this increases generally their output performance. This would be more effective than increasing the FUI funding devoted to large firms. Our results reveal that large firms do not need R&D subsidies to fund their projects, and therefore the clusters policy is not important for them when it funds their R&D projects. However, the clusters policy develops structuring projects such as the platforms of innovation which offer services or resources and develops innovation ecosystems allowing cooperation, knowledge sharing to strengthen the monitoring capacities of large firms which can develop commercially new activities due to this.

Limitations and avenue for future research

Although this thesis contributes to the on-going literature of public innovation policy evaluations, it suffers from some weaknesses and several limitations which potentially influenced the overall results. In this section, we will identify the main limitations of the thesis and make suggestions for improvement for future research.

In chapter 2, the first limitation concerns the availability of data. Indeed, it was not possible to have data for the whole EU-27 countries at the same geographical level (heterogeneous NUTS levels). Moreover, while our empirical study allows us to assess the impacts of the 5th and 6th Framework Programmes on the European regional innovation, it does not provide insight on the knowledge spillovers mechanisms and on networking and collaboration. It may be interesting to make a deeper analysis in future research to analyze the effects of proximity (geographical or sectorial) but also the spatial dimension with knowledge spillovers through regions. It may make sense also to assess the policy according to the activity sectors in which regions are specialized. Moreover, we found that the effects are heterogeneous between leading and lagging countries. It may be interesting to examine the effectiveness of such policy by comparing the impacts among the EU top 6 performing countries (Germany, France, United Kingdom, Italy, Netherlands, and Sweden) which file 86% of all EU-27 patents and represent 78% of total public research and development spending in the EU-27 countries. These countries have implemented various national policy approaches and therefore it will be interesting to analyze the impacts of national policies on the effectiveness of the European policies.

In the chapters 3 and 4, although robustness checks show that the findings are robust, results should be interpreted with much caution because of some main limitations. Firstly, the lack of data on firms characteristics and activities for a long period make it difficult to evaluate the true impacts of the competitiveness clusters policy. The non-experimental nature of data and the bias due to the non-random selection process of public funding of R&D activities is a commonly known issue when identifying the true effects of such policies. As a consequence, it was not possible to have a random sampling and we have proposed alternative non-experimental techniques which adequately account for bias and selection issues. Using data available for a longer period when analyzing the effects of the clusters policy may bring new insight into the understanding of the real policy impacts.

Secondly, the availability of several instruments (direct and indirect) that support firms' activities also makes it difficult to evaluate the real impacts of the clusters policy. Several policy instruments supporting firms such as the R&D tax credit (CIR) and other policy instruments should be controlled to improve these results. We plan to improve the results in these two chapters by using a quasi-experimental design with three treatments (multiple treatments): cluster adhesion, FUI projects participation and benefiting from fiscal incentives (CIR).

Thirdly, the weakness or absence of significant impacts on output performance may be explained by the fact that the policy is unsuccessful or that it was highly successful and has generated large positive spillovers for nonparticipant firms. The main characteristic of clusters policies is related to their capacities to generate positive externalities and knowledge spillovers for nonparticipant firms. Therefore, as for the not accounting for the several instruments, evaluating the impact of this policy without accounting for knowledge spillovers and externalities may cause under or over-estimation of the real effects of such policies. A better access to more rich data and more evaluations at the level of territories would bring new insights in the way that R&D activities diffuse to enhance firms' performance in the framework of the clusters policy.

Fourthly, it also may be interesting to tackle this evaluation issues by considering a networking approach of cooperation between innovation actors. There is a possibility to examine the effects of the policy in terms of collaboration dynamics within the innovation system and compare the results with those found in this two chapters.

Finally, in addition to the need of more evaluations focusing on the output performance, we think that it is necessary to complement these econometric evaluations with some case studies at the level of clusters and at the sectoral and specialization levels but also with advanced qualitative analyses. This may help to better understand the how to shift (process) from R&D expenditure towards an increase of economic performance and productivity which are different depending on the activity sectors but also between SMEs and large firms.

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DOCTOR OF PHILOSOPHY OF THE COMMUNAUTÉ UNIVERSITÉ
GRENOBLE ALPES - GRENOBLE APPLIED ECONOMIC LABORATORY

*Title: Macro and Micro Impacts Evaluation of Public Innovation Policies:
Evidence From European Regions and French Firms*

This thesis aims at measuring the effects of innovation policies. It first focuses on the effects of the European Union (EU) policy titled Framework Programmes for Research and Development (FPs) on the regional innovation of the EU 27 countries. Thereafter, it brings a deep analysis of the effects of the French Competitiveness Clusters policy on firms' innovation process and on their performance. The originality of the thesis lies in the mobilization of innovative macro and micro-econometric techniques to evaluate public policies. The results of this work will inform the role and effectiveness of the Framework Programmes for Research and Development in regional innovation dynamics, but also the effectiveness of the Competitiveness Clusters policy on French firms' performance in terms of innovation, incentives for private investments, job creation and market competitiveness.

*Sujet: Évaluations Macro et Micro des Impacts des Politiques Publiques
d'Innovation: Résultats Empiriques sur des Données des Régions
Européennes et des Entreprises Françaises*

Cette thèse a pour objectif de mesurer les effets des politiques d'innovation. D'abord, elle se penche sur les effets de la politique de l'Union Européenne (UE) intitulée Programmes Cadres de Recherche et Développement (PCRDT) sur l'innovation des régions des 27 pays de l'UE. Ensuite, elle apporte une analyse approfondie des effets des Pôles de Compétitivité sur le processus d'innovation des entreprises françaises et leurs performances. L'originalité de la thèse réside essentiellement dans la mobilisation de techniques novatrices d'évaluation macro et micro-économétriques des politiques publiques. Les résultats de ces travaux éclaireront le rôle et l'efficacité des Programmes Cadres de Recherche et Développement dans les dynamiques régionales d'innovation mais également l'efficacité de la politique des Pôles de Compétitivité sur les performances des entreprises françaises en termes d'innovation, d'incitation à l'investissement privée, de création d'emploi et de compétitivité sur le marché.