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Documents de travail GREDEG
GREDEG Working Papers Series

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GREDEG WP No. 2015-26

<http://www.gredeg.cnrs.fr/working-papers.html>

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R&D policies in France: New evidence from a NUTS3 spatial analysis

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Abstract

The French policy-mix for R&D and innovation has deeply evolved in recent years and is nowadays, one of the most generous and market-friendly system in the world. This paper investigates the (evolutive) effects of this policy-mix by using a unique database containing information on the amount of R&D tax credit, regional, national and European subsidies received by firms in all French metropolitan NUTS3 regions over the period 2001-2011. By estimating a Spatial Durbin model with regimes and fixed effects, we provide new evidence on the efficiency of the French policy-mix. First, a yardstick competition between NUTS3 regions for R&D investment driven by negative spatial spillovers is found. Second, it seems that national subsidies are the only instrument able to generate a significant leverage effect on privately-financed R&D. Third, due to the context of spatial competition, the three other policies studied (Tax Credit, Regional and European subsidies) do not generate significant leverage or crowding-out effect. Fourth, we highlight the presence of structural breaks in our data that correspond to the last two important reforms of the French tax credit. Consequently, the effect of R&D policies and especially R&D tax credit are likely to change over time and influence ex-post evaluation results.



JEL Classification: H25, O31, O38

Keywords: Additionality, French policy-mix, Private R&D investment, Spatial panel

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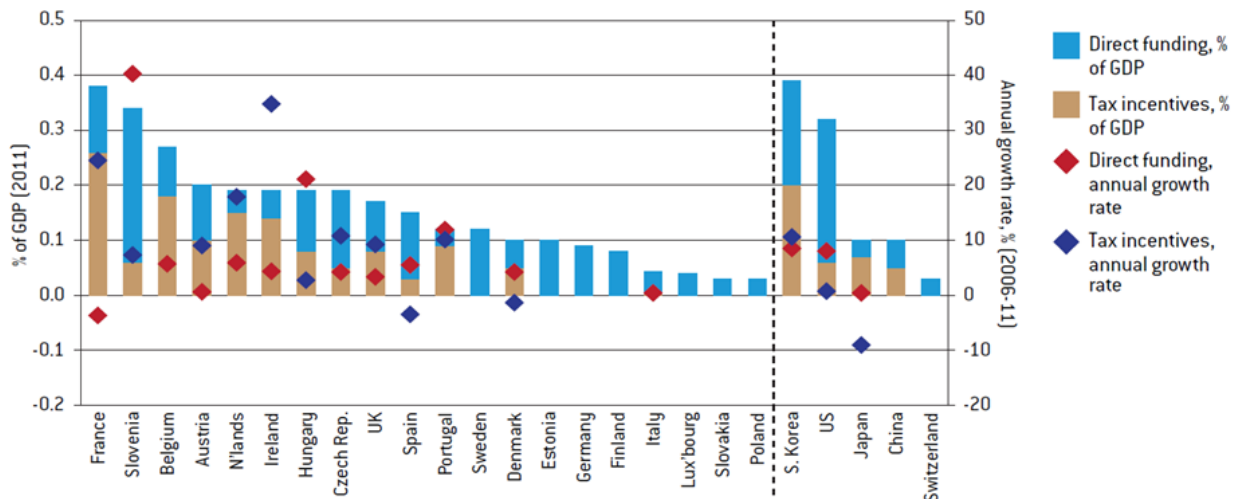
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1 Introduction

Considering the importance of R&D and innovation on firm performances, the existence of diverse forms of externalities enhancing the social return to R&D and its macroeconomic impact on future growth and competitiveness, most countries over the world have set financial public support in favor of private R&D investments. States have many measures at their disposal and their policy mix choices are diverse. While some countries do not offer a tax credit for R&D (Sweden, Finland, Germany), others are strongly oriented toward fiscal assistance (Canada, Japan, The Netherlands, France). The share of direct aids is also highly variable across OECD countries.

Compared to its main competitors, the French case is singular. First the multitude of programs and public policies results in strong public intervention on corporate R&D and innovation. Even more remarkable is the evolution since the early 2000's that involved the inversion of the ratio between direct and indirect support to R&D, following the reform of the R&D tax credit system in 2004 and 2008 (shifting from an incremental to a pure volume based system without any ceiling limits). Indeed, according to the OECD, in 2011, France ranks 7th for direct support (0.12% GDP) and is the most generous country for indirect support (0.26% GDP) (see Figure 1). This same year, the amount of (direct and indirect) financial support for private R&D has been evaluated at around 7.7bn. The sole tax credit system in France represented 5.2 bn of fiscal revenue loss for the French government. Ever since this amount has still been increasing, which has led many economists as well as politicians to cast doubt on the effectiveness of such measures.

Figure 1: Government support for business R&D: Subsidies vs Tax incentives.



Notes: Data for Belgium, Ireland and Spain refer to 2010 instead of 2011. Data for Luxembourg refers to 2009.
Source: Bruegel on the basis of OECD Science, Technology and Industry Scoreboard (2013), Veugelers (2014).

During this period of reforms for the tax credit, firms located in France have also benefited from many direct support as subsidies or grants. Although, the share of such measures in the French policy-mix structurally decreased, some main evolutions in terms of objectives and instruments should be noted. Along with the decreasing trend of subsidies coming from the Ministry of Defense, since 2005, we have observed the development

of the Competitiveness Cluster policy and the increasing targeting of industrial and societal strategic domains. Such evolutions have reinforced the territorial dimension of policies and led to the increase of the share of regional policies in the French policy-mix, even though this share still remains weak in the global policy mix.

On the whole, such a generous system which aimed at correcting the main market failures reducing the private incentives to invest in R&D, has certainly helped to sustain the private effort in R&D in France during the 2000's. Indeed, in spite of a difficult macroeconomic context, the total share of corporate-financed R&D increased slightly. However it remains far behind those of its main European and international competitors. According to OECD data (see Table 1) the French share of private R&D expenditure in GDP has risen to 1.4 percent in 2011 but keeps on being relatively low in comparison with other large countries (1.6 percent as OECD average, 2 percent for Germany and 2.6 percent for Japan). More, this increase in corporate Domestic Expenditure in R&D (DERD) didn't contribute to the total increase of R&D expenditure in GDP which sticks around 2.2% in France.

Table 1: Business Domestic Expenditure in R&D (% GDP) in 2011.

Country	Business DERD	Publicly-financed Business DERD	Total DERD
France	1.4	0.4	2.19
Germany	2.0	0.1	2.80
Italy	0.7	0.0	1.21
Japan	2.6	0.1	3.38
Korea	3.1	0.4	3.74
United Kingdom	1.1	0.2	1.69
United States	1.9	0.3	2.77

Source: OECD on line database.

Therefore, the widespread use of public funds in order to support private R&D in times of economic slowdown raises compelling questions on the effectiveness of these policy instruments. So far, evaluations of the efficiency of R&D policies that have been carried out in various countries still report ambiguous results. Moreover, the number of studies that are comparable in terms methodology is too small and the quality of evaluation studies is also mixed.

Reviewing the main studies that try to estimate the impact of R&D subsidies, Zúñiga-Vicente et al. (2014) show that the empirical evidence on the effectiveness of public subsidies is still mixed and therefore inconclusive. Results supporting the additionality hypothesis prevail, but there are also contributions in favor of the substitution hypothesis while, others demonstrate that there exists no significant effect.

As far as indirect support (such as R&D tax credit) is concerned, the conclusion is a little bit more consensual. In its recent Taxation Report, the European Commission (2014) notes that the vast majority of existing studies conclude that R&D tax credits are effective in stimulating investment. Still, the estimates of the size of this effect are widely diverging and are not always comparable across countries. Although the literature clearly points out that take-up rates for subsidies and R&D tax incentives differ with the type of firms and that these two instruments have important specificities in their way to address market failures and interact each other, few studies consider together direct and indirect financial support to private R&D. Some exceptions are Lhuillery

et al. (2013), Busom et al. (2014) and Montmartin and Herrera (2015) but still there is no clear-cut answer in the literature to the questions of whether these instruments act as complements or substitutes to private investment in R&D or which has a better impact than the other. Once more the specific design and implementation of instruments appear as crucial elements of their own and common efficiency.

Consequently the results of these evaluations cannot really be applied to the current French case whose generosity has no historic precedent. Existing evaluations on the French case mainly concern the period previous to the 2008 reform of R&D Tax Credit. The main debates are on the efficiency of the Competitiveness Cluster policy on the one hand and of the fiscal policy in favor of private R&D on the other hand.

To summarize, when considered separately the Competitiveness Cluster subsidies have been showed to have a positive impact on the R&D carried on by SMEs (Bellego and Dortet-Bernadet, 2013) while tax credit demonstrated also an additionality effect on private investment in R&D (Mulkay and Mairesse, 2013). However, considering together the effect of subsidies and tax credit (new version of Bellego and Dortet-Bernadet, 2014; and Lhuillery et al., 2013), recent studies have more difficulties to highlight important and significant additionality effects even though they never bring to light substitution effects. So far, none of those studies presented an ex-post evaluation of the 2008 tax credit reform in France. Moreover, while the spatial dimension of innovation and the existence of geographical externalities are considered as main elements characterizing R&D based growth model and have justify the development of clusters policies in most countries (in particular in France in 2005), no evaluation studies explicitly considered the existence and impact of spatial externalities.

Thus, the objective of this paper is to investigate the effect of the French policy-mix in favor of private R&D by using a unique database that cover all French metropolitan NUTS3 regions over the period 2001-2011. Assembling fiscal and survey data, we gathered information concerning the amount of total R&D tax credit, regional, national and European subsidies received by firms carrying on R&D activities in each region and their total investment in R&D. To run our analysis, we first develop a simple theoretical model based on Howe and McFetridge (1976), that provides one explanation of the ambiguous empirical results obtained concerning the effect of R&D policies. Indeed, depending on key parameter values crowding-out as well as crowding-in effects can emerge. Also, this framework can be extended easily to spatial interactions. It will base our empirical estimates. More precisely, we develop a Spatial Durbin model with regimes and fixed effects. This kind of spatial model allows us to take into account the spatial dependence that exists between units but also the potential structural change on the considered period.

This paper adds to the literature on the evaluation of R&D policies through three main ways: (i) this paper considers at the same time different components of the R&D policy-mix; regional, national and European subsidies as well as Tax Credit; (ii) spatial interdependencies and in particular the possible existence of a yardstick competition between NUTS3 regions in France are investigated; (iii) this paper also measures the potential structural change in the behavior of firms that can be related to strong changes of R&D policies over time.

Our empirical estimates highlight the following core results. First, the assumption of yardstick competition between NUTS3 regions in France is validated. Indeed, the spatial dependence of private R&D investment is

negative and strongly significant. Second, we find evidence of a leverage effect of R&D subsidies coming from national level whereas local/regional and European subsidies do not seem to generate significant leverage or crowding-out effect. Hence, positive externalities related to national subsidies lead to positive total marginal effect of subsidies even if the competition between regions for the development of private R&D on their territory is high. The other studied policies do not generate significant leverage or crowding-out effect. This is due to the fact that these policies, contrary to what happen for national subsidies, generate a negative indirect effect which counterbalances their positive direct effect. Fourth, the macroeconomic situation of the country influences strongly the level of privately-financed R&D investment in NUTS3 region. More precisely, we estimate that GDP generates a leverage effect on the private R&D as an increase of 1% of GDP in all NUTS3 regions increases privately-financed R&D by 1,3%. Finally, the last result concerns the presence of structural breaks in our data that correspond to the last two important reforms of the French tax credit. Indeed, even though the influence of tax credit on private R&D is not significant over the whole period, the estimated coefficient significantly changes for the two later periods. This could imply that the reforms of 2004 and 2008 have contributed to the development of potential future windfall effects.

On the whole, this analysis on spatially aggregated data appears as complementary to the main microeconomic analyses developed on the French case. It is in line with the main results previously obtained in terms of additionality and adds to previous interpretation by highlighting essential phenomena of structural change and spatial dependence that have not been analyzed so far.

After presenting the simple theoretical framework that we will use in order to explain the possible existence of crowding-in as well as crowding-out effects of public support to private R&D and base our empirical model (section 2), we present the related empirical literature and the main existing evidence on the impact of tax credit and subsidies in section 3. Data and the evolutions of the French policy mix over the period 2001-2011 are detailed in section 4. Section 5 presents the methodological strategy to spatial panel data and section 6 presents some main descriptive statistics of our data and discusses the empirical results in detail. Conclusions are presented in section 7.

2 The Theoretical Framework

2.1 A simple model of R&D investment

The model developed in this paper is based on the frameworks proposed by Howe and McFetridge (1976) and David et al. (2000). We consider that at a given period of time t , there is a fixed but relatively large number of firms in each NUTS3 regions. We assume that each firm has some potential R&D projects in the pipeline and is able to estimate the rate of return and the cost of capital of its R&D projects. R&D projects are perfectly divisible so that each firm faces a marginal rate of return (MRR) and a marginal cost of capital (MCC) curve depending on its level of R&D expenditure. We assume that first and second derivatives of the MCC and MRR curves with respect to R&D investment have the same sign for all firms. Consequently, by aggregating MRR

curves and MCC curves of firms located in one NUTS3 region, we obtain a MRR and MCC curve for each NUTS3 region. Based on David et al. (2000) framework, we specify the following properties for the *MRR* and *MCC* curves at the NUTS3 level:

$$MRR_i = f(R_i, X_i), \quad \frac{\partial f}{\partial R_i} < 0, \quad \frac{\partial^2 f}{\partial R_i^2} > 0, \quad (1)$$

$$MCC_i = f(R_i, Z_i), \quad \frac{\partial f}{\partial R_i} > 0, \quad \frac{\partial^2 f}{\partial R_i^2} < 0, \quad (2)$$

where $i = 1, \dots, N$ refers to the spatial unit (here NUTS3), R_i is the level of private R&D investment in NUTS3 region i , X_i and Z_i represent a set of variables that influence the MRR and the MCC curves respectively. The focus of this paper is to better understand and evaluate the effect of R&D policies (subsidies and tax credit). These kinds of variables are natural candidates as Z and/or X variables. It is common knowledge that R&D policies have complex effects on the firm behavior (see David et al., 2000, for a detailed discussion). To summarize, due to numerous direct and indirect effects, it seems that R&D policies influence both the MRR and MCC curves of a firm and hence the related aggregate curve at a NUTS3 level. If there is a relative consensus on the fact that the direct effects of R&D policies are higher on the marginal cost of capital than on the marginal rate of return, it is less obvious concerning the indirect effects (like learning, training or reputation effects). In order to take in account these complex effects of R&D policies, we specify the following functions for both the MRR and MCC curves:

$$MRR_i = \delta_i R_i^\beta \left[\sum_{r=1}^{K_r} \sigma_r (X_{ri})^{-\rho} \right]^{-v/\rho}, \quad \beta < 0, \quad \rho \neq 0, \quad \sum_r \sigma_r = 1, \quad (3)$$

$$MCC_i = \psi_i R_i^\alpha \left[\sum_{l=1}^{K_l} \mu_l (Z_{li})^{-\rho} \right]^{-u/\rho}, \quad \alpha > 0, \quad \rho \neq 0, \quad \sum_l \mu_l = 1, \quad (4)$$

where $\delta_i > 0$ and $\psi_i > 0$ are NUTS3 region's specific time-invariant elements of the MRR and MCC curves, $X_{ri} \geq 0$, $r = 1, \dots, K_r$ and $Z_{li} \geq 0$, $l = 1, \dots, K_l$ represent measures of public policy variables and other variables affecting the *MRR* and *MCC* curves respectively. In the CES part of the function, the returns to scale are given by $v \in [0, 1]$ for X variables and by $u \in [0, 1]$ for the Z variables. The constant elasticity of substitution between two X variables and between two Z variables is given by $\eta = 1/(1 + \rho)$. The complexity of R&D policy effects on both curves is included through the generalized CES function. This choice implies that we consider R&D policies and other influential variables as imperfect substitutes for firms private R&D cost and profitability. From a theoretical point of view, the advantage is twofold: (1) we allow a specific influence for all variables on the MRR and MCC curves and (2) the number of variables (the number of R&D policies) can generate positive or negative effects on the two curves.

The equilibrium amount of private R&D in a i -th NUTS3 region is obtained when the aggregate MRR curve crosses the MCC curve, that is:

$$R_i = \left(\frac{\delta_i \left[\sum_{r=1}^{K_r} \sigma_r (X_{ri})^{-\rho} \right]^{-v/\rho}}{\psi_i \left[\sum_{l=1}^{K_l} \mu_l (Z_{li})^{-\rho} \right]^{-u/\rho}} \right)^{1/(\alpha-\beta)}. \quad (5)$$

As shown in Hoff (2004), we can apply a translog approximation for a N-variables CES function assuming that the elasticity of substitution is in the neighborhood of unity. Then we can rewrite (5) as:

$$\begin{aligned} \log R_i \approx & \frac{1}{\alpha - \beta} \left(\log \frac{\delta_i}{\psi_i} + \sum_{r=1}^{K_r} \lambda_r \log X_{ri} + \sum_{r=1}^{K_r} \sum_{s=r}^{K_r} \lambda_{rs} \log X_{ri} \log X_{si} \right) \\ & - \frac{1}{\alpha - \beta} \left(\sum_{l=1}^{K_l} \theta_l \log Z_{li} + \sum_{l=1}^{K_l} \sum_{k=l}^{K_l} \theta_{lk} \log Z_{li} \log Z_{ki} \right), \end{aligned} \quad (6)$$

where the parameters obey to:

$$\begin{aligned} \lambda_r &= v \sigma_r \quad \theta_l = u \mu_l, \\ v &= \sum_r \lambda_r \quad u = \sum_l \theta_l, \\ \lambda_{rs} \mid_{r \neq s} &= \frac{-2\lambda_{rr}}{1 + \sum_{i \neq (r,s)} \frac{\lambda_i}{\lambda_s}}, \quad \theta_{lk} \mid_{l \neq k} = \frac{-2\theta_{ll}}{1 + \sum_{i \neq (k,l)} \frac{\theta_i}{\theta_l}}. \end{aligned} \quad (7)$$

As previously discussed, public support to private R&D is likely to influence both the MRR and MCC curves. Other variables like interest rates or demand can also influence both curves. Hence, to simplify the model we will assume that all X and Z variables influence potentially both MRR and MCC curves. We integer all X and Z variables into a new V set of variables. We can thus rewrite (6) as:

$$\log R_i = \frac{1}{\alpha - \beta} \left(\log \frac{\delta_i}{\psi_i} + \sum_{k=1}^K (\lambda_k - \theta_k) \log V_{ki} + \sum_{k=1}^K \sum_{l=k}^K (\lambda_{kl} - \theta_{kl}) \log V_{ki} \log V_{li} \right), \quad (8)$$

where $V_{ki} \geq 0$, $k = 1, \dots, K$ and $K = K_r \cup K_l$. Using this specification, we do not impose that all V variables influence both the MRR and MCC curves. Indeed, some variables can influence only the MRR curve so that for such variables, we have $\lambda_k \neq 0$ and $\theta_k = 0$. Some others can only influence the MCC curve so that $\lambda_k = 0$ and $\theta_k \neq 0$. An important implication of this simple model is that it highlights the channels through which public policies can globally generate leverage or crowding out effect. Indeed, the partial derivative of expression (8) highlights two distinct effects of R&D policies:

$$\frac{\partial \log R_i}{\partial \log V_{ki}} = \frac{\partial \left[\sum_{k=1}^K (\lambda_k - \theta_k) \log V_{ki} \right]}{\partial \log V_{ki}} + \frac{\partial \left[\sum_{k=1}^K \sum_{l=k}^K (\lambda_{kl} - \theta_{kl}) \log V_{ki} \log V_{li} \right]}{\partial \log V_{ki}}. \quad (9)$$

The first term of (9) is the direct effect of the policy, that is the effect of the policy without considering its external effects. The second term of (9) highlights the indirect effect of the R&D policies, that is the effect

that the policy generates on other variables which influence the R&D investment level. The elasticity of R&D investment with respect to a given policy is the sum of the direct effect which is linear ($\lambda_k - \theta_k$) and the indirect effect which is non linear and composed of all external effects. Consequently, we can distinguish two main cases concerning the elasticity of R&D investment with respect to a given policy:

Case where the policy generates a leverage effect: $\partial \log(R_i)/\partial \log(V_{ki}) > 0$

1) $\lambda_k - \theta_k > 0$.

In this case, the direct effect of the policy is positive. The indirect effect can be positive or negative but is smaller in magnitude than the direct effect.

2) $\lambda_k - \theta_k < 0$.

In this case, the direct effect of the policy is negative. The indirect effect is strongly positive and higher in magnitude than the direct effect.

Case where the policy generates a crowding-out effect: $\partial \log(R_i)/\partial \log(V_{ki}) < 0$

1) $\lambda_k - \theta_k > 0$.

In this case, the direct effect of the policy is positive. The indirect effect is negative and higher in magnitude than the direct effect.

2) $\lambda_k - \theta_k < 0$.

In this case, the direct effect of the policy is negative. The indirect effect can be positive or negative but it is smaller in magnitude compared to the direct effect.

2.2 The spatial extension of the model

In some sense, the MCC and MRR curves (1) and (2) are relatively acceptable for closed units. Nevertheless, in an open context and especially when R&D activities are concerned, it is difficult to assume a complete independence between behavior of one unit and the behavior of other units (especially if they are within the same country). The empirical literature on the geography of innovation (see Autant-Bernard et al., 2013) has highlighted the existence and the importance of spatial spillovers generated by R&D activities. More recent empirical papers focused on R&D policies as those of Wilson (2009) or Montmartin and Herrera (2015) have also highlighted the existence of strong spatial externalities generated by R&D policies. The obvious translation of these empirical evidences in our framework is to model the influence of private R&D investment and public funds received by others units (here NUTS3 region) on the MRR and MCC curves of a particular unit. Obviously the influence of each location $j \neq i$ on the i -th NUTS3 region would not be uniformly distributed. Again, the geography of innovation literature highlights the importance of different forms of proximity and especially the geographical proximity in the transmission of knowledge spillovers. In other words, the diffusion of knowledge spillovers is geographically bounded. To introduce these elements in our framework, we extend (1) and (2) in the following way:

$$MRR_i = f \left(R_i, X_i, \sum_{j \neq i} w_{ji} R_j \right), \quad \frac{\partial f}{\partial R_i} < 0, \quad \frac{\partial^2 f}{\partial R_i^2} > 0, \quad (10)$$

$$MCC_i = f \left(R_i, Z_i, \sum_{j \neq i} w_{ji} R_j \right), \quad \frac{\partial f}{\partial R_i} > 0, \quad \frac{\partial^2 f}{\partial R_i^2} < 0, \quad (11)$$

where w_{ji} is a measure of proximity between unit j and unit i . We define the following functions for the MCC and MRR curves:

$$MRR_i = \delta_i R_i^\beta \left(\sum_{j \neq i} w_{ji} R_j \right)^\varphi \left[\sum_{r=1}^{K_r} \sigma_r (X_{ri})^{-\rho} \right]^{-v/\rho}, \quad \beta < 0, \quad \rho \neq 0, \quad \sum_r \sigma_r = 1, \quad (12)$$

$$MCC_i = \psi_i R_i^\alpha \left(\sum_{j \neq i} w_{ji} R_j \right)^\omega \left[\sum_{l=1}^{K_l} \mu_l (Z_{li})^{-\rho} \right]^{-u/\rho}, \quad \alpha > 0, \quad \rho \neq 0, \quad \sum_l \mu_l = 1. \quad (13)$$

As for the basic model of section 2.1, the equilibrium amount of private R&D in the i -th NUTS3 region is obtained when the aggregate MRR curve crosses MCC curve, that is:

$$R_i = \left(\frac{\delta_i \left[\sum_{r=1}^{K_r} \sigma_r (X_{ri})^{-\rho} \right]^{-v/\rho}}{\psi_i \left[\sum_{l=1}^{K_l} \mu_l (Z_{li})^{-\rho} \right]^{-u/\rho}} \right)^{1/(\alpha-\beta)} \left(\sum_{j \neq i} w_{ji} R_j \right)^{\frac{\varphi-\omega}{\alpha-\beta}}, \quad (14)$$

which can be rewrite using a translog approximation as:

$$\begin{aligned} \log R_i = & \frac{1}{\alpha - \beta} \log \frac{\delta_i}{\psi_i} + \frac{(\varphi - \omega)}{\alpha - \beta} \log \left(\sum_{j \neq i} w_{ji} R_j \right) \\ & + \frac{1}{\alpha - \beta} \left(\sum_{k=1}^K (\lambda_k - \theta_k) \log V_{ki} + \sum_{k=1}^K \sum_{l=k}^K (\lambda_{kl} - \theta_{kl}) \log V_{ki} \log V_{li} \right), \end{aligned} \quad (15)$$

where $V_{ki} \geq 0$, $k = 1, \dots, K$ and $K = K_r \cup K_l$. This last expression highlights another channel, compared to (8), that can explain the apparition of crowding-out or leverage effect for a public policy. Indeed, expression (14) shows that the total effect of a public policy on private R&D investment is the result of three elements. The two first are the direct and indirect effect presented in equation (8) and refer to the within "unit" (in-NUTS3 region) effect of the policy, that is, the influence of public fund received on the in-unit R&D investment. The third effect refers to the between "unit" (out-NUTS3 region) effect that is the influence of R&D investment choice made by others NUTS (which itself depends on public policies implemented by others units) on the R&D investment of i -th region. In other words, this effect measured by $(\varphi - \omega)/(\alpha - \beta)$ refers to spatial-spillovers effect of R&D investment across the NUTS3 regions. The sign of this spatial-spillovers effect of R&D investment could be positive or negative between NUTS of a given country. Indeed, we can easily imagine the existence of a yardstick competition for R&D investment between the NUTS3 regions within a country (where labor mobility is high). On the contrary, we can also imagine the existence of positive spatial spillovers between R&D investment of NUTS3 driven by cumulative learning, training and cooperation effects. To summarize, the integration of spatial dependence in our model is likely to play an important role in the explanation of the net effect of public policies on the private R&D investment.

3 Related Empirical Literature

As shown in the previous section, from a theoretical point of view, the net effect of public support on the level of privately financed R&D is ambiguous. Consequently there is a necessity to develop empirical studies trying to evaluate the use of public funds to support firms' R&D activities.

3.1 Evaluation of the impact of R&D subsidies

In their recent review on studies evaluating the impact of R&D subsidies, Zúñiga-Vicente et al. (2014) show that although methodological differences may hamper efficient comparisons of results between different empirical studies, the main conclusion is that the additionality hypothesis prevails. Approximately 60% of the 77 considered studies find that public subsidies are complementary and thus 'add' to private R&D investment. There are also valuable contributions in favor of the substitution hypothesis while others demonstrate no significant effect. The second finding is in line with David et al. (2000), who reviewed 33 empirical studies, finding 11 studies reporting net substitution. About three-fourth out of the existing studies were conducted at the microeconomic level, whereas the remaining studies used aggregate data by industry or by country and it is worth noting that the main results are the same whatever the level of aggregation considered.

Zúñiga-Vicente et al. (2014) as well as García-Quevedo (2004) in their meta-analysis of this literature could not explain the heterogeneity of results by methodological differences in studies. This means that the heterogeneity in the effectiveness of R&D subsidies is probably due to differences in policy instruments and country characteristics. Subsidies generally are implemented through a great diversity of programs. Even if we only consider those implemented at the national level they involved different Ministries and each defines its specific targets and objectives. Recent approaches take into account the bargaining characteristics of subsidies when using game models to analyze strategic interactions between firms and public authorities along the process of project selection (Takalo et al., 2013). They show that crowding-out effects are reinforced when subsidies are high, concern large projects and are oriented towards 'picking the winner' strategies. Moreover within most of the OECD and European countries, an increasing share of R&D subsidies are allocated within the framework of clusters policies. Evaluation of clusters policies has been carried out in diverse countries where the performances of firms and territories are linked to their different components such as the effect of geographical/sectoral agglomeration, the networking effects or the financial support¹. The heterogeneity in methodology is too great to allow us to synthesize the results but associated with the results that have been obtained in the field of the geography of innovation (Autant-Bernard et al., 2013) it is possible to state that there is an impact of the geography of R&D activities on the capacities of firms to invest in R&D and react to subsidies.

¹See notably OECD (2009) or for difference in difference analyses Nishimura and Okamuro (2011), Falck et al. (2010) and Brossard and Moussa (2014) on the French case. One can also refer to Varga et al. (2014) for new results showing the complex impacts of agglomeration and networking for clusters policies.

3.2 Evaluation of the impact of R&D tax credit policies

Using either counterfactual methods or estimations of structural demand function for R&D investment, the vast majority of studies surveyed in the European Commission report (European Commission, 2014) conclude that R&D tax credits are effective in stimulating investment in R&D.

The estimates of the size of this effect are however, widely diverging and are not always comparable across countries. Studies that are considered as more rigorous find that one euro of foregone tax revenue on R&D tax credits raises expenditure on R&D by less than one euro. It is also worth noting that the effects of R&D tax incentives on R&D expenditure vary across sub-groups of firms depending on their size. However contradictory results are also obtained. While in some countries, small and medium sized enterprises (SMEs) tend to respond more strongly to the support for R&D, the reverse has been found somewhere else. Evidences suggesting that knowledge spillovers of large firms exceed those of small firms, tend also to weaken the case for targeting tax incentives towards SMEs - even when SMEs would increase their R&D expenditure more strongly in response to those incentives. More consensual is the evidence that the impact for start-up firms can exceed the average impact which has incited public authorities to implement fiscal instrument specifically targeted toward new firms. The Jeunes Entreprises Innovantes (JEI) measure in France enters this category. On the whole the different reviews on this literature (reported in European Commission, 2014) show that the impact of R&D tax credits may be highly sensitive to their design and organization.

One aspect that has been strongly discussed recently is whether incremental schemes perform better than volume-based schemes. The evidence on which type of scheme is more effective is mixed. Considering that incremental R&D tax incentives may trigger firms to change the timing of their R&D investment plans (for example, making it more attractive for firms to gradually increase their R&D investment than to do a single large investment at one time), and result in higher administrative and compliance costs while not being significantly more effective than volume-based schemes, the European Commission presents the volume-based schemes as a better practice. These arguments explain that the vast majority of instruments implemented have recently switched to a volume-based scheme even though the risk of crowding-out effects may be higher for volume-based scheme.

3.3 Considering together direct subsidies and tax incentives

Very few studies take into account both direct subsidies and tax incentives at the same time. Nevertheless the different instruments do not concern all firms with the same probability and they can choose which policy they want to apply to. Corchuelo and Martínez-Ros (2009) showed that in Spain, R&D tax incentives and subsidies are complements since firms that receive a grant are more likely to also apply for an R&D tax incentive. Spain is also particular because a very low share of eligible firms effectively benefit from tax credit (Labeaga et al., 2014). In France Duguet (2012) noted that R&D tax credit recipients tend to be smaller and have a higher R&D intensity in comparison to companies using R&D subsidies. Frequently, while firms are able to use both subsidies and tax incentives, studies that evaluate the returns to each of these instruments rarely take into

account multiple treatments. Ignoring multiple treatments might lead to biases in estimation results as other evidence suggest that there are notable differences between firms that use only one and firms that use several measures.

Dumont (2013) found that firms who used just one of the policy tools had the highest additional effect. Bérubé and Mohnen (2009) find that Canadian firms benefiting from both tax incentives and direct grants introduced more new products to the market than firms that only benefited from R&D tax incentives.

The limited empirical evidence indicates that interactions between different policy measures probably exist. The importance and direction of interaction effects depends, of course, on the national settings and on the characteristics of specific instruments. Still, policy makers should be aware of unintended side effects when multiple instruments are provided to firms.

3.4 Contributions based on aggregated data

It should be noted that, even if it is generally argued that longitudinal micro data (at firm, establishment or plant level that allow addressing questions at the very same level at which decisions are taken) are preferable, there are also outstanding empirical contributions based on aggregate data on the effect of financial public support on private R&D decisions. One would rather consider that studies with aggregate and micro data complement each other (European Commission, 2014).

Indeed while microeconomic data allow accounting for heterogeneity among those agents (firms, establishment or plants) that are potential beneficiaries of public policies, they often lack of information on the diversity of the amount and sources of public funding received by firms. They also necessitate crossing off diverse datasets which results in a drastic reduction of the sample size. In particular, counterfactual analyses often cannot be applied to large firms even though they receive the largest amount of financial support. The representativeness of the sample used and the associated selection bias constitute strong constraints for micro-econometric strategies of estimation. Finally, the difficulties to obtain long time series also constrain the capacity to analyze temporal effect.

On the other hand, macro-econometric studies allow to consider the global effort made by governments on a diversity of instruments. Moreover, they measure some effects that will influence the macroeconomic impacts of financial support and cannot be grasped at the microeconomic level. Indeed the macroeconomic impact of a measure does not only refer to the individual behavior of firms in reaction to the used instruments but it also measures the distortions generated by policy instruments between firms and industries. Indeed, if these measures can encourage beneficiary firms and sectors to increase their R&D investments, they create distortions vis à vis non-beneficiary firms and sectors and probably cause a reduction in the latters' R&D investments. Macro-econometric studies have also contributed to the analysis of policy mixes. Papers realized on OECD countries in different time periods conclude that within a jurisdiction (here a country), direct and indirect support are substitute in stimulating private investment in R&D (Guellec and Van Pottelsberghe de la Potterie, 1997; Montmartin and Herrera, 2015). In other words, it appears that when a country raises the level of indirect

support, it decreases the incentive effects of direct support and vice-versa. Some elements can be advanced to explain such inter-effect but cannot constitute satisfying rationales for their existence. Among them, we can mention the different uses of these instruments between SME and big firms or the structural evolution (in favor of fiscal incentives) of the ratio between direct and indirect support inside OECD countries.

Finally macro-econometric analyses have also contributed to the measure of external complementarity between instruments, i.e. complementarity between instruments implemented in different jurisdictions. Wilson (2009) evaluates the sensitivity of firms' R&D investment located in one American state to in-state and out-of-state tax credits (from neighboring states). His results show that if firms react positively to in-state tax credit, they also react negatively to the out-of state tax credits. More precisely, this reaction is estimated to be of the same magnitude implying a zero effect of these "local" tax credits at the macroeconomic level. Using OECD countries data, Montmartin (2013) concludes to the existence of an external complementarity of financial support at the country level. It should be noted that these two opposite results are obtained at different geographical level. They may therefore suggest that the existence of an external complementarity or substitutability depends on the geographical unit retained. One simple explanation of this could be the geographical limits of firms' capacity to react to R&D incentives. Indeed, we can easily understand that it is easier for firms to change their location within one country than between countries in reaction to tax incentives.

Thus, even though approaches using aggregated data bring forth interesting complement for the analysis of public policies, they still remain scarce. Moreover, so far, they only use panels of OECD countries. Only Wilson's paper (2009) concerns the infra-national level. Yet this level of analysis using spatially aggregated data within countries allows for original approaches. Interest for regional data is threefold:

- i) It facilitates the identification of structural change in terms of public policies within a country thereby allowing finer interpretation of policy mix and instrument design;
- ii) It allows for finer and more relevant spatial approaches as data better correspond to the level at which knowledge externality effects are highlighted by the literature on clusters or on the Geography of Innovation;
- iii) Such approaches also allow to take into account, at the territorial level, the combined effect of extensive and intensive margin. Indeed, micro-econometric studies are generally focused on extensive margin (i.e. impact on the intensity of R&D investment within firms that already develop R&D activities). However, leverage effect at the territorial level may result not only from intensive but also from extensive margin (i.e. the entry of new firms in R&D activities).

Regional differences in terms of structuration by firm size and of entrepreneurial activities have long been underlined (see the numerous publications from OECD or European Commission on regional entrepreneurial or innovation capacities) and this may have important implications on the impact of public incentives to invest in R&D. For France, the highly agglomerated spatial structure and the evolution of the policy since the early 2000's has contributed to reinforce the relevance of such spatial approaches. The notably important debate about the efficiency of the 'pure-volume' tax credit and the role of Competitiveness Poles strengthened the relevance of these approaches all the more that the existing evaluations on the French case have neglected the spatial dimension.

4 Data and Evolution of the French Policy Mix

4.1 Data

We constructed a balanced panel on 94 French departments (excluding Corsica and overseas departments) over the period 2001-2011. French departments correspond to NUTS3 European territorial zones. Data have been provided by the French Ministry of Research and are issued from two main sources: the R&D survey and the fiscal database on R&D tax credit.

R&D expenditure and subsidies

The R&D survey is collected each year by the French Ministry of Research² and provides information at the firm level on their R&D activities and especially on the financing sources for R&D. The amount of subsidies is detailed distinguishing those coming, not only from the different French Ministries, but also from the European community and territorial authorities (essentially regional councils).

This survey database is organized into three files: the first at the enterprise level gives information allowing to characterize the firms, the second at the R&D sector level gives information on the financial sources used by the firms to develop their R&D activities and the third at the department level gives information on the R&D executed in each department by firms (expenditure and staff).

As our objective is to estimate the reactivity of firms to different types of financial support to R&D, data on professional organizations (such as technical centers for example), which cannot directly benefit from the R&D tax credit have been excluded from our database. In order to correctly geo-localized R&D expenditure and the corresponding subsidies in each department we had to match the different files and redistribute the subsidies proportionally to the R&D executed in each department and sector by each firm. Finally some methodological considerations³ have led us to restrict the time scope to the period 2001-2011.

This database allows us to distinguish different types of subsidies according to their sources of financing: *SubCEE* (European subsidies received from the European Commission); *SubNat* (Total of the subsidies received from diverse French Ministries, National Subsidies); and *SubReg* (Subsidies received from local authorities, i.e. regions and departments essentially).

Tax credit

The tax credit file is collected by the fiscal administration. It is not a survey, it is exhaustive and it details at the firm level the amount of R&D that has been declared and the amount of tax credits that has been granted. Data have been provided to us by the General Direction for Research and Innovation of the Ministry of Research and aggregated at the department level. Matching these data with those coming from the R&D survey at the department level has involved some methodological choices.

We had a first problem which is that the amount of tax credit received in each department does not correspond to the amount of R&D declared. Indeed it matches only for enterprises which are independent or

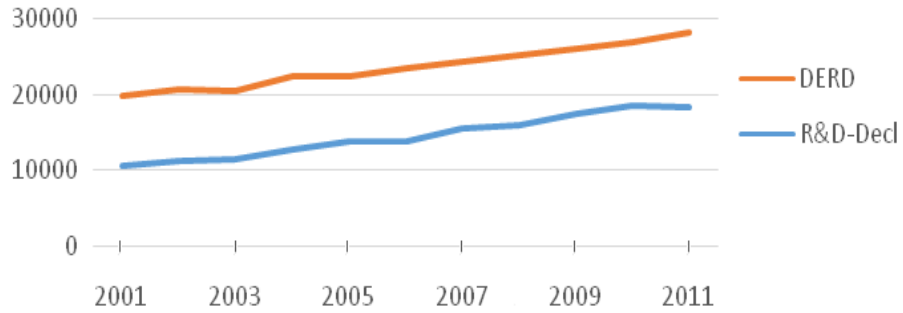
²See acknowledgment at the end of this paper.

³Before 2001 for example only enterprises which employ at least 1 full time researcher are considered in the survey. Since then on the contrary the survey provides also information on all the enterprises that carry on R&D even though they employ none or less than one researcher. Hence it offers better information on small firms.

members of a group which are not fiscally integrated. In the case of fiscally integrated group, only one enterprise (a financial holding frequently) really benefits from the tax credit while the basis for this tax credit is the R&D declared in the whole enterprises of this group regardless of their location.

A second problem stems from the difference between the two sources of information we use for R&D expenditure. On the one hand, we extract from the R&D survey, the dependent variable which measures R&D expenditure executed within the department by private firms (private DERD). On the other hand, from the fiscal base we have information on the R&D declared by firms in each department in order to benefit from the tax credit policy. Differences between these two measures come partly from the scope of the different sources in terms of firms and also from the types of R&D expenditure considered. The R&D survey is non-exhaustive and possibly integrates firms which have R&D activities but do not apply for tax credit⁴ whereas the fiscal database is exhaustive but only for firms applying for tax credit. As far as R&D expenditure is concerned, it should be noted that the tax credit basis for each firm not only includes the R&D internally executed but also part of the subcontracted R&D expenditure. Globally the temporal trends for the DERD and the declared R&D are the same whereas DERD is systematically higher than the declared R&D (Figure 2).

Figure 2: Evolution of Declared R&D and DERD 2001-2011 (in millions euros).



Source: French Ministry of Research (MENESR), own calculations.

Location of tax credit

In order to take into account the possible location biases due to fiscal organization of firms and groups, we constructed a relocalized measure for Tax Credit, named TC in the remaining of this paper. For each year, the total national amount of tax credit is relocalised within each department according to their national share of DERD for each category of enterprise ($s \in \{1, \dots, S\}, S = 5$)⁵. The following methodology is used.

First, we estimate the internal R&D expenditures of a category s in a given NUTS i at time t :

$$DERD_{i,s,t} = \left(\frac{DRD_{i,s,t}}{\sum_{s=1}^S DRD_{i,s,t}} \times DERD_{i,t} \right),$$

⁴As mentioned Dugué (2012, pp. 5), diverse reasons can explain that firms that could apply to the R&D tax credit do not apply for it in practice. This fact is well known at the Ministry of Research and seems to derive from either a bad knowledge of tax deductions or from the erratic nature evolution of growth tax credit. The latter point is consistent with the fact that when the system was extended to the level of R&D in 2004, some firms entered the system for the first time, while they were performing R&D for a longtime.

⁵1: enterprise with 1 to 50 employees; 2: 51 to 250 employees; 3: 251 to 500 employees; 4: 501 to 2000 employees; 5: more than 2000 employees. However, data from the R&D survey cannot provide us with the distribution of DERD among the different categories of enterprises in each department. Hence we used information on the proportion of R&D declared in each category of enterprises in order to estimate the amount of R&D in each category of enterprise.

where DRD is the amount of declared R&D for a sector s in a given NUTS i (original fiscal data). We then calculate the average tax credit rate for a given sector s :

$$TCA_{s,t} = \frac{1}{N} \sum_{i=1}^N \left(\frac{TC_{i,s,t}}{DERD_{i,s,t}} \right).$$

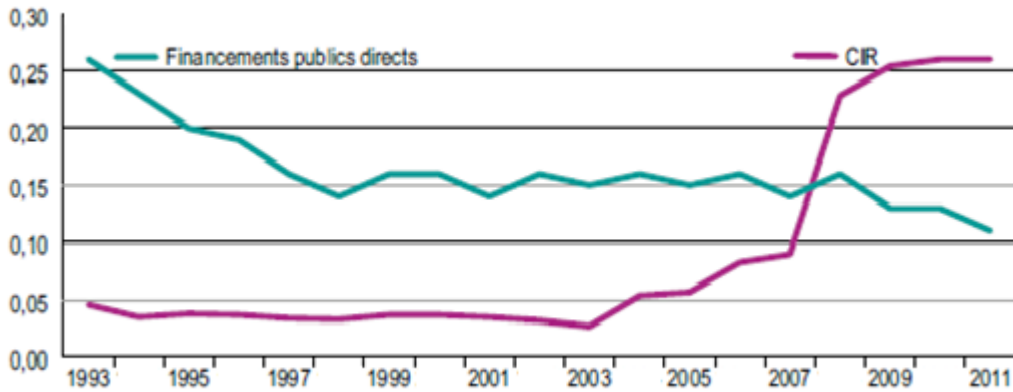
The amount of tax credit that would theoretically be obtained by each NUTS3 at time t is finally estimated by:

$$TC_{i,t} = \sum_{s=1}^S [TCA_{s,t} \times DERD_{i,s,t}].$$

4.2 Brief history of the French R&D policy mix

Collected data cover the 2001-2011 period which means that it integrates different important reforms of the French public policies for R&D. During the early 2000's, France, along with the United States, was cumulating important direct aids for enterprises with generous fiscal incentives. After a decrease due to the reduction of the financing coming from Defense during the 1990's, the intensity of direct aids stabilized around 0.15% GDP (Figure 3). Following 2005, the launching of the Competitiveness Pole policies resulted in a slight increase, until the crisis of 2008 and a new reduction of military expenditure which led to the weakening of direct subsidies.

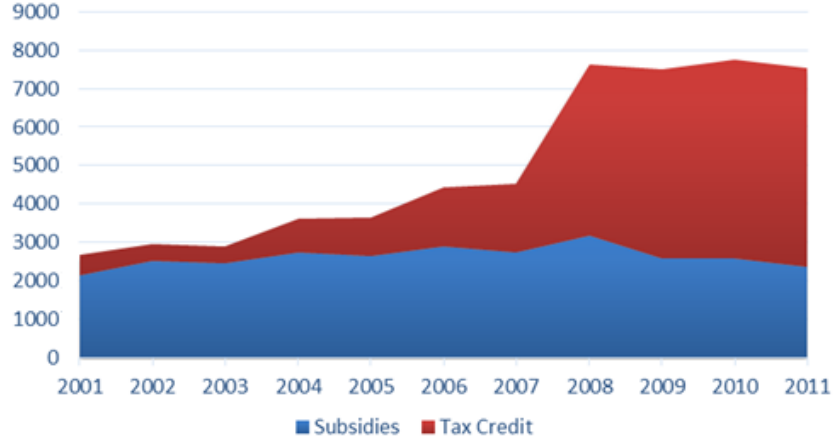
Figure 3: Evolution of public support for business R&D in France 1993-2011 (%GDP).



Source: French Ministry of Research (MENESR-DGRI, CEGIR), 2014 (Financements publics directs= Subsidies; CIR = Tax Credit).

By contrast the intensity of aids resulting from tax credit has increased since 2004, surpassing the whole direct support from 2008 onward and representing 0.26% GDP in 2011. All in all, between 2008 and 2011, the rate of public financing of private R&D in France has reached a high level of 7.7 Billion euros representing 0.38% GDP (Figure 4), substantially higher than in the United States or Canada which also strongly support firms' R&D investment.

Figure 4: Financial support to private R&D in France 2001-2011 (in millions euros).



Source: French Ministry of Research (MENESR), own calculations.

In 2004 France has switched to a system associating an incremental and a volume scheme and since 2008, tax credit in France is calculated on a pure volume basis without ceiling (Table A.1 in Appendix A). The expenditure, which is considered as basis for the tax credit, is defined as the DERD according to the Frascatti manual, but with some supplementary expenditures related to patenting and technological watch notably for weak amount. It incorporates also some specific calculations linked to tax arrangements. In 2011, the applicable rates were 30% of R&D expenditure to 100 M EUR (40% for the first year of entry in R&D activities, 35% for the second year) and 5% beyond. Thus the amount of tax credit is logically concentrated on large firms that largely invest in R&D while small enterprises receive a higher share of tax credit compared to their share of declared R&D expenditure. This strengthening of the tax credit support incited an increasing number of firms to apply and notably the smaller ones. Nearly 20,000 enterprises applied for the year 2011 and nearly 15,000 have benefited from tax credit for that year, representing 5.2 bn EUR of fiscal loss. Enterprises of less than 50 employees represented 71.2% of beneficiary for 16% of the total declared expenditure and 18% of the total amount of tax credit. At the opposite side, the 1.4% beneficiary with more than 2000 employees receive more than 44% of the total amount of Tax Credit (French Ministry of Research, MENESR, 2014).

5 Econometric Strategy

Considering our theoretical objectives and the spatial-temporal characteristics of our data, our strategy uses panel data models which can be described as follow. We denote by i the spatial unit (in our case, NUTS3 regions) and by n the total number of regions ($i = 1, 2, \dots, n$). The time unit is denoted by t and T denotes the total number of observations in the temporal dimension ($t = 1, 2, \dots, T$). A simple *pooled model*, is considered in vector form for spatial units at time t :

$$y_t = x_t \beta + \varepsilon_t, \quad (16)$$

with $\varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2 I_n)$ and y_t is a vector of order $(n \times 1)$, x_t is a matrix of $n \times (k + 1)$ dimension with $\beta' = [\beta_0 \ \beta_1 \ \dots \ \beta_k]$, which imposes homogeneity on the intercept and slope coefficients across all regions. Estimation of this model can be carried out by either ordinary least square (OLS) or maximum likelihood (ML).

The principal criticism of the *pooled model* is that it does not account for temporal and cross-section heterogeneity. Cross-section units probably differ in relation to their background variables that is time-invariant variables that do affect the dependent variable. Examples of such variables are differences in the percentages of urban/rural areas, poverty rate, rights and values in labor market, crime, religion, etc. These variables are usually time-invariant and space-specific, which also are difficult to measure. Similarly, it is possible to justify the inclusion of time-period specific effects based on the idea that they control for all spatial-invariant variables whose omission could bias the time-series estimations (Hsiao, 2003).

Model (16) can be relaxed to take account of such spatial-specific and time-period specific effects transforming the model in the following way:

$$y_t = x_t \beta + \mu + \eta_t \iota_n + \varepsilon_t, \quad (17)$$

with $\varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2 I_n)$ and $\mu' = [\mu_1, \mu_2, \dots, \mu_n]$, ι_n a $(n \times 1)$ vector.

Model (17) captures cross-section (or spatial) heterogeneity among regions, μ_i ($i = 1, 2, \dots, n$), and time-period heterogeneity η_t . The spatial-specific effects can be treated as fixed effects or random effects. In the fixed effects model, a dummy variable is introduced for each spatial unit and, in the random effects model, μ_i is treated as a normal random variable *i.i.d.* with zero mean and variance σ_μ^2 .

Choosing between random or fixed effects depends on the kind of data and the research objective: if the dataset is a random sample of the population and the objective is to obtain an unconditional inference about the population then it necessitates estimation with random effects. In contrast, if the dataset contains all units of population and the objective is about this specific population then the inference is conditional on the sample and fixed effects should be specified.

So far, the spatial dependence among the regions at each point in time is still missing. This dependence can be introduced into the model (16) obtaining the so-called spatial panel data models, which mainly adopt three forms: (a) spatially lagged dependent variable as an explanatory variable, $W y_t$; (b) spatially lagged error term, $W u_t$; (c) spatially lagged explanatory variables, $W x_t$. These different ways to introduce spatial dependence generate new models.

The first model, so-called the spatial lag model (SLM), is defined as:

$$y_t = \rho W y_t + x_t \beta + \varepsilon_t, \quad (18)$$

with $\varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2 I_n)$. The parameter ρ captures the contemporary spatial dependence of the explained variable. W is the spatial weight matrix. The spatial weight is a $n \times n$ positive matrix, pre-specified by the researcher and describes the arrangement of the cross-sectional units in the sample (Anselin, 1988). The elements of W , w_{ij} ,

are non-zero when i and j are hypothesized to be neighbors, and zero otherwise. By convention, the diagonal elements w_{ii} are equal to zero, that is, the self-neighbor relation is excluded.

If we introduce a spatially autoregressive process into the error term, we obtain the spatial error model (SEM) defined as:

$$\begin{aligned} y_t &= u_t x_t \beta + u_t, \\ u_t &= \lambda W u_t + \varepsilon_t, \end{aligned} \tag{19}$$

with $\varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2 I_n)$. This model only takes the spatial dependence as a nuisance parameter, λ , in the standard error.

The third model only introduces spatially lagged explanatory variables, $W x_t$, to obtain the spatial lag “in explanatory variables” model (SLX) defined as:

$$y_t = x_t \beta + W x_t \theta + \varepsilon_t, \tag{20}$$

with $\varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2 I_n)$.

The combination of SLM with SLX produces the spatial Durbin model (SDM) defined as:

$$y_t = \rho W y_t + x_t \beta + W x_t \theta + \varepsilon_t. \tag{21}$$

The SDM introduces the spatial effects of explanatory variables in order to take into account the spatial local dependence. Also, the inclusion of the spatial endogenous variable, $W y_t$, produces a contemporary global dependence in all regions. The model in equation (21) is similar to the one obtained in the theoretical section. The previous models are nested in the SDM and they can be obtained as a restricted model of (21). For example, if we impose the following restriction:

$$\theta = -\beta \rho, \tag{22}$$

and introduce it in the equation (21), we obtain:

$$\begin{aligned} y_t &= \rho W y_t + x_t \beta + W x_t (-\rho \beta) + \varepsilon_t, \\ (I_n - \rho W) y_t &= (I_n - \rho W) x_t \beta + \varepsilon_t, \\ y_t &= x_t \beta + (I_n - \rho W)^{-1} \varepsilon_t. \end{aligned} \tag{23}$$

The last equation (23) presents a similar specification of the spatial error model (19), changing the parameter ρ by λ . Then, it becomes easy to test if the *SDM* model (21) can be reduced to model (19). Knowing this, we

can apply a post-estimation Wald test or LR test of spatial common factor where the null hypothesis represents $H_0 : SEM$, restriction (22), and the alternative hypothesis, $H_1 : SDM$, equation (23).

The SLM is obtained imposing linear restrictions on SDM model: $\theta = 0$. The SLX model is equal to a SDM under the individual restriction of $\rho = 0$. Also, combining the usual panel data model (17) and the spatial Durbin model, we obtain the following core model:

$$y_t = \rho W y_t + x_t \beta + W x_t \theta + \mu + \eta_t \iota_n + \varepsilon_t,$$

which takes into account the individual heterogeneity in cross-section, the temporal effects and the spatial interdependence in a general form that can be reduced to other more simple spatial models.

Another alternative to the Spatial Durbin model is the Spatial Durbin Error Model, SDEM:

$$\begin{aligned} y_t &= x_t \beta + W x_t \theta + \mu + \eta_t \iota_n + u_t, \\ u_t &= \lambda W u_t + \varepsilon_t, \end{aligned}$$

The most General Nested Spatial model (GNS) includes the three different spatial effects ($W y_t$, $W x_t$ and $W u_t$). Empirical literature does not take the GNS model as point of departure due to the fact that its parameters are weakly identified (Vega and Elhorst, 2013). The selection has to be made between SDM and SDEM which are the most complex models in a spatial context (both models are not nested in one another).

Regarding specific effects, we include fixed effects as we are only concerned with a specific country (France) and because the dataset contains all units of population. As Beenstock and Felsenstein (2007, pp. 178) remark, ‘if the sample happens to be the population’, specific effects should be considered fixed since each observation represents itself and has not been sampled randomly. Also, Elhorst (2014, pp. 56) point out : ‘... the fixed effects model is generally more appropriate than the random effects model since spatial econometricians tend to work with space-time data of adjacent spatial units located in unbroken study areas, such as all counties of a state or all regions in a country’.

Usual fixed effects procedure in spatial models will yield biased estimates of some parameters. Lee and Yu (2010) analytically derive, dependent on n and T , the size of the bias and propose some corrections of the cross-sectional dependence among the observations at each point in time. We consider this correction in all the estimations presented in the next section.

The estimates that include a spatially lagged dependent variable as an explanatory variable, require an additional step to interpret the results. For example, some empirical studies that introduce spatial models use point estimates of one or more spatial variables to test the hypothesis about the importance of spillover effects. However, LeSage and Pace (2009) pointed out that this may lead to erroneous conclusions, and it is necessary to take into account the partial derivative of the impact from changes to the explanatory variables to interpret correctly the different model specifications.

Under a Spatial Durbin model, the relevance of spatial spillovers comes from to the presence of Wy and Wx as explanatory variables. By taking the expected value of the dependent variable,

$$E(y_t) = (I - \rho W y_t)^{-1} [x_t \beta + W x_t \theta], \quad (24)$$

the matrix of partial derivatives of $E(y_t)$ with respect to the $k - th$ explanatory variable of x_t in unit 1 up to unit n can be represented as:

$$\begin{aligned} \left[\begin{array}{ccc} \frac{\partial E y}{\partial x_{1k}} & \cdots & \frac{\partial E y}{\partial x_{nk}} \end{array} \right]_t &= \left[\begin{array}{ccc} \frac{\partial E y_1}{\partial x_{1k}} & \cdots & \frac{\partial E y_1}{\partial x_{nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial E y_n}{\partial x_{1k}} & \cdots & \frac{\partial E y_n}{\partial x_{nk}} \end{array} \right], \\ &= (I_n - \rho W)^{-1} \left[\begin{array}{ccc} \beta_k & \cdots & w_{1n} \theta_k \\ \vdots & \ddots & \vdots \\ w_{n1} \theta_k & \cdots & \beta_k \end{array} \right], \\ &= (I_n - \rho W)^{-1} [\beta_k I_n + \theta_k W], \end{aligned} \quad (25)$$

where w_{ij} is the $(i, j) - th$ element of W , β_k is the $k - th$ element of the vector β , and θ_k is the $k - th$ element of the vector θ , given a time t .

The expression in (25) is the total effect and it can be broken down into direct and indirect effects. The *direct effect* captures the effect in own region of the unit change in explanatory variable. Since this effect is particular to each region, LeSage and Pace (2009) propose to report this effect by the average of the diagonal elements of $(I_n - \rho W)^{-1} [\beta_k I_n]$. The *indirect effect*, known as spatial spillover, is reported as the average of the row sums of non-diagonal elements of the matrix $(I_n - \rho W)^{-1} [\theta_k W]$. The significance of these effects can be obtained using Monte Carlo simulation through random shocks on the error term.

Finally, we have two general ways to specify our final model. On the one hand, a usual way is to apply a sequential procedure, known as Specific-to-general modelling (*Stge*) or “bottom-up” approach: (1) estimate an initial model without spatially lagged variables, as model of equation (16); (2) test for spatial autocorrelation process and specific effects; (3) if the null hypothesis of no-autocorrelation is rejected, apply a remedial procedure including some or all spatial effects (the same step is applied respect to specific effects).

On the other hand, we start with a very general model that is over-parameterized, known as General-to-Specific modelling (*Gets*) (Hendry, 1979) or “top-down” approach. In the Hendry approach, the model is progressively simplified using a sequence of tests. In our case, this general model can be a SDM or a SDEM model. Mur and Angulo (2009) compare the performance of both approaches in spatial econometrics using Monte Carlo simulations with results quite diffuse (not finding conclusive evidence supporting one approach against the other), but *Gets* approach seems to be more robust to the existence of anomalies in the data generating process⁶.

⁶More details about the discussion between *Gets* and *Stge* in spatial econometrics can be found in Florax et al. (2003); Hendry (2006); Florax et al. (2006) and Mur and Angulo (2009).

6 Empirical Results

6.1 Descriptive statistics

As indicated in the summary statistics in Table 2, our dependent variable ($DERD$) measures the amount of R&D expenditure privately financed by firms (i.e. once all public subsidies and tax credit have been deduced) indexes by NUTS3 region and year. Explanatory variables are GDP , the amount of national subsidies ($SubNat$), European subsidies ($SubCEE$), regional subsidies ($SubReg$) and tax credit (TC) received by firms carrying on R&D in the corresponding NUTS3 region. For tax credit, we introduced a time lag of one year (LTC : for lagged TC).

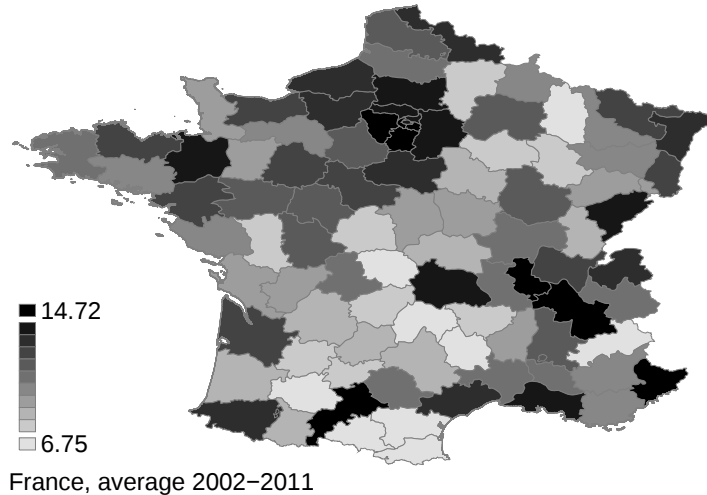
Table 2: Summary Statistics (pooled).

Variables	Obs.	Mean	S.D.	Min.	Max.
Dependent					
$\log(DERD)$	940	11.01	1.68	0.00	14.84
Explanatories					
$\log(GDP)$	940	16.29	0.88	14.08	19.04
$\log(LTC)$	940	8.50	1.93	0.00	13.23
$\log(SubNat)$	940	7.81	2.33	0.00	13.50
$\log(SubCEE)$	940	4.68	3.05	0.00	10.81
$\log(SubReg)$	940	4.31	2.65	0.00	10.38

Note: $\log(LTC)$ is the natural log of tax credit in the previous period, $\log(TC_{t-1})$.

Concerning the spatial structure of our dependent variable, we observe in Figure 5 a high concentration of R&D investment in a few number of NUTS3 regions which are rather dispersed on the territory and surrounded by NUTS3 regions where R&D investment is low.

Figure 5: Spatial distribution of Logarithm of private R&D.



Due to the main changes of the French tax credit policy in 2004 and 2008 we suspect the existence of structural change in our data following this two dates. This is why we consider 3 different periods in our data: the first covering the three first years from 2002 to 2004, the second from 2005 to 2008, while the third period goes from 2009 to 2011 (Table 3).

Table 3: Descriptive statistics by period.

Variables	Mean	S.D.	p25	Median	p75
<i>Period 2002-2004</i>					
$\log(Derd)$	10.89	1.70	9.69	10.99	12.09
$\log(GDP)$	16.18	0.87	15.58	16.20	16.72
$\log(LTC)$	7.29	1.74	6.12	7.43	8.49
$\log(SubNat)$	7.45	2.39	6.04	7.39	8.92
$\log(SubCEE)$	4.65	2.94	2.76	5.00	6.88
$\log(SubReg)$	3.30	2.56	0.00	3.77	5.34
<i>Period 2005-2008</i>					
$\log(Derd)$	11.07	1.63	9.97	11.12	12.22
$\log(GDP)$	16.31	0.88	15.72	16.33	16.87
$\log(LTC)$	8.43	1.65	7.33	8.52	9.55
$\log(SubNat)$	7.89	2.30	6.61	7.81	9.23
$\log(SubCEE)$	4.42	3.24	0.00	5.04	6.96
$\log(SubReg)$	4.41	2.72	2.52	5.01	6.39
<i>Period 2009-2011</i>					
$\log(Derd)$	11.03	1.72	9.95	11.10	12.19
$\log(GDP)$	16.37	0.90	15.77	16.38	16.87
$\log(LTC)$	9.80	1.61	8.74	9.89	10.92
$\log(SubNat)$	8.08	2.27	6.97	8.12	9.46
$\log(SubCEE)$	5.05	2.88	3.76	5.60	7.09
$\log(SubReg)$	5.21	2.29	4.01	5.66	6.81

6.2 Estimations of spatial models

Specification choice

Our empirical specification starts with a theory-consistent model and admissibly data⁷ as proposed by the Hendry approach. We use a general SDM⁸ with structural breaks in two periods:

$$\begin{aligned}
y_t = & \beta_{00} + \sum_{k=1}^5 \beta_{0k} x_{kt} + \Delta \beta_{10} + \sum_{k=1}^5 \beta_{1k} \Delta x_{kt} + \Delta \beta_{20} + \sum_{k=1}^5 \beta_{2k} \Delta x_{kt} \\
& + \sum_{k=1}^5 \theta_{0k} W x_{kt} + \sum_{k=1}^5 \theta_{1k} W \Delta x_{kt} + \sum_{k=1}^5 \theta_{2k} W \Delta x_{kt} + \rho W y_t + \mu + \eta_t \iota_n + \varepsilon_t,
\end{aligned} \tag{26}$$

where $y = \log(DERD)$, $x_1 = \log(GDP)$, $x_2 = \log(LTC)$, $x_3 = \log(SubNat)$, $x_4 = \log(SubCEE)$, $x_5 = \log(SubReg)$, with Δ as the change in the variable of period (2005-2008) or (2002-2004) with respect to period (2009-2011), considered as base period. The first subscript in coefficients identifies the period: 0 (2009-2011), 1 (2005-2008) and 2 (2002-2004). The spatial matrix was constructed using contiguity criterion.

The initial specification (26) is based on expression (15) provided by the theoretical model. We exclude the interaction effects in (26) because those effects are too highly correlated with non-spatial variables which would imply strong bias. In fact, this initial specification can be seen as a special case of the theoretical model

⁷We have run an exploratory analysis of data and applied the usual tests of stationarity, endogeneity and dependence in cross-section but also estimate a non-spatial fixed effect model. All results are presented in Tables of Appendix A.

⁸As we said in the methodology part of the paper, another alternative model is the SDEM. In Appendix B, we present the comparative results of SDM and SDEM for general and final specification.

developed in section 2 where the generalized CES part of MCC and MRR curves tend to a simple Cobb-Douglas part. Table 4 presents the results from the estimation of (26).

Table 4: Estimation of general Spatial Durbin model with regimes.

<i>Non-spatial coefficients</i>	<i>coef.</i>	<i>s.e.</i>	<i>t - test</i>
PERIOD 2009-2011			
$\log(GDP)$	0.180	0.410	0.44
$\log(LTC)$	-0.033	0.043	-0.76
$\log(SubNat)$	0.032	0.025	1.32
$\log(SubCEE)$	0.011	0.013	0.83
$\log(SubReg)$	0.004	0.013	0.27
PERIOD 2005-2008			
$\Delta \log(GDP)$	-0.169*	0.087	-1.93
$\Delta \log(LTC)$	0.073*	0.041	1.77
$\Delta \log(SubNat)$	0.008	0.039	0.19
$\Delta \log(SubCEE)$	0.003	0.015	0.17
$\Delta \log(SubReg)$	0.010	0.016	0.67
PERIOD 2002-2004			
$\Delta \log(GDP)$	-0.247***	0.081	-3.06
$\Delta \log(LTC)$	0.160***	0.029	5.55
$\Delta \log(SubNat)$	-0.003	0.024	-0.13
$\Delta \log(SubCEE)$	0.015	0.017	0.89
$\Delta \log(SubReg)$	-0.000	0.067	-0.03
<i>Spatial coefficients</i>	<i>coef.</i>	<i>s.e.</i>	<i>t - test</i>
PERIOD 2009-2011			
$W \times \log(GDP)$	1.111***	0.560	1.99
$W \times \log(LTC)$	-0.007	0.084	-0.09
$W \times \log(SubNat)$	0.033	0.055	0.61
$W \times \log(SubCEE)$	-0.024	0.022	-1.05
$W \times \log(SubReg)$	0.010	0.025	0.04
PERIOD 2005-2008			
$W \times \Delta \log(GDP)$	0.324**	0.147	2.20
$W \times \Delta \log(LTC)$	-0.144	0.091	-1.59
$W \times \Delta \log(SubNat)$	0.012	0.057	0.21
$W \times \Delta \log(SubCEE)$	0.006	0.027	0.21
$W \times \Delta \log(SubReg)$	-0.029	0.034	-0.84
PERIOD 2002-2004			
$W \times \Delta \log(GDP)$	0.340**	0.168	2.02
$W \times \Delta \log(LTC)$	-0.125	0.079	-1.59
$W \times \Delta \log(SubNat)$	-0.003	0.060	-0.06
$W \times \Delta \log(SubCEE)$	0.029	0.036	0.82
$W \times \Delta \log(SubReg)$	-0.045	0.030	-1.48
Fixed coefficients to all periods	<i>coef.</i>	<i>s.e.</i>	<i>t - test</i>
Spatial parameter ($\hat{\rho}$)	-0.117***	0.046	-2.56

Notes: Δ captures the increment of each period respect to period 2009-2011. *, ** and *** denotes significance at 10%, 5% and 1%.

Constant terms omitted. Estimation MLE-FE using xsmle (Belotti et al., 2014) with robust s.e. and Lee-Yu correction (Lee and Yu, 2010).

Note that we have detected potential outliers in the data and all estimations presented in this paper include dummies variables controlling for the influence of these observations. Obviously, this first specification is not optimal due to numerous non-significant coefficients. In order to select the most adequate specification, we apply a sequence of different restriction tests over general model to obtain a more parsimonious specification. Table 5 shows the results of different hypothesis tested. Concerning the modelling of the spatial effect, we find evidence in favor to SDM model and we reject SLM, SEM and SLX model (see the first three rows of Table 5).

Table 5: Summary of restriction hypothesis over SDM model.

Null Hypothesis	Wald test	Chi-sq (f.d.)	p-value	Selected model
<i>SLM</i> : $\theta_{0k} = 0, \theta_{1k} = 0, \theta_{2k} = 0,$ $\forall k = 1, \dots, 5.$	35.67	$\chi^2_{1-\alpha}(15)$	0.002	<i>Specification SDM,</i> <i>equation (26)</i>
<i>SEM</i> : $\theta_{0k} = -\rho\beta_{0k}, \theta_{1k} = -\rho\beta_{1k},$ $\theta_{2k} = -\rho\beta_{2k},$ $\forall k = 1, \dots, 5.$	36.67	$\chi^2_{1-\alpha}(15)$	0.001	<i>Specification SDM,</i> <i>equation (26)</i>
<i>SLX</i> : $\rho = 0$	6.53	$\chi^2_{1-\alpha}(1)$	0.011	<i>Specification SDM,</i> <i>equation (26)</i>
<i>Non structural breaks in all periods**</i> $\Delta\beta_{10} = 0, \Delta\beta_{20} = 0,$ $\beta_{1k} = 0, \beta_{2k} = 0,$ $\theta_{1k} = 0, \theta_{2k} = 0,$ $\forall k = 1, \dots, 5.$	82.30	$\chi^2_{1-\alpha}(21)^*$	0.000	<i>Specification SDM,</i> <i>equation (26)</i>
<i>Non structural breaks in variables**</i> $\Delta\beta_{10} = 0, \Delta\beta_{20} = 0$	0.02	$\chi^2_{1-\alpha}(1)^*$	0.876	<i>Non structural breaks</i> <i>in constant</i>
$\Delta\beta_{13} = 0, \Delta\beta_{23} = 0$ $\Delta\theta_{13} = 0, \Delta\theta_{23} = 0$	0.38	$\chi^2_{1-\alpha}(4)$	0.984	<i>Non structural breaks</i> <i>in log(SubNat)</i>
$\Delta\beta_{14} = 0, \Delta\beta_{24} = 0$ $\Delta\theta_{14} = 0, \Delta\theta_{24} = 0$	2.13	$\chi^2_{1-\alpha}(4)$	0.711	<i>Non structural breaks</i> <i>in log(SubCEE)</i>
$\Delta\beta_{15} = 0, \Delta\beta_{25} = 0$ $\Delta\theta_{15} = 0, \Delta\theta_{25} = 0$	3.18	$\chi^2_{1-\alpha}(4)$	0.528	<i>Non structural breaks</i> <i>in log(SubReg)</i>
$\Delta\beta_{11} = 0, \Delta\beta_{21} = 0$ $\Delta\theta_{11} = 0, \Delta\theta_{21} = 0$	10.36	$\chi^2_{1-\alpha}(4)$	0.035	<i>Structural breaks</i> <i>in log(GDP)</i>
$\Delta\beta_{12} = 0, \Delta\beta_{22} = 0$ $\Delta\theta_{12} = 0, \Delta\theta_{22} = 0$	38.00	$\chi^2_{1-\alpha}(4)$	0.000	<i>Structural breaks</i> <i>in log(LLTC)</i>

Notes: * one restriction omitted for redundant. ** We apply different paths to reduce the irrelevant structural breaks, in all cases we detect significant coefficients of GDP and LLTC.

The last two rows of Table 5 present the results of structural break test between periods. We detect a joint structural break when we consider all variables but when we test the presence of break for each variable individually, we only detect structural break in the effect of $\log(GDP)$ and $\log(LLTC)$. The effect of other explanatory variables does not show a significant variation between periods. We thus consider that the coefficients of these variables are stable in the model within all periods. Information from Table 5 lead us to propose the following final specification:

$$\begin{aligned}
y_t = & constant + \beta_{01} \log(GDP) + \beta_{02} \log(LLTC) + \beta_{11} \Delta \log(GDP) + \beta_{12} \Delta \log(LLTC) \\
& + \beta_{21} \Delta \log(GDP) + \beta_{22} \Delta \log(LLTC) + \theta_{01} W \log(GDP) + \theta_{02} W \log(LLTC) \\
& + \theta_{11} W \Delta \log(GDP) + \theta_{12} W \Delta \log(LLTC) + \theta_{21} W \Delta \log(GDP) + \theta_{22} W \Delta \log(LLTC) \\
& + \beta_3 \log(SubNat) + \beta_4 \log(SubCEE) + \beta_5 \log(SubReg) + \theta_3 W \log(GDP) + \theta_4 W \log(LLTC) \\
& + \theta_5 W \Delta \log(GDP) + \rho W y_t + \mu + \eta_t \epsilon_n + \epsilon_t,
\end{aligned} \tag{27}$$

Structural breaks and spatial dependence

Table 6 presents the estimation of model (27). Note that due to the spatial component, the value of coefficients presented in Table 6 should not be interpreted directly, marginal effects will be presented in table 7 in the next paragraph. Nevertheless, one important result emerge from Table 6. Indeed, the spatial parameter (ρ) is negative and strongly significant. This clearly suggests the presence of a negative spatial dependence. Most of empirical works using spatial data highlight a positive spatial correlation between units, that is, the presence of positive spatial spillovers. Concerning R&D investment, very few study take into account the spatial dependence of R&D investment.

Table 6: Estimation of selected Spatial Durbin model with regimes.

<i>Non-spatial coefficients</i>	<i>coef.</i>	<i>s.e.</i>	<i>t – test</i>
PERIOD 2009-2011			
$\log(GDP)$	0.130	0.387	0.33
$\log(LTC)$	-0.036	0.044	-0.81
PERIOD 2005-2008			
$\Delta \log(GDP)$	-0.117	0.076	-1.54
$\Delta \log(LTC)$	0.075**	0.033	2.27
PERIOD 2002-2004			
$\Delta \log(GDP)$	-0.204***	0.065	-3.14
$\Delta \log(LTC)$	0.162***	0.027	5.98
<i>Spatial coefficients</i>	<i>coef.</i>	<i>s.e.</i>	<i>t – test</i>
PERIOD 2009-2011			
$W \times \log(GDP)$	1.244***	0.470	2.65
$W \times \log(LTC)$	-0.048	0.078	-0.61
PERIOD 2005-2008			
$W \times \Delta \log(GDP)$	0.231*	0.131	1.77
$W \times \Delta \log(LTC)$	-0.103	0.082	-1.26
PERIOD 2002-2004			
$W \times \Delta \log(GDP)$	0.258*	0.145	1.78
$W \times \Delta \log(LTC)$	-0.075	0.072	-1.05
<i>Fixed coefficients to all periods</i>	<i>coef.</i>	<i>s.e.</i>	<i>t – test</i>
$\log(SubNat)$	0.035*	0.018	1.93
$\log(SubCEE)$	0.016**	0.007	2.36
$\log(SubReg)$	0.008	0.007	1.18
$W \times \log(SubNat)$	0.038*	0.021	1.79
$W \times \log(SubCEE)$	-0.013	0.012	-1.05
$W \times \log(SubReg)$	-0.019	0.013	-1.47
<i>Spatial parameter ($\hat{\rho}$)</i>	-0.115***	0.047	-2.45

Notes: Δ captures the increment of each period respect to period 2009-2011. *, ** and *** denotes significance at 10%, 5% and 1%.

Constant term omitted. Estimation MLE-FE using xsmle (Belotti et al., 2014) with robust s.e. and Lee-Yu correction (Lee and Yu, 2010).

The most recent work of Montmartin and Herrera (2015), based on aggregated national data of 25 OECD countries, highlights a positive spatial dependence of private R&D investment.

As shown in the literature review, contradictory results obtained concerning the in-state and out-of state effects of local (states) R&D tax credit lead us to think that the spatial dependence of R&D investment could be far different within a country and between countries⁹.

⁹Different researchers show that the level of aggregation data have an important impact on the value of spatial coefficients. This problem is related to the modifiable areal unit problem (MAUP) i.e change of spatial support and ecological fallacy (zoning problem in spatial literature, Openshaw, 1977). These problems highlight the fact that econometric results are not comparable if the level of aggregation is different. More details in Gotway and Young (2002) and Wrigley (1995).

If we look at Table 6, our data are in line with evidence on in-state evaluations (Wilson 2009) as our estimates show a strong negative spatial dependence between NUTS3 private R&D investment in France. In other words, the private R&D investment in a given NUTS3 French region is negatively affected by the level of private R&D investment of its neighbors. This seems to validate the hypothesis of a yardstick competition between French NUTS3 regions for R&D investment.

Table 6 also highlights the presence of different regimes in our data, i.e, different reactions of the NUTS3 R&D expenditures according to the period considered. The structural breaks are related to two variables, namely, the GDP and the level of Tax Credit. This is not a surprising result. Indeed, the French economy dynamics has been strongly affected by the 2008 financial crisis and the French R&D policy-mix has greatly evolved during the period of study and especially in 2004 and 2008 where two important reforms of the French R&D tax credit were made. These two elements are likely to change the behavior of R&D firms which explains our choice to evaluate the presence of two breaks in our data around years (2004-2005) and (2008-2009).

Table 6 shows that Tax Credit and GDP do not play the same roles on structural breaks. Indeed, the structural breaks observed are only related to the in-region level of tax credit whereas they are related to both in-region and out-of-region level of GDP.

Looking at estimated changes in coefficient values for 2002-2004 and 2005-2008 period (using 2009-2011 as base) in Table 6, we observe that the coefficient change for the in-state level of tax credit is positive and strongly significant. The change is estimated to be 0.075 for period 2005-2008 (compared to the base) and 0.162 for period 2002-2004, showing a rather important reduction of the capacity of Tax Credit to foster private R&D investment associated with the shift to a volume scheme. This highlights a stronger change in terms of behavior between the base and 2002-2005 than between the base and the 2005-2008 period. This is clearly understandable because in 2002, the French Tax credit was only incremental while after 2008, it turns exclusively to volume.

Concerning the GDP, our results suggest a negative and significant coefficient change for the in-state level of GDP and a positive and significant coefficient change for the out-state level of GDP. Looking at estimated changes in coefficient values in Table 6, we see that the coefficient change for the in-state level of GDP is estimated to be -0.117 for period 2005-2008 (non significant) and -0.204 for period 2002-2004 (significant). This highlights a stronger change in terms of behavior between the base and 2002-2004 than between the base and the 2005-2008 period. The coefficient change for the out-state level of GDP is estimated to be 0.231 for period 2005-2008 and 0.258 for period 2002-2004. Thus it seems that the change in the investment behavior comes more from global GDP dynamics rather than local GDP dynamics.

Marginal effects

In order to provide clearly interpretative results from our estimates, we need to include into the analysis the spatial effects of all variables. Table 7 presents the estimated marginal direct and indirect effects of our five main variables (see Section 5 for details).

Table 7: Marginal Effects of Spatial Durbin model with regimes.

VARIABLE	PERIOD		
	2002-2004	2005-2008	2009-2011
<i>Direct effects</i>			
$\log(GDP)$	-0.107	-0.020	0.103
$\log(LTC)$	0.129**	0.045	-0.035
$\log(SubNat)$	0.034*	0.034*	0.034*
$\log(SubCEE)$	0.017**	0.017**	0.017**
$\log(SubReg)$	0.008	0.008	0.008
<i>Indirect effects</i>			
$\log(GDP)$	1.390***	1.354***	1.125***
$\log(LTC)$	-0.126*	-0.143**	-0.037
$\log(SubNat)$	0.031	0.031	0.031
$\log(SubCEE)$	-0.014	-0.014	-0.014
$\log(SubReg)$	-0.018	-0.018	-0.018
<i>Total effects</i>			
$\log(GDP)$	1.282***	1.333***	1.228***
$\log(LTC)$	0.004	-0.098	-0.071
$\log(SubNat)$	0.065***	0.065***	0.065***
$\log(SubCEE)$	0.003	0.003	0.003
$\log(SubReg)$	-0.010	-0.010	-0.010

Note: *, ** and *** denotes significance at 10%, 5% and 1%. Estimation MLE-FE with robust s.e. and Lee-Yu correction (Lee and Yu, 2010) using xsmle (Belotti et al., 2014), no. simulations=999.

In terms of total effect, two main variables significantly influence the private investment in R&D in all period, namely, the level of GDP and the level of national subsidies. Both have a positive and significant effect. We estimate that an increase of 1% of the GDP in all NUTS3 region increases the privately-financed R&D investment of approximately 1,3%¹⁰. Note that this effect of the GDP is relatively stable over time and seems to highlight a leverage effect of GDP on R&D investment. Table 7 also shows that the effect of GDP is largely due to the significant positive indirect effect. Indeed, the direct effect of GDP is never significant and appears small in magnitude compared to the indirect effect. This clearly highlights that within France, privately-financed R&D investment in one specific NUTS3 is more dependent on macroeconomic conditions than on local conditions.

We estimate that an increase of 1% of the national subsidies in all NUTS3 region generates a 0,065% increase in privately-financed R&D investment. In other words, we find evidence of a stable leverage effect of national subsidies. Table 7 also shows that the total effect of national subsidies is mainly due to the significant positive direct effect. The indirect effect of subsidies is never significant even if it is similar in magnitude to the direct effect. Consequently, it seems that the leverage effect of national subsidies is more related to the target choice (direct effect) than to the spatial-spillovers effect. It is interesting to see that national subsidies are the only instrument (on the four that have been studied) that generates a positive indirect effect. Said differently, this is the only policy that generates positive spatial spillovers in a context of yardstick competition between NUTS3 regions. On the whole, these results confirm numerous studies showing the additionality of direct subsidies (Guellec and Van Pottelsberghe de la Potterie, 2003).

¹⁰However, the test of an elasticity equal to one is not rejected for the three periods.

For the other variables, we do not find any significant influence over our period. Nevertheless, some important elements emerge when looking at Table 7. First, if the total effect of the French Tax Credit system is insignificant, it is the result of some significant direct and indirect effects. More precisely, during the first period (2002-2004), we estimate that an increase of Tax credit of 1% in region i increases by 0,13% the private R&D investment in that region. Still, at the same time, we estimate that an increase of Tax credit of 1% in all other regions decreases by 0,13% the private R&D investment in region i . Consequently, if the government increases of 1% the level of tax credit in all regions, then it will have a total effect near zero because the positive direct effect of the policy is completely annihilated by its negative indirect effect. During the second period (after the reform of 2004), the direct effect decreases in magnitude and becomes insignificant whereas the indirect effect increases and is still significant. In other words, it seems that the reform of 2004 has decreased the positive direct effect of the French Tax Credit and increased its negative indirect effect. Nevertheless, this change has not been strong enough to generate a significant crowding-out effect (the total effect is negative but insignificant). Finally, in the last period (after the reform of 2008), the direct effect decreases again in magnitude, becomes negative but still is insignificant while the indirect effect decreases and becomes insignificant. It seems that the 2008 reform has decreased the positive direct effect of the French Tax Credit but also its negative indirect effect. In total, these changes have not generated significant results for the period 2008-2011. Based on evidence of structural change, we can nevertheless assume that potential windfall effects of the 2004 and 2008 reforms take time to appear in data.

Concerning the European subsidies, Table 7 shows that such policy generated significant positive direct effect but also negative indirect effect. Indeed, we estimate that a 1% increase in European subsidies in region i increases the private R&D investment of 0,017% in that region. Nevertheless, we also estimate that a 1% increase in the European subsidies in all other regions decreases the private R&D investment of 0,014% in region i . In total, the effect of European subsidies is not significant. European subsidies can be seen as useful in the sense that they are able to generate a leverage direct effect for a targeted region (if others regions are not subsidized). In some sense, it suggests that a more concentrated allocation of European subsidies could improve their total effect. For the regional subsidies, our estimation suggests that this kind of support does not significantly influence the private R&D investment. It is important to note here that this does not mean that regional subsidies are useless. They can have specific local impacts that compensate each other and then results in no significant average effects. Even though they are not significant, it is also worth noting that direct effects of local subsidies always have a positive sign whereas competition between region results in negative indirect effects.

All of these results highlight the importance of spatial or indirect effects on the whole influence of policies. As a negative spatial dependence appears between NUTS3 French regions, we find evidence of a spatial substitutability effect for most of public policies except for national R&D subsidies where a spatial complementarity appears. This induces that other policies are not able to generate a global leverage effect. From a policy-mix perspective, our results suggest a mixed efficiency: one instrument is able to generate a global leverage effect whatever the regimes, the others do not generate significant crowding-out effects.

7 Conclusion

The French policy-mix for R&D and innovation is one of the most generous and market-friendly system in the world especially since the 2008 reform of French R&D Tax credit. This is also probably the policy-mix for R&D and innovation that has faced the most important changes during the last decade. The main objective of this paper has been to investigate the effect of the French policy-mix by using a unique database that covers all French metropolitan NUTS3 regions over the period 2001-2011. Information concerning the amount of R&D tax credit but also the amount of regional, national and European subsidies received by firms in each region have been mobilized. To our knowledge, this is the first study that proposes an evaluation of a policy-mix (four different instruments) at this geographical level.

In order to better base our empirical approach, we first developed a simple theoretical model based on Howe and McFetridge (1976). This allowed us to highlight the conditions under which a R&D policy leads to a leverage or a crowding-out on private R&D investment. Thus, this framework provided a basis to explain contrasting empirical results. Thanks to its simplicity, we extended the model by integrating the existence of spatial interaction between regions. The specifications tested in this paper are directly related to this spatial version of the model. More precisely, we estimated a Spatial Durbin model with regimes and fixed effects which allowed us to take into account the spatial dependence that exists between NUTS3 regions but also the potential structural change on the considered period.

The empirical results obtained provide interesting elements on the French policy-mix for R&D and innovation. First, the assumption of a yardstick competition between NUTS3 regions in France has been validated. Indeed, we found a negative spatial dependence between private R&D investment in NUTS3 regions which is strongly significant whatever the specification retained. Second, the national subsidies is the only instrument which generates a significant leverage effect on the privately-financed R&D. Nevertheless, the three other policies (tax credit, regional and European subsidies) do not generate significant crowding-out effect. This last result is clearly due to the existence of antagonistic effects of these policies: a positive direct effect counterbalances a negative indirect effect related to the yardstick competition. Third, the macroeconomic condition of the country as a whole is a crucial factor that generates leverage effect on privately-financed R&D. Indeed, we estimate that an increase of 1% of GDP in all NUTS3 regions in France will increase the privately-financed R&D by 1.3%. Finally, we found structural breaks in our data that correspond to the last two important reforms of the French tax credit. Even though the influence of tax credit on private R&D is not significant over the whole period, the estimated coefficient significantly changes for the two later period showing that the 2004 and 2008 reforms seem to have contributed to the development of potential future windfall effects.

Most of these results, in terms of additionality, are in line with those previously obtained at micro and macro level but add to previous interpretation by highlighting essential phenomena of structural change and spatial dependence that have not been analyzed so far. Many other works at this geographical level using spatial econometric method are needed especially on the French case. For instance, in this paper, we have assumed that the spatial dependence between NUTS3 regions is global. Looking at Figure 5 which represents

the geography of R&D investment in French NUTS3 regions, it seems that the spatial dependence is not uniform. Spatial Econometric methods dealing with local spatial dependence (as Geographically Weighted Regression) could provide finer results on the effect of policy-mix but also on the characteristics of the existing yardstick competition between NUTS3 regions.

Acknowledgments

This work is part of the project RENEWAL funded by the ANR, French National Research Agency. We wish to thank the National Council for Statistical Information for allowing us using the data from the French R&D Survey and Frédérique Sachwald for the data on Tax Credit. A particular mention to Marylin Rosa for her work on Tax Credit data and Sylvie Chalaye (EuroLIO) for helping us processing R&D data. We also wish to express our thank to the participants in the RENEWAL/ANR project for the discussion we had on the previous version of this paper.

Appendix A: Design of R&D tax credit and preliminary checks

Table A.1: Design of the R&D Tax Credit in France 1983-2013.

Design of tax credit	Year of reform	Formula of research tax credit	Maximum amount (in million euros)
Incremental	1983	$0.25 * [RD(t) - RD(t-1)]$	€0.4 M.
	1985	$0.50 * [RD(t) - RD(t-1)]$	€0.7 M.
	1988	$0.50 * [RD(t) - RD(t-1)]$ $0.30 * [RD(t) - RD(1987)]$	€1.5 M.
	1991	$0.50 * \left[RD(t) - \left[\frac{RD(t-1) + RD(t-2)}{2} \right] \right]$	€6.10 M.
Mixed incremental and in volume	2004	$0.45 * [RD(t) - RD(t-1)] + 0.05 * RD(t)$	€8 M.
	2006	$0.40 * [RD(t) - RD(t-1)] + 0.10 * RD(t)$	€10 M.
	2007	$0.45 * [RD(t) - RD(t-1)] + 0.10 * RD(t)$	€16 M.
In volume	2008	$0.30 * RD(t)$, if $RD(t) \leq 100$ M €	—
		$30 + 0.05 * [RD(t) - 100]$, if $RD(t) > 100$ M €	
		$0.50 * RD(t)$ if first year in tax credit scheme	
		$0.40 * RD(t)$ if second year in tax credit scheme	
	2011	$0.30 * RD(t)$, if $RD(t) \leq 100$ M €	—
		$30 + 0.05 * [RD(t) - 100]$, if $RD(t) > 100$ M €	
		$0.40 * RD(t)$ if first year in tax credit scheme	
		$0.35 * RD(t)$ if second year in tax credit scheme	
	2013	$0.30 * RD(t)$, if $RD(t) \leq 100$ M €	—
		$30 + 0.05 * [RD(t) - 100]$, if $RD(t) > 100$ M €	
		20% innovation expenditures (for SMEs only)	€0.4 M.

Note: $RD(t)$ is the amount of R&D in year t .

Source: Bozio et al. (2014).

We present previous checking test in Table A.2, A.3 and A.4. These tests are based on univariate results and on non-spatial panel models. Table A.2 shows the common tests for unit roots in heterogeneous panel data. As we can see, all tests reject the null hypothesis of unit root in $\log(DERD)$ and explanatory variables.

Table A.2: Unit Root Test to Dependent variable.

Method		$H_0 : I(1)$ $H_1 : I(0)$	Conclusion	
Unit root specific for each region		Statistic	p-value	
$\log(DERD)$	Harris-Tzavalis test*	-0.30	0.00	$I(0)$
	IPS Z-t-tilde-bar	-2.88	0.00	$I(0)$
	Pesaran's CADF test	-9.25	0.00	$I(0)$
$\log(GDP)$	Harris-Tzavalis test*	-0.31	0.03	$I(0)$
	IPS Z-t-tilde-bar	-2.88	0.00	$I(0)$
	Pesaran's CADF test	-5.53	0.00	$I(0)$
$\log(LLTC)$	Harris-Tzavalis test*	-0.13	0.00	$I(0)$
	IPS Z-t-tilde-bar	-9.43	0.00	$I(0)$
	Pesaran's CADF test	-5.76	0.00	$I(0)$
$\log(SubNat)$	Harris-Tzavalis test*	-0.04	0.00	$I(0)$
	IPS Z-t-tilde-bar	-9.60	0.00	$I(0)$
	Pesaran's CADF test	-3.76	0.00	$I(0)$
$\log(SubCEE)$	Harris-Tzavalis test*	-0.15	0.00	$I(0)$
	IPS Z-t-tilde-bar	-8.96	0.00	$I(0)$
	Pesaran's CADF test	-2.51	0.04	$I(0)$
$\log(SubReg)$	Harris-Tzavalis test*	-0.09	0.00	$I(0)$
	IPS Z-t-tilde-bar	-10.20	0.00	$I(0)$
	Pesaran's CADF test	-9.61	0.00	$I(0)$

Notes: IPS (Im, Pesaran and Shin, 2003). For Pesaran (2007) test we report the standardized Z-tbar statistic and its p-value. The tests to $H_0 : I(1)$ included a constant and trend. *: HT test assumes common unit root in panel.

Table A.3: Average Cross-section Correlation.

Variable	CD-Test		abs (corr.)
	Statistic	p-value	
$\log(DERD)$	35.70	0.000	0.359
<i>residuals</i>	3.37	0.001	0.315

Note: The results are based on CD test (Pesaran, 2004).

Table A.4: Endogeneity tests.

Variable	C test	
	Statistic	p-value
$\log(GDP)$	0.418	0.518
$\log(LTC)$	2.513	0.113
$\log(SubNat)$	1.236	0.266
$\log(SubCEE)$	0.337	0.561
$\log(SubReg)$	1.293	0.255

Note: The results are based on the difference between Sargan-Hansen tests.

Table A.4 shows the test of cross-section independence of dependent variables and the residuals. Residuals were obtained of fixed effects model without spatial effects using the five explanatory variables.

Appendix B: Robustness check

Table B.1 shows the estimation of two non-nested models, SDM and SDEM.

Table B.1: Estimation of general model with regimes. SDM and SDEM.

Alternative Models	SDM	SDEM
<i>Non-spatial coefficients</i>	<i>coef.</i>	<i>coef.</i>
PERIOD 2009-2011		
$\log(GDP)$	0.180	0.100
$\log(LTC)$	-0.033	-0.028
$\log(SubNat)$	0.032	0.033
$\log(SubCEE)$	0.011	0.012
$\log(SubReg)$	0.004	0.004
PERIOD 2005-2008		
$\Delta \log(GDP)$	-0.169*	-0.152*
$\Delta \log(LTC)$	0.073*	0.068*
$\Delta \log(SubNat)$	0.008	0.006
$\Delta \log(SubCEE)$	0.003	0.002
$\Delta \log(SubReg)$	0.010	0.010
PERIOD 2002-2004		
$\Delta \log(GDP)$	-0.247***	-0.227***
$\Delta \log(LTC)$	0.160***	0.154***
$\Delta \log(SubNat)$	-0.003	-0.006
$\Delta \log(SubCEE)$	0.015	0.015
$\Delta \log(SubReg)$	-0.000	0.000
<i>Spatial coefficients</i>		
PERIOD 2009-2011		
$W \times \log(GDP)$	1.111***	1.007*
$W \times \log(LTC)$	-0.007	-0.044
$W \times \log(SubNat)$	0.033	0.038
$W \times \log(SubCEE)$	-0.024	-0.023
$W \times \log(SubReg)$	0.010	0.002
PERIOD 2005-2008		
$W \times \Delta \log(GDP)$	0.324**	0.275*
$W \times \Delta \log(LTC)$	-0.144	-0.109
$W \times \Delta \log(SubNat)$	0.012	-0.005
$W \times \Delta \log(SubCEE)$	0.006	0.007
$W \times \Delta \log(SubReg)$	-0.029	-0.022
PERIOD 2002-2004		
$W \times \Delta \log(GDP)$	0.340**	0.286*
$W \times \Delta \log(LTC)$	-0.125	-0.081
$W \times \Delta \log(SubNat)$	-0.003	-0.021
$W \times \Delta \log(SubCEE)$	0.029	0.023
$W \times \Delta \log(SubReg)$	-0.045	-0.036
<i>Fixed coefficients to all periods</i>		
<i>Spatial parameter ($\hat{\rho}$)</i>	-0.117***	
<i>Spatial parameter ($\hat{\lambda}$)</i>		-0.070*
<i>Information Criteria</i>		
<i>AIC</i>	360.367	366.019
<i>BIC</i>	554.728	565.121

Notes: Δ captures the increment of each period respect to period 2009-2011. *, ** and *** denotes significance at 10%, 5% and 1%. W contiguity.

Constant terms omitted. Estimation MLE-FE using xsmle (Belotti et al., 2014) with robust s.e. and Lee-Yu correction (Lee and Yu, 2010).

The estimations of SDEM and SDM obtain similar values, and significance, for almost all coefficients. In both cases the estimated spatial coefficient, $\hat{\rho}$ and $\hat{\lambda}$, is negative and significant. Looking at the results of general specification model, the information criteria gives us a preference in favor of SDM.

Applying a similar procedure of Table 6, we obtain the same final specification using SDEM or SDM. The estimation of this model under SDEM and SDM is compared in Table B.2.

Table B.2: Comparison between SDM and SDEM. Final specification.

Alternative Models	SDM	SDEM
<i>Non-spatial coefficients</i>	<i>coef.</i>	<i>coef.</i>
PERIOD 2009-2011		
$\log(GDP)$	0.130	0.088
$\log(LTC)$	-0.036	-0.035
PERIOD 2005-2008		
$\Delta \log(GDP)$	-0.117	-0.124
$\Delta \log(LTC)$	0.075**	0.078**
PERIOD 2002-2004		
$\Delta \log(GDP)$	-0.204***	-0.213***
$\Delta \log(LTC)$	0.162***	0.164***
<i>Spatial coefficients</i>		
PERIOD 2009-2011		
$W \times \log(GDP)$	1.244***	1.152***
$W \times \log(LTC)$	-0.048	-0.033
PERIOD 2005-2008		
$W \times \Delta \log(GDP)$	0.231*	0.249*
$W \times \Delta \log(LTC)$	-0.103	-0.113
PERIOD 2002-2004		
$W \times \Delta \log(GDP)$	0.258*	0.284*
$W \times \Delta \log(LTC)$	-0.075	-0.096
<i>Fixed coefficients to all periods</i>		
$\log(SubNat)$	0.035*	0.034
$\log(SubCEE)$	0.016**	0.017**
$\log(SubReg)$	0.008	0.008
$W \times \log(SubNat)$	0.038*	0.028
$W \times \log(SubCEE)$	-0.013	-0.014
$W \times \log(SubReg)$	-0.019	-0.019
<i>Spatial parameter</i> $(\hat{\rho})$	-0.115***	
<i>Spatial parameter</i> $(\hat{\lambda})$		-0.063
<i>Information Criteria</i>		
<i>AIC</i>	339.559	345.905
<i>BIC</i>	477.034	488.120

Notes: Δ captures the increment of each period respect to period 2009-2011. *, ** and *** denotes significance at 10%, 5% and 1%. W contiguity. Constant term omitted. Estimation MLE-FE using xsmle (Belotti et al., 2014) with robust s.e. and Lee-Yu correction (Lee and Yu, 2010)-

The selection between SDEM and SDM is difficult due an identification problem. As mentioned by Gibbons and Overman (2012, pp. 178), “only the overall effect of neighbors’ characteristics is identified, not whether they work through exogenous or endogenous neighborhood effects”. However, in our empirical case, the difference between both models is clear: SDM shows a significant coefficient of spatial endogenous effect and, in the SDEM, the spatial coefficient is not significant. Also, the AIC and BIC select the SDM model.

Also, we check the robustness of final model using a different criterion of neighbors but with similar characteristics in terms of connectivity.*** Table B.3 shows the information of contiguity matrix used in the text and the alternative weighting matrix based on the 5 nearest neighbors.

Table B.3: Comparison between spatial weighting matrix.

MATRIX INFORMATION	CONTIGUITY	5 NEAREST NEIGHBOURS
<i>Number of regions</i>	94	94
<i>Number of nonzero links</i>	480	470
<i>Min. number of neighbors</i>	2	5
<i>Mean of neighbors</i>	5.11	5
<i>Max. number of neighbors</i>	10	5
<i>Percentage non zero weights</i>	5.43	5.32

Table B.4 presents the main information of estimation using contiguity and the 5-nearest neighbors. The results are similar in terms of spatial autocorrelation, negative and significant in both cases, with a better adjustment under contiguity. With respect to marginal effects, $\log(GDP)$ and $\log(SubNat)$ are significant in both cases, with a lower coefficient of $\log(GDP)$ using the 5-nearest neighbors but the statistical test of equal unity is not rejected, similar to the estimate of contiguity model.

Table B.4: SDM model estimates and marginal effects using different weighting matrices.

SPATIAL MATRIX		CONTIGUITY		5 NEAREST NEIGHBOURS		
Spatial parameter ($\hat{\rho}$)		−0.115**		−0.084*		
Information Criteria						
AIC		339.559		348.962		
BIC		477.034		486.437		
VARIABLE	2002-2004	2005-2008	2009-2011	2002-2004	2005-2008	2009-2011
Direct effects						
log(<i>GDP</i>)	−0.107	−0.020	0.103	−0.032	0.059	0.167
log(<i>LTC</i>)	0.129**	0.045	−0.035	0.127**	0.046	−0.028
log(<i>SubNat</i>)	0.034*	0.034*	0.034*	0.034*	0.034*	0.034*
log(<i>SubCEE</i>)	0.017**	0.017**	0.017**	0.018**	0.018**	0.018**
log(<i>SubReg</i>)	0.008	0.008	0.008	0.009	0.009	0.009
Indirect effects						
log(<i>GDP</i>)	1.390***	1.354***	1.125***	0.869***	0.811***	0.660*
log(<i>LTC</i>)	−0.126*	−0.143**	−0.037	−0.103	−0.117**	−0.033
log(<i>SubNat</i>)	0.031	0.031	0.031	0.042**	0.042**	0.042**
log(<i>SubCEE</i>)	−0.014	−0.014	−0.014	−0.013	−0.013	−0.013
log(<i>SubReg</i>)	−0.018	−0.018	−0.018	−0.009	−0.009	−0.009
Total effects						
log(<i>GDP</i>)	1.282***	1.333***	1.228***	0.837*	0.870*	0.827*
log(<i>LTC</i>)	0.004	−0.098	−0.071	0.024	−0.071	−0.061
log(<i>SubNat</i>)	0.065***	0.065***	0.065***	0.076***	0.076***	0.076***
log(<i>SubCEE</i>)	0.003	0.003	0.003	0.004	0.004	0.004
log(<i>SubReg</i>)	−0.010	−0.010	−0.010	−0.000	−0.000	−0.000

Note: *, ** and *** denotes significance at 10%, 5% and 1%. Estimation MLE-FE with robust s.e. and Lee-Yu correction (Lee and Yu, 2010) using xsmle (Belotti et al., 2014), no. simulations=999.

References

- Anselin, L. (1988). *Spatial econometrics: Methods and models*, Volume 4. Kluwer Academic Publishers, Dordrecht.
- Autant-Bernard, C., M. Fadaïro, and N. Massard (2013). Knowledge diffusion and innovation policies within the European regions: Challenges based on recent empirical evidence. *Research Policy* 42(1), 196–210.

- Beenstock, M. and D. Felsenstein (2007). Spatial vector autoregressions. *Spatial Economic Analysis* 2(2), 167–196.
- Bellego, C. and V. Dortet-Bernadet (2013). The French cluster policy and the R&D spending of SME and intermediate-sized enterprises. Technical report, Institut National de la Statistique et des Études Économiques.
- Bellego, C. and V. Dortet-Bernadet (2014, October). The impact of participation in competitiveness clusters on SMEs and intermediate enterprises. *Economie & Statistique* 471, 65–83.
- Belotti, F., G. Hughes, and A. P. Mortari (2014). XSMLE: Stata module for spatial panel data models estimation. *Statistical Software Components*.
- Bérubé, C. and P. Mohnen (2009). Are firms that receive R&D subsidies more innovative? *Canadian Journal of Economics/Revue canadienne d'économie* 42(1), 206–225.
- Bozio, A., D. Irac, and L. Py (2014). Impact of research tax credit on R&D and innovation: evidence from the 2008 French reform. *Banque de France Working Paper*.
- Brossard, O. and I. Moussa (2014). The French cluster policy put to the test with differences-in-differences estimates. *Economics Bulletin* 34(1), 520–529.
- Busom, I., B. Corchuelo, and E. Martínez-Ros (2014). Tax incentives... or subsidies for business R&D? *Small Business Economics* 43(3), 571–596.
- Corchuelo, B. and E. Martínez-Ros (2009). The effects of fiscal incentives for R&D in Spain. *Business Economic Series. Universidad Carlos III de Madrid. Departamento de Economía de la Empresa* 09-23.
- David, P. A., B. H. Hall, and A. A. Toole (2000). Is public R&D a complement or substitute for private R&D? A review of the econometric evidence. *Research Policy* 29(4), 497–529.
- Duguet, E. (2012). The effect of the incremental R&D tax credit on the private funding of R&D an econometric evaluation on French firm level data. *Revue d'économie politique* 122(3), 405–435.
- Dumont, M. (2013). The impact of subsidies and fiscal incentives on corporate R&D expenditures in Belgium (2001-2009). *Reflets et perspectives de la vie économique* 1, 69–91.
- Elhorst, J. P. (2014). Matlab software for spatial panels. *International Regional Science Review* 37(3), 389–405.
- European Commission (2014). A study on r&d tax incentives final report. *Taxation Papers, Working Paper* (52).
- Falck, O., S. Heblich, and S. Kipar (2010). Industrial innovation: Direct evidence from a cluster-oriented policy. *Regional Science and Urban Economics* 40(6), 574–582.
- Florax, R. J., H. Folmer, and S. J. Rey (2003). Specification searches in spatial econometrics: the relevance of Hendry's methodology. *Regional Science and Urban Economics* 33(5), 557–579.

- Florax, R. J., H. Folmer, and S. J. Rey (2006). A comment on specification searches in spatial econometrics: The relevance of hendry's methodology: a reply. *Regional Science and Urban Economics* 36(2), 300–308.
- García-Quevedo, J. (2004). Do public subsidies complement business R&D? A meta-analysis of the econometric evidence. *Kyklos* 57(1), 87–102.
- Gibbons, S. and H. G. Overman (2012). Mostly pointless spatial econometrics? *Journal of Regional Science* 52(2), 172–191.
- Gotway, C. A. and L. J. Young (2002). Combining incompatible spatial data. *Journal of the American Statistical Association* 97(458), 632–648.
- Guellec, D. and B. Van Pottelsberghe de la Potterie (1997). Does government support stimulate private R&D? *OECD economic studies* 29, 95–122.
- Guellec, D. and B. Van Pottelsberghe de la Potterie (2003). The impact of public R&D expenditure on business R&D. *Economics of innovation and new technology* 12(3), 225–243.
- Hendry, D. F. (1979). Predictive failure and econometric modelling in macroeconomics: The transactions demand for money. In P. Ormerod (Ed.), *Economic Modelling: Current Issues and Problems in Macroeconomic Modelling in the UK and the US*, Chapter 9, pp. 217–242. Heinemann Education Books, London.
- Hendry, D. F. (2006). A comment on §specification searches in spatial econometrics: The relevance of hendry's methodology. *Regional Science and Urban Economics* 36(2), 309–312.
- Hoff, A. (2004). The linear approximation of the CES function with n input variables. *Marine Resource Economics*, 295–306.
- Howe, J. and D. G. McFetridge (1976). The determinants of R&D expenditures. *Canadian Journal of Economics* 9(1), 57–71.
- Hsiao, C. (2003). *Analysis of panel data*. Econometric Society Monographs, no. 34. Cambridge University Press.
- Labeaga, J., E. Martínez-Ros, and P. Mohnen (2014). Tax incentives and firm size: effects on private R&D investment in Spain. Technical report, United Nations University-Maastricht Economic and Social Research Institute on Innovation and Technology (MERIT).
- Lee, L.-f. and J. Yu (2010). Estimation of spatial autoregressive panel data models with fixed effects. *Journal of Econometrics* 154(2), 165–185.
- LeSage, J. and R. Pace (2009). *Introduction to spatial econometrics*. Statistics: A Series of Textbooks and Monographs. Chapman and Hall, CRC press.
- Lhuillery, S., M. Marino, and P. Parrotta (2013). Evaluation de l'impact des aides directes et indirectes à la R&D en France. *mimeo*.

- MENESR (2014). L'état de l'enseignement supérieur et de la recherche en France. *Ministère de l'Education Nationale, de l'Enseignement Supérieur et de la Recherche*.
- Montmartin, B. (2013). Intensité de l'investissement privé en R&D dans les pays de l'OCDE. *Revue économique* 64(3), 541–550.
- Montmartin, B. and M. Herrera (2015). Internal and external effects of R&D subsidies and fiscal incentives: Empirical evidence using spatial dynamic panel models. *Research Policy* 44(5), 1065–1079.
- Mulkay, B. and J. Mairesse (2013). The R&D tax credit in France: Assessment and ex ante evaluation of the 2008 reform. *Oxford Economic Papers*, gpt019.
- Mur, J. and A. Angulo (2009). Model selection strategies in a spatial setting: Some additional results. *Regional Science and Urban Economics* 39(2), 200–213.
- Nishimura, J. and H. Okamuro (2011). Subsidy and networking: The effects of direct and indirect support programs of the cluster policy. *Research Policy* 40(5), 714–727.
- Openshaw, S. (1977). A geographical solution to scale and aggregation problems in region-building, partitioning and spatial modelling. *Transactions of the institute of british geographers*, 459–472.
- Pesaran, M. (2004). General diagnostic tests for cross section dependence in panels. *CESifo working paper series*.
- Takalo, T., T. Tanayama, and O. Toivanen (2013). Market failures and the additionality effects of public support to private R&D: Theory and empirical implications. *International Journal of Industrial Organization* 31(5), 634–642.
- Varga, A., D. Pontikakis, and G. Chorafakis (2014). Metropolitan Edison and cosmopolitan Pasteur? Agglomeration and interregional research network effects on European R&D productivity. *Journal of Economic Geography* 14(2), 229–263.
- Vega, S. H. and J. P. Elhorst (2013). On spatial econometric models, spillover effects, and w. In *53rd ERSA Congress, Palermo, Italy*.
- Veugelers, R. (2014). Undercutting the future? European research spending in times of fiscal consolidation. Technical report, Bruegel Policy Contribution.
- Wilson, D. J. (2009). Beggar thy neighbor? The in-state, out-of-state, and aggregate effects of R&D tax credits. *The Review of Economics and Statistics* 91(2), 431–436.
- Wrigley, N. (1995). Revisiting the modifiable areal unit problem and the ecological fallacy. In A. Cliff, P. Gould, A. Hoard, and N. Thrift (Eds.), *Diffusing geography: Essays Presented to Peter Haggett*, pp. 123–181. Wiley-Blackwell, Oxford.

Zúñiga-Vicente, J. Á., C. Alonso-Borrego, F. J. Forcadell, and J. Galán (2014). Assessing the effect of public subsidies on firm R&D investment: A survey. *Journal of Economic Surveys* 28(1), 36–67.

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