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Abstract

Using a unique database containing information on the amount of R&D tax credits and regional, national and European subsidies received by firms in French NUTS3 regions over the period 2001-2011, we provide new evidence on the efficiency of R&D policies taking into account spatial dependency across regions. By estimating a spatial Durbin model with regimes and fixed effects, we show that in a context of yardstick competition between regions, national subsidies are the only instrument that displays total leverage effect. For other instruments internal and external effects balance each other resulting in insignificant total effects. Structural breaks corresponding to tax credit reforms are also revealed.

JEL Classification:H25, O31, O38

Keywords: Additionality, French policy mix, R&D investment, Spatial panel, Structural break.

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1 Introduction

Considering the importance of innovation for firms' performance as well as the diverse types of externalities inherent in R&D activities, most countries have established public financial support favoring private R&D investment. States have many measures at their disposal, and their policy mix choices are diverse. While some countries do not offer tax credits for R&D (Sweden, Finland, Germany), others are strongly oriented toward fiscal assistance (Canada, Japan, The Netherlands, France).

Globally we have witnessed two main type of evolutions during the 2000s. First, fiscal incentives (indirect support) have been progressively gaining in importance to the detriment of subsidies in most of the developed countries. Second, subsidies and grants (direct support) has been more and more designed to foster collaborative R&D and interactions among a diversity of partners, especially at the local and regional level, with the objective to enhance the performance of innovation systems based on agglomeration and clusters dynamics.

Although following these general tendencies, France has established a unique system compared to its primary competitors. First, the multitude of programs and public policies results in strong public intervention in corporate R&D and innovation. More remarkable is the inversion of the ratio between direct and indirect support to R&D following the reform introducing a volume scheme for the R&D tax credit in 2004 and its reinforcing in 2006 and 2008 (when a pure volume-based system without ceiling limits is implemented). Indeed, according to the OECD, in 2011, France ranked 7th for direct support (0.12% GDP) and was the most generous country for indirect support (0.26% GDP, 5.2 B EUR of fiscal revenue loss).

During this period, some major evolutions in terms of objectives for direct support should also be noted. Based on the literature on agglomeration and economic geography of innovation, we have observed the development of the competitiveness cluster policy and the increased targeting on industrial and societal strategic domains. Not only, such evolutions have led to an increase in the share of regional policies in the French policy mix but, most of all these evolutions have reinforced the territorial dimension of national R&D policies when targeting some territories more than others.

On the whole, this generous system has certainly helped to sustain private support of R&D in France during the 2000s. Indeed, despite a difficult macroeconomic context, the total share of corporate-financed R&D increased slightly, but it remains far behind that of its main competitors. According to OECD data, the French share of private R&D expenditure in GDP has risen to 1.4 percent in 2011 but remains relatively low in comparison with other large countries (1.6 percent for the OECD average, 2 percent for Germany and 2.6 percent for Japan). Moreover, this increase in corporate Domestic Expenditure on R&D (DERD) did not contribute to the total increase in R&D expenditure in GDP, which remains approximately 2.2% in France.

Therefore, the widespread use of public funds to support private R&D in times of economic slowdown raises compelling questions about the effectiveness of these policy instruments.

Up to now reviews of studies attempting to estimate the impact of R&D subsidies (Zúñiga-Vicente et al. (2014)) show mixed results and are therefore inconclusive. As far as indirect support (such as R&D tax credits) 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. It seems that the results largely depends on the context and specific design and implementation of the instruments.

Consequently, the results of these evaluations cannot really be applied to France, whose generosity has no historic precedent. Existing evaluations of the French case mainly concern the period prior to the 2008 R&D tax credit reform.

Moreover, while the spatial dimension of innovation has justified the development of cluster policies in most countries (in particular, in France in 2005), no evaluation studies have explicitly considered the existence and impact of spatial dependencies. Yet, if the spatial structuration of R&D activities within countries matters one can expect a bias in the estimates that do not take the spatial dimension into account. Indeed, outcome differences between France and Germany for instance may not only be explained by differences in policy choices but also by differences in the spatial structuration of innovative activities. The continuum of agglomeration which characterize a large part of the German territory creates a very different context of spatial interactions compared to the French case where innovative agglomerations are dispersed across the territory and often surrounded with zones of very low innovative activities.

Thus, the objective of this paper is to implement a spatial model using regionally aggregated data in order to investigate the effect of the French policy mix in favor of private R&D. Assembling fiscal and survey data, we gathered information concerning the amount of total R&D tax credits and regional, national and European subsidies received by firms conducting R&D activities in each French metropolitan NUTS3 region and their total investment in R&D over the period 2001-2011. To run our analysis, we first develop a simple theoretical model based on Howe and McFetridge (1976) that provides one explanation for the ambiguous empirical results obtained concerning the effect of R&D policies. Indeed, depending on the key parameter values, crowding-out as well as crowding-in effects can emerge. Also, this framework can be easily extended to spatial interactions and will provide a basis for our empirical estimates. More precisely, we estimate a spatial Durbin model with regimes and fixed effects. This type of spatial model allows us to take into account not only the spatial dependency between units but also the potential structural change due to changes in policies during the considered period.

This paper offers three main contributions to the literature on the geography of innovation and evaluation of R&D policies: (i) it investigates spatial interdependencies and in particular the possible existence of a yardstick competition between NUTS3 regions for R&D investment in France that can hamper the global effects of policy instruments; (ii) it simultaneously considers different components of the R&D policy mix–regional, national and European subsidies and allows interpretation of the results in terms of total, direct (internal to each region) and indirect (external) marginal effects of each instrument on private R&D spending;(iii) it also measures the potential structural change in the behavior of firms that can be related to the mid-2000's strong changes in French R&D policies.

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, in terms of total effect, only national subsidies show significant positive marginal effect, whereas local/regional and European subsidies do not appear to generate significant leverage or crowding-out total effects. The positive direct effects are compensated by negative indirect effects for these instruments. Such a result suggests that national subsidies (which are often sectorally or territorially targeted) are more efficient than other instruments in exploiting the complementarity between French regions. Third, the presence of a structural break in our data distinguishing the period before and after 2006 is revealed and could imply that the reinforcement of the tax credit in 2006 and 2008 have contributed to the development of potential future windfall effects. Finally, it should also be noted that the macroeconomic situation of the country is more influential on the level of privately financed R&D investment in the NUTS3 regions than the level of internal activities.

On the whole, this analysis of spatially aggregated data appears to be complementary to the main microeconomic analyses developed on the French case. It is also in line with the main results previously obtained in terms of additionality and adds to previous interpretations by highlighting the essential phenomena of spatial dependency, which have not yet been analyzed.

The remainder of the paper is organized as follows. In section 2 we present the related empirical literature that develops additionality measures for the evaluation of R&D policies and summarize the main existing evidence on the impact of tax credits and subsidies. In Section 3 we present the data and the main descriptive statistics which highlight the spatial and temporal features. Section 4 describes the theoretical framework and how it is used as basis for our empirical model. Section 5 discusses the empirical results in detail. Conclusions are presented in Section 6.

2 Related Empirical Literature

We will precise the notion of additionality and its measure before summarizing the main results that emerge from the existing empirical literature on the efficiency of R&D policies.

2.1 Measuring policy efficiency in terms of additionality

Theoretically the basic idea is that public support will be efficient if it targets projects that would not be undertaken by firms without the grants. Otherwise, incentives will be ineffective because they will not lead to additional investment. Two main measures of efficiency in terms of input additionality[1] have been used:
- The "Bang for the Buck" (BFTB) measure consists in comparing the policy expenditures with the additional amount of R&D spent by private firms. For tax credit for example, when the ratio of the amount of R&D generated by the R&D tax incentives on the net tax revenue loss is higher than 1 this describes a pure additionality effect (also called crowding-in or leverage effect showing a complementarity between public and private funds), when it is comprised between 0 and 1 it reveals a partial crowding-out effect and a full crowding-

[1] This is the additionality concerning R&D spending. We do not consider here other forms of additionality such as output additionality (in terms of innovation for example) or behavioral additionality.

out if it is equal to 0 (showing then perfect substitution between public and private funds).

- R&D price elasticity measures the percentage change in R&D investment due to a percent change in the user cost of R&D capital, tax credit and subsidies being considered as elements that reduce the user cost of R&D. Resulting from a structural model of demand for R&D, this measure cannot be directly interpreted in terms of additionality, a BFTB ratio should be recalculated (Mohnen and Lokshin, 2009).

There are however, different phenomena that can hamper the expected additionality effects of the implemented policies on business-financed investment in R&D:

- Opportunistic behaviors from firms can lead to windfall effects.
- At the macroeconomic level, distortions between firms or industries may also result in global crowding-out effects if the incentives for the supported firms or sectors are overcompensated by the resulting disincentives in the non-supported firms/sectors.
- At the spatial level, other mechanisms can contribute to reduce the expected leverage effects. Papers on the economic geography of innovation have long highlighted the existence and importance of spatial dynamics in R&D activities. Empirically, this literature demonstrates the specific role of geographical proximity in the transmission of knowledge spillovers (Autant-Bernard et al., 2013). Hence, it reveals the existence of positive agglomeration effects based on the local nature of knowledge externalities and also the resulting territorial competition between territories to attract R&D investment. Thus, as space appears non neutral for innovation activities, one may expect the existence of spatial interdependency phenomena implying that innovation activities within one place depends on innovative activities in other places. On the whole, crowding-out effect may appear if the negative effect of territorial competition overcompensates the positive effect of spatial knowledge flows.

Such a diversity of possible effects may explain that, to date, evaluations of the efficiency of the R&D policies conducted in various countries still report ambiguous results that largely depends on the context.

2.2 Evaluation of the direct impact of financial support

In their recent review of studies evaluating the impact of R&D subsidies, Zúñiga-Vicente et al. (2014) show that the additionality hypothesis prevails. Approximately 60% of the 77 considered studies find that public subsidies are complementary. There are also contributions in favor of the substitution hypothesis, while others demonstrate no significant effect which is in line with David et al. (2000), who reviewed 33 empirical studies. Approximately three-fourths of the existing studies were conducted at the microeconomic level, whereas the remaining studies used aggregate data by industry or by country; it is worth noting that the main results are the same regardless of the level of aggregation.

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 are generally implemented through a greatly diverse set of programs. Even if we only consider those implemented at the national level, they involve different ministries, and each defines its specific targets and objectives. Recent studies providing us with more specific result when diffentiating countries and schemes (see for example in Research Policy 2017: Freitas et al.; Hottenrott et al.; Huergo and Moreno; Wang et al. or also Le and Jaffe).

Concerning tax credit, 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. Most rigorous findings reports that one euro of tax revenue foregone on R&D tax credits raises expenditure on R&D by less than one euro. Moreover, considering only the impact on high tech sectors on a large sample of OECD countries, Brown et al. (2017) recently find a negative impact of R&D tax credit. 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 support for R&D, the reverse has been found in others. Evidence suggesting that knowledge spillovers from large firms exceed those of small firms tend also to weaken the case for targeting tax incentives towards SMEs - even if SMEs will increase their R&D expenditure more strongly in response to those incentives.

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 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, as in France, even though the risk of crowding-out effects may be higher (Brown et al., 2017).

Very few studies simultaneously take into account both direct subsidies and tax incentives. Corchuelo and Martínez-Ros (2009) showed that in Spain, R&D tax incentives and subsidies are complements because firms that receive a grant are more likely to also apply for an R&D tax incentive. In France, Duguet (2012) noted that R&D tax credit recipients tend to be smaller and have 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. Dumont (2013) found that firms who used just one of the policy tools had the highest additional effect. However, 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.

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 substitutes 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-effects but cannot constitute a satisfying rationale for their existence. Among them, we can mention the different uses of these instruments between SMEs and large firms or the structural evolution (in favor of fiscal incentives) of the ratio between direct and indirect support inside OECD countries.

On the whole, the limited empirical evidence indicates that interactions between different policy measures probably exist. However, little is known concerning the importance and direction of such interaction effects.

2.3 Introducing the spatial dimension within R&D policy evaluations

Within most of the OECD and European countries, an increasing share of R&D subsidies are allocated within the framework of cluster policies. Evaluations of cluster policies have been conducted in diverse countries where the performance of firms and territories are linked to their different components such as the effect of geographical/sectoral agglomeration, networking effects or financial support[2]. The heterogeneity in methodology is too great to allow us to synthesize the results but, associated with the main findings of the literature on the geography of innovation (Autant-Bernard et al., 2013), it is possible to state that there is an impact from the geography of R&D activities on the capacity of firms to invest in R&D and react to public support.

Despite these evidence of the role of the geography of innovative activities on the performances of firms, so far, very few evaluations studies consider the role of agglomeration and the possibilities of spatial dependencies that can biased econometric estimations.

To our knowledge only two macro-econometric analyses using spatial econometrics have contributed to the measurement of interactions between instruments implemented in different jurisdictions. Using OECD country data, Montmartin (2013) concludes that external complementarity of financial support exists at the country level. Wilson (2009) focuses on the US case and evaluates the sensitivity of firms' R&D investments located in one U.S. 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 credits, they also react negatively to out-of state tax credits. More precisely, this reaction is estimated to be of the same magnitude, implying a zero effect from these "local" tax credits at the macroeconomic level. It should be noted that these two opposite results are obtained at different geographical levels. They may therefore suggest that the existence of external complementarity or substitutability depends on the geographical unit retained. One simple explanation for this could be that agglomeration economies are often observed at intra-countries agglomeration levels. Also there is geographical limits in the capacity of firms' 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 response to incentives. More generally, the level of aggregated data has an important impact on the value of the spatial coefficients.[3]

[2]See, notably, OECD (2009) for difference in difference analyses; Nishimura and Okamuro (2011) and 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 cluster policies.

[3]This problem is related to the modifiable areal unit problem (MAUP), i.e, the 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 are provided in Gotway and Young (2002) and Wrigley (1995).

2.4 Using infra-national spatially aggregated data

It should be noted that even if it is generally argued that longitudinal micro data (which allow questions to be addressed at the same level at which decisions are made) 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 studies with aggregate and micro data to complement each other (European Commission, 2014).

On the one hand, while microeconomic data allow accounting for heterogeneity among agents that are potential beneficiaries of public policies, they often lack information on the diverse amounts and sources of public funding received by firms. They also necessitate crossing 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 estimation strategies. Finally, the difficulties of obtaining long time series also constrain the capacity to analyze a temporal effect.

On the other hand, macro-econometric studies allow consideration of the global effort made by governments using a diversity of instruments. Moreover, they measure some effects that will influence the macroeconomic impacts of financial support and that cannot be grasped at the microeconomic level. Indeed, the macroeconomic impact of a measure not only refers to the individual behavior of firms in reaction to the used instruments but also measures the distortions generated by policy instruments between firms and industries. As shown in the previous section, macro-econometric studies have also contributed to the analysis of policy mixes when taking into account possible interactions between instruments implemented within the same jurisdiction or in different jurisdictions.

Thus, even though approaches using aggregated data bring forth interesting complements for the analysis of public policies, they still remain scarce. Moreover, to date, they only use panels of OECD countries. Only Wilson (2009)'s paper 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) Concerning the direct effect (internal to the zone), it allows for finer and more relevant analysis as data better correspond to the level at which agglomeration effects can impact on firms' innovative activities. It also allows consideration, at the territorial level, of the combined effect of the extensive and intensive margins. Indeed, micro-econometric studies are generally focused on the extensive margin (i.e., impact on the intensity of R&D investment within firms that already develop R&D activities). However, leverage effects at the territorial level may result not only from the intensive but also from the extensive margin (i.e., the entry of new firms in R&D activities).

ii) It is relevant for the implementation of spatial econometric models that allow to take account of spatial dependency between different spatial entities when estimating the effects of public policies.

iii) Considering spatial entities within a same institutional context (a country), it facilitates the identification of structural changes due to public policies changes within this country thereby allowing a finer interpretation of policy mix and instrument design.

For France, the highly agglomerated spatial structure and the evolution of the policy since the early 2000s has contributed to reinforcing 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 even more because the existing evaluations of the French case have neglected the spatial dimension.

3 Data and Evolution of the French Policy Mix

3.1 Data

We constructed a balanced panel for 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 Research[4] and provides information at the firm level on R&D activities and particularly on the sources of R&D financing. 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).

As our objective is to estimate the reactivity of firms to different types of financial support for R&D, data on professional organizations (such as technical centers), which cannot directly benefit from the R&D tax credit, have been excluded from our database. Some methodological considerations[5] 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., essentially regions and departments).

Tax credit

The tax credit file is collected by the fiscal administration. 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 have 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 from the R&D survey at the department level has involved some methodological decisions.

[4]See acknowledgment at the end of this paper.

[5]Before 2001, for example, only enterprises that employ at least 1 full- time researcher are considered in the survey. After that date, the survey provides information on all enterprises that conduct R&D even if they employ no or fewer than one researcher. Hence, it offers better information on small firms.

In short, the most difficult problem we faced concerns the geolocation of R&D tax credit. Indeed, 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 that are independent or members of a group that are not fiscally integrated. In the case of a fiscally integrated group, only one enterprise (frequently, a financial holding) really benefits from the tax credit, while the basis for this tax credit is the R&D declared in the entire enterprise of this group regardless of their location.

To account for possible location biases due to the fiscal organization of firms and groups, we constructed a relocalized measure for Tax Credit (TC). For each year, the total national tax credit amount is relocalized within each department according to their national share of DERD for each category of enterprise ($s \in \{1, ..., S\}, S = 5$)[6]. More details on the calculation used for relocation of Tax Credit are given in Appendix A.

3.2 Descriptive statistics and data analysis

As indicated in the summary statistics in Table 1, 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 deducted) indexed 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 conducting R&D in the corresponding NUTS3 region. For tax credit, we introduced a time lag of one year (LTC for lagged TC) in order to reduce the endogeneity problem.

Table 1: 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: $\log(\cdot)$ is the natural log, and for tax credit is the log of previous period, $\log(TC_{t-1})$.

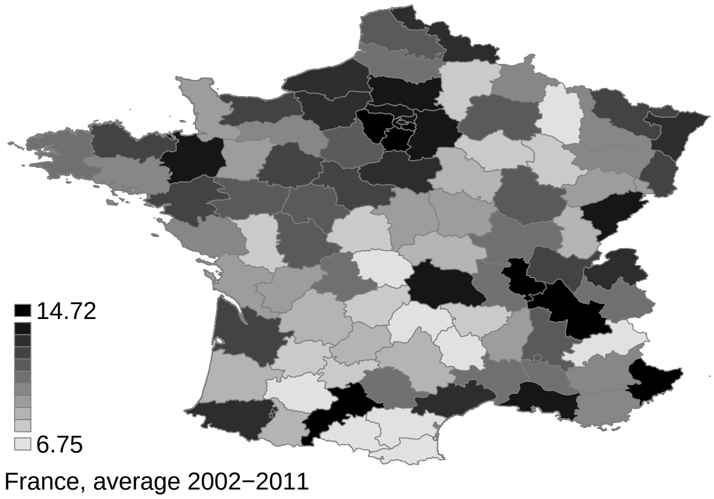
Spatial structuration

Concerning the spatial structure of our dependent variable, we observe in Figure 1 a high concentration of R&D investment in a few NUTS3 regions, which are rather dispersed across the territory and surrounded by NUTS3 regions with low R&D investment.

It should be noted also that this structuration is rather stable all along the period. The GINI index measuring the concentration of R&D is 0.74 in 2002 and decrease to 0.70 in 2006 before stabilising around 0.71 between 2007 and 2011.

[6] 1: 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.

Figure 1: Spatial distribution of the logarithm of private R&D.



Temporal change

Collected data cover the 2001-2011 period, which means that they integrate different important reforms of French public policy for R&D. During the early 2000s, France, along with the United States, was combining important direct aid for enterprises with fiscal incentives. However, by the middle of the 2000's, major changes occur based on a new philosophy for the French policy mix in favor of private R&D.

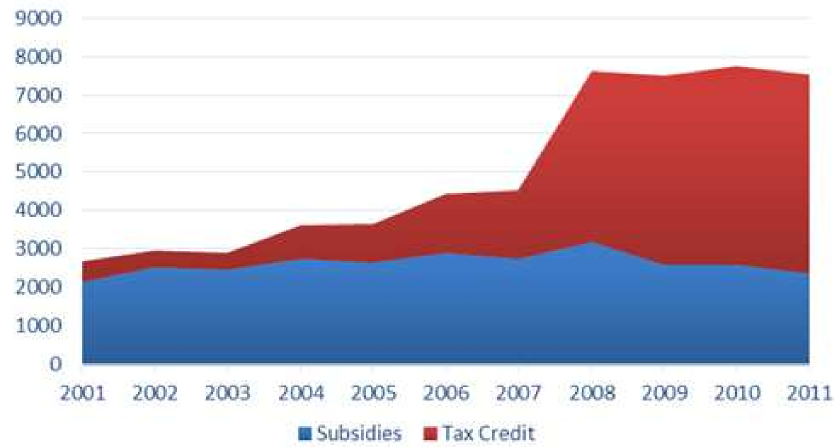
First, following 2005, the launch of the competitiveness pole policies resulted in new criteria for supporting projects where sectoral and territorial strategies dominate. Associated with the evolution of the European regional policy which clearly puts emphasis on the necessity to develop regional strategies for research and innovation in the 2007-2013 program, this has contributed to increase the share of regional subsidies in the total direct public aids for private R&D. More importantly, strategies aiming at reinforcing networking and agglomeration effects are becoming central.

Second, in 2004, France started to switch from a pure incremental system of tax credit towards a volume scheme which has been reinforced in 2006 and 2007 and, since 2008, tax credit in France has been calculated on a pure volume basis without a ceiling (Table A.1 in Appendix A).

Thus, the amount of the tax credit is logically concentrated on large firms that heavily invest in R&D, while small enterprises receive a higher share of tax credit compared to their share of declared R&D expenditure.

Looking at our data, such changes translated in several main evolutions from mid-2000's onward. First, this strengthening of the tax credit support motivated an increasing number of firms to apply, notably, the smaller firms. Nearly 20,000 enterprises applied in 2011, and nearly 15,000 benefited from tax credit for that year, whereas they were 3,000 in 2002. However, the choice of a volume scheme contributed to increase the amount of tax credit allocated to large firms. Indeed, in 2011, enterprises with fewer than 50 employees represented 71.2% of the beneficiaries for 16% of the total declared expenditure and 18% of the total amount of tax credit. At the opposite side, the 1.4% of beneficiaries with more than 2000 employees received more than 44% of the total amount of tax credit (French Ministry of Research, MENESR, 2014). Finally the global feature is that of a sharp increase in the share of R&D expenditure covered by tax credit starting from around 2006 (see Figure 2 for an illustration of these changes).

Figure 2: Financial support for private R&D in France 2001-2011 (in millions euros).



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

Due to this primary changes of the French policy mix, incentives scheme as well as the characteristics of the population of beneficiaries have been modified from mid-2000's onward. Consequently, we suspect that a structural change in the effect of R&D policies exists in our data distinguishing the early 2000's and late 2000's. We thus implement Chow tests to detect the presence of structural break. As it is difficult to a priori select the precise year for the break, we test years 2006, 2007, 2008, 2009 and 2010 as candidates. The results obtained are reported in Table A.5 of Appendix A and show that year 2010 non reject the null hypothesis of no structural break at 5%, but we find significant evidence the presence of global structural break (in all variables) for the other years. To select the break date, we compare the quality of linear fixed-effect model estimations for each potential year. According to our three main information criteria (Log-likelihood, AIC, BIC) presented in Table A.6 of Appendix A, the estimation using 2006 as break is clearly the most efficient. Following the previous discussion on the changes of the French Policy Mix during the mid-2000, this result it is not so surprising and we decide to select this year for the break in terms of policies effect. Table 2 presents the descriptive statistics using 2006 as break.

Table 2: Descriptive statistics by period.

Variables	Mean	S.D.	p25	Median	p75
			Period 2002-2005		
log($Derd$)	10.91	1.70	9.70	11.03	12.12
log(GDP)	16.20	0.87	15.60	16.23	16.73
log(LTC)	7.47	1.74	6.33	7.57	8.74
log($SubNat$)	7.48	2.40	6.15	7.36	9.00
log($SubCEE$)	4.55	2.99	2.38	4.94	6.87
log($SubReg$)	3.40	2.60	0.00	3.87	5.46
			Period 2006-2011		
log($Derd$)	11.07	1.67	9.98	11.12	12.20
log(GDP)	16.34	0.89	15.75	16.36	16.87
log(LTC)	9.19	1.73	8.21	9.17	10.29
log($SubNat$)	8.04	2.25	6.90	8.09	9.40
log($SubCEE$)	4.76	3.10	2.18	5.43	7.07
log($SubReg$)	4.93	2.51	3.78	5.50	6.73

4 From the theory to the empirical specification

4.1 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 region. 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 for these 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) function depending on its level of R&D expenditure. We assume that the first and second derivatives of the MCC and MRR functions with respect to R&D investment have the same sign for all firms. Consequently, by aggregating the MRR functions and MCC functions of firms located in one NUTS3 region, we obtain a MRR and MCC function for that region. Based on David et al. (2000) framework, the MRR and MCC functions at the NUTS3 level should have the following properties:

$$\frac{\partial MRR_i}{\partial R_i} < 0, \quad \frac{\partial^2 MRR_i}{\partial R_i^2} > 0,$$

$$\frac{\partial MCC_i}{\partial R_i} > 0, \quad \frac{\partial^2 MRR_i}{\partial R_i^2} < 0,$$

where $i = 1, ..., N$ refers to the spatial unit (here, NUTS3), R_i is the level of private R&D investment in NUTS3 region i. Obviously the marginal rate of return as well as the marginal cost of capital of R&D projects are also affected by R&D public policies and the dynamics of the region. It is common knowledge that R&D policies have multiple effects on firm behavior (see David et al., 2000 for a detailed discussion). If there is a relative consensus on the fact that most R&D policies influence the marginal cost of capital more than the marginal rate of return, they can also generate significant external effects such as learning, training or reputation effects, which can improve the marginal rate of return in the long run. To take into account these multiple effects of R&D policies, we specify generalized CES functions to describe the MRR and MCC for a NUTS3 region:

$$MRR_i = \delta_i R_i^{\beta} \left[\sum_{k=1}^{K} \sigma_k (X_{ki})^{-\rho}\right]^{-v/\rho}, \quad \beta < 0, \quad \rho \neq 0, \quad \sum_{k=1}^{K} \sigma_k = 1, \tag{1}$$

$$MCC_i = \psi_i R_i^{\alpha} \left[\sum_{k=1}^{K} \mu_k (X_{ki})^{-\rho}\right]^{-u/\rho}, \quad \alpha > 0, \quad \rho \neq 0, \quad \sum_{k}^{K} \mu_k = 1, \tag{2}$$

where $\delta_i > 0$ and $\psi_i > 0$ are NUTS3 regions' specific time-invariant elements of the MRR and MCC functions, and $X_{ki} \geq 0$, $k = 1, ..., K$ represent measures of public policy variables and other variables affecting both the MRR and MCC functions. The returns to scale for the X variables are given by $v \in [0, 1]$ in the MRR function and by $u \in [0, 1]$ in the MCC function. These functions also assume a constant elasticity of substitution between two X variables given by $\eta = 1/(1 + \rho)$. These generalized CES functions take into account of the various R&D policy effects previously discussed. Indeed, R&D policies and other influential variables are assumed to be imperfect substitutes for firms' private R&D cost and profitability. Moreover, it allows a specific influence for all variables on the MRR and MCC functions and the number of variables can generate positive or negative effects on the two functions. In other words, more public policies do not necessarily imply more efficiency (and vice-versa).

The equilibrium amount of private R&D in the $i - th$ NUTS3 region is obtained when the aggregate MRR function equals the MCC function, that is,

$$R_i = \left(\frac{\delta_i}{\psi_i} \frac{\left[\sum_{k=1}^{K} \sigma_k (X_{ki})^{-\rho}\right]^{-v/\rho}}{\left[\sum_{k=1}^{K} \mu_k (X_{ki})^{-\rho}\right]^{-u/\rho}} \right)^{1/(\alpha-\beta)}. \tag{3}$$

This last expression implies non-linear specific effect of each X variables on the level of private R&D investment. If such expression can be estimated using non-linear estimators, the interpretation of estimates in terms of impact for public policy is difficult.

As our final objective is to extend this simple framework by including spatial dependence, we will need to obtain a specification that is amenable to estimation with spatial econometric techniques. In that objective, we follow Behrens et al. (2012) who linearize their equilibrium expression using a first-order Taylor approximation around $\rho = 0$. As in our model, we use N-variables CES functions, we can use the translog approximation proposed in Hoff (2004) which extend the famous Kmenta (1967) result applicable to the two-variables case. Nevertheless, to use such approximation, we need to be sure that the assumption that $\rho \to 0$ is adequate.[7] In that objective, we estimate (4) by nonlinear least-squares according to different initial values for ρ. The results of these non-linear regression are summarized in Table 3.

[7] Note that most paper using first-order Taylor approximation do not check if this assumption is adequate.

Table 3: Summary of Nonlinear least-squares.

Estimation	**Initial value for ρ**	$\widehat{\rho}$	**RSS**
1	0.60	0.8052	10859.76
2	0.30	0.0253	125.2563
3	0.20	0.2007	4934.874
4	0.10	0.0159	360.3023
5	0.10	0.0316	121.5327

This table shows that non-linear regressions which estimate a value of ρ near zero (regression 2, 4 and 5) fit clearly better our data as the sum of square residuals are very low in that cases. Thus, it suggests that the assumption $\rho \to 0$ seem to be reasonable and that a translog approximation of (4) is acceptable. Following Hoff (2004), equilibrium equation (3) can be approximated by:

$$\log R_i = \frac{1}{\alpha - \beta}\left(\log\frac{\delta_i}{\psi_i} + \sum_{k=1}^{K_r}(\lambda_k - \theta_k)\log X_{ki} + \sum_{k=1}^{K}\sum_{l=k}^{K}(\lambda_{kl} - \theta_{kl})\log X_{ki}\log X_{li}\right), \tag{4}$$

where $X_{ki} \geq 0$, $k = 1, ..., K$ and where the parameters obey to:

$$\begin{aligned}
&\lambda_k = v\sigma_k \quad \theta_k = u\mu_k, \\
&v = \sum_{k=1}^{K}\lambda_k \quad u = \sum_{k=1}^{K}\theta_k, \\
&\lambda_{kl}\mid_{k\neq l} = \frac{-2\lambda_{kk}}{1 + \sum_{j\neq(k,l)}\frac{\lambda_j}{\lambda_l}}, \quad \theta_{lk}\mid_{l\neq k} = \frac{-2\theta_{ll}}{1 + \sum_{j\neq(k,l)}\frac{\theta_j}{\theta_l}}.
\end{aligned} \tag{5}$$

An important implication of this simple model is that it highlights the channels through which R&D public policies can globally generate leverage or crowding out effects. Indeed, the partial derivative of expression (4) with respect to a policy k highlights two distinct effects of R&D policies:

$$\frac{\partial \ln R_i}{\partial \ln X_{ki}} = (\lambda_k - \theta_k) + 2(\lambda_{kk} - \theta_{kk})\ln X_{ki} + \sum_{l\neq k}^{K}(\lambda_{kl} - \theta_{kl})\ln X_{li}. \tag{6}$$

The two first terms of (6) refers to the non-linear individual effect of the policy (without considering its interactions effect on the other policies). The last term of (6) highlights the sum of indirect effect generated by the R&D policy on the R&D investment via its influence on the effect of other policies. Thus, our simple theoretical model endogenously provide different explanation for the mixed results presented by the empirical literature on the effect of R&D policies. Indeed, negative or positive effect of a policy can be due to (1) its direct effects on the MCC and MRR functions, (2) the existence of a threshold effect and (3) the existence of strong interactions effects between policies.

The spatial extension of the model

In some sense, MCC and MRR functions (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 complete independence between the behavior of one unit and the behavior of other units (especially if they are within the same country). It is especially the case for France as highlighted by Figure 1. Papers on the economic geography of innovation highlight the existence and importance of spatial dynamics in R&D activities that do not necessarily remain confined within administrative frontiers (Morgan, 2004; Crescenzi et al., 2007; Bathelt and Cohendet, 2014). More recent empirical papers focused on R&D policies such 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 other units (here, NUTS3 regions) 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 empirical literature on the geography of innovation highlights the importance of different forms of proximity and especially geographical proximity in the transmission of knowledge spillovers (Autant-Bernard et al., 2013). Hence, assuming that spatial knowledge externalities are a major source of dependancies between R&D policies implemented in different jurisdictions, we introduce these elements in our framework, by extending MRR (1) and MCC (2) functions in the following way:

$$MRR_i = \delta_i R_i^{\beta} \left(\sum_{j \neq i} w_{ji} R_j \right)^{\varphi} \left[\sum_{k=1}^{K} \sigma_k (X_{ki})^{-\rho} \right]^{-v/\rho}, \quad \beta < 0, \quad \rho \neq 0, \quad \sum_{k=1}^{K} \sigma_k = 1, \tag{7}$$

$$MCC_i = \psi_i R_i^{\alpha} \left(\sum_{j \neq i} w_{ji} R_j \right)^{\omega} \left[\sum_{k=1}^{K} \mu_k (X_{ki})^{-\rho} \right]^{-u/\rho}, \quad \alpha > 0, \quad \rho \neq 0, \quad \sum_{k=1}^{K} \mu_k = 1, \tag{8}$$

where w_{ji} is a measure of proximity between unit j and unit i. As for the simple model, the equilibrium amount of private R&D in the $i-th$ NUTS3 region is obtained when the aggregate MRR function equals the MCC function. By applying a translog approximation using the fact that ρ is in neighborhood of 0, we can write:

$$\begin{aligned} \log R_i = {} & \frac{1}{\alpha - \beta} \log \frac{\delta_i}{\psi_i} + \frac{(\varphi - \omega)}{\alpha - \beta} \log \left(\sum_{j \neq i} w_{ji} R_j \right) \\ & + \frac{1}{\alpha - \beta} \left(\sum_{k=1}^{K} (\lambda_k - \theta_k) \log X_{ki} + \sum_{k=1}^{K} \sum_{l=k}^{K} (\lambda_{kl} - \theta_{kl}) \log X_{ki} \log X_{li} \right), \end{aligned} \tag{9}$$

where $X_{ki} \geq 0$ and $k = 1, ..., K$. This last expression highlights another channel, compared to (4), that can explain the appearance of a crowding-out or leverage effect for a public policy. Indeed, expression (9) shows that the total effect of a public policy on private R&D investment is the result of three elements. The first two are the individual and interactions effects presented in equation (4) and refer to the within "unit" (in-NUTS3 region) effect of the policy, that is, the influence of the public funds 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 the R&D investment choices made by other NUTS (which itself depends on the public policies implemented by the other NUTS) on the R&D investment of the $i-th$ region. In other words, the effect measured by $(\varphi - \omega)/(\alpha - \beta)$ refers to spatial effects of R&D investment across the NUTS3 regions. The sign of this spatial effect of R&D investment could be positive or negative between the 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). However, we can also imagine the existence of positive spatial dependence between the R&D investment of NUTS3 regions 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 explaining the net effect of public policies on private R&D investment.

4.2 A theoretically consistent specification

In the previous section, we have developed a simple model of R&D investment to help us to understand the mixed result of the empirical literature but also to theoretically set up our empirical specification. Expression (9) corresponds, in spatial econometric terms, to a Spatial Durbin model (SDM). Nevertheless, the empirical spatial dependence could be in reality much more complex than that reflected in our simple theoretical model. To be sure that our theoretical framework match with our data in terms of spatial effect, we need to check if the Spatial Durbin model fit better than other spatial econometric models.

We have two general ways to specify the appropriate spatial empirical model. On the one hand, the usual way is to apply a sequential procedure, known as specific-to-general modeling ($STGE$) or a "bottom-up" approach (Florax and Folmer, 1992): (1) estimate an initial model without spatially lagged variables; (2) test for a 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 with respect to specific effects).

On the other hand, we could start with a very general model that is over-parameterized, known as general-to-specific modeling ($GETS$) (Hendry, 1979) or a "top-down" approach. In the Hendry approach, the model is progressively simplified using a sequence of tests. Mur and Angulo (2009) compare the performance of both approaches in spatial econometrics using Monte Carlo simulations with quite diffuse results (not finding conclusive evidence supporting one approach against the other), but $GETS$ approach appears to be more robust to the existence of anomalies in the data generating process.[8] We therefore will apply the Hendry approach to determine our final specification.

The spatial dependence and the Hendry strategy

The spatial dependence among the regions at each point in time is introduced into panel data models using a spatial weight matrix denoted W. The spatial weight is a $n \times n$ positive matrix, pre-specified by the researcher, that 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.

The introduction of spatial effects can take three main forms: (a) spatially lagged dependent variable as an explanatory variable, Wy_t; (b) spatially lagged error terms, Wu_t and (c) spatially lagged explanatory variables, Wx_t. The most general spatial model is the General Nesting Spatial (GNS) model, which includes the three different spatial effects. Denoting the spatial unit by i (in our case, NUTS3 regions), the total number of regions

[8] More 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).

by n ($i = 1, 2, \dots, n$) and the time unit by t ($t = 1, 2, \dots, T$), we can write the GNS model as

$$\begin{aligned} y_t &= \rho W y_t + x_t \beta + W x_t \theta + \mu + \eta_t \iota_n + u_t, \\ u_t &= \lambda W u_t + \varepsilon_t, \end{aligned} \tag{10}$$

with $\varepsilon_t \sim \mathcal{N}\left(0, \sigma_\varepsilon^2 I_n\right)$; y_t is a vector of order $(n \times 1)$, x_t is a matrix of $n \times (k+1)$ dimension with $\beta^{'} = [\beta_0, \, \beta_1, \, \cdots, \, \beta_k]$. $\mu^{'} = [\mu_1, \mu_2, \dots, \mu_n]$ captures cross-sectional (or spatial) heterogeneity among regions, ι_n is a $(n \times 1)$ vector and η_t captures time-period heterogeneity.

In (10), the parameter ρ captures the contemporary spatial dependence of the explained variable, the parameter λ captures the spatial dependence in the error term and θ captures spatial local dependence by introducing the spatial effects of the explanatory variables. The empirical literature does not take the GNS model as point of departure because its parameters are weakly identified (Vega and Elhorst, 2013). We therefore need to impose some restrictions on parameters to work with simpler spatial models. The spatial econometric literature suggests two alternatives to the GNS model (as a point of departure for the Hendry approach), which include only two of the three spatial effects. The first which corresponds to our theoretical framework is as the Spatial Durbin Model (SDM) and imposes the restriction $\lambda = 0$ in (10). The second is the Spatial Durbin Error Model (SDEM) and imposes the restriction $\rho = 0$ in (10). These two models are not nested in one another such that empiricists need to estimate both and compare their efficiency. Obviously, some or all spatial effects included in the SDM and/or SDEM models could be insignificant. In this case, the Hendry approach requires estimating the simplest spatial models, including only one spatial effect. We have three different candidates. The first is the Spatial Lag Model (SLM), which includes only the spatially lagged dependent variable as an explanatory variable, i.e, imposes the restriction $\lambda = 0$ and $\theta = 0$ in (10). The second option is the Spatial Error Model (SEM), which includes only the spatially lagged error term, i.e, imposes the restriction $\rho = 0$ and $\theta = 0$ in (10). Finally, the third is the Spatial Lag of X model (SLX), which includes only the spatially lagged explanatory variables, i.e, imposes the restriction $\rho = 0$ and $\lambda = 0$ in (10).

To select the most adequate specification, we apply the sequence of different restriction tests over the general model to obtain a more parsimonious specification. Table B.1 of Appendix B shows the results for different hypotheses tested. Concerning the modeling of the spatial effect, we find evidence in favor of the SDM model because (1) we reject the SLM, SEM and SLX models (see Table B.1) and (2) we show that SDEM model is less efficient (see Table B.2 of Appendix B). Consequently, our theoretical framework is consistent with data.

5 Estimation results

In this section we present our principal model, a SDM model, obtained after applying a sequence of different tests. As shown in Appendix A and B, our dependent and independent variables are stationary and we do not detect any problems of endogeneity and cross-section dependency. Interaction effects between policies in expression (9) are excluded because those effects are too highly correlated with non-spatial variables, which would imply a strong bias. Later on, after having detected a global structural break in our data in 2006, we run individual structural break on each variable in order to check whether the change concerns all variables or not. As shown in Table B.2 of Appendix B, only the effects of GDP and Tax Credit policy on privately-financed R&D seem to have significantly changed between the period 2001-2005 and 2006-2011. It should be noted that these results are valid regardless of whether or not spatial effects are included in the estimation.

Final specification choice

Summarising, we estimate a general SDM model with the following final specification:

$$\begin{aligned}
\log(DERD) = {} & \beta_{01}\log(GDP) + +\beta_{11}\triangle\log(GDP) + \beta_{02}\log(LLTC) + \beta_{12}\triangle\log(LLTC) \\
& + \beta_3\log(SubNat) + \beta_4\log(SubCEE) + \beta_5\log(SubReg) \\
& + \theta_{01}W\times\log(GDP) + \theta_{11}W\times\triangle\log(GDP) + \theta_{02}W\times\log(LLTC) + \theta_{12}W\times\triangle\log(LLTC) \\
& + \theta_3 W\times\log(SubNat) + \theta_4 W\times\log(SubCEE) + \theta_5 W\times\log(SubReg) \\
& + \rho W\times\log(DERD) + \mu + \eta_t\iota_n + \varepsilon_t, \qquad (11)
\end{aligned}$$

where $\triangle$ is the change in the period (2006-2011) with respect to base period (2001-2005). The first subscript in the coefficients $\log(GDP)$ and $\log(LLTC)$ identifies the period: 0 for 2001-2005 and 1 for 2006-2011. The spatial matrix W was constructed using a contiguity criterion.

We have detected two outliers in the data and all estimations presented in this paper include dummy variables controlling for the influence of these observations. The 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 of the presented estimations.

Structural breaks and spatial dependence

Table 4 presents the estimation of model (11). One important result emerges from Table 4. Indeed, the spatial parameter ($\widehat{\rho}$) is negative and strongly significant suggesting the presence of negative spatial dependency. This result is in line with evidence on in-state evaluations (Wilson, 2009) and shows that 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. It is worth noting here that, due to the spatial component $\widehat{\rho}$, the value of coefficients presented in table 4 should not be interpreted directly; marginal effects will be presented in Table 5 in the following subsection.

Table 4: Estimation of a general spatial Durbin model with structural breaks.

Non-spatial coefficients	$coef.$	$s.e.$	$t-test$
	PERIOD 2002-2005		
$\log(GDP)$	0.129	0.377	0.342
$\log(LTC)$	0.157**	0.050	3.125
$\log(SubNat)$	0.035*	0.017	2.014
$\log(SubCEE)$	0.016*	0.007	2.376
$\log(SubReg)$	0.010	0.006	1.772
	PERIOD 2006-2011		
$\triangle\log(GDP)$	0.181***	0.048	3.774
$\triangle\log(LTC)$	−0.149***	0.029	−5.073
Spatial coefficients	$coef.$	$s.e.$	$t-test$
	PERIOD 2002-2005		
$W\times\log(GDP)$	1.256**	0.463	2.713
$W\times\log(LTC)$	−0.107	0.071	−1.495
$W\times\log(SubNat)$	0.044*	0.021	2.072
$W\times\log(SubCEE)$	−0.016	0.011	−1.520
$W\times\log(SubReg)$	−0.011	0.011	−0.968
	PERIOD 2006-2011		
$W\times\triangle\log(GDP)$	−0.182**	0.109	−1.668
$W\times\triangle\log(LTC)$	0.042	0.057	0.726
Fixed coefficients to all periods	$coef.$	$s.e.$	$t-test$
$Spatial\ parameter\ (\widehat{\rho})$	−0.119**	0.046	−2.581

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

Marginal effects

To provide clearly interpretative results from our estimates, we need to obtain the final effect of all variables. Table 5 presents the estimated marginal direct and indirect effects of our five main variables.

Table 5: Marginal effects of spatial Durbin model with structural break.

~~VARIABLE~~	**PERIOD**	
	2002-2005	**2006-2011**
	Direct effects	
$\log(GDP)$	0.114	0.293
$\log(LTC)$	0.163***	0.011
$\log(SubNat)$	0.033*	0.033*
$\log(SubCEE)$	0.017***	0.017***
$\log(SubReg)$	0.010*	0.010*
	Indirect effects	
$\log(GDP)$	1.151***	0.977**
$\log(LTC)$	−0.121*	−0.064
$\log(SubNat)$	0.037*	0.037*
$\log(SubCEE)$	−0.017*	−0.016*
$\log(SubReg)$	−0.011	−0.011
	Total effects	
$\log(GDP)$	1.265***	1.269***
$\log(LTC)$	0.042	−0.053
$\log(SubNat)$	0.070***	0.070***
$\log(SubCEE)$	0.001	0.001
$\log(SubReg)$	−0.001	−0.000

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

In terms of the total effect, two main variables significantly influence the private investment in R&D in all periods, namely, the level of GDP and the level of national subsidies. Both have a positive significant effect. We estimate that an increase of 1% in the GDP in all NUTS3 region increases privately financed R&D investment by approximately over 1.2%.[9] Note that this effect of the GDP is relatively stable over time and reveals a leverage effect from GDP on R&D investment. Table 5 also shows that the effect of GDP is largely due to a 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 or regional conditions than on pure local conditions.

We estimate that an increase by 1% of the national subsidies in all NUTS3 regions generates a 0.071% increase in privately financed R&D investment (which translates into an increase of 1.071% of total R&D expenditures). In other words, we find evidence of a stable leverage effect of national subsidies. Table 5 also shows that the total effect of national subsidies is due to positive direct and indirect effects. Indeed, both direct and indirect effects of subsidies are significant and similar in magnitude. It suggests that national subsidies towards different NUTS3 regions are geographically complementary to boost the firms R&D investment.

It is interesting to note that national subsidies are the only instrument (of the four that have been studied) that generate positive indirect spatial effects in the context of yardstick competition between NUTS3 regions. On the whole, this confirms the results obtained by a number of macroeconometric studies showing the additionality of direct subsidies (Guellec and Van Pottelsberghe de la Potterie, 2003). Our study however better explains this macroeconomic result while showing the spatial complementarity of national subsidies distributed within NUTS3 region.

For the other R&D policy variables, we do not find any significant influence over our period. Nevertheless, some important elements emerge when looking at Table 5. First, if the total effect of the French tax credit system is insignificant, this effect is the result of some significant direct and indirect effects. More precisely, during the first period (2002-2005), we estimate that a 1% increase in the amount of tax credit received by region i increases by 0.16% the private R&D investment in that region. Nevertheless, the fact that all other regions benefit also from a similar increase[10] will reduce the private R&D investment in region i by 0,115%. Consequently, if the level of tax credit increases simultaneously in all regions, the macroeconomic impact will be near zero (in terms of leverage effect) due to the compensation between direct and indirect effects of the policy. In other words, as the tax Credit is a pure national policy, its total effect reflects the French spatial structure of R&D investment which translates into a negative spatial dependence.

During the second period (which begins after the reform of 2004), both direct and indirect effects decrease in magnitude and becomes insignificant. In other words, it appears that the change towards a volume-based tax credit scheme has contributed to reduce the influence of this instrument on the privately-financed R&D.

[9]However, the test of an elasticity equal to one is not rejected for the two periods.

[10]Which is obviously the case because the Tax credit policy is not geographically differentiated.

Nevertheless, this change has not been strong enough to generate a significant crowding-out effect (the total effect becomes negative but is insignificant).

Concerning the European subsidies, Table 5 shows that this policy generated significant positive direct effects but also negative indirect effects leading to insignificant total effects. 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 other regions are not subsidized). In some sense, it suggests that a more concentrated allocation of European subsidies could improve their total effect. It seems to be also the case concerning the regional subsidies even if our estimates suggest that this type of support has less influence on privately-financed R&D. It is important to note that this does not mean that regional subsidies are useless. They can have specific local impacts that compensate each other and then result in no significant total effects. Even though they are not significant, it is also worth noting that the direct effects of local subsidies always have a positive sign, whereas competition between regions results in negative indirect effects.

All of these results highlight the importance of spatial indirect effects on the total influence of R&D policies. As a negative spatial dependence appears between NUTS3 French regions, we find evidence of a spatial substitutability effect for most public policies except for national R&D subsidies, for which a spatial complementarity appears. This suggests that by contrast with other policies, direct subsidies that are more sectorally targeted and specialised, are more efficient to take advantage of the complementarity between regions.

6 Conclusion

The French policy mix for R&D and innovation is one of the most generous and market-friendly systems in the world, particularly since the 2004-2008 reforms of French R&D Tax credit. It is likely also the policy mix for R&D and innovation that has experienced 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 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 has been mobilized. To our knowledge, this is the first study that proposes to use a spatial model to evaluate a policy mix (four different instruments) at this geographical level.

As a foundation for 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 an R&D policy leads to a leverage or a crowding-out effect 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 regime and fixed effects, which allowed us to take into account the spatial dependency that exists between NUTS3 regions but also the structural change in the effects of R&D policies on R&D investment during the considered period.

The empirical results obtained highlight interesting spatial effects that influence the total impact of R&D policies in France. First, the assumption of a yardstick competition for R&D investment between NUTS3 regions in France has been validated. Indeed, we found negative spatial dependence between private R&D investment in NUTS3 regions that is strongly significant regardless of the specification retained. Second, in this context national subsidies are the only instrument that cumulates positive direct (intra-region) and indirect (external) effects and thereby generates a significant total leverage effect on privately financed R&D. Nevertheless, the three other policies (tax credit and regional and European subsidies) do not generate significant crowding-out effects. This last result is clearly due to the existence of antagonistic effects for these policies: a positive direct effect counterbalances a negative indirect effect related to the yardstick competition. Thus within the French policy mix, national subsidies appear efficient to create complementarity between regions. Third, our spatial model also allows us to show that the macroeconomic condition of the country as a whole is more influential on R&D investment that the local economic activity. Indeed, we estimate that an increase of 1% in GDP in all NUTS3 regions in France will increase privately financed R&D by 1.3%. Finally, we clearly highlight the presence of regime in the influence of R&D policies and more specifically the Tax credit policy. Even though the influence of tax credit on privately-financed R&D is not significant over the entire period, the estimated coefficient significantly changes between the 2001-2005 and the 2006-2011 periods. This change may be directly related to the profound change of the French Tax credit system from a pure incremental-based scheme (until 2004) to a pure volume-based scheme (after 2008).

Most of our results, in terms of additionality of R&D policies, are in line with those previously obtained at the micro and macro levels but add to previous interpretations and help understanding ambiguous existing results by highlighting the essential phenomena of spatial dependency and structural change, which have not been previously analyzed. However, more needs to be done at this geographical level in order to understand the role of specific spatial features on the efficiency of R&D and innovation policies. For instance, in this paper, we have assumed that the spatial dependency between NUTS3 regions is global. Looking at Figure 2, which represents the geography of R&D investment in France's NUTS3 regions, it appears that the spatial dependency is not uniform. This suggests that future research should look more deeply into finer features of spatial dependency. For instance, Spatial Econometric methods addressing local spatial dependency (such as geographically weighted regression) could provide finer results on the effect of the policy mix but also on the characteristics of the existing yardstick competition between NUTS3 regions.

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Appendix A: Design of the 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	$0.50 * \left[RD(t) - [\frac{RD(t-1)+RD(t-2)}{2}]\right]$	€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 $RD(t)$ <= 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 $RD(t)$ <= 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 $RD(t)$ <= 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).

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 ($s \in \{1, ..., S\}, S = 5$)[11]. 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:

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

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:

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

[11] 1: 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.

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

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

Preliminary Tests

We now present preliminary tests 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 can be seem, all tests reject the null hypothesis of unit root in log($DERD$) and the explanatory variables.

Table A.2: Unit Root Test for the Dependent and Explanatory variables.

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

Table A.3: 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: Average Cross-section Correlation.

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

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

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

Table A.5 shows the Chow test for a linear panel model using all variables presented in Table 1. All models contain control variables to outliers.

Table A.5: Global structural break. Panel Chow test.

Year	Chow test	
	F-statistic	**p-value**
2006	6.33	0.000
2007	3.46	0.004
2008	4.28	0.000
2009	3.80	0.002
2010	2.17	0.053

Note: Linear Panel Model with FE by cross-section and time without spatial effects. Outlier controls are incluided.

Using the significant structural break, we have four possible break: 2006, 2007, 2008 and 2009. We select the most efficient model using different information criteria. The information of these models are presented in Table A.6.

Table A.6: Information Criteria for different years.

Year	**Log-likelihood**	**AIC**	**BIC**
2006	−59.422	156.843	248.915
2007	−81.865	201.731	293.802
2008	−77.269	192.538	284.610
2009	−74.342	186.684	278.755

Note: Linear Panel Model with FE by cross-section and time without spatial effects. Outlier controls are incluided.

Appendix B: Spatial selection model and robustness check

Table B.1 shows the results for different hypotheses tested. We find evidence in favor of the SDM model because (1) we reject the SLM, SEM and SLX models.

Table B.1: Summary of restriction hypothesis over SDM model.

Null Hypothesis	Wald test	Chi-sq (f.d.)	p-value	Selected model
SLM : $\theta_{0\mathrm{k}} = 0$, $\theta_{1k} = 0$, $\forall k = 1, \ldots, 5$.	20.59	$\chi^2_{1-\alpha}(7)$	0.004	*Specification SDM, equation*
SEM : $\theta_{0\mathrm{k}} = -\rho\beta_{0\mathrm{k}}$, $\theta_{1\mathrm{k}} = -\rho\beta_{1\mathrm{k}}$, $\forall k = 1, \ldots, 5$.	21.64	$\chi^2_{1-\alpha}(7)$	0.003	*Specification SDM, equation*
SLX : $\rho = 0$	6.66	$\chi^2_{1-\alpha}(1)$	0.001	*Specification SDM, equation*

Notes: SDM model using FE with structural break in 2006 and controlling for outliers.

Table B.2 present the Chow test for the SDM model. We detect a joint structural break when we consider all variables, but when we test the presence of a break for each variable individually, we only detect a 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.

Table B.2: Summary of Chow test to different restriction hypothesis over SDM model.

Null Hypothesis	Wald test	Chi-sq (f.d.)	p-value	Selected model
*Non structural breaks in all periods*** $\triangle\beta_{10} = 0$, $\beta_{1\mathrm{k}} = 0, \theta_{1\mathrm{k}} = 0$, $\forall k = 1, 2$.	92.36	$\chi^2_{1-\alpha}(5)$	0.000	*Specification SDM, equation*
*Non structural breaks in variabels***				
$\triangle\beta_{11} = 0$, $\triangle\theta_{11} = 0$	14.25	$\chi^2_{1-\alpha}(2)$	0.000	*Structural breaks in* $\log(GDP)$
$\triangle\beta_{12} = 0$, $\triangle\theta_{12} = 0$	28.55	$\chi^2_{1-\alpha}(2)$	0.000	*Structural breaks in* $\log(LLTC)$

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

Table B.3 shows the estimation of two non-nested models, SDM and SDEM. The estimations of SDEM and SDM obtain similar values and significance for almost all coefficients. In both cases, the estimated spatial coefficient, $\widehat{\rho}$ and $\widehat{\lambda}$, respectively, is negative and significant. Looking at the results of the general specification model, the information criteria are in favor of SDM.

Table B.3: Comparison between SDM and SDEM. Final specification.

Alternative Models	SDM	SDEM
Non-spatial coefficients	*coef.*	*coef.*
PERIOD 2002-2005		
$\log(GDP)$	0.129	0.062
$\log(LTC)$	0.157***	0.152***
PERIOD 2006-2011		
$\triangle \log(GDP)$	0.182***	0.168***
$\triangle \log(LTC)$	−0.149***	−0.143***
Spatial coefficients		
PERIOD 2002-2005		
$W \times \log(GDP)$	1.256***	1.213***
$W \times \log(LTC)$	−0.107	−0.107
PERIOD 2006-2011		
$W \times \triangle \log(GDP)$	−0.182*	0.137
$W \times \triangle \log(LTC)$	0.042	0.018
Fixed coefficients to all periods		
$\log(SubNat)$	0.035**	0.033*
$\log(SubCEE)$	0.016**	0.017**
$\log(SubReg)$	0.010*	0.010*
$W \times \log(SubNat)$	0.044**	0.034
$W \times \log(SubCEE)$	−0.016	−0.017
$W \times \log(SubReg)$	−0.011	−0.012
Spatial parameter $(\widehat{\rho})$	−0.119***	
Spatial parameter $(\widehat{\lambda})$		−0.079*
Information Criteria		
AIC	231.641	235.970
BIC	359.636	363.964

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

The selection between SDEM and SDM is difficult due to 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 for the 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 the final model using a different criterion of neighbors but with similar characteristics in terms of connectivity. Table B.4 shows the information of contiguity matrix used in the text and the alternative weighting matrix based on the 5 nearest neighbors.

Table B.4: Comparison between spatial weighting matrix.

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

Table B.5 presents the main estimation information 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.5: SDM model estimates and marginal effects using different weighting matrices.

SPATIAL MATRIX	CONTIGUITY		5 NEAREST NEIGHBOURS	
Spatial parameter ($\widehat{\rho}$)	−0.119***		−0.094*	
Information Criteria				
AIC	231.642		237.257	
BIC	359.636		365.251	
VARIABLE	**2002-2005**	**2006-2011**	**2002-2005**	**2006-2011**
	Direct effects			
log(GDP)	0.114	0.293	0.097	0.267
log(LTC)	0.163***	0.011	0.161***	0.013
log($SubNat$)	0.033*	0.033*	0.032*	0.032*
log($SubCEE$)	0.017***	0.017***	0.018***	0.018***
log($SubReg$)	0.010*	0.010*	0.011*	0.011*
	Indirect effects			
log(GDP)	1.151***	0.977**	0.899**	0.820*
log(LTC)	−0.121*	−0.064	−0.109*	−0.081*
log($SubNat$)	0.037*	0.037*	0.040*	0.041*
log($SubCEE$)	−0.017*	−0.016*	−0.009	−0.008
log($SubReg$)	−0.011	−0.011	−0.011	−0.011
	Total effects			
log(GDP)	1.265**	1.269***	0.997**	1.087**
log(LTC)	0.042	−0.053	0.051	−0.068
log($SubNat$)	0.070***	0.070***	0.072***	0.073***
log($SubCEE$)	0.001	0.001	0.008	0.010
log($SubReg$)	−0.001	−0.000	0.000	0.000

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

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