The impact of the French policy mix on business R&D: How geography matters

Benjamin Montmartin[a], Marcos Herrera[b], Nadine Massard[c],*

[a] SKEMA Business School, Université Côte d'Azur (GREDEG), OFCE Sciences PO, Sophia-Antipolis F-06560, France
[b] CONICET – IELDE, National University of Salta, Av. Bolivia 5150, A4408FVY Salta, Argentina
[c] Université Grenoble Alpes, CNRS, INRA, Grenoble INP, GAEL, F-38400 Saint-Martin d'Hères, France

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ABSTRACT

Based on a spatial extension of an R&D investment model, this paper measures the macroeconomic impact of the French R&D policy mix on business R&D using regional data. Our measure takes into account not only the direct effect of policies but also indirect effects generated by the existence of spatial interaction between regions. Using a unique database containing information on the levels of various R&D policy instruments received by firms in French NUTS3 regions over the period 2001–2011, our estimates of a spatial Durbin model with structural breaks and fixed effects reveal the existence of a negative spatial dependence among R&D investments in regions. In this context, while a-spatial estimates would conclude that all instruments have a crowding-in effect, we show that national subsidies are the only instrument that is able to generate significant crowding-in effects. On the contrary, it seems that the design, size and spatial allocation of funds from the other instruments (tax credits, local subsidies, European subsidies) lead them to act (in the French context) as beggar-thy-neighbor policies.

1. Introduction

Considering the importance of the diverse types of market failure inherent in R&D activities, most countries have established public financial support favoring private R&D investment (Montmartin and Massard, 2015). States have many measures at their disposal, among which subsidies and tax credits are the most commonly used.

However, in times of constrained public finance, issues emerge regarding the effectiveness of such policy instruments.

To date, reviews of studies evaluating the impact of R&D subsidies (Zúñiga-Vicente et al., 2014; Dimos and Pugh, 2016) or tax credits (Castellacci and Lie, 2015; Gaillard-Ladinska et al., 2015) yield mixed results and are therefore inconclusive. On the whole, it seems that, much more than the econometric methodology employed, it is the sectoral or national context and the specific design and implementation of the instruments that can explain the heterogeneity of extant empirical results. Specifically, reviews highlight the importance of two main contextual elements, both of which create interaction effects that are generally ignored in existing evaluation studies. The first refers to the implementation of the policy mix in most countries using a diversity of instruments acting simultaneously toward the objective of fostering business R&D. However, evaluation studies that consider simultaneously the diverse instruments and their possible interactions are still rare, although notable recent contributions exist (see Dumont, 2017, in particular). The second contextual element that should be considered for robust evaluation studies concerns the role of spillovers that create indirect impacts of policy instruments on other beneficiaries as well as non-beneficiaries. Indeed, while the economics of innovation literature has long highlighted the role of knowledge spillovers or other types of interactions among actors, thus far, few evaluation studies of public incentives for business R&D have explicitly considered the existence and impact of such phenomena. We argue that not only can the ignorance of such issues lead to biased estimates, but moreover, the mechanisms at stake deserve better consideration to draw lessons on the conditions for the efficiency of public policies.

In particular, if geography matters for the emergence and diffusion of knowledge spillovers, which is soundly supported by the literature on the geography of innovation (Autant-Bernard et al., 2013; Massard and Autant-Bernard, 2017), one may expect different effects of public incentives to R&D investment depending on the spatial distribution of the R&D activities and the locations of beneficiaries. Theoretically, spatial dependencies can either create positive knock-on effects through knowledge spillovers or, on the contrary, reinforce negative competitive pressure between territories: with incentives enhancing investment

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* Corresponding author.
E-mail addresses: benjamin.montmartin@skema.edu (B. Montmartin), mherreragomez@conicet.gov.ar (M. Herrera), Nadine.Massard@univ-grenoble-alpes.fr (N. Massard).

in some territories to the detriment of others. Hence, the macro-economic impact of spatial dependencies is generally undetermined by theory, and the total crowding-in or crowding-out effects can depend on which of these forces overcomes the other.

Thus, one of the objectives of this paper is to apply a spatial model to regional data to better investigate the macroeconomic effect of a mix of public supports in favor of private R&D by taking into account potential spatial effects.

To that end, France appears to be a particularly relevant case for two main reasons. First, the spatial distribution of R&D activities in France is highly agglomerated and exhibits substantial regional disparities. In this context, the debate on the driving force vs. the competitive effects of agglomeration is a sensitive issue for public policy. As an illustration, outcome differences between France and Germany, for instance, may be explained not only by differences in policy choices but also by differences in the spatial dispersion of innovative activities. The continuum of agglomeration that characterizes a large part of the German territory creates a very different context of spatial interactions compared to the French case, which seems more subject to shadow effects because innovative agglomerations are dispersed across the territory and often surrounded with zones of very low innovative activities. Second, the French policy mix for R&D has evolved substantially in recent years and is now one of the most generous systems in the world, comprising complex direct and indirect supports. Specifically remarkable is the inversion of the ratio between direct and indirect support for R&D following a reform that introduced a volume scheme for the R&D tax credit in 2004 and its reinforcement in 2006 and 2008 (when a pure volume-based system without upper limits was implemented). Indeed, according to the OECD,[1] 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).

This paper investigates the effects of the French policy mix on private R&D investment by using a unique database containing regionally aggregated information on the amount of public support received by firms in all French metropolitan NUTS3 regions over the period 2001–2011. These data allow us to distinguish four types of policy: R&D tax credits and regional, national and European subsidies. To run our analysis, we first develop a simple theoretical model of regional R&D investment based on Howe and McFetridge (1976) and extended to spatial interactions 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 and crowding-in effects can emerge. This framework will provide a basis for our empirical estimates. More precisely, we estimate a spatial Durbin model with temporal regimes and fixed effects. This type of spatial model allows us to take into account the heterogeneity of regions through regional fixed effects, the dependency between neighboring regions and potential structural changes in policies' impact due to changes in policies' design during the considered period.

Thus, our analysis offers three main contributions to the literature on the evaluation of R&D policies: (i) it simultaneously considers different components of the R&D policy mix, regional, national and European subsidies and tax credits, and allows interpretation of the results in terms of the total marginal effect of each instrument on private R&D spending; (ii) allowing us to split this total effect into the direct effect (internal to the considered region) and the indirect effect (resulting from spatial dependencies between regions), it investigates how the geography of R&D activities may affect the macroeconomic effects of policy instruments; and (iii) it also measures the potential change in the impact of policies that can be related to substantial changes in the design of the policy mix, especially the switch from an incremental to a pure volume-based scheme for R&D tax credits in France.

From a global point of view, our results suggest the relative efficiency of the French policy mix for R&D in the sense that no policies generate significant crowding-out effects and one policy is able to generate a significant crowding-in effect. Specifically, we provide three core findings. First, we observed the presence of a significant negative spatial dependence among R&D investments in NUTS3 regions. This refers to the polarization of R&D investments into a limited number of hubs that are geographically distant and surrounded by laggard regions. In this context marked by shadow effects, untargeted state policies or competitive local policies are likely to act as beggar-thy-neighbor policies. Second, in this geographical context, while a-spatial estimations focusing on the direct (within-region) effect would conclude that there is crowding-in of all instruments, we show that national subsidies are in reality the only instrument that generates significant crowding-in effects. For the other instruments, it seems that their positive direct effect is eliminated by negative indirect (between-region) effects due to the negative spatial dependence with neighboring regions. In other words, it seems that tax credits and regional and European subsidies foster competition among regions and thus act as beggar-thy-neighbor policies, resulting in a neutral total effect. On the contrary, national subsidies (which are often sectorally or territorially targeted) appear to be efficient in exploiting the complementarity between French regions, creating positive interregional spillovers that outweigh the negative spatial dependence among regions. The last main result is the evidence that the passage from a purely incremental scheme to a pure-volume scheme for the French tax credit modified the response of firms to this policy. Indeed we find a strong negative change in the impact of the tax credit on R&D investment between the first period (2002–2005) and the second (2006–2011). This corroborates the idea that a pure volume-based scheme generates more windfall effects than incremental schemes.

The remainder of the paper is organized as follows. In Section 2, we present the related existing literature. Section 3 describes the regional model of R&D investment that constitutes our theoretical framework. In Section 4, we present the data and the main descriptive statistics, highlighting the spatial and temporal features of R&D activities and policies in France. The empirical estimation strategy is described in Section 4.3. Section 5 discusses the empirical results in detail. Conclusions are presented in Section 6.

2. Related empirical literature

2.1. Recent advances in the evaluation of the direct impact of financial support

Theoretically, the basic idea is that public support will be efficient if it targets projects that would not be undertaken by firms without such grants. Otherwise, incentives will be ineffective because they will not lead to additional investment. Methodologically, different measures of efficiency in terms of input additionality[2] have been used in the empirical literature (Mohnen and Lokshin, 2009), the objective of which consists in comparing the policy expenditures with the additional amount of R&D spent by private firms. When policy expenditure is more than compensated for by the additional amount of business R&D spending, this describes a pure additionality effect (also called the crowding-in or leverage effect, indicating a complementarity between public and private funds). On the contrary, partial or full crowding-out effects appear when there is a partial or full substitution between public and private funds.

Various phenomena have been theoretically analyzed that can hamper the expected additionality effects of implemented policies. The

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[2] 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.

most frequently discussed is the possibility of opportunistic behaviors by firms that can lead to windfall effects (Dimos and Pugh, 2016). Different policy designs are compared according to their risk of giving rise to substitution strategies between public and private financing. This argument is the starting point of most of the empirical studies evaluating the direct impact of financial support for business R&D in different countries and periods. Reviews from Zúñiga-Vicente et al. (2014), Castellacci and Lie (2015), Gaillard-Ladinska et al. (2015) and Dimos and Pugh (2016) show that although the additionality hypothesis prevails (or at least there is no evidence of crowding-out), no clear global feature emerges. Important differences remain between instruments (tax credits, subsidies or others forms of public support), and there is also considerable heterogeneity in the effects depending on the characteristics of firms or on the context.

Instead of increasing the number of studies that focus on one instrument and often one country or one sector, these authors call for the development of approaches that allow for a comparison and better understanding of the factors creating heterogeneity in outcomes. Among the most recent studies in this vein, we select only a few that offer interesting insights relevant to our perspective.

2.1.1. The development of policy-mix analyses

Major advances have been seen in the development of multi-instrument analyses. Indeed, as firms can generally benefit from a considerable variety of fiscal aids and direct supports, studies should consider multiple treatments for evaluation. Hottenrott et al. (2017), Huergo and Moreno (2014) and Wang et al. (2017) offer original contributions by considering different types of grants or comparing support offered via subsidies and loans, with a combination of these vehicles appearing beneficial. More interesting for our purposes are papers that consider tax credits as part of a policy mix with other types of support. Generally, these recent papers contribute to strongly mitigate the positive results obtained when the impact of tax credits is estimated alone (European Commission, 2014). Specifically addressing the policy mix combining R&D tax credits and subsidies, some micro-econometric studies conclude that the two associated schemes have positive impacts (Corchuelo and Martínez-Ros (2009) for the Spanish case, Duguet (2012) for France, Bérubé and Mohnen (2009) for Canada; Haegeland and Møen (2007) for Norway and Czarnitzki and Lopes-Bento (2014) in the German case). Other studies show how the effect of one instrument is reduced by the introduction of another. Marino et al. (2016) analyze the impacts of subsidies in the presence or absence of a tax credit regime for the French case. They show that crowding-out effects appear to be more pronounced under the R&D tax credit regime. Dumont (2017), considering the Belgian case, shows that the effectiveness of R&D support decreases when firms combine subsidies with several tax benefits. Macro-econometric studies have also contributed to the analysis of policy mixes. Papers conducted on OECD countries in different time periods simultaneously analyze the impact of direct and indirect support in stimulating private investment in R&D (Guellec and Van Pottelsberghe de la Potterie, 1997; Montmartin and Herrera, 2015). In a recent contribution also comparing different types of public R&D policy mixes in a large sample of OECD countries, Brown et al. (2017) find a negative impact of R&D tax credits. In other words, it appears that when associated with important direct support, the impact of indirect support is lower. It should be noted that such results revealing possible crowding-out effects have one of three main characteristics: they are obtained from macroeconometric approaches, and thus implicitly include not only the intensive but also the extensive margin and possible distortionary phenomena across firms and industries; they use continuous and not binary variables to measure the treatment, the latter of which are recommended by Dimos and Pugh (2016) to make better estimations; or they concern Belgium or France, which are the two most generous countries in the world in terms of public support for private R&D. Hence, these are possible explanations of the differences in results compared to the rest of the literature, although full confirmation would

necessitate further analyses.

2.1.2. Introducing spillovers and possible distortions

Another set of papers is worth mentioning here because in their attempts to understand different sources of heterogeneity, they have begun to perform analyses addressing spillovers and distortions. Indeed, although they are clearly theoretically established, distortions across firms or industries that may create indirect effects are rarely considered by the empirical literature on the evaluation of public support for private R&D. However, distortionary effects across firms or industries may also result in global (macroeconomic) crowding-out effects if the incentives for the supported firms or sectors are outweighed by the resulting disincentives affecting non-supported firms/sectors. Only a few macroeconometric approaches implicitly take this phenomenon into account when measuring additionality at the country level. Some, cited in the reviews above, consider the variation in the effects of public incentives across sub-groups of firms depending on firm size and report contradictory results. 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 other countries. Evidence suggesting that knowledge spillovers from large firms exceed those from small firms also tend to weaken the case for targeting tax incentives towards SMEs – even if SMEs will more substantially increase their R&D expenditures in response to such incentives. More recently, sectoral sources of heterogeneity have been investigated, including the original contributions of Castellacci and Lie (2015) and Freitas et al. (2017). These papers show that the effects of R&D tax credits vary across sectors and that the overall effects of R&D tax credits depend on the interplay between the direct impact on a given sector and indirect impacts on other sectors due to intersectoral spillover effects. However, although these issues have important implications for policy choices in terms of sectoral targeting, no existing studies offer sound estimations of such phenomena.

In this paper, we wish to emphasize another source of heterogeneity and indirect effects that is still largely ignored by the empirical literature: the spatial dimension.

2.2. Introducing the spatial dimension into R&D policy evaluation

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 spillovers and the resulting competition among territories to attract R&D investment. Thus, as space appears non-neutral for R&D and innovation activities, one may expect two main implications in terms of additionality measures. First, there may be spatial heterogeneity: firms in different territories may react differently to similar public incentives. Second, spatial interdependency phenomena imply that R&D activities within one place depend on R&D activities in other places. These dependencies may be positive when they result from knowledge spillovers and contribute to the diffusion of the initial incentive effects to neighbors. They may also be negative if the competition between regions create distortion: the positive incentive impact in one region translating into a negative impact for neighboring regions. At the macroeconomic level, one would only observe a change in the relative weight of regions with respect to R&D investment with no significant overall impact. Moreover, there is a possibility that crowding-out effects will appear if the negative spatial dependence outweighs the positive effect of spatial knowledge spillovers. Thus far, however, very few evaluation studies have considered the role of spatial heterogeneity due to agglomeration and the possibilities of spatial dependencies among actors. As for the other sources of heterogeneity and spillover mentioned above, ignoring these phenomena can lead not only to biased econometric estimations

but also prevent public authorities from making informed choices concerning the design of their policy mix.

To our knowledge, only two macro-econometric analyses using spatial econometrics have contributed to the measurement of interactions between instruments implemented in different, neighboring 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 the R&D investments of firms 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, these reactions are estimated to be of the same magnitude, implying no 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 considered. One simple explanation for this is that agglomeration economies are often observed at intra-country agglomeration levels. There are also geographical limits to the capacity of firms' to react to R&D incentives. Indeed, it is clearly easier for firms to change their investment locations within one country than between countries in response to incentives.

2.2.1. Advantage of regionally aggregated data for evaluation

To our knowledge, only Wilson (2009)'s paper uses aggregated data at the intra-national level. We argue, however, that this level of analysis using regional aggregated data within countries allows for original approaches and that these data are the most relevant for addressing spatial issues in the evaluation. The advantage of regional data for the evaluation of public support for business R&D is threefold:

(i) They make it possible to better account for spatial/territorial heterogeneity. Compared to country-level, regional data allow for finer and more relevant analysis, as regional data better correspond to the level at which local knowledge spillovers and agglomeration effects can impact firms' innovative activities. Regional data also provide location information that is not usually possible to obtain for each firm in large microeconomic databases. Using regional data also allows for the consideration, at the territorial level, of the combined effect of the extensive and intensive margins. Indeed, micro-econometric studies are generally focused on the intensive margin (i.e., impact on the intensity of R&D investment within firms that already pursue 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 into R&D activities).

(ii) These data are relevant for the evaluation of a multilevel policy mix combining the regional, national and European levels. Indeed, while the political economy of multilevel interventions is largely developed within diverse federal frameworks or in the European context, we are not aware of studies introducing this dimension of the policy mix into evaluation exercises. Lanahan and Feldman (2015) contributes to the debate concerning innovation policies in a federal context, and some papers based on the CIS survey compare the impact of national and European supports on firm performance. However, none of them introduce regional policies. However, the European context has recently contributed to reinforcing regional issues while simultaneously questioning their efficiency. In this respect, consider Breidenbach et al. (2016), who reveal the risk of negative overall impacts of regional policies when they are too targeted on attractivity issues and thereby contribute to reinforce the negative impact of competition between regions. Therefore, the regional level appears to be a particularly interesting setting to study policy mix implemented via multilevel intervention within the European context and implement spatial econometric models that allow us to measure the relative

implications of different forms of spatial dependencies across regions (positive or negative) when estimating the overall effects of public policies.

(iii) Considering spatial entities within a single institutional context (a country), regional data facilitate the identification of temporal structural changes due to public policy changes within this country, thereby allowing a finer interpretation of the impacts in terms of the characteristics of the policy mix and instrument design.

In France, the highly agglomerated spatial structure and the evolution of the policy mix since the early 2000s has contributed to reinforcing the relevance of such spatial approaches using regional data.

In the following section, we develop a theoretical framework for the analysis of regional R&D investment that will form the basis for our empirical study using French regional data.

3. Theoretical framework

3.1. A regional model of R&D investment

The model developed in this paper is based on the conceptual R&D investment framework proposed by Howe and McFetridge (1976) and David et al. (2000). The idea is 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, meaning 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. The MRR is a decreasing function of and the MCC is an increasing function of the level of R&D expenditure. Obviously those functions are also strongly influenced by other variables such as public R&D policies (see David et al., 2000 for a detailed discussion).

The difficulty we face is to translate the complexity of this microeconomic conceptual framework into a regional analytic framework. First, we assume that at a given point in time t, there is a fixed but relatively large number of firms in each region such that the MRR and MCC functions for a region are simply the aggregation of the MRR and MCC functions of firms located in that region. Second, we specify generalized CES functions to describe the complex influence of R&D policies on the MRR and MCC functions of a region. This functional form allows R&D policies and other influential variables to be imperfect substitutes for firms' private R&D cost and profitability. Moreover, it allows each variable to have a specific influence on the MRR and MCC functions and the number of variables can have positive or negative effects on the two functions. In other words, having more public policies does not necessarily imply greater efficiency (or vice versa).

Thus, we define the MRR and MCC functions in region i as:

$$\text{MRR}_i = \delta_i R_i^{\beta} \left[\sum_{k=1}^{K} \sigma_k (X_{ki})^{\rho} \right]^{\nu/\rho}, \qquad \beta < 0, \ \rho \neq 0, \ \sum_{k=1}^{K} \sigma_k = 1, \tag{1}$$

$$\text{MCC}_i = \psi_i R_i^{\alpha} \left[\sum_{k=1}^{K} \mu_k (X_{ki})^{\rho} \right]^{\lambda/\rho}, \qquad \alpha > 0, \ \rho \neq 0, \ \sum_{k}^{K} \mu_k = 1, \tag{2}$$

where $\delta_i > 0$ and $\psi_i > 0$ are region i's specific time-invariant elements of the MRR and MCC functions, R_i is the level of private R&D investment, and $X_{ki} \geq 0$, $k = 1, \ldots, K$ represent public policy variables and other variables affecting both the MRR and MCC functions. μ_k and σ_k are the share parameters of the CES functions representing the importance of each variable in the MCC and MRR functions. $\alpha \in]0, \ \infty[$ and $\beta \in] - \infty, \ 0[$ represent the elasticity of MCC and MRR, respectively, with respect to R&D investment. $\lambda > 0$ and $\nu > 0$ represent the returns to scale for the X variables in the MCC and MRR functions. These functions also assume a constant elasticity of substitution between two X variables given by $\eta = 1/(1 - \rho)$.

The equilibrium amount of private R&D in the i-th region is

obtained when the aggregate MRR function equals the MCC function, that is,

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

This last expression implies a non-linear specific effect of each X_k variable on the level of private R&D investment. Consequently, the theoretical impact of a policy variable k is complicated to discuss and interpret. Nevertheless, if the elasticity of substitution between X variables is near 1 (i.e., if $\rho \to 0$), expression (3) can be rewritten (using the translog approximation proposed in Hoff, 2004) as:

$$\ln R_i = \frac{1}{\alpha-\beta} \left(\ln \frac{\delta_i}{\psi_i} + \sum_{k=1}^{K} [v\sigma_k - \lambda\mu_k] \ln X_{ki} \right) + o(\rho), \tag{4}$$

Where $o(\rho)$ represents all-non linear and cross effects of X variables and the linear approximation error. As shown in Appendix A.1, our dataset seems to support the hypothesis that $\rho \to 0$, and thus, in what follows, we assume that $o(\rho)$ is negligible. Using this approximation, our model is able to provide important implications for the channels through which public R&D policies generate crowding-in or crowding-out effects on R&D investment. To see this, we study the elasticity of R&D investment with respect to a public policy k:

$$\frac{d \ln R_i}{d \ln X_{ki}} = \frac{[v\sigma_k - \lambda\mu_k]}{\alpha-\beta}. \tag{5}$$

This last expression highlights the six parameters (α, β, v, λ, σ_k and μ_k) that are critical to explain the effect of a public policy at the regional level.

Let us consider first the denominator of (5) that refers to the shape of the MCC and MRR functions with respect to the level of R&D investment (α and β). The lower the value of $\alpha - \beta$ is, the greater the effect of public policies on R&D investment. An extreme case appears when regions face inelastic MRR and MCC functions ($\alpha \to \infty$ and $\beta \to -\infty$). Indeed, in that case, public policies are not able to influence the MRR and MCC functions and public policies generate only crowding-out effects. An inelastic MRR function will appear when there is no possibility for regions to appropriate the innovation benefits or there is no innovation potential. An inelastic MCC function will appear when regions are composed of asset-constrained firms that cannot access external funding. Another extreme case appears when regions face perfectly elastic MCC and MRR functions ($\alpha \to 0$ and $\beta \to 0$). In that case, public policies strongly influence R&D investment, as regions are fully able to benefit from them, which will result in a crowding-in effect. Thus, a crowding-out effect of public policies is more likely to occur in a region where supported firms are asset-constrained and face limited technological opportunities. Hence, empirical evidence of the heterogeneity of policy effects depending on the characteristics of firms and sectors may be theoretically explained, and this model has the advantage of theoretically supporting the possibility that regions with different firm demographics and/or different sectoral specializations will react differently to public R&D policies.

The second part of the elasticity (numerator) involves the returns to scale of public policies and their share parameters. From a theoretical perspective, most effects of public support for R&D will materialize through an impact on the MCC function (see David et al., 2000). Indeed, the external effects of public policies, such as potential learning, training or reputation effects, will take more time to influence the MRR function. This is why we will focus the discussion on the two parameters related to the MCC function, λ and μ_k. $\lambda \in]0, \infty[$ measures the returns to scale of a public policy on the MCC function. For asset-constrained regions, we can easily imagine that the returns to scale of R&D support are greater than for non-constrained regions (see Zúñiga-Vicente et al., 2014). Indeed, for those regions, signaling effects may imply greater returns of R&D support on the MCC function by allowing

them to, for instance, access external capital. Consequently, increasing returns to scale of public policies are more likely to appear for asset-constrained regions. μ_k represents the share parameter of a public policy k in the MCC function (which should be negative, as public support decreases costs). In other words, it represents the importance of a public policy in the MCC of regions. Let us assume a simple tax credit of 1% of total R&D investment for the whole country. Then, the value of μ_k will be very low, as will be the net effect of the policy on R&D investment. Assume now that for the same cost, policy-makers change the policy and implement a 10% tax credit for asset-constrained regions. Then, for those regions, the value of μ_k will be much higher, and we can expect a greater effect of the policy on R&D investment. Thus, our model suggests that a public policy is more likely to generate a crowding-out effect on R&D investment if its financial endowment is too low and/or untargeted. This echoes the finding in empirical literature of the necessity of using a continuous measure of the policies instead of only dichotomous variable because efficiency is not only a question of benefiting or not from the policy but also a question of how large the financial support is.

3.2. The spatial extension of the model

Thus far, our model has assumed closed regions. Nevertheless, as highlighted above, it is difficult to assume complete independence of R&D investment choices between actors located in neighboring regions. To translate the empirical evidence of spatial interactions into our framework, we introduce into the model an influence of private R&D investment by other regions on the MRR and MCC functions of a particular region. Obviously, the influence of each region $j \neq i$ on region i 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 and competitive interactions (Autant-Bernard et al., 2013). Hence, assuming that spatial proximity is a major source of dependency between private R&D investment decisions, we introduce these elements into our framework by extending the MRR (1) and MCC (2) functions in the following way:

$$\text{MRR}_i = \delta_i R_i^\beta \left(\sum_{j \neq i} w_{ji} R_j \right)^\varphi \left[\sum_{k=1}^{K} \sigma_k (X_{ki})^\rho \right]^{v/\rho}, \qquad \beta < 0, \rho \neq 0, \sum_{k=1}^{K} \sigma_k = 1, \tag{6}$$

$$\text{MCC}_i = \psi_i R_i^\alpha \left(\sum_{j \neq i} w_{ji} R_j \right)^\omega \left[\sum_{k=1}^{K} \mu_k (X_{ki})^\rho \right]^{\lambda/\rho}, \qquad \alpha > 0, \rho \neq 0, \sum_{k=1}^{K} \mu_k = 1, \tag{7}$$

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

$$\ln R_i = \frac{1}{\alpha-\beta} \ln \frac{\delta_i}{\psi_i} + \frac{(\varphi-\omega)}{\alpha-\beta} \ln \left(\sum_{j \neq i} w_{ji} R_j \right) + \frac{1}{\alpha-\beta} (\sum_{k=1}^{K} [v\sigma_k - \lambda\mu_k] \ln X_{ki}) + o(\rho). \tag{8}$$

With this last expression, the elasticity of R&D investment with respect to a public policy k becomes:

$$\frac{d \ln R_i}{d \ln X_{ki}} = \frac{(\varphi-\omega)}{\alpha-\beta} \frac{d \ln \left(\sum_{j \neq i} w_{ji} R_j \right)}{d \ln X_{ki}} + \frac{[v\sigma_k - \lambda\mu_k]}{\alpha-\beta}. \tag{9}$$

A new element of the elasticity of R&D investment appears, which measure the influence of a public policy k on R_i due to spatial

dependence. Indeed, R_i is influenced by R_j, which itself is influenced by R_i and, thus, the level of public support k received by region i. More generally, the introduction of a spatial dimension into our model implies that public support received by firms in neighboring regions will also influence the reactions of local firms. The impact of spatial dependence on the efficiency of public support depends on the elasticities of the MCC (ω) and MRR (φ) functions with respect to the level of neighboring R&D investment. In the economic literature, the net effect of R&D spillovers depends on two well-known effects (see Montmartin and Massard, 2015): the "standing on shoulders" and the "fishing in the same lake" effects. If the "standing on shoulders" effect is strong, R&D executed by neighbors will benefit local firms and could lead to a decrease in the costs of some R&D projects in the pipeline (a negative value for ω). Importantly the "standing on shoulders" effect is likely to appear when technological opportunities are high. If the "fishing in the same lake" effect is strong, this will reinforce competitive pressure, and thus, more R&D projects undertaken in neighboring regions can decrease the returns of R&D projects in the local firms' pipelines (a negative value of φ). This effect is likely to appear in sectors where there are patent races and/or low technological opportunities. Consequently, the influence of spatial dependence on the efficiency of public policies is likely to be driven by the net effect of R&D spillovers. In other words, we argue that the empirical measure of spatial dependence is in part responsible for the net effect of R&D spillovers between regions. Obviously, a negative spatial dependence would tend to reduce the net positive effect of public policies at the macroeconomic level. Thus, it appears very important to take into account spatial dependence to assess the impact of public policies.

4. Descriptive statistics and empirical stategy

Based on this theoretical background, we develop an empirical analysis of the French case.

4.1. 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. The data were provided by the French Ministry of Research and obtained from two main sources: the R&D survey and the fiscal database on R&D tax credits.

4.1.1. R&D expenditure and subsidies

The R&D survey is collected each year by the French Ministry of Research and provides information at the firm level on R&D activities and, particularly, on domestic R&D expenditures (DERD) and the sources of R&D financing.

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 responsiveness of business R&D 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[3] led us to restrict the time considered to the period 2001–2011.

This database allows us to distinguish different types of subsidies

according to their sources of financing: *SCEE* (European subsidies received from the European Commission); *SNAT* (total of the subsidies received from various French Ministries, i.e., national subsidies); and *SREG* (subsidies received from local authorities, i.e., essentially regions and departments). However subsidies information is given at the firm/sector level. So, in order to correctly geo-localized 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.

4.1.2. Tax credit

The tax credit file is collected by the fiscal administration. It is exhaustive and details at the firm level the amount of R&D that has been declared and the amount of tax credits that have been granted. Aggregated data at the department (NUTS3) level were provided to us by the General Directorate for Research and Innovation of the Ministry of Research. Matching these data with those from the R&D survey at the department level involved some methodological decisions. In short, the most difficult problem we faced concerns the location of R&D tax credits. The amount of tax credits received in each department does not correspond to the amount of R&D declared and executed by firms. 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) actually benefits from the tax credit, while the basis for this tax credit is the R&D declared by the all enterprises in this group regardless of their location. Therefore, to account for possible location biases due to the legal and fiscal organization of firms and groups, we computed a relocalized measure for tax credit (TC) using this localized information contained in the R&D survey. Further details on the calculation used for relocation of the TC are given in Appendix B.

Table 1 gives the main statistics for our variables pooled over the period considered. Our dependent variable (DERDF) refers to the privately financed part of the DERD (once all subsidies and tax credits are deducted). Note also we use the one period lag of Tax credit (LTC) as the level of Tax credit receive in t is based on R&D spending in $t-1$. Consequently, we will not able to exploit information in year 2001 and we focus on the period 2002–2011.

4.2. The evolution of the French policy mix

A complete description of the objectives and selection schemes of each innovation policy instrument implemented in France during the 2000s is beyond the scope of this article. Indeed, a recent report of France Strategy (Pisani-Ferry et al., 2016) highlights the sharp increase in the number of devices at the disposal of actors to foster innovation, from 30 in 2000 to 62 in 2015. In the following section we show how our data allows us to summarize such a complex landscape. By focusing on 4 main groups of instruments (TC, regional, national and European subsidies), we illustrate how their main objectives and characteristics may impact on the spatial dimension of R&D activities in France. The stated priority of French authorities during the 2000s was to foster private R&D spending as this objective mobilizes two thirds of French public means dedicated to innovation policies (Pisani-Ferry et al., 2016) and explains for a large part the switch toward a tax-credit driven policy mix. While this objective covers all the policy instruments, their precise scheme may or may not be associated with other objectives.

4.2.1. The switch toward a tax-credit-driven policy mix

Our data cover the 2001–2011 period, which means that the period contains various important reforms to French public R&D policy. During the early 2000s, France, combined important direct aid for enterprises with fiscal incentives. However, in the middle of the 2000s, major changes occurred.

In 2004, France started to switch from a purely incremental system of tax credits toward a volume-based scheme, a reform that was

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[3] Before 2001, for example, only enterprises that employ at least 1 full-time researcher were 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.

Table 1
Summary statistics (pooled) – in millions of Euros.

Variables	Obs.	Mean	S.D.	p50	Min.	Max.
Dependent						
DERDF	940	204.521	415.045	64.499	−0.415	2790.547
Explanatories						
GDP	940	18676	23349	12408	1400	191969
LTC	940	22.458	54.935	5.361	0	557.090
SNAT	940	26.057	85.229	2.449	0	726.508
SCEE	940	1.681	4.395	0.184	0	49.352
SREG	940	0.705	2.167	0.126	0	32.246

Table 2
Importance of direct support by source of financing (% DERD).

Variables	Mean	S.D.	p50	Min.	Max.
Period 2002–2005					
SNAT/DERD	6.95	10.73	2.88	0	69.66
SCEE/DERD	0.52	0.84	0.22	0	8.23
SREG/DERD	0.25	0.88	0.06	0	14.05
Period 2006–2011					
SNAT/DERD	7.46	11.21	3.84	0	81.53
SCEE/DERD	0.46	0.95	0.27	0	16.83
SREG/DERD	0.60	1.19	0.20	0	13.99

reinforced in 2006 and 2007, and since 2008, these tax credits in France have been calculated on a pure volume basis without a ceiling. Consequently, the global trend is that of a sharp increase in the share of R&D expenditures covered by the tax credit starting from around 2006 (see Fig. 1 for an illustration of these changes). More precisely, TC represents 3% of DERD in 2002–2004, then increases to 11% in 2005–2008 and is set at 22% in 2009–2011.

Due to this primary change in the French policy mix, the incentive scheme and the characteristics of the population of beneficiaries were modified from mid-2000s onward. Consequently, we suspect that a structural change in the effect of R&D policies may exist in our data distinguishing the early 2000s from the late 2000s.

4.2.2. The multi-level subsidies policy

Concerning subsidies, after 2005, the launch of the competitiveness pole policies in France resulted in new criteria for supporting projects in which sectoral and territorial strategies dominate. Associated with the evolution of European regional policy, which clearly puts emphasis on the necessity of developing regional strategies for research and innovation in the 2007–2013 program, this contributed to increase the share of regional subsidies in the total direct public aid for private R&D. More important, strategies designed to reinforce networking and agglomeration effects are becoming central which may have implications in terms of spatial dependence.

The data in Table 2 confirm a slight increase in the importance of regional subsidies in the French policy mix after 2005. Their importance compared to national subsidies, however, remains very low, which may limit their efficiency.

Concerning European subsidies, we observe a reduction in the average subsidy during the second period, which is associated with greater heterogeneity in the allocation and suggests greater concentration of such support in specific regions.

4.2.3. The spatial structuration of business R&D investment and policy

Focusing now on the spatial distribution of R&D activities and policies, we observe in Fig. 2 a high concentration of privately financed R&D investment in a few NUTS3 regions, which are rather dispersed across the territory and surrounded by NUTS3 regions with low private R&D investment. It should be noted that this structure, which reveals a negative dependence between neighboring regions, is fairly stable throughout the period considered. It is also interesting to see in Fig. 3 that the spatial concentration of GDP measure by the Gini coefficient is substantially lower than the spatial concentration of private R&D spending, suggesting a more important impact of the spatial dimension on the latter.

By contrast, Fig. 3 also shows that the spatial distribution of public support has evolved and exhibits contrasting tendencies. National subsidies are the most concentrated. Tax credits are the least concentrated instruments, and their dispersion increased with the reforms introduced between 2004 and 2008. Interestingly, whereas the total amount of regional subsidies increased over our period, the Gini coefficient decreased, revealing a more extensive than intensive process (an increasing number of regions developing local policies).

Tax credits that cover a larger part of R&D spending for SMEs than for large firms display a slightly lower index of spatial concentration than private R&D investment. However, as it is a market driven instrument that leaves the strategic orientation of R&D up to private firms, it largely follows the underlying spatial dynamics of private investment in R&D. Subsidies, on the contrary, are generally mission-oriented and sector-targeted instruments.

The two main objectives followed by subsidy programs in France, along with the development of private R&D are: the development of public/private collaboration on the one hand, and support for entrepreneurship and the development of young, innovative firms on the other hand. Oriented toward strategic actors and sectors, national subsidies in France are traditionally highly concentrated. Two main
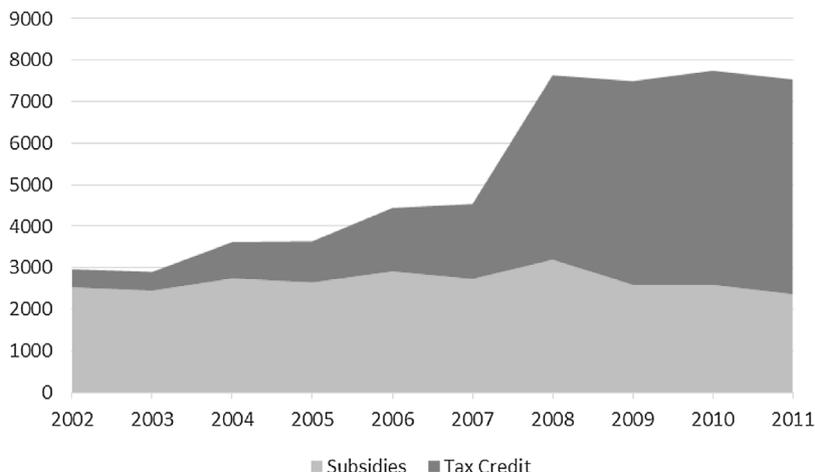
Fig. 1. Financial support for private R&D in France 2002–2011 (in millions of Euros).
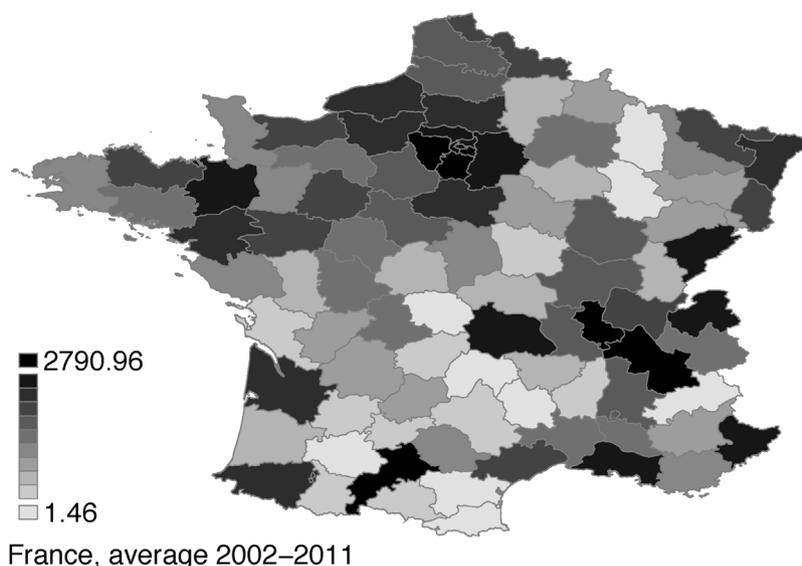*Source*: French Ministry of Research (MENESR), own calculations.

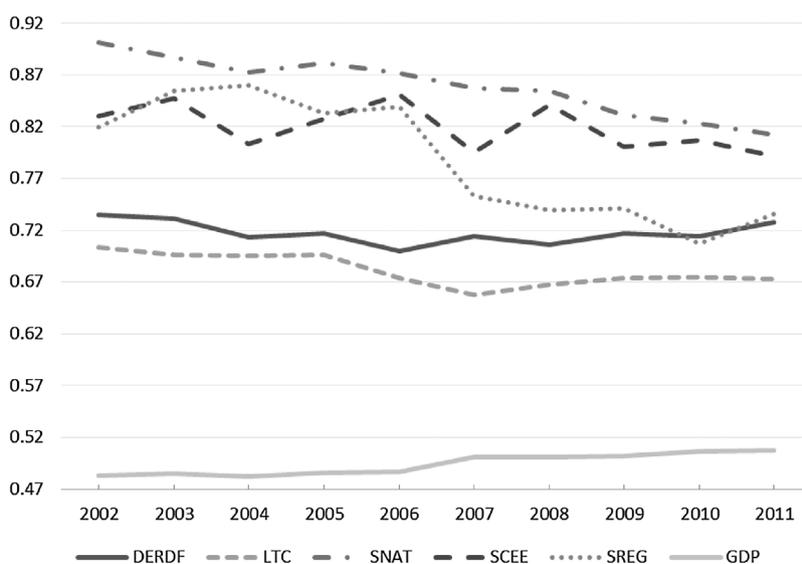**Fig. 2.** Spatial distribution of the private R&D – in Euro thousands.

Fig. 3. Evolution of the Gini coefficient for R&D, subsidies and tax credit.

evolutions, however, may explain the important decrease of the concentration of national subsidies during the period. The first is the important reduction of the subsidies dedicated to support the defense sector, which is highly concentrated in big firms. The second corresponds to the development of the National Agency of Research (ANR) and the Competitive Cluster Policy (labeling of the 71 clusters covering the entire French territory), which introduced a diversification in the sector and actors supported and gave incentives to cross-regional collaborative projects. By contrast, regional subsidies are more oriented toward the endogenous development of innovative activities when they support entrepreneurship or SMEs. Also, when regional subsidies support collaborative activities they clearly select projects depending on the involvement of local actors, encouraging collaboration within regions much more than interregional collaboration. This orientation toward the attractiveness of territory may create competitive pressures between regions, even though the extensive growth in the number of regions that implemented innovation policies has resulted in an important reduction in their spatial concentration.

Finally, European subsidies for R&D are mostly issued from the Frameworks Programs for R&D and are highly selective in terms of

sectors as well as scientific excellence, leading to a high concentration level. They also aim to foster collaborative projects, however, international collaborations are privileged and European subsidized projects generally involve a few actors from the same country. Therefore, there is competition between the actors and regions within a country in order to access European funding in specific scientific fields.

4.3. The empirical strategy

Our empirical strategy entails developing the correct empirical specification to assess the crowding-in or crowding-out effect of the French policy mix for R&D in line with our theoretical model. Our strategy comprises two steps: (1) detect the main econometric issues affecting panel data and (2) detect the presence of spatial dependence.

If panel data are more interesting in terms of inference, their use also implies more potential problems, as we face both time and cross-sectional dimensions. The main common problems are heteroskedasticity, serial correlation, cross-section correlation, endogeneity and stationarity. In general, only the first problem implies inefficiency of the OLS estimator whereas the others imply inconsistency and

inefficiency. We thus decide to start the empirical strategy by identifying which of those problems are present in our dataset. We conduct all necessary tests using the FE estimator (panel OLS estimator). All detailed test results are reported in Appendix C. These results show that we face two main problems in our data: cross-sectional dependence and heteroskedasticity in the error term. At this step, we suspect that the presence of cross-sectional correlation could be due to the presence of spatial dependence in R&D investment, as suggested by our theoretical model. Concerning the problem of heteroskedasticity, we can easily address it by correcting for the variance/covariance matrix of the error term. The three other common problems do not seem to be present. Indeed, various serial correlation tests reject the assumption of first-order correlation. Concerning endogeneity, we might well suspect problems related to omitted variables because (1) the true theoretical model could be dynamic rather than static, and (2) some of the explanatory variables might be endogenous. However, the results in Appendix C show that we do not detect important problems related to omitted variables because we reject the null hypothesis of endogeneity for all explanatory variables (using LTC, i.e., a one-year lag for the TC variable), and the estimation of a dynamic model shows that the dynamic coefficient is insignificant. Finally, the various unit root tests that we implemented show that both the endogenous and exogenous variables are stationary, and thus, we avoid spurious regression problems.

Before switching to the second step of our empirical strategy, we decide to check for outliers in our dataset that can partially explain the problems of heteroskedasticity and cross-sectional correlation. We identify two outliers: the Midi-Pyrénés region and the Creuse region in 2010. We thus decide to control for these two outliers using dummies. Finally, one important point to check when we use a static model with temporal data is the existence of structural changes in the effect of the explanatory variables. Indeed, the important reforms to the French policy mix for R&D discussed in the previous section could have structurally changed firms' behavior and thus modified their reaction to public policies. To identify the presence of structural changes, we run global Chow tests using different years as the date of the change. The results presented in Appendix D clearly detect the presence of changes in the values of the coefficients between the two periods (regardless of what year is considered as the break). Nevertheless, although we detect the presence of structural changes, these initial results do not tell us which year is best to capture this change in the effect of the explanatory variables. To decide this, we run four different FE estimates with different years as the break and compare their efficiency. As shown in Table D.2, the FE estimations indicate clearly that 2006 is the best candidate for the break point. Detecting a joint structural break in 2006 when we consider the whole model does not mean that the coefficients of all the explanatory variables have structurally changed between the two periods. We thus have to test for the presence of a break individually for each variable. The results of these Chow tests are reported in Table D.3 in appendix. We only detect a structural break in the effect of GDP and TC. This thus implies that the effects of European, national and local subsidies do not show any significant variation between periods, and we can assume that the coefficients of these variables are stable throughout the studied period.

The objective of the second step of our empirical strategy is to test for and model the presence of spatial dependence in the data. Indeed, our theoretical model and the presence of cross-section correlation in

our data suggest this.

In econometrics, the spatial dependence among the regions at each point in time is modeled using a spatial weight matrix denoted $\mathbf{W}$. The spatial weight is a positive square matrix, pre-specified by the researcher, that describes the arrangement of the cross-sectional units in the sample (Anselin, 1988). The elements of $\mathbf{W}$, w_{ij}, are non-zero when i and j are hypothesized to be neighbors, zero otherwise. By convention, the diagonal elements w_{ii} are equal to zero, that is, we exclude a unit being its own neighbor. In this paper, we construct our spatial matrix using a contiguity criterion.[4]

Starting from the basic econometric model $\mathbf{y}_t = \mathbf{X}_t\boldsymbol{\beta} + \mathbf{u}_t$, where $\mathbf{y}_t$ is a vector of order $(n \times 1)$, $\mathbf{X}_t$ is a matrix of $n \times (k + 1)$ dimension with $\boldsymbol{\beta}' = [\beta_0, \beta_1, ..., \beta_k]$ and $\mathbf{u}_t$ as a composite error term. We can model three channels of spatial dependence using a spatial matrix $\mathbf{W}$: (1) a global spatial dependence through the dependent variable ($\mathbf{Wy}_t$); (2) a local spatial dependence through the explanatory variables ($\mathbf{WX}_t$); and (3) a global spatial dependence through the error term ($\mathbf{Wu}_t$). The table below summarize the different empirical spatial models[5]:

The introduction of spatial effects in empirical applications could be motivated either due to data specificity, *data-driven specification*, or on a theoretical background, *theory-driven specification*, following a formal specification of spatial interaction in an economic model (Anselin, 2002). Our theoretical model assumes that there exists a global spatial dependence in the private R&D investment of regions that corresponds to spatial dependence in our dependent variable ($\mathbf{Wy}_t$), or to a *SLM* in Table 3. However, the empirical spatial dependence could in reality be much more complex than that reflected in our framework and we use a data-driven specification in order to explore alternative models. Under the data-driven specification, there are 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). 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 this paper, we apply Hendry's approach because Mur and Angulo (2009) shows that the *GETS* approach is more robust to the existence of anomalies in the data generating process.[6]

Following Hendry's strategy, we should start with the most general spatial models. The spatial econometric literature suggests two alternatives (LeSage and Pace, 2009; Elhorst, 2014): The first is the spatial Durbin model (SDM), which includes the spatial lag of endogenous ($\mathbf{Wy}_t$) and exogenous variables ($\mathbf{WX}_t$). The second, the spatial Durbin error model (SDEM) includes the spatial lag of the error term ($\mathbf{Wu}_t$) and the exogenous variables ($\mathbf{WX}_t$). These two models are not nested in one another, meaning that empiricists need to estimate both and compare their efficiency. In order words, we have to select between:

SDM: $\qquad \mathbf{y}_t = \rho\mathbf{Wy}_t + \mathbf{X}_t\boldsymbol{\beta} + \mathbf{WX}_t\theta + \mathbf{u}_t,$ (10)

SDEM: $\qquad \mathbf{y}_t = \mathbf{X}_t\boldsymbol{\beta} + \mathbf{WX}_t\theta + \mathbf{u}_t, \quad \mathbf{u}_t = \lambda\mathbf{Wu}_t + \varepsilon_t.$ (11)

Table 4 summarizes the results obtained from the estimation of the SDM and SDEM (complete results are available upon request). As both models introduce spatial dependence through the explanatory variables ($\mathbf{WX}_t$), we focus the comparison of these two models on their key difference: the channel of global spatial dependence. Indeed, global spatial dependence is embedded in the dependent variable ($\mathbf{Wy}_t$) in the SDM,

Table 3
Empirical alternatives of spatial models.

Model	Complete name	$\mathbf{Wy}_t$	$\mathbf{WX}_t$	$\mathbf{Wu}_t$
SLX	Spatial lag in *x*'s	×	✓	×
SEM	Spatial error model	×	×	✓
SLM	Spatial lag model	✓	×	×
SDM	Spatial Durbin model	✓	✓	×
SDEM	Spatial Durbin error model	×	✓	✓

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[4] The robustness of the results were checked using different weight matrices. These results are available upon request.

[5] Here, we do not consider the GNS model (which includes $\mathbf{Wy}_t$, $\mathbf{WX}_t$ and $\mathbf{Wu}_t$) or the SARAR model (which includes $\mathbf{Wy}_t$ and $\mathbf{Wu}_t$) as empirical spatial models because their parameters are weakly identified; see LeSage and Pace (2009) and Elhorst (2014) for details.

[6] Further details on the relative merits of *GETS* and *STGE* in spatial econometrics can be found in Florax et al. (2003, 2006 and Mur and Angulo (2009).

Table 4
Comparison between alternative Durbin models: SDM versus SDEM.

Indicator	SDM	SDEM
Global spatial dependence parameter	$\hat{\rho}$ = −0.119***	$\hat{\lambda}$ = −0.079*
AIC	231.641	235.970
BIC	359.636	363.964

Note: Estimation QMLE-FE with robust s.e. and the Lee–Yu correction.
  * Significance at the 10% levels.
  *** Significance at the 1% levels.

whereas it is embedded in the error term for the SDEM. Our results show that the global spatial dependence through the dependent variable ($\mathbf{W}y_t$) is significant at the 1% level, whereas it is just significant, at the 10% level, through the error term. This is clearly in favor of the SDM, which is confirmed by the two information criteria.

Nevertheless, if SDM is preferred over SDEM, this does not mean that SDM is the best spatial model for our data. Indeed, if for instance the effect of spatially lagged explanatory variables ($\mathbf{W}X_t$) is not significant, then the SLM is better than the SDM. The second step of Hendry's approach thus consists in comparing the efficiency of the SDM over three nested (simpler) spatial models: the SLM, SLX and SEM. We thus perform Wald's restriction tests on the SDM, which are summarized in Table 5.

Our results clearly point the superiority of the SDM over the SLM, SEM and SLX models. Indeed, all Wald tests strongly reject the null hypothesis of preferring a simpler spatial model over an SDM. Consequently, the spatial dependence in our data seems to be more complicated than suggested by our theoretical model. Indeed, we have to include not only the spatial lag of R&D investment ($\mathbf{W}y_t$) but also the spatial lag of the explanatory variables ($\mathbf{W}X_t$). Consequently, public policies implemented in neighboring regions influence both directly (through local spatial dependence) and indirectly (through global spatial dependence of R&D investment) the R&D investment in a particular region.

5. Empirical model and results

The previous section allowed us to define the following characteristics for our final specification: A static SDM with structural change in the effect of GDP and tax credits. This model will be able to address both the cross-sectional dependence and heteroskedasticity detected in the FE model. This empirical model is in line with the theoretical model, which will help us to interpret our empirical estimates. We can now write our empirical model for a region as follows:

$$
\begin{aligned}
\ln(\text{DERDF}_t) &= \beta_1 \ln(\text{GDP}_t) + \triangle\beta_1 \ln(\text{GDP}_t) + \beta_2 \ln(\text{LTC}_t) \\
&\quad + \triangle\beta_2 \ln(\text{LTC}_t) \\
&\quad + \beta_3 \ln(\text{SNAT}_t) + \beta_4 \ln(\text{SCEE}_t) + \beta_5 \ln(\text{SREG}_t) \\
&\quad + \theta_1 \ln(\mathbf{W}\text{GDP}_t) + \triangle\theta_1 \ln(\mathbf{W}\text{GDP}_t) + \theta_2 \ln(\mathbf{W}\text{LTC}_t) \\
&\quad + \triangle\theta_2 \ln(\mathbf{W}\text{LTC}_t) \\
&\quad + \theta_3 \ln(\mathbf{W}\text{SNAT}_t) + \theta_4 \ln(\mathbf{W}\text{SCEE}_t) + \theta_5 \ln(\mathbf{W}\text{SREG}_t) \\
&\quad + \rho \ln(\mathbf{W}\text{DERD}_t) + \mathbf{u}_t,
\end{aligned}
$$

(12)

Table 5
Summary of restriction hypothesis on the *SDM*.

Null hypothesis	Wald test	*p*-Value	Selected model
SLM	20.59	0.004	SDM
SEM	21.64	0.003	SDM
SLX	6.66	0.010	SDM

Note: Estimations using QMLE-FE with robust s.e. and the Lee–Yu correction.

where $\triangle$ represents the change in the coefficient value in the period 2006–2011 with respect to the baseline period 2001–2005. $\mathbf{W}$ refers to the row-normalized spatial matrix that was constructed using a contiguity criterion such that $\mathbf{W}GDP$ represents the weighted mean of GDP from neighboring regions. ρ is the measure of the global spatial dependence, while the $\boldsymbol{\theta}_k$ parameters measure the local spatial dependence of the exogenous variables. $\mathbf{u}_t = \boldsymbol{\mu} + \eta_t \boldsymbol{\iota}_n + \boldsymbol{\varepsilon}_t$ refers to component error term that includes individual and time fixed-effects. By including individual fixed effects,[7] we control for all unobservables that are region-specific and time-invariant such as the economic structure, geography of economic activities and local agglomeration effects. By including temporal fixed effects, we control for all unobservables that are time-specific and common to all regions such as the impact of the 2008 economic crisis. Finally, $\boldsymbol{\varepsilon}_t$ represents the idiosyncratic error term.

In the previous section, we detected two outliers in the data, and all estimations presented in this paper include dummy variables controlling for the influence of these observations.

5.1. Detection of spatial effects

Table 6 presents the estimation of model (12). At this stage, we focus on the measure of the spatial component in the model. In the presence of significant spatial dependence $\hat{\rho}$, the values of coefficients presented in Table 6 should not be interpreted directly; marginal effects measuring the efficiency of public policies should be recalculated while taking into account the spatial effects. They will be presented and interpreted in Table 7 in the following subsection.

The last part of the table presents the estimates of the global spatial dependence existing between private R&D investment in French regions ($\hat{\rho}$). We find evidence of negative spatial dependence, which highlights the singularity of the geography of R&D investment in France. Indeed, looking at Fig. 2, we immediately see that the negative spatial dependence for France traduces the polarization of privately financed R&D investment into a limited number of hubs that are 1) geographically distant and 2) surrounded by regions that are laggards in privately financed R&D. In that sense, the introduction of global spatial dependence into our empirical model allows us to take into account the economic geography structure of private R&D investment in France.

Table 6 also highlights the presence of local spatial dependence. However, only two explanatory variables drive this local dependence. Indeed, it seems that private R&D investment in a region is positively influenced by the dynamics of neighboring regions (ln$\mathbf{W}GDP$) and their ability to receive national funds (ln$\mathbf{W}SNAT$). This clearly indicates that the private R&D investment in one location is more sensitive to overall regional dynamics than to purely local dynamics. Moreover, the local dependence working through national subsidies can be explained by the increasing geographical consideration in the allocation of those subsidies. Indeed, a significant share of national subsidies are implemented through the competitiveness pole policies or other mechanisms that support projects in which sectoral and territorial strategies dominate. Moreover, as most of the clusters financed under this policy cross different neighboring NUTS3 regions, it is not surprising to find such local dependence.

To discuss the efficiency of the French policy mix for R&D, we need to calculate the marginal effects because the coefficients in Table 6 do not take into account the global spatial dependence of R&D investment. We refer the reader to LeSage and Pace (2009) and Montmartin and Herrera (2015) who describe how we can derive marginal effects from spatial econometric estimates. The advantage of marginal effects

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[7] Note that the introduction of individual fixed effects 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 for the cross-sectional dependence among the observations at each point in time. We consider this correction in all of the presented estimations.

Table 6
Estimation of a general spatial Durbin model with structural break.

Local coefficients	Coef.	s.e.	t-Test
ln(GDP)	0.129	0.377	0.342
ln(LTC)	0.157**	0.050	3.125
ln(SNAT)	0.035*	0.017	2.014
ln(SCEE)	0.016*	0.007	2.376
ln(SREG)	0.010	0.006	1.772
Change (△ coefficients) in 2006–2011 compared to 2002–2005			
ln(GDP)	0.181***	0.048	3.774
ln(LTC)	− 0.149***	0.029	− 5.073

Local spatial coefficients	Coef.	s.e.	t-Test
ln(WGDP)	1.256**	0.463	2.713
ln(WLTC)	− 0.107	0.071	− 1.495
ln(WSNAT)	0.044*	0.021	2.072
ln(WSCEE)	− 0.016	0.011	− 1.520
ln(WSREG)	− 0.011	0.011	− 0.968
Change (△ coefficients) in 2006–2011 compared to 2002–2005			
ln(WGDP)	− 0.182**	0.109	− 1.668
ln(WLTC)	0.042	0.057	0.726

Global spatial coefficient	Coef.	s.e.	t-Test
Spatial parameter ($\hat{\rho}$)	− 0.119***	0.046	− 2.581

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

Table 7
Marginal effects of SDM versus FE model with structural break.

MODEL	SDM		FE	
Variable	Periods		Periods	
	2002–2005	2006–2011	2002–2005	2006–2011
Direct effects				
GDP	0.114	0.293	0.219	0.372
LTC	0.163***	0.011	0.165***	0.018
SNAT	0.033*	0.033*	0.030*	0.030*
SCEE	0.017***	0.017***	0.018**	0.018**
SREG	0.010*	0.010*	0.010*	0.010*
Indirect effects				
GDP	1.151***	0.977**	n/a	n/a
LTC	− 0.121*	− 0.064	n/a	n/a
SNAT	0.037*	0.037*	n/a	n/a
SCEE	− 0.017*	− 0.016*	n/a	n/a
SREG	− 0.011	− 0.011	n/a	n/a
Total effects				
GDP	1.265***	1.269***	0.219	0.372
LTC	0.042	− 0.053	0.165***	0.018
SNAT	0.070***	0.070***	0.030*	0.030*
SCEE	0.001	0.001	0.018**	0.017**
SREG	− 0.001	− 0.001	0.010*	0.010*

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

derived from a spatial econometric model is that we can divide them into direct and indirect effects. The direct effect captures the effect in the own region of a unit change in the explanatory variables. The indirect effect captures the effect in the own region of a unit change in the

explanatory variables in all other regions through neighbor relationships. Table 7 reports the total marginal effects by period and divides them into direct and indirect effects. For comparison purposes, Table 7 also shows the marginal effects obtained from an FE estimator robust to heteroskedasticity (which would be efficient in the absence of spatial dependence).

5.2. The importance of spatial effects: the SDM versus a-spatial model

Before analyzing in detail the results provided by our spatial model, we briefly discuss the importance of using regional data to account for spatial dependence when assessing the global impact of policies. By comparing the marginal effects provided by the two models, it clearly appears that marginal effects from an FE model correspond to the marginal direct effects of the SDM. In other words, applying an a-spatial econometric model to regional data within the same country entails considering each region as a closed economy, which would obviously lead to strong bias. Table 7 clearly highlights this point. By considering regions as Robinson islands, the FE estimator produces upward bias in the effect of most public policies, as we can see by comparing the total marginal effects obtained by these two models.

5.3. The efficiency of the French Policy Mix

Let us start with a few words on the role of the control variable: GDP. We estimate that a 1% increase in the GDP in all NUTS3 regions increases privately financed R&D investment by approximately 1.2%.[8] Note that this effect of GDP is relatively stable over time. Table 7 also shows that the total 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 region is more dependent on macroeconomic or regional conditions than on pure local conditions. This is not surprising in the sense that R&D projects are not focused on a particular local market.

Concerning the efficiency of the French policy mix, our results place greater emphasis on the idea of a neutral effect, i.e., a one-for-one dollar effect. Indeed, as our dependent variable is privately financed R&D (amount of R&D spending minus all public funds and fiscal incentives received), the sign of the coefficients directly indicates whether a policy generates a crowding-in or a crowding-out effect. When a policy generates no significant effect it means that the policy is not able to increase the level of privately financed R&D.

Interestingly, it appears that only national subsidies are able to generate significant crowding-in effects on R&D investment. Indeed, our results do no reject the hypothesis of an insignificant effect of the three other policy tools. Nevertheless, we do not accept the hypothesis of a crowding-out effect for any policies. We will now discuss our results in more detail using the computed direct and indirect marginal effects.

We start with the only policy tool demonstrating a capacity to generate crowding-in effects: national subsidies. We estimate that a 1% increase in the national subsidies in all NUTS3 regions will be able to generate a 0.071% increase in privately financed R&D investment. Table 7 also shows that the total effect of national subsidies is due to positive direct and indirect effects. Indeed, both the direct and indirect effects of subsidies are significant and similar in magnitude. This suggests that national subsidies directed toward different NUTS3 regions are geographically complementary and boost firms' R&D investment. The implications of our theoretical model and the specificity of those subsidies are able to partially explain our result. Indeed, our theoretical

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

model suggests that a public policy is more likely to generate a crowding-in effect if its financial endowment is high and/or the policy is targeted. National subsidies were the most important R&D policy tool in France until 2009 and represent more than 7% of total private R&D expenses during our period of study. Contrary to tax credits, national subsidies are necessarily targeted toward territories (cluster policies), SMEs and/or specific sectors. Thus, this policy tool is able to take into account the specificity of the French geography of innovative activities, reinforcing the complementarity between territories and limiting pure competitive effects.

We now focus on our result on the tax credit policy. We find evidence of a neutral impact of the French tax credit system. Nevertheless, this global result conceals interesting implications for the French policy mix, as both temporal and spatial effects are at work. Indeed, contrary to other policies, we detect a change in the effect of tax credits on R&D investment that corresponds to the transition from a purely incremental scheme to a pure-volume scheme. Indeed, while we find evidence of a strong positive, direct effect of tax credits in the first period (2002–2005), this effect disappears in the second (2006–2011). This is in line with microeconomic studies such as Lokshin and Mohnen (2012) or Marino et al. (2016). The global neutral effect of tax credits is also explained by the presence of a significant negative indirect effect that counterbalances the positive direct effect. This is principally because French tax credit policy is untargeted, meaning that it cannot overcome the existence of negative spatial dependence in R&D investment in France. In a sense, if tax credits benefit regional R&D hubs in France and drive their investment in R&D, this comes at the expense of laggard neighboring regions, implying a neutral total effect.

Concerning the two other sources of direct support, regional subsidies and European subsidies, we find evidence of a neutral total impact. One explanation suggested by our theoretical model is that the size of such policies (0.5% of total private R&D spending) is not sufficient to generate a visible crowding-in effect at the regional level.[9] Indeed, it is interesting to note that the estimated impact decreases with the size of the policy. The direct elasticity of R&D investment with respect to the received national subsidies is estimated at 0.033, and these subsidies represent more than 7% of private R&D spending. The elasticity with respect to European subsidies is estimated at 0.017, and they represent just over 0.5% of private spending. Finally, the elasticity with respect to regional subsidies is estimated at 0.01, and they represent less than 0.5% of private spending. Moreover, our results highlight a difference in the impacts of these latter two sources of financing. Indeed, European subsidies generate strong positive direct effects that are counterbalanced by weak negative indirect effects. Regional subsidies generate weak direct effects and non-significant negative indirect effects. The difference in the direct effects of the two policies can be explained by the fact that European subsidies exceeds regional subsidies and are more spatially concentrated. Indeed, by nature, European policies can more efficiently target sectors and territories than local policies. European subsidies can be seen as useful in the sense that they are able to generate a "direct" crowding-in effect for a targeted region (if other regions are not subsidized). In a sense, this suggests that further increasing the concentration of European subsidies could improve their total impact. These two policies also generate negative indirect effects that contrast with the positive effects found for national subsidies. That can be partially explained by the fact that collaborative incentives provided by European and local funds are more likely to encourage competition effects between French territories rather than to encourage complementarity effects. Indeed, European support targets

collaborative projects with European partners, whereas local policies target more collaborative projects between local actors. By contrast, the national subsidies appear to be the only source of direct support capable of leveraging the complementarity among French regions by financing collaborative projects that involve actors from various French regions. This null total effect of European and regional public support does not mean that such efforts are not useful, but they are not capable of introducing a global leverage effect.

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 has experienced what are likely its most important changes over the past decade. The main objective of this paper has been to investigate the macroeconomic impact on private R&D investment 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 credits and the amounts of regional, national and European subsidies received by firms in each region was used to this effect. To our knowledge, this is the first study that uses a spatial model to evaluate a policy mix (four different instruments) using regional data.

As the basis for our empirical approach, we developed a simple regional R&D investment model based on Howe and McFetridge (1976). This allowed us to highlight some conditions that increase the likelihood that an R&D policy generates a crowding-in or a crowding-out effect on private R&D investment. Among our findings, our model suggests that the regional impact of public R&D support can vary greatly according to the local economic structure (sectorial specialization, financial constraints of local firms) and the design of the policy (size and targeting). Moreover, by introducing interactions among regions, our model also highlights the importance of taking into account the existence of localized R&D spillovers to correctly assess the impact of a policy. Indeed, such spillovers generate spatial dependence in the level of R&D investment that can strongly influence the overall impact of a policy.

Our final empirical specification combined the elements provided by this theoretical model with a data-driven analysis. Indeed, due to the important changes in the French policy mix during the past decade, we detected the presence of structural breaks in the effects of some explanatory variables. Thus, we finally estimated a spatial Durbin model (SDM) with regime and fixed effects, which allowed us to take into account the spatial dependency that exists between NUTS3 regions and the structural changes in the effects of R&D policies on R&D investment during the considered period.

Most of the empirical results we obtain confirm the theoretical predictions of our theoretical model. The first main result is the presence of a significant negative spatial dependence in privately financed R&D investment in NUTS3 regions. This result reveals one specificity of the geography of R&D activities in France: the polarization of business R&D investment into a limited number of hubs that are geographically distant and surrounding by laggard regions. In this context in which hubs are strengthening at the expense of laggard regions, untargeted state policies or competitive local policies are likely to act as beggar-thy-neighbor policies. This element partly explains why we find that French tax credits and local subsidies do not generate crowing-in effects at the regional level.

The second main result, which stems from the first, is that evaluating the French policy mix with an a-spatial model would lead to strong upward bias in the effect of these policies. Whereas we find that national subsidies are the only instrument that generates significant crowding-in effects on R&D investment, an a-spatial model would lead to the same conclusion for all policies studied. This is because the latter approach does not take spatial dependence into account.

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[9] This does not mean that regional or European subsidies are without utility. Indeed, even if the size of those policies implies a neutral impact at the regional level, such policies can increase R&D investment at the firm or consortium level, or also contribute to other policy objectives such as the development of public/private collaborations, for example.

The third main result is that we found evidence that the design of policies (size and targeting) is extremely important for their efficiency, as suggested by our theoretical model. Indeed, although we found that national subsidies are able to generate a visible crowding-in effect, European and local subsidies seem to have a neutral effect. National policies represent more than 7% of private R&D spending, whereas European subsidies and local subsidies represent only 0.5%.[10] Moreover, an important share of national subsidies support collaborative projects through clusters that cross different regions, whereas the two other policies support collaborative projects with foreign partners or local partners. Consequently, European and local subsidies are more likely to encourage competition effects between French territories rather than to encourage complementarity effects.

The last main result is evidence that the passage from a purely incremental scheme to a pure-volume scheme for the French tax credit modified the response of firms to this fiscal incentive. In line with the results provided by Lokshin and Mohnen (2012) or Marino et al. (2016), we find a strong negative change in the impact of tax credits on R&D investment between the first period (2002–2005) and the second (2006–2011). This corroborates the idea that a purely volume-based scheme generates more windfall effects than an incremental scheme.

Finally, from a global perspective, our results highlight a rather limited effectiveness of the French policy mix for R&D in the sense that no policies generate significant crowding-out effects and one is able to generate significant crowding-in effects. Nevertheless, our paper also reveals some problems with the decisions made during the 2000s that did not improve (namely, reduced) the effectiveness of the French policy mix for R&D. Indeed, the choice to switch to a tax-credit-driven policy mix does not seem to be very effective for two reasons. First, contrary to national subsidies, tax credits are not targeted, and their total effect is thus strongly influenced by the negative spatial dependence of R&D investment existing across French regions. Second, by choosing a volume-based scheme, the natural effectiveness of tax credits is decreased. Another limitation of the reform of the French policy mix concerns the subsidies allocated by local authorities, which increased structurally in the period considered. Because, by definition, such subsidies increase competition between territories with a very unequal geography of R&D activities, they are more likely to operate as beggar-thy-neighbor policies. Thus, from a policy-maker perspective, our empirical findings suggest different ways to improve the effectiveness of the French policy mix for R&D. One improvement could be to modify the tax credit scheme. Indeed, reintroducing an incremental component, especially for large firms, could significantly reduce observed windfall effects and free up funds to increase the financial endowments of institutions awarding national grants (like BPI France or the Competitive Cluster Policy). Another way to increase the effectiveness of the tax credit scheme would be to introduce a more targeted approach, for instance, by implementing different levels of tax credits by region and/or sector. Such changes could allow a significant increase in the effectiveness of the French Tax credit policy by taking into account both the negative spatial dependence between

French regions and the heterogeneous reaction of industries to fiscal incentives. Another modification that could increase the effectiveness of the French policy-mix for R&D would be to create a political coordination mechanism between local policy-makers in order to reduce competition effects and increase complementary effects between French regions.

However, our results concern a period prior to the discussion and implementation of the "smart specialization" strategy in Europe (Foray, 2014). It would be interesting to more specifically analyze the role of regional R&D subsidies in this new context to determine whether this strategy has contributed to improving the total efficiency of regional R&D policies. Indeed, solutions to reduce the negative indirect effects of local policies and increase their local impact, even when their weight remains rather low, necessitate regions having better capacity to focus their policies toward the identification and valorization of their complementarity with others.

Our results also suggest other avenues for future research. Extending the period of analysis would allow us to develop a dynamic model to distinguish short-run and long-run effects and consider the impact on innovation performance (see Minniti and Venturini, 2017 for instance). A null impact of policy on the amount of business R&D spending may indeed translate into a positive impact on innovation if policies help firms to improve the productivity of R&D activities. Finally, confirming the importance of spatial analysis for policy evaluation would require the extension of our analysis to other countries with different spatial configurations and possibly positive spatial dependence for private R&D, such as Germany.

Appendix A. Non-linear estimates

In this appendix, we present a non-linear estimation of model (3). To obtain these non linear estimates, we first run an FE model to obtain estimated values for the coefficients that we use as starting values in the non-linear estimates. We use five explanatory variables in both the FE and non-linear models to explain the level of privately financed R&D (ln(*DERDF*)): ln(*GDP*), ln(*LTC*) (lag of Tax credit), ln(*SNAT*) (National Subsidies), ln(*SCEE*) (European Subsidies) and ln(*SREG*) (Regional subsidies).

Table A.1 summarizes the non-linear estimates we obtain under different initial values of ρ and the constant.

As we can see from the table, model better fits the data when the ρ parameter is near zero. Consequently, in main body of the paper, we assume that ρ → 0.

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[10] This implies that these policies are less visible at the aggregate level but does not mean that such policies are useless at the microeconomic level.

Table A.1
Summary of nonlinear least-squares.

Estimation	Initial value for ρ	Initial value for constant	Estimated ρ	RSS
1	0.60	10	0.8052	10859.76
2	0.30	10	0.0315	141.5327
3	0.20	10	0.1996	4960.819
4	0.15	10	0.1779	4615.252
5	0.10	10	0.0010	1397.778
6	0.10	30	0.0008	157.9092
7	0.10	50	0.0013	118.1107

Appendix B. Location of tax credit

General problems concerning the location of the amount tax credit received in each region is that the necessary information is dispersed into different databases. On the one hand information on the spatial distribution of R&D investment of firms is available through the R&D survey collected each year by the French Ministry of Research and can be easily aggregated at the NUTS3 level. On the other hand, information on TC is collected by fiscal authorities and aggregated at NUTS3 level by French Ministry of Research. However, TC is attributed to the address of head-quarters or fiscal holdings for fiscally integrated groups, which do not correspond to the place where R&D is effectively carried on. So in order to correctly geolocalized tax credit in each region we constructed a relocalized measure using fiscal information and localized information contained in the R&D survey. As the design of TC is different according to the size of beneficiaries, we took into account this dimension. For each year, we first calculate, for each department, the 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 NUTS3 region i at time t:

$$\text{DERD}_{i,s,t} = \left(\frac{\text{DRD}_{i,s,t}}{\sum_{s=1}^{S} \text{DRD}_{i,s,t}} \times \text{DERD}_{i,t} \right),$$

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

$$\text{TCA}_{s,t} = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{\text{TC}_{i,s,t}}{\text{DERD}_{i,s,t}} \right).$$

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

$$\text{TC}_{i,t} = \sum_{s=1}^{S} [\text{TCA}_{s,t} \times \text{DERD}_{i,s,t}].$$

Appendix C. Checking common issues on panel data

In this appendix, we report statistical tests related to the main issues encountered in panel data: serial correlation, heteroskedasticity, cross-sectional correlation, endogeneity and stationarity. All of these tests are obtained using a static FE model, our five main explanatory variables and temporal dummies.

C.1 Serial correlation

Table C.1 presents two different first-order serial correlation tests in the residuals (obtained after FE estimation).

The two versions of Born and Breitung tests reject the presence of first-order serial correlation. We therefore conclude that that there is an absence of first-order serial correlation in the residuals.

C.2 Heteroskedasticity

The Table C.2 presents an LR test of heteroskedasticity. This tests compare GLS estimates under heteroskedasticity within panels with a GLS estimates under homoscedasticity. If there is no problem of heteroskedasticity, then the goodness-of-fit values of the two estimates should be similar and the LR statistic should be low, leading us to accept the null hypothesis of no heteroskedasticity.

The results presented in Table C.2 strongly reject the null hypothesis of the absence of heteroskedasticity. As a consequence, we have to correct for the variance/covariance matrix of the residuals to account for the presence of heteroskedasticity.

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[11] 1: enterprises with 1–50 employees; 2: enterprises with 51–250 employees; 3: enterprises with 251–500 employees; 4: enterprises with 501–2000 employees; 5: enterprises with 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 to fiscal authorities in each category of enterprises in order to estimate the amount of R&D in each category of enterprise.

Table C.1
Serial correlation of residuals.

Test	Null hypothesis	Stat	p-Value
Born and Breitung. HR-test	no $AR(1)$ process	−0.730	0.466
Born and Breitung. LM-test	no $AR(1)$ process	0.200	0.843

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

Table C.2
LR test for heteroskedasticity.

Test	d.f.	Chi-2 stat	p-Value
LR-test	93	1389.18	0.000

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

Table C.3
Cross-section correlation.

Variable	CD-test		Abs (corr.)
	Statistic	p-Value	
ln(*DERDF*)	35.70	0.000	0.359
residuals	3.37	0.001	0.315

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

C.3 Cross-sectional correlation

Table C.3 presents the results of the CD-Test that detects cross-sectional correlation. The null hypothesis of this test is the absence of cross-sectional correlation.

We applied the CD test to the residuals obtained after an FE estimation and to our dependent variable. Both tests reject the null hypothesis of no cross-sectional dependence. Consequently, the FE estimator is inconsistent and inefficient.

C.4 Endogeneity

Concerning endogeneity, we could easily suspect problems of omitted variables because (1) the true theoretical model could be dynamic rather than static, and (2) some of the explanatory variables may be endogenous. To check these two points, we first estimates a dynamic model using two different estimators (FE and 2-step GMM) and check the significance of the coefficient related to the temporal lag of the dependent variable, i.e., DERDF at t-1 (named LDERDF). Table C.4 presents the estimation results.

As we can see from Table C.4, the coefficient of the past level of privately financed R&D (LDERDF) is never significant, regardless of the estimator used. Consequently, our static specification is preferred over a dynamic specification, and no endogeneity is suspected in a dynamic framework.

The second point related to endogeneity is that some of our explanatory variables could be endogenous. To avoid the endogeneity problem with the tax credit variable (which is a percentage of R&D spending), we decided to use its first-order temporal lag (i.e., TC at t-1, named LTC). Table C.5 presents the C-Test for endogeneity detection for all explanatory variables.

As we can see from this table, for all explanatory variables, we never reject the null hypothesis of the exogeneity of the regressors. Consequently, we are confident that we are working with exogenous explanatory variables.

C.5 Stationarity

It is important to verify the stationarity of both the right- and left-hand sides of our empirical model, as estimates on non-stationary variable can lead to spurious regression problems. Table C.6 presents three different unit root tests for stationarity for both the dependent and explanatory

Table C.4
Dynamic models: FE & 2-step GMM Arellano–Bond estimators.

Variable	FE			2-step GMM AB		
	Coefficient	t-Stat	p-Value	Coefficient	t-Stat	p-Value
ln(*LDERDF*)	−0.088	−0.78	0.437	−0.148	−0.99	0.323
ln(*GDP*)	0.064	0.11	0.912	−0.873	−0.99	0.322
ln(*LTC*)	0.191	0.29	0.770	−0.181	−2.17	0.030
ln((*SNAT*)	0.784	1.58	0.118	0.072	1.59	0.113
ln(*SCEE*)	0.017	1.96	0.053	−0.002	−0.26	0.792
ln(*SREG*)	0.016	2.31	0.023	0.020	2.73	0.006

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

Table C.5
Endogeneity tests.

Variable	C test	
	Statistic	p-Value
ln(GDP)	0.418	0.518
ln(LTC)	2.513	0.113
ln(SNAT)	1.236	0.266
ln(SCEE)	0.337	0.561
ln(SREG)	1.293	0.255

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

Table C.6
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[a]	−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[a]	−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[a]	−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[a]	−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[a]	−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[a]	−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.
[a] The HT test assumes a common unit root in the panel.

variables.

As we can see from this table, whatever the unit root test used or variable considered, we always reject the null hypothesis of non-stationary panels. Consequently, we are confident that we are working with stationary variables.

Appendix D. Detecting temporal changes in estimated coefficients

Given the importance of changes in the French policy mix for R&D during the period covered in this study, we may suspect that the behavior of firms in regions have changed. To test this assumption, we run different Chow tests to check the stability of our estimated coefficients over time.

We start by checking for the presence of a global structural break by testing simultaneously the stability of all coefficients between two periods. As we do not know which is the best candidate year for the break, we report in Table D.1 global structural break tests for five different break year candidates.

As we can see from Table D.1, except for the year 2010, we always reject the null hypothesis of the stability of all coefficients. As a consequence, this table highlights the presence of a global structural break in the effect of our explanatory variable. To choose the best year for the break between our four candidates (2006, 2007, 2008 and 2009), we run FE estimates and compare their efficiency using different information criteria. The information criteria of these models are presented in Table D.2.

The three information criteria select the year 2006 as the best year to capture the change in the effect of the explanatory variables. A last point is

Table D.1
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. Outlier controls are included.

Table D.2
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 included.

Table D.3
Chow-test for explanatory variable, break year: 2006.

Variable	Null-hypothesis	*F*-statistic	*p*-Value
GDP	$\triangle\beta_{GDP} = 0$	12.59	0.0004
LTC	$\triangle\beta_{LTC} = 0$	32.61	0.0000
SNAT	$\triangle\beta_{SNAT} = 0$	0.09	0.7655
SCEE	$\triangle\beta_{SCEE} = 0$	1.07	0.3010
SREG	$\triangle\beta_{SREG} = 0$	0.44	0.5063

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

necessary to correctly specify the temporal change in our data. If we detect a global structural break in 2006, we do not know whether this break comes from changes in the coefficients of all explanatory variables of only some of them. We thus need to run a Chow test to verify individually the stability of the coefficients of all explanatory variable. The results of these tests are provided in Table D.3.

Δ represents the coefficient change for the variable for the period 2006–2011 with respect to the baseline period 2002–2005. The individual Chow tests clearly highlight that only two variables explain the global structural break that we detected previously. We reject at less than 1% the null hypothesis of coefficient stability for the GDP and the tax credit variables. For the other variables, we accept the null hypothesis of coefficient stability over the two periods.

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