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C21, O31, O52, R12

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Corinne Autant-Bernard ^{*}and James P. LeSage [†]

August 30, 2018

Abstract

Past literature has used conventional spatial autoregressive panel data models to relate patent production output to knowledge production inputs. However, research conducted on regional innovation systems points to regional disparities in both regions ability to turn their knowledge inputs into innovation and to access external knowledge. Applying a heterogeneous coefficients spatial autoregressive panel model, we estimate region-specific knowledge production functions for 94 NUTS3 regions in France using a panel covering 21 years from 1988 to 2008 and 4 high-technology industries. A great deal of regional heterogeneity in the knowledge production function relationship exists across regions, providing new insights regarding spatial spillin and spillout effects between regions.

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1 Introduction

Aquaro, Bailey and Pesaran (2015) make the observation that space-time panel data samples covering longer time spans are becoming increasingly prevalent. They propose exploiting sample data along the time dimension to produce estimates for all spatial regions. Allowing for heterogeneous coefficients for each spatial unit holds an appeal in circumstances where one has theoretical reason to believe that the nature of the relationship being examined as well as the level of interaction between regions differs greatly.

This is very likely to be the case in the processes of regional knowledge production and diffusion. Research conducted on regional innovation systems points to regional disparities in both their ability to turn their knowledge inputs into innovation and to access external knowledge.

Research conducted for the past two decades on regional innovation systems points to the importance of environmental and institutional factors in the innovation process (Bathelt and Cohendet 2014). These factors reflect a variety of region-specific features such as social and business network structure, social and demographic stratification, educational achievement, governance, or science-industry relationships. Storper (1997) also stresses the importance of cultural factors in reducing transaction costs and fostering untraded interdependencies which could contribute to regional cooperation that impacts innovation. As noted by Spigel (2016), the experience of regions such as the *Third Italy* and Silicon Valley points to the importance of regional cultures in formation of territorial systems. Based on this innovation system approach, regional practitioners have an incentive to build upon local specificities to set up their regional innovation strategy.

Geography thus creates distinctive spatial environments that shape regional variation in inventive activity. This variation may affect both the ability to turn internal knowledge inputs into effective innovations (through entrepreneurship, local interactions, trust and so on) and the ability to connect with external knowledge (through inter-regional interactions mainly supported by collaboration or mobility). We can therefore expect regional variability in the ability to benefit from local R&D input efforts and to benefit from and generate interregional spillovers. However, the empirical literature has devoted very little attention to these issues and the knowledge production function model used in the literature does not account for these regional differences. This is due to the fact that the concept was borrowed from models of firm behavior and adapted to regions. Difficulties thus appear when we shift focus from firms to regions (Hallachain and Leslie, 2007). In spite of very few attempts to analyze the differences in ability of individual regions to generate or benefit from spillovers, a region-specific investigation is absent from the literature. Only a few

studies allow for identification of heterogeneous relationships between innovative inputs and outputs. They produce separate estimates for different groups of regions to test whether knowledge spillovers are equally conducive to innovation in all contexts.

Two studies that attempt to analyze differences in regional ability to generate within region agglomeration economies are Varga (2000) and Van Oort and Bosma (2013). Varga (2000) provide separate estimates of local academic knowledge transfer using the regional level of agglomeration. He finds that regions with low agglomeration of high tech employment do not benefit from academic research spending. Van Oort and Bosma (2013) distinguish between large, medium-sized and small urban regions, as well as objective-1 and non-objective-1 regions. According to their results, regions containing large as well as medium-sized cities should produce more substantial productivity effects from human capital, patenting activity and entrepreneurship.

In the same vein, some studies assess variation in inter-regional spillovers effects. The study by Crecenzi and Rodriguez-Pose (2012) stresses important heterogeneity in the ability to generate inter-regional knowledge spillovers. Estimating a regional knowledge production function for both India and China, they find no evidence of spatial knowledge spillovers in China, while India exhibits significant ones. Comparing EU15 regions and the group of EU12, Paci and Marrocu (2013) find much more substantial knowledge spillovers for regions from the new accession countries than for the historical EU regions. Charlot, Crecenzi and Musolesi (2015) confirm this result. They estimate distinct nonparametric functions for objective 1 and non-objective 1 EU regions, finding significant differences in regions' ability to benefit from both internal and external knowledge. Contrary to what happens in leading regions, the only significant driver for lagging regions is external human capital. No significant effects arise from internal human capital, and internal and external R&D. In addition, they introduce cross-effects between internal and external R&D and between internal and external human capital to investigate the role played by absorptive capacities. They find positive coefficients associated with these cross-variables, pointing to different regional abilities to access inter-regional knowledge depending on internal knowledge capacities. In addition, they show that when internal R&D expenditure is too small, very high level of extra-regional R&D may be detrimental for local innovation (shadow effect). Caragliu and Nijkamp (2012) provide similar evidence on the EU regional absorptive capacity. Lower levels of regional cognitive capital reduce the ability to exploit locally produced new knowledge as well as new knowledge originating from outside. Although they clearly stress heterogeneity in regional effects of knowledge generation and diffusion, all these studies fail to provide a coherent region-specific investigation. This is because their knowledge

production function estimates are based on homogeneous coefficients, assuming that the ability to generate and benefit from spatial knowledge diffusion is the same for all regions or groups of regions. Regional knowledge production function estimates therefore ignore regional structural processes occurring in regional knowledge generation (Uallachain and Leslie, 2007).

It is worth noting that several attempts have been made to introduce regional features into the knowledge production setting along with traditional R&D inputs (specialization and diversity indices, concentration or urbanization, etc.), but Uallachain and Leslie (2007) argue that augmenting knowledge production functions with regional characteristics runs a high risk of confounding causes and effects. To avoid this limitation, Uallachain and Leslie (2007) contrast a knowledge production function and a regional structure model to explain US regional patenting variation. Their results show that the knowledge production function is inferior compared with an approach that uses fundamental regional structure conditions, when seeking to identify determinants of commercial invention. However their approach is based on tests of separate regression models that neglect regional structure when estimating the KPF, and disregarding the impact of R&D inputs when running the regional structure model.

In contrast, we allow R&D inputs to produce heterogenous effects on patenting therefore allowing regional structure conditions to impact what Uallachain and Leslie (2007) call “additions to economically valuable knowledge”. This may have important policy implications, since important regional differences make place-based policy recommendations more attractive.

We examine four industry-specific knowledge production function relationships using a balanced space-time panel consisting of 94 French departments. In the case of France and many other countries, knowledge production is concentrated in a relatively small group of regions. Conventional spatial econometric investigations require a large group of (contiguous) regions to produce reasonable estimates of the role played by spatial dependence/interaction between regions. This leads to conventional panel data models, that produce a set of parameters describing the relationship between the different explanatory variables and the dependent variable based on N regions over T time periods. Essentially, these parameters reflecting the relationship between regional knowledge production and regional inputs to production are restricted to be the same (homogeneous) for all regions and time periods in the sample.

Panel data models typically allow for region-specific and time-specific fixed effects in an attempt to overcome the restrictive assumption that coefficients are the same over all

time periods and regions. Introducing fixed effects allows for region- and time-specific differences in the model intercept. In spatial autoregressive models, the level of spatial interaction between observed outcomes over time and space is assumed the same for all regions and time periods.

In contrast, this paper relies on a heterogeneous coefficient spatial autoregressive (HSAR) model allowing for variation in the level of spatial dependence/interaction as well as knowledge production function coefficients, intercepts and noise variances across each region. A Bayesian variant of the Aquaro, Bailey and Pesaran (2015) heterogeneous coefficient spatial autoregressive (HSAR) model specification proposed by LeSage and Chih (2016) is used. This allows us to incorporate prior information and rely on Markov Chain Monte Carlo (MCMC) estimation procedures in place of the quasi maximum likelihood (QML) procedure proposed by Aquaro, Bailey and Pesaran (2015).

A ridge regression type prior is used for two reasons. One is that knowledge production function inputs (explanatory variables) in our model exhibit collinear relationships because they are highly correlated. Belsley, Kuh and Welsch (1980) describe how ridge regression can overcome collinearity between explanatory variables in regression models. Collinearity between production function inputs is a widely occurring phenomena, which can be exacerbated when variables for certain regions exhibit little variation over the time dimension of the sample. Prior information of the type described here can overcome this problematical situation by augmenting small eigenvalues of the explanatory variables matrix which stabilizes estimates and increases precision of estimates. A second motivation for the ridge-type prior is that we know that innovation is primarily an urban phenomena with rural regions not producing a great deal of innovation. Since our HSAR model produces estimates for all regions, use of the ridge-type prior will shrink small coefficients from rural regions toward zero values, which de-emphasizes rural regions. This results in relatively more emphasis on larger urban region coefficients.

In section 2 we set forth the HSAR model from Aquaro, Bailey and Pesaran (2015) along with our use of the Bayesian extension of the model proposed by LeSage and Chih (2016). A ridge regression variant of the model that we use in our knowledge production function application is described in Section 3. Interpretation of estimates from heterogeneous SAR models is discussed in Section 4 drawing on ideas described in LeSage and Chih (2016). They show that partial derivatives for the HSAR model can be used to determine how each region's dependent variable (knowledge output in our case) responds to changes in own- and other-region explanatory variables (knowledge production inputs in our case). Specifically, changes in inputs of neighbors to *each* region produce *spillin* impacts on each region. It is

also the case that changes in each region’s inputs produce *spillover* impacts on neighboring regions.

Finally, section 5 applies the model to knowledge production relationships for 94 NUTS3 regions in France, using a panel covering 21 years from 1988 to 2008, and 4 high-technology industries: chemistry, pharmaceutical, mechanics and materials. Since there are large differences in regional knowledge outputs and inputs, as well as in the strength of spatial dependence between regions, a heterogeneous coefficient specification seems desirable for this type of relationship.

2 The heterogeneous coefficients SAR/SDM model

Aquaro, Bailey and Pesaran (2015) propose the heterogeneous SAR model (which we label HSAR hereafter). The model can be written as in (1), where w_{ij} represents the i, j th element of a doubly stochastic spatial weight matrix with $w_{ii} = 0$.¹

$$HSAR: y_{it} = \alpha_i + \psi_i \sum_{j=1}^N w_{ij} y_{jt} + \sum_{k=1}^K \beta_i^k x_{it}^k + \varepsilon_{it}, \quad i = 1, \dots, N, \quad t = 1, \dots, T \quad (1)$$

The model coefficients contain subscripts i that range over the N regions, allowing for different intercepts (α_i), coefficients (β_i^k) for each of the K explanatory variables, and spatial dependence levels (ψ_i). The intercept parameter is also allowed to vary across regions, providing region-specific fixed effects that capture time-invariant factors.

The K explanatory variables $x_{it}^k, k = 1, \dots, K$ are assumed exogenous, and we require that covariance matrices $E(x_{it}^k x_{jt}^{k'}), \forall i, j, k$ are time-invariant and finite as well as non-singular.² The requirement of time-invariance arises because we are using the time dimension of the sample data to estimate parameters for each regional unit, $i = 1, \dots, N$. The region-specific disturbances are assumed distributed independently, and for our purposes we can assume these follow independent normal distributions with a different variance estimate σ_i^2 for each region.

The HSAR model can be written in matrix notation shown in (2) by stacking regional units,

¹A doubly stochastic matrix is one with both row and columns sums equal to one. We will have more to say about normalization of the spatial weight matrix in these models when we discuss interpretation of the model estimates.

²In the case of our informative ridge-type priors described in section 3, the non-singularity assumption can be relaxed.

$$y_t = \alpha + \Psi W y_t + \sum_{k=1}^K B^k x_t^k + \varepsilon_t \quad (2)$$

where $\alpha = (\alpha_1, \alpha_2, \dots, \alpha_N)'$, $\Psi = \text{diag}(\psi)$, $\psi = (\psi_1, \psi_2, \dots, \psi_N)'$, $W = w_{ij}$, $i, j = 1, \dots, N$, $B^k = \text{diag}(\beta_1^k, \beta_2^k, \dots, \beta_N^k)$, $x_t^k = (x_{1t}^k, x_{2t}^k, \dots, x_{Nt}^k)'$, $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \dots, \varepsilon_{Nt})'$, $\sigma^2 = (\sigma_1^2, \sigma_2^2, \dots, \sigma_N^2)'$.

The data generating process for the HSAR model can be written as:

$$y_t = (I_N - \Psi W)^{-1} \left(\alpha + \sum_{k=1}^K B^k x_t^k + \varepsilon_t \right) \quad (3)$$

Assuming Gaussian errors, the log-likelihood for the HSAR model takes the form (See Aquaro, Bailey and Pesaran (2015), equation 45):

$$\begin{aligned} \ell(\theta) = & -\frac{NT}{2} \ln(2\pi) - \frac{T}{2} \sum_{i=1}^N \ln \sigma_i^2 + T \ln |I_N - \Psi W| \\ & - \frac{1}{2} \sum_{t=1}^T \left((I_N - \Psi W) y_t - \sum_{k=1}^K B^k x_t^k \right)' \Sigma_t^{-1} \left((I_N - \Psi W) y_t - \sum_{k=1}^K B^k x_t^k \right) \end{aligned} \quad (4)$$

where θ denotes a vector of model parameters. In (4), $\Sigma_t = \text{diag}(\sigma_1^2, \sigma_2^2, \dots, \sigma_N^2)$.

Aquaro, Bailey and Pesaran (2015) set forth assumptions required for identification, and prove consistent asymptotic normality for quasi-maximum likelihood (QML) model estimates. The assumptions made are relatively straightforward extensions of those invoked in the spatial econometrics literature to the case of dependence parameters and coefficients for each region, $i = 1, \dots, N$. Since our Bayesian estimates are likelihood-based, they share the same consistent asymptotic properties as the QML estimates of Aquaro, Bailey and Pesaran (2015) in cases when normal prior distributions are centered on the true parameters, or where prior variances of normal prior distributions approach infinity.

3 A Bayesian ridge regression variant of the HSAR model

Bayesian estimation requires that prior distributions be assigned for the model parameters. LeSage and Chih (2016) set forth a Markov Chain Monte Carlo (MCMC) estimation procedure based on normal priors for the parameters $\alpha_i, \beta_i, \psi_i$, $i = 1, \dots, N$, in conjunction with gamma priors for the parameters σ_i , $i = 1, \dots, N$.

In our application of the model, the dependent variable vector y_t represents patents in year t for each of the 94 French NUTS3 regions for a specific industry (chemistry, pharma-

ceutical, mechanics or materials).³ The number of patents were smoothed over a two-year period to reduce noise arising from annual variation, since our analysis seeks to focus on long-run equilibrium phenomena. Two production inputs were used. One is lagged private R&D expenditures made by the specific industry for each of the 94 regions in each year (also smoothed, over the previous two-year period).⁴ The second input consists of region- and time-specific scientific publications relating specifically to each industry (also smoothed over the previous two-year period).⁵ Publications serve as a proxy for publicly available inputs to the regional production function for each industry, region and time period. Both the dependent and independent variables were transformed using logs, with the log of one plus the variable vector was used to avoid problems with zero values.

Attempts to produce QML estimates of the model parameters indicated collinearity problems. These arose because the model attempts to exploit variation over time (in our case 21 years) to provide region-specific estimates of the model parameters $\alpha_i, \beta_i, \psi_i, \sigma_i^2, i = 1, \dots, N$. Some regions exhibit minimal variation over time in patent outputs or knowledge production inputs.⁶ To see the problem that arises in this case, consider that if there were no variation over time in one of the inputs, we would have an explanatory variable matrix with a perfect linear relationship between the intercept vector and the non-varying input vector. Another possible source of collinearity is the fact that the two knowledge production inputs are likely to be highly correlated. That is, regions with growing private R&D inputs are also likely to have growing public inputs, and vice versa for regions where both inputs reflect a downward trend over time.

Belsley, Kuh and Welsch (1980) demonstrate how ridge regression can be used to augment small eigenvalues of the explanatory variables matrix that arise in the face of near linear relationships between explanatory variables (collinearity). We take a Bayesian approach that draws on this idea. For each β_i we specify a normal prior, where for notational simplicity in this development we subsume the intercept term in the matrix x_{it} and vector of coefficients β_i :

$$p(\beta_i) \sim N(\bar{\beta}_i, \bar{\Sigma}_{\beta,i}), \quad i = 1, \dots, N \quad (5)$$

³These are patent applications in the fields of chemistry, pharmaceutical, mechanics or materials based on the location of the inventor. Source: OECD, REGPAT database, June 2012.

⁴Private R&D expenditure in the field (thousands of euros). Source: R&D Survey, French Ministry of Research. This variable was lagged by two years, and smoothed over a two-year period. For example, if the dependent variable reflected patents smoothed over the 1990 and 1991 years, the R&D variable was based on the years 1988 and 1989.

⁵Number of scientific publications in the field (affiliation's location). Source: PASCAL (INIST-CNRS).

⁶We note that the smoothing and log-transformation tends to decrease variation over time, but are helpful scaling/smoothing transformations typically used in the knowledge production literature.

where $\bar{\beta}_i$ is a $K \times 1$ vector of prior means equal to zero and $\bar{\Sigma}_{\beta,i}$ is a $K \times K$ prior variance-covariance matrix, with K being the number of parameters in β_i . The prior mean of zero acts as a “shrinkage prior” that tends to bias the coefficients (by a very small amount) towards the prior mean of zero. As a prior variance we use $\Sigma_{\beta,i} = 0.01 \times I_K$, which reflects the type of variance-covariance matrix that would be used in a Bayesian application of ridge regression (e.g., Shi, Abdel-Aty and Lee, 2016).

Intuitively, the value of 0.01 replaces very small eigenvalues (for example one with a value of $1e - 12$) while not having a great deal of impact on larger eigenvalues (for example one with a value of 2.0). This overcomes the problem of an ill-conditioned matrix inverse $(X'X)^{-1}$, by using $(X'X + 0.01I_K)^{-1}$ in its place (see Belsley, Kuh and Welsch, 1980 for details and examples).

For the spatial dependence parameters $\psi_i, i = 1, \dots, N$ we assign no prior distribution. LeSage and Chih (2016) show how to estimate this parameter using Metropolis-Hastings (M-H) sampling, which we employed here. A restriction that $-1 < \psi < 1$ is imposed to ensure stability of the spatial autoregressive process by rejecting M-H candidate draws that do not fall within this range (see LeSage and Chih 2016 for details).

For the parameters σ_i^2 an inverse Gamma(\bar{a}, \bar{b}) distribution in (6) is used.

$$\begin{aligned} p(\sigma_i^2) &= \frac{\bar{b}^{\bar{a}}}{\Gamma(\bar{a})} (\sigma^2)^{-(\bar{a}+1)} \exp(-\bar{b}/\sigma^2) \\ \sigma^2 &> 0, \bar{a}, \bar{b} > 0 \end{aligned} \tag{6}$$

We note that as values of $\bar{a}, \bar{b} \rightarrow 0$, this prior distribution becomes uninformative, and we set \bar{a}, \bar{b} to small values of $1e - 04$. As is traditional, we assume the priors for the parameters $\beta_i, \psi_i, \sigma_i^2$ are independent.

LeSage and Chih (2016) set forth the conditional posterior distributions for each of the parameters conditional on all others, and describe a Markov Chain Monte Carlo approach to estimating the model. They also provide Monte Carlo results to demonstrate that their MCMC approach to estimation produces estimates similar to the QML estimates from Aquaro, Bailey and Pesaran (2015). Our estimates were produced using their MCMC procedure.

4 Interpreting the heterogeneous SAR model estimates

This discussion is based on LeSage and Chih (2016), who provide a comparison of homogeneous SAR and heterogeneous SAR model interpretation. In the presence of spatial

dependence between regional units, changes in the characteristics of region i (X_i) can impact outcomes in region i (y_i) as well as outcomes in neighboring regions, as well as outcomes in neighbors to those neighboring regions, and so on. LeSage and Chih (2016) show that the partial derivatives of the reduced form HSAR model take the form in (7).

$$\begin{aligned} \partial y / \partial X^{k'} &= \begin{pmatrix} \partial y_1 / \partial x_1^k & \partial y_1 / \partial x_2^k & \dots & \partial y_1 / \partial x_N^k \\ \partial y_2 / \partial x_1^k & \partial y_2 / \partial x_2^k & \dots & \partial y_2 / \partial x_N^k \\ \vdots & \vdots & \ddots & \vdots \\ \partial y_N / \partial x_1^k & \partial y_N / \partial x_2^k & \dots & \partial y_N / \partial x_N^k \end{pmatrix} \\ &= (I_N - \Psi W)^{-1} B^k \end{aligned} \quad (7)$$

Expression (7) is an $N \times N$ matrix, since a change in a single region's k th knowledge inputs could impact own-region knowledge output, plus (potentially) output of all other regions. This results in an $N \times 1$ vector of impacts from changing a single region i 's k th knowledge production input. Regression models are usually interpreted by taking into account changes in each of the $i = 1, \dots, N$ observations associated with a change in the k th knowledge input, leading to a series of N different $N \times 1$ vectors of impacts on knowledge output, which make up the $N \times N$ matrix in (7).

The main diagonals of the matrices represent own-partial derivatives ($\partial y_i / \partial X_i^k$), showing how a change in the k th input would *directly* impact each region's y_i output value, while the off-diagonal elements are cross-partial derivatives ($\partial y_j / \partial X_i^k$) showing the spatial spillover impacts on other region's outputs.

For the case of the heterogeneous coefficient models where emphasis is on observation-level variation in the parameters, LeSage and Chih (2016) propose using the N diagonal elements of the matrix in (7) to produce *direct effects* estimates for each of the N regions. These show how changes in each of the knowledge inputs for region i impact region i knowledge output, $i = 1, \dots, N$.

We follow the proposal of LeSage and Chih (2016) to use the cumulative sum of off-diagonal elements in each row of (7) to produce a vector of region-specific *cumulative spillin effects*. These of course are consistent with partial derivatives showing how changes in neighboring regions' knowledge inputs produce a spillin impact on each region i 's knowledge output, e.g., ($\partial y_i / \partial x_j, j \neq i$).

They also propose a vector of region-specific *cumulative spillout effects* constructed using the sum of off-diagonals of the columns. These measure how changes in region i knowledge inputs impact neighboring regions $j \neq i$, e.g., ($\partial y_j / \partial x_i, j \neq i$) knowledge output.

To see how the heterogeneous SAR model allows for spillin and spillover effects to impact neighbors, neighbors to neighbors, neighbors to neighbors of neighbors, and so on, consider the infinite series expansion of the matrix of partial derivatives for the k th explanatory variable: $(I_N - \Psi W)^{-1} B^k$ shown in (8).

$$(I_N - \Psi W)^{-1} B^k = I_N B^k + (\Psi W) B^k + (\Psi W)^2 B^k + (\Psi W)^3 B^k \dots \quad (8)$$

For the case where the matrix W assigns equal weights to the r nearest neighboring regions, (non-zero elements equal to $1/r$ for these regions), the matrix W^2 points to second-order neighboring regions, those that neighbor the m nearest regions. The matrix W^3 reflects third-order neighboring regions, those that are neighbors to the neighboring regions, and so on for higher-order powers of W . The diagonal matrix of dependence parameters Ψ is upper-bounded by a value of one, so higher powers of $(\Psi W)^k$ assign less weight to higher-order neighbors. An intuitively appealing aspect of this is that relationships are stronger between low-order neighboring regions than higher-order, so this aspect of the heterogeneous SAR models meshes nicely with prior beliefs expressed in spatial econometrics.

LeSage and Chih (2016) suggest use of a doubly-stochastic weight matrix because region-specific variation in the spillin and spillover effects estimates would in this case more closely reflect variation across regions due to variation in the regional coefficient estimates ψ_i, β_i^k . They point out that use of a traditional row-stochastic weight matrix will result in spillin and spillover impacts that reflect differences in the number of row- and column elements of the weight matrix, differences in values assigned to these elements, as well as variation in the coefficient estimates for ψ_i, β_i^k . Since the spirit of the heterogeneous coefficient SAR specification is to explore the impact of parameter variation over regional observations, they recommend use of doubly-stochastic weight matrices in the HSAR model specification. Part of regional heterogeneity does result from the spatial configuration and therefore from the number of neighbors. Our approach aims to neutralize this to study the economic effects not related to access to a large number of neighbors.

It is instructive to consider an example from LeSage and Chih (2016) involving a small 3×3 matrix of the partial derivatives, when we have only three regions located in a straight line. For this case, they calculate an analytic inverse for $(I_3 - \Psi W)^{-1} B^k$, shown in (9).

$$(I_3 - \Psi W)^{-1} B^k = \frac{1}{D} \begin{pmatrix} \beta_1^k(1 - w_{23}\psi_2\psi_3) & \beta_2^k\psi_1 & \beta_3^k\psi_1\psi_2w_{23} \\ \beta_1^k\psi_2w_{21} & \beta_2^k & \beta_3^k\psi_2w_{23} \\ \beta_1^k\psi_2\psi_3w_{21} & \beta_2^k\psi_3 & \beta_3^k(1 - w_{21}\psi_1\psi_2) \end{pmatrix} \quad (9)$$

$$D = 1 - \psi_2(\psi_1w_{21} + \psi_2w_{23})$$

Direct effects for region i from the i th main diagonal element depend on own-region β_i as well as dependence parameters and weight matrix elements. Other regions coefficients $\beta_j, j \neq i$ do not influence the magnitude of direct effects estimates.

The cumulative spillin effects for region 1 involve estimates of other regions' β_2, β_3 , as well as the dependence parameters and weight matrix elements. Those for region 2 involve estimates of other regions' β_1, β_3 , along with the dependence parameters and weight matrix elements, as do those for region 3.

In contrast, the cumulative spillout effects for region 1 involve only estimates of β_1 in conjunction with the dependence parameters and weight matrix elements. This result is similar to that found for direct effects estimates. The same is true for spillout effects for regions 2 and 3, with these involving only estimates of β_2 and β_3 , respectively (as well as the dependence parameters and weight matrix elements).

These facets of the direct, spillin and spillout effects will become clearer when we present estimation results from application of the model to our French knowledge production function.

In addition to calculating estimates of the direct and cumulative spillin and spillout effects used to interpret the HSAR model, we also need estimates of dispersion for purposes of inference. Inference centers on whether the direct and spillin/spillout effects arising from changes in each of the K knowledge inputs are significantly different from zero. To do this we used retained samples of ψ_i, β_i^k from the MCMC estimation procedure to produce an empirical distribution for the direct, spillin and spillout effects. The posterior mean/median and standard deviations or quantiles based the empirical distributions for direct, spillin and spillout effects were used for inference. Gelfand et. al (1990) show that this produces valid inferences in cases such as ours where the effects estimates reflect non-linear combinations of the underlying parameters ψ_i, β_i^k .

5 HSAR knowledge production function estimates

Following the standard literature in the field we consider a two-factor KPF in *Cobb Douglas* form (see Qian and Acs, 2013). The dependent variable is corporate innovative output and

the explanatory variables are industry-specific R&D and university research.

$$K = R_1^\beta U_2^\beta e^\varepsilon \tag{10}$$

Where K is knowledge or innovative output, R is industry R&D, U is university R&D, and ε is a stochastic error term. We estimate the relationship between annual patents (log-transformed and smoothed over a two-year period) and past periods private and public knowledge inputs proxied by private R&D expenditures and scientific publications.

We therefore estimate the linear panel model in (1) with y_{it} the knowledge output of region i at time t . Two explanatory variables are included in X_{it} : RD_{it} which accounts for private R&D inputs and PUB_{it} which accounts for public R&D inputs. β_i are the two elasticity coefficients between knowledge inputs and knowledge creation in region i .

A separate intercept term was estimated for each region which accommodates time-invariant fixed effects. The time period of our panel covers 21 years from 1988 to 2008 and 94 NUTS3 regions in France. Figure 1 shows a map of the NUT3 regions of France, which coincide with metropolitan French “départements,” which are administrative units.⁷ They roughly correspond to a city and its suburbs, since French *departments* were historically defined in relation to the distance surrounding a central town, based on one day travel time by horse.

Patents come from the REGPAT-OECD database recording patent applications at the European Patent Office. They are located according to the location of the inventor, ensuring a proper reflection of the geographical area where the innovation was produced. The dependent variable includes less than 10% of zeros (702 observations over 7 896 observations). This share however varies according to the industry under consideration. It is very weak in Mechanics and Materials (less than 5%) but more substantial in Chemistry (9%) and Pharmaceutical (20%). An interesting point regarding the HSAR specification used here is that we are fitting different distributions to each observation, producing in essence a mixture of normals. It is well-known that mixtures of normal distributions can fit arbitrary distributions. The means that the zero issue that plagues homogeneous coefficient models that fit a single distribution to all observations of the dependent variable are lessened by the HSAR specification. Private R&D expenditure come from the French R&D survey conducted by the Ministry of Research and Technology. Public R&D expenditure is not available at the NUTS3 level. Public research effort is thus proxied by the number of scientific publications (source : PASCAL-INIST database). It is worth noting that map-

⁷The map shows island regions 2A and 2B for Corsica which were excluded from our sample.

ping industry-specific innovation inputs and output required these various databases to be aligned. The patents are split into technical fields (IPC codes). Private R&D data is collated according to the French Activities Classification (NACE) and scientific publications are recorded in various scientific disciplines. These classifications are not nested, each of them relying on its own logic. Making these databases mutually coherent was completed using an original classification produced previously (see Autant-Bernard and LeSage, 2010 for more details).⁸

Based on this classification, four separate industries were examined: chemistry, pharmaceutical, mechanics and materials. These four industries allows us to cover various technological levels and various knowledge production systems, in which public and private research play different parts.



Figure 1: Map of France NUTS3 regions

⁸To do this, we first converted our patent and R&D data from French classifications to international classifications (respectively IPC and ISIC). This was done on the basis of the OST report, allowing use of the link between IPC and ISIC made by researchers from the MERIT (Verspagen, Moergastel and Slabbers). Using the OST report that details each scientific field, we built the concordance with the public research classification. See Autant-Bernard and LeSage, 2010 for more details

In reference to (1), w_{ij} is a measure of spatial proximity between region i and region j . The spatial weight matrix was based on six nearest neighboring regions, converted to doubly stochastic form. ψ_i is the parameter showing the strength of dependence among knowledge output of region i and its neighbors.

The HSAR model was estimated without informative prior distributions assigned to the parameters $\psi_i, \alpha_i, \sigma_i$, and the ridge prior assigned to the parameters β_i . Posterior estimates were constructed using MCMC draws.⁹ As a test for convergence of the MCMC sampler, posterior means and standard deviations for the parameter estimates constructed from two runs of 2,000 retained draws were compared, and found to be nearly identical to the first three decimal digits.

Table 1 shows estimates from a homogeneous static panel model of the type used in the spatial econometrics literature on knowledge production functions. The table shows coefficient estimates for β, ρ as well as scalar summary estimates of direct and cumulative indirect effects. The direct and cumulative indirect effects estimates are the scalar summary measures proposed by LeSage and Pace (2009), extended to the static panel model case by Elhorst (2014). They reflect own- and cross-partial derivatives for the model. The table shows estimates based on a six nearest neighbors spatial weight matrix (transformed to doubly stochastic form) as well as a first-order contiguity weight matrix that assigns equal weight to neighboring regions defined as those with common borders (transformed to doubly stochastic form). This was done as a test of sensitivity to the type of spatial weight matrix used. The two sets of estimation results indicate a lack of sensitivity to the weight matrix specification, consistent with arguments made by LeSage and Pace (2014).

We see positive coefficients β for both knowledge inputs, positive spatial dependence, and positive direct and indirect (spillover) effects estimates for all industries that are significant at the 95% or 99% levels. A one percent increase in private R&D expenditure increases region i patenting activity by 0.8% in the pharmaceutical industry and by 0.3% in the mechanical industry. Indirect or spillover effects are smaller than direct effects except for the case of the pharmaceutical industry. Chemistry exhibits a low level of spatial dependence ($\rho = 0.0329$) significant at the 95% level. This leads to very small spillover effects that are significant at the 95% level.

⁹We used 2000 retained draws from a set of 2500, with the first 500 draws excluded as “burn-in” for the MCMC sampler. Two different runs of the MCMC sampler with different starting values were used to produce a total of 4000 retained draws. From the 4000 retained draws, every fourth draw was used to eliminate serial dependence in the draws, resulting in a set of 1000 draws. These were used in the matrix expression in (7) to produce 1000 separate estimates of direct, spillin and spillout effects for each knowledge input variable.

Table 1: Homogeneous coefficients panel model estimates

	Six nearest neighbors weight matrix			
Estimates	chemistry	pharmaceutical	mechanics	materials
R&D β	0.4797**	0.7839**	0.2469**	0.4158**
PUB β	0.3330**	0.3193**	0.3219**	0.3257**
ρ	0.2179**	0.0329*	0.5669**	0.3069**
Direct effects				
R&D	0.4838**	0.7831**	0.2674**	0.4236**
PUB	0.3358**	0.3200**	0.3478**	0.3313**
Indirect effects				
R&D	0.1297**	0.0264*	0.3036**	0.1766**
PUB	0.0901**	0.0106*	0.3952**	0.1382**
	First-order contiguity weight matrix			
Estimates	chemistry	pharmaceutical	mechanics	materials
R&D β	0.4681**	0.7772**	0.2609**	0.4058**
PUB β	0.3433**	0.3164**	0.3302**	0.3367**
ρ	0.2139**	0.0419*	0.5489**	0.2979**
Direct effects				
R&D	0.4736**	0.7779**	0.2883**	0.4164**
PUB	0.3475**	0.3164**	0.3638**	0.3453**
Indirect effects				
R&D	0.1217**	0.0337*	0.2914**	0.1617**
PUB	0.0893**	0.0136*	0.3679**	0.1342**

** indicates significance at the 99% level
 * indicates significance at the 95% level

5.1 Summary estimates for the 94 regions

Before turning to discussion of region-specific estimates, we present a summary of differences across the four fields by considering the number of regions with significant direct, spillover and spillover effects for the two knowledge input variables for each field. Table 2 shows the number of regions where direct effects are significant for public and private inputs for each field (at both the 99% and 95% levels). These results show that private (R&D expenditure) inputs have a significant direct effect in fewer regions than public inputs (scientific publications) in all of the four fields (using either the 99% or total cases reported in the table).

As shown in the table, the number of regions where spillover effects are significant is the same as those where direct effects are significant for each of the two types of inputs. This follows from the discussion of interpretation of the model estimates in section 3. Recall that the coefficient β_i^k for region i appears in both the direct effect for input k , and in the spillover effect expression for input k . The coefficients for other regions $j \neq i$ do not appear in the direct or spillover effect expressions. However, different spatial dependence parameters and spatial weight matrix elements play a role in determining these two types of effects estimates. If the spatial dependence parameters are positive and significant, this produces the type of result we see in Table 2. Table 4 shows estimates of the spatial dependence parameters ψ_i for each region, where we see that almost all are positive and significant at the 99% or 95% level.

An examination of region-specific estimates of direct impacts arising from public inputs to knowledge production will show that own-region knowledge output is significantly influenced by these inputs (scholarly publications) in regions with large cities and/or universities. It follows from the coincidence of significant direct and spillover impacts associ-

ated with public inputs for regions with large cities and/or universities that public inputs (scholarly publications) in these regions will have a cumulative spillover impact on knowledge production of neighboring regions. Similarly, regions where R&D expenditures have a direct and significant impact on knowledge output will also have significant cumulative spillover impacts on knowledge production of neighboring regions.

Table 2: Number of regions with significant direct, spillin and spillover estimates

	chemistry			pharmaceutical			mechanics			materials		
	99%	95%	total	99%	95%	total	99%	95%	total	99%	95%	total
Direct effects												
R&D	21	7	28	15	7	22	10	9	19	9	13	22
PUB	28	4	32	25	10	35	30	13	43	31	8	39
Spillover effects												
R&D	21	7	28	15	7	22	10	9	19	9	13	22
PUB	28	4	32	25	10	35	30	13	43	31	8	39
Spillin effects												
R&D	79	12	91	49	21	70	75	14	89	67	18	85
PUB	84	8	92	70	9	79	94	0	94	90	3	93

Turning to the summary of regions exhibiting significant effects presented in Table 2 for private and public inputs, we see many more regions that experience significant spillin impacts, and this is true across all fields. This means that the direct impacts estimated based on the homogeneous coefficient model are actually driven by a small set of regions which generate positive effects benefiting the region itself as well as neighboring regions. Recall from the discussion of section 3 that the cumulative spillin effects involve estimates of the β_i^k coefficients from many neighboring regions, in addition to the dependence parameters ψ_i from many regions. The large number of regions with significant cumulative spillin effects estimates results from the fact that with higher levels of spatial dependence, regions that neighbor those producing significant spillover impacts, or are neighbors to neighbors of the regions that neighbor those producing significant spillover impacts (and so on for higher order neighbors) will experience significant spillin effects. This is because we cumulate spillin effects arising from neighboring regions, neighbors to the neighboring regions, neighbors to the neighbors of the neighbors, and so on. With high levels of spatial dependence the weight given to neighbors of neighbors and other higher-order neighbors does not decay rapidly.

From Table 2, it is clear that the pharmaceutical field has fewer regions (70 and 79 for R&D expenditures and publications, respectively) that experience significant spillin effects. On the other hand, the mechanical field results indicate that nearly all regions in France experience spillin effects that are significant (89 and 94 regions for R&D expenditures and publications, respectively).

These results partially reflect the fact that with a small sample of 94 regions and a spatial weight matrix based on six neighboring regions (or first-order contiguity), powers of

the matrices W^2, W^3, W^4 result in assigning non-zero weight to a large number of regions from the entire sample/country.

Another way to summarize the estimates is using the median and standard deviation of the direct, spillin and spillout estimates over the 94 regions, for each of the four fields. Because of the presence of effects estimates for some regions that are near zero and not statistically significant, the median of the effects is more representative of the typical magnitude of these effects, allowing a comparison across the four fields considered here. Table 3 shows this type of summary for the direct, spillin and spillout effects estimates.

Table 3: Medians and standard deviation of direct, spillin and spillout estimates over 94 regions

	chemistry	pharmaceutical	mechanics	materials
Ψ estimates				
Median	0.7188	0.6236	0.8503	0.7622
Std.	0.2270	0.2623	0.1596	0.1896
PUB direct effects				
Median	0.0865	0.0803	0.1164	0.1092
Std.	0.1251	0.1750	0.1429	0.1221
PUB Spillin effects				
Median	0.2063	0.1959	0.4226	0.2618
Std.	0.1049	0.1274	0.1110	0.0901
PUB Spillout effects				
Median	0.1528	0.0996	0.3424	0.2138
Std.	0.2276	0.2249	0.4508	0.2478
R&D direct effects				
Median	0.0726	0.0506	0.0610	0.0598
Std.	0.1215	0.1145	0.1018	0.0982
R&D Spillin effects				
Median	0.1803	0.1011	0.2570	0.1778
Std.	0.1105	0.1127	0.1086	0.1052
R&D Spillout effects				
Median	0.1318	0.0615	0.1981	0.1162
Std.	0.2132	0.1666	0.3414	0.2156

Table 3 also shows median and standard deviations of the spatial dependence estimates ψ for the 94 regions. Dependence between regions and their neighboring regions measured by the parameter $\psi_i, i = 1, \dots, N$ is positive with a relatively large magnitude in all four fields. This magnitude exceeds the one estimated based on the homogenous SAR model. Imposing a unique homogenous coefficient would therefore bias downward the spatial autocorrelation estimates.

From the table, we see the highest (median) level of spatial dependence between each region and its neighbors in the mechanics field and the lowest in the pharmaceutical field. This does not imply that there are less spillovers in the pharmaceutical field, but that they are mediated by other channels than physical proximity. Spatial proximity matters more for knowledge diffusion in mechanical and material than in pharmacy and chemistry. The specific pattern of the geography of innovation in each industry may explain this result.

Mechanics exhibits a more widespread distribution of public and private innovative activities and records the largest direct and indirect effects from both public and private research. Conversely, pharmacy is the most spatially polarized sector and it is also the one in which the estimated effects are the lower. This variability in the spatial pattern of innovative activities across industry can be observed through the standard deviation in the number of patents by NUTS3 regions (223 in mechanics vs 795 pharmacy) or through the share of top 10 patenting regions in each field (47% in mechanics vs 71% in pharmacy). An uneven distribution over space would reduce the opportunity to benefit from local knowledge spillovers arising from public and private research.

Interestingly, a similar result arises for the direct effects emanating from public research : Mechanics and materials exhibit the highest impacts while pharmacy records the lowest ones. These public research direct effects can be considered as spillovers from science to industry since our dependent variable, patents, mainly captures the output of private research. The uneven distribution of patents would therefore not only hampers knowledge spillovers between nearby regions, but also within regions knowledge spillovers, from science to industry.

Conversely, the impact of the spatial structure is less pronounced for private R&D direct effects. The medians of the effect estimates are rather similar among the four sectors, ranging from 0.5 to 0.7. This supports the idea that the spatial organization would matter for spillovers effects, whereas it would not matter for the ability of private firms to turn their own R&D inputs into innovative output. Additional investigations would however be requested to determine the exact role played by the spatial distribution of innovative activities in each industry, and the potential other factors that may explain the sectoral variation in both direct and indirect effects.

Direct effect estimates for PUB are larger in the typical region for the fields of mechanics and materials, and the PUB direct effects are larger than those for R&D in all four fields. This result is consistent with past results from France (Autant-Bernard and LeSage, 2011). We should however be careful in comparing public and private inputs here since they do not rely on a similar indicator. While it is widely acknowledged that R&D expenditures are not necessarily the main input for knowledge creation, Cohen, Nelson and Walsh (2002) identified that published papers and reports are the key channels through which university research impacts private knowledge creation. Our definition of industry is also narrower for patent and private R&D than the one resulting from the scientific publication classification. The regional level of scientific publications may therefore capture some inter-sectoral effects while our private R&D indicator is more focused on intra-sectoral impacts.

The largest direct effects for R&D are in the chemistry field, with the smallest in pharmaceuticals. In spite of the high R&D intensity (10% of the pharmaceutical sales revenue is invested in R&D activities), pharmaceutical innovation does not benefit as greatly from R&D expenditure as the other industries. The high level of risk in this field and the duration of investment (e.g., it takes 10 to 15 years to find an active ingredient) may explain this result.

Spillin effects for PUB in the typical region are larger than for R&D in all four fields, and the same can be said of PUB spillover effects versus those from R&D in all four fields. It is perhaps not surprising that publicly available knowledge inputs play a greater role in regional spillin and spillover impacts of knowledge production than private inputs. Spillin and spillover effects are larger than direct effects, but the reader should recall that the spillin and spillover impacts are cumulated over all regions, based on off-diagonal row- and column-elements. So, these larger spillin and spillover magnitudes do not conflict with the intuition that spatial spillovers represent second-order impacts that should be smaller than direct (own-region) impacts of knowledge production inputs on knowledge output.

For the case of the PUB input, spillin effects are larger than spillover effects in all four fields, suggesting that firms operating within regions are better at acquiring (publicly available) knowledge from scholarly work done in other regions (spillin) than are academics/scholars of exporting their field-specific knowledge to firms operating in neighboring regions (spillover). This result is quite intuitive: spillover effects come from a single region whereas spillin effects arise from all the other regions. Let us consider for instance the access to external knowledge based on the content of publications: Region i can potentially access scientific documents published by all other regions. Conversely, region i contributes an increase to the global stock of publication in proportion of its own scientific production, which is by definition smaller than the national flow of publications. In other words, each region's scientific production exerts a smaller influence on the overall knowledge output in one field than the impact produced by the evolution of this field on the knowledge output of this single region.

The R&D input exhibits this same pattern where spillin effects are larger than spillover effects in all four fields. In the context of private knowledge production inputs, this suggests that firms operating in one region are able to exploit collaborative or other types of arrangements (e.g. licensing) with firms operating in many different (neighboring) regions to enhance knowledge production. Spillover effects measure the impact of R&D expenditures by firms operating in a single region on knowledge output of firms operating in other (neighboring) regions. We will see that a small set of regions act as producers of knowledge

spillover effects on their neighbors.

5.2 Region-specific estimates

Table 5 and Table 6 show the heterogeneous coefficient spatial autoregressive panel (HSAR) model estimates of direct effects estimates for public and private knowledge inputs. The six nearest neighbors weight matrix (transformed to doubly stochastic form) was used to produce these estimates. These reflect the elasticity impact of changes in knowledge inputs on knowledge output. All significant estimates are positive in the case of both knowledge inputs, as we would expect.

Table 5 shows 18 regions where scientific publications in all of the fields: chemistry, pharmacy, mechanical engineering and materials science, have a positive and significant direct effect on patenting activity in these fields (at the 99% or 95% levels). It is not surprising that many of these 18 regions are those where larger cities or universities are located. For example, Alps-Maritimes where the city of Nice is located, Bouches-du-Rhône where Marseille University is located, Haute Garonne where the city of Toulouse with its universities are located, Gironde with the University of Bordeaux, Indre-et-Loire with the city of Tours, Isère, with the city of Grenoble and its university, Loire Atlantique with the city of Nantes and its university, Nord with the city of Lille and its many universities, including Université Lille 1 - Sciences technologies, Rhône with the large city of Lyon and its universities, Seine Maritime with the city and university of Rouen, and of course regions in the vicinity of Paris.

Table 6 shows direct effects for private inputs to knowledge production in the same format as Table 5. There are 5 regions where private (R&D) inputs have a significant impact (at the 95% or 99% level) on knowledge output in all four fields. This contrasts with the 18 regions where publicly available inputs (scholarly publications in the fields) has a significant impact on all four fields. It suggests that private inputs are more localized in specific regions, whereas publicly available knowledge (scientific publications) is useful in more regions, likely those that have university expertise to exploit this type of information in the innovation process.

Table 7 and Table 8 show the heterogeneous coefficient spatial autoregressive panel (HSAR) model estimates of spillover effects for public and private knowledge inputs. Only a few regions act as producers of knowledge spillover effects on their neighbors. Three main explanations for this result can be found in the literature. The first one refers to agglomeration economies. While within and between regions knowledge flows would be favored by local concentration of economic activities (Bentlage, Thierstein and Lüthi, 2014),

all regions would not benefit from those effects. A critical mass of agglomeration must be reached (Capello et al. 2015, Guevara et al. 2016). In addition, the most innovative firms are those that access international sources of knowledge (Simmie, 2003). These highly innovative firms tend to concentrate in a minority of key metropolitan areas (Simmie, 2003). Few regions therefore act as central nodes for knowledge transfer. However, these arguments hold for few regions only since the regions that produce the highest spillover effects in our sample are not always the most agglomerated ones. If Paris, Rhône, Essonne and Bouches-du-Rhône are among the most agglomerated areas, this is not the case for Puy-de-Dôme or Haute-Savoie for instance which produce, in spite of their relatively low levels of urbanization, spillover effects from both public and private knowledge inputs. Another explanation lies in labor mobility of highly skilled workers. Agrawal, Cockburn and McHale (2006) find that patent citations to the prior location of the inventor are approximately 50% greater than if they had never lived there, suggesting that mobility is important for determining knowledge flows. The polarization of high skilled labor mobility among few regions may thus explain that only a few regions would act as knowledge hubs. Indeed, inter-regional flows of human capital are highly concentrated in the EU. Compared to the US, scientists, engineers or graduate mobility is weak and mainly takes place between a handful of nearby regions (Dahl and Sorenson, 2010; Marinelli, 2013). This may explain why some relatively small regions located close to large ones (Haute-Savoie for instance located near Grenoble in Isère region and Lyon in Rhône region) might benefit from knowledge exchanges based on inward- and outward-migration. Finally, the unbalanced structure of interregional networks can also explain why few central regions act as knowledge hubs. Breschi and Lenzi (2016) argue that networks of inventors within and between cities contribute to enriching and renewing the knowledge base. Their results based on US cities tend to confirm that these networks ease faster access to fresh external knowledge. However, such networks are not widespread. They are mainly asymmetrical and hierarchical. Maggioni, Nosvelli and Uberti (2014) find that knowledge flows within inter-regional EU research networks follow a hub-and-spoke structure where the balance of power among networks members is very unequal.

A systematic analysis of all the region specific effects would require meticulous attention that goes far beyond the scope of this paper. However, some interesting insights can be pointed out, at least for the largest regions. While most of the top universities and the highest patenting activity occurs in the Paris region, show larger impacts of public research in Lyon, Bordeaux and Toulouse. Figure 2, Figure 3, and Figure 4 show the direct, spillover and spillover impacts for the case of public R&D in the materials industry group to illustrate

this.

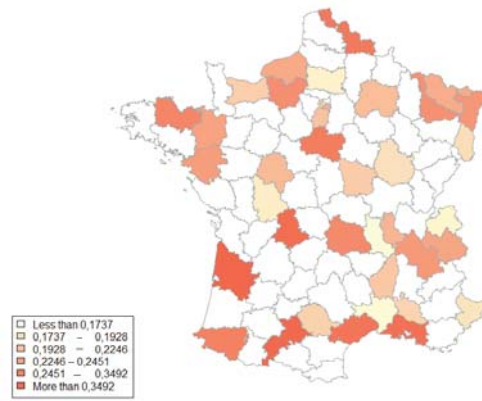


Figure 2: Direct effects of Public R&D Materials industry

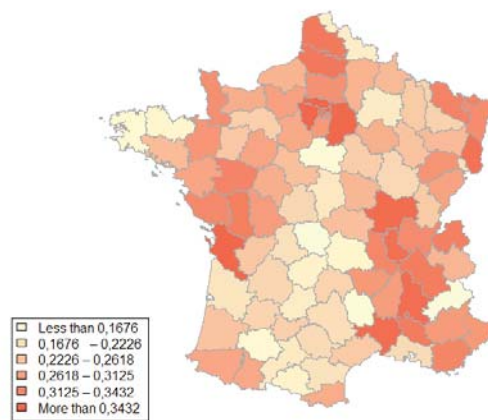


Figure 3: Spillin effects of Public R&D Materials industry

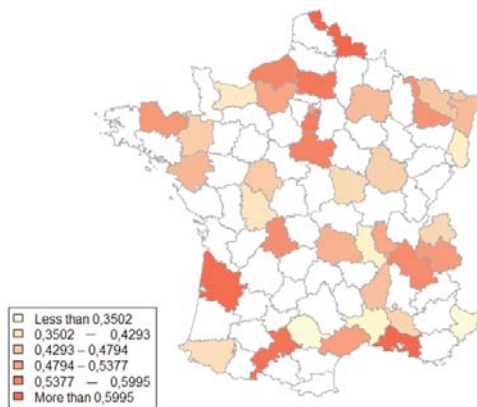


Figure 4: Spillout effects of PUB R&D Materials industry

Without elaborating on all of the regional features likely to explain these results, an examination of the underlying data (for all four regional innovation systems) showed that the intensity of public research (number of publications per thousand employments) or the intensity of fundamental research (number of publications per patent) did not differ

strongly between Paris and the other large city regions. This suggests an explanation the explanation might be found on the private R&D side. One striking fact of Paris region is the weak intensity of private R&D, measured in terms of private expenditure, total research employment or number of private scientists. While Paris region concentrates a very large share of the total economic activities, the relative weight of private R&D is reduced compare to its weight in Grenoble, Lyon or Bordeaux regions. Most of the firms in Paris region would therefore suffer from a lack of absorptive capacity to absorb the huge amount of public research produced locally. This interpretation would however require further research to be confirmed. In particular, a more pragmatic explanation may rely on the bias in publication records towards the capital city. The scientific outputs of the large public organizations such as CNRS are sometimes localized in Paris because the headquarter is in Paris, preventing us to identify the exact location of the author. This does not occur for patent data which are localized according to the address of the inventor. This may thus also explain why the patent elasticity to public research is lower in Paris.

Figure 5, Figure 6, and Figure 7 show the direct, spillin and spillout impacts for the case of private R&D in the chemistry industry group to illustrate this.

In relation to the high level of concentration of public research in the capital city, one could expect public research carried out in Paris region to generate higher spillout effects than any other French region. This is however not the case, and Lyon and Grenoble produce larger public spillouts in some of the four industries. The explanation may lie in the very peculiar pattern of knowledge diffusion in France. Using scientific or technological collaboration as a proxy for knowledge diffusion, the EuroLIO study (2016) shows a hierarchical organization of inter-regional ties.¹⁰

The Paris region is characterized by a network of distant ties with all other French metropolitan areas, while main cities in each region display more local ties with secondary urban centers. We must recall here that our spillout and spillin effects give higher weights to knowledge produced by nearby neighbors (something inherent in spatial autoregressive processes). It is thus not surprising to find higher effects in peripheral regions where local knowledge exchange prevails than in the Paris region. So, the Paris region does not necessarily generate less spillout impacts, but these effects are not strongly locally driven.

Another peculiarity of the Paris region is that private R&D effects are not significant in Paris except in the pharmaceutical industry, whereas they are positive in all industries in Lyon, Toulouse and the Bordeaux regions. One explanation may lie in the fact that the Paris region has a relatively weak intensity of private R&D as discussed above, but

¹⁰Caractérisation des potentiels et des collaborations technologiques et scientifiques des nouvelles Régions françaises. EuroLIO report to the Fédération Nationale des Agences d' Urbanisme, 2016.

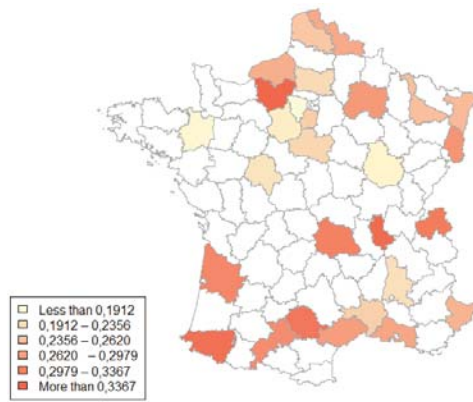


Figure 5: Direct effects of Private R&D Chemistry industry

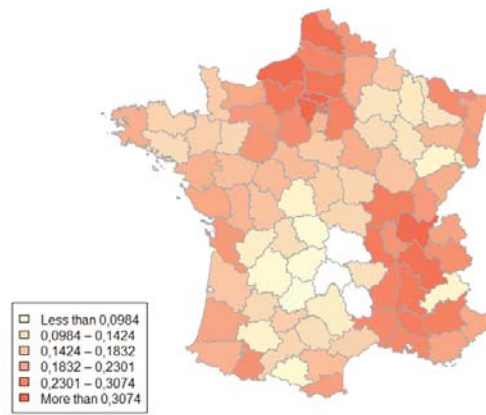


Figure 6: Spillin effects of Private R&D Chemistry industry

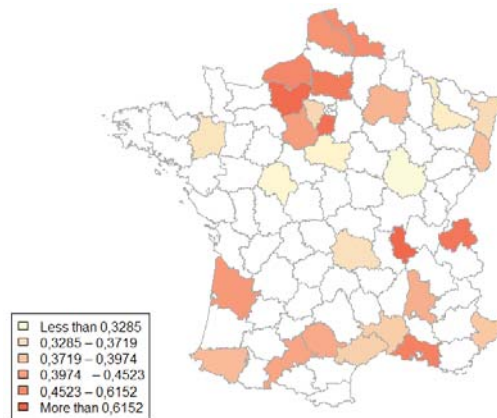


Figure 7: Spillout effects of Private R&D Chemistry industry

another explanation might come from the specific features of innovative firms localized in Paris region. We know that firm size impacts their ability to patent. If large firms are granted most of the patents, the propensity to patent given the level of R&D expenditure is higher for small firms (Audretsch, 2004). It would thus be interesting to explore to what extent innovative firms in the Paris region are larger than in the other regions and to what

extent this could induce different returns from private R&D.

6 Conclusions

Although it has important implications in terms of regional public policies, standard knowledge production functions do not allow us to identify if some regions are less likely to benefit from internal and external knowledge or to generate spillover effects. Our heterogeneous coefficients spatial autoregressive panel model is capable of producing estimates of knowledge production function parameters for each region in the sample. We therefore allow for differences in the level of spatial dependence between regions as well as knowledge production function coefficients, intercepts and disturbance variances.

Based on NUTS3 French data in four different industries, the results point to spatially varying processes of knowledge production and diffusion. First, all regions do not successfully turn their public and private knowledge inputs into patented innovations, nor do all regions generate knowledge spillovers. In other words, only a small set of regions generate positive effects benefiting the region itself as well as neighboring regions. Second, public research produces more systematic effects than private R&D both within and between regions, confirming that R&D expenditure are not necessarily the main input for knowledge creation, and that more fundamental research generates greater spillovers. Third, more regions experience significant spillover impacts than spillover effects. This is true across all four fields examined here, which is consistent with the view that regional actors rely more on external knowledge to innovate than they can contribute to increase this external stock of knowledge. In addition the number of regions that experience significant spillover or spillover effects varies across industries. Public spillover and spillover effect are more systematic in mechanics, whereas private spillover and spillover effects prevail in chemistry.

However, we must admit that our spatially varying effects remain as a black-box. This opens up an avenue for research to explain why such differences occur. Why some regions fail to turn R&D inputs into effective innovations? What are the features of the regions that successfully tie down global knowledge? What are the channels through which regions generate significant spillover effects on their neighbors? Many rationales could be derived from the literature to answer these questions: Social capital, labor mobility, network embeddedness, but also within region spatial organization. For instance, distinguishing various types of EU regions according to their morphological (agglomerated, urban and rural) and functional features (value-added activities, quality of production factors, density of external linkages and cooperation networks and quality of urban infrastructure), Capello et al. (2015) show that economic resilience increases with the size of cities, but depends also on

the type of functions hosted in them. Investigating how regional ability to generate knowledge may vary according to the regional organization and how it explains the capability of cities and urban systems to act as sources of regional resilience are promising issues. In the same vein, Spigel (2016) explores how local culture can explain regional heterogeneity in entrepreneurial practices and more widely how these practices help create distinctive regional economic structures. The cultural factors behind regional variation in knowledge production and diffusion should be investigated as well. Finally, this paper explores the spillover versus spillout effects of knowledge production, but an additional issue arises that would need further investigation: variation in ability to exchange knowledge within regions. This issue is closely interconnected with spillover effects. Indeed, spillover effects may result from individuals' ability to tie down external knowledge, but also from the ability to circulate knowledge within the region. As supported by the absorptive capacity theory (Cohen and Levinthal, 1989), spillover effects may be reinforced if external knowledge would be transferred to the relevant actors that can make use of it.

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Table 4: HSAR panel model ψ estimates

Region	chemistry	pharmaceutical	mechanics	materials
AIN	0.8235 **	0.9595 **	0.8394 **	0.6911 **
AISNE	0.5742 **	0.2326 **	0.6259 **	0.7121 **
ALLIER	0.4566 **	0.7153 **	0.6736 **	0.7433 **
ALPES-DE-HAUTE-PROVENCE	0.7387 **	0.6788 **	0.4352 **	0.6741 **
HAUTES-ALPES	0.1463 **	0.0579	0.2840 **	0.1337 **
ALPES-MARITIMES	0.7527 **	0.8783 **	0.8983 **	0.8979 **
ARDECHE	0.9026 **	0.3740 **	0.9654 **	0.7815 **
ARDENNES	0.5946 **	0.4254 **	0.9158 **	0.7784 **
ARIEGE	0.2144*	0.7564 **	0.5187 **	0.4191 **
AUBE	0.4415 **	0.1939	0.8324 **	0.8598 **
AUDE	0.6175 **	0.4533 **	0.5502 **	0.4460 **
AVEYRON	0.4405 **	0.2961 **	0.8832 **	0.5339 **
BOUCHES-DU-RHONE	0.8923 **	0.4724 **	0.8311 **	0.6360 **
CALVADOS	0.5729 **	0.7911 **	0.6326 **	0.7857 **
CANTAL	0.1424	0.2264	0.5697 **	0.8688 **
CHARENTE	0.2751 **	0.2130	0.9556 **	0.5250 **
CHARENTE-MARITIME	0.8664 **	0.6694 **	0.6890 **	0.9150 **
CHER	0.7617 **	0.4859 **	0.9613 **	0.4572 **
CORREZE	0.3287*	0.4341*	0.6221 **	0.4823 **
COTE-D'OR	0.7457 **	0.6516*	0.7137 **	0.6557 **
COTES-D'ARMOR	0.6423 **	0.5892 **	0.6232 **	0.4738*
CREUSE	0.2766 **	0.2435*	0.4022 **	0.1016*
DORDOGNE	0.4726*	0.6616 **	0.8666 **	0.7086 **
DOUBS	0.5551 **	0.4648 **	0.6614 **	0.7358 **
DROME	0.9513 **	0.7373 **	0.9637 **	0.9025 **
EURE	0.9663 **	0.7906 **	0.9422 **	0.9418 **
EURE-ET-LOIR	0.6153 **	0.8879 **	0.8504 **	0.6779 **
FINISTERE	0.8008 **	0.8310 **	0.8807 **	0.2530
GARD	0.8936 **	0.8967 **	0.9711 **	0.8538 **
HAUTE-GARONNE	0.8218 **	0.6193 **	0.8924 **	0.7180 **
GERS	0.1961 **	0.4136 **	0.5498 **	0.2849 **
GIRONDE	0.8324 **	0.4690*	0.9193 **	0.8681 **
HERAULT	0.6678 **	0.8891 **	0.7994 **	0.7938 **
ILLE-ET-VILAINE	0.7710 **	0.7234 **	0.9429 **	0.8601 **
INDRE	0.3093 **	0.2164*	0.9674 **	0.5765 **
INDRE-ET-LOIRE	0.8574 **	0.9083 **	0.9638 **	0.8101 **
ISERE	0.9252 **	0.7715 **	0.9155 **	0.9162 **
JURA	0.6606 **	0.4916 **	0.6824 **	0.5401 **
LANDES	0.6526 **	0.5656 **	0.7847 **	0.5416 **
LOIR-ET-CHER	0.5539 **	0.5792 **	0.9664 **	0.6175 **
LOIRE	0.8673 **	0.5354 **	0.8845 **	0.8023 **
HAUTE-LOIRE	0.3381 **	0.1670	0.6388 **	0.7738 **
LOIRE-ATLANTIQUE	0.8280 **	0.7696 **	0.9100 **	0.7727 **
LOIRET	0.6646 **	0.8716 **	0.6331 **	0.3478 **
LOT	0.3113*	0.2974	0.6234 **	0.6437 **
LOT-ET-GARONNE	0.4690 **	0.5751 **	0.6940 **	0.5540 **
LOZERE	0.0909	0.1187	0.2473 **	0.2038 **
MAINE-ET-LOIRE	0.6728 **	0.8434 **	0.9710 **	0.8543 **
MANCHE	0.7264 **	0.4530 **	0.8197 **	0.7225 **
MARNE	0.7651 **	0.5445*	0.9665 **	0.6543 **
HAUTE-MARNE	0.4877 **	0.1928	0.9471 **	0.7038 **
MAYENNE	0.4337 **	0.4986 **	0.8125 **	0.5862 **
MEURTHE-ET-MOSELLE	0.6658 **	0.8771 **	0.8125 **	0.7387 **
MEUSE	0.3312 **	0.2140*	0.5026 **	0.5908 **
MORBIHAN	0.6514 **	0.6041 **	0.7683 **	0.7582 **
MOSELLE	0.8744 **	0.8434 **	0.9305 **	0.8817 **
NIEVRE	0.5480 **	0.3295	0.9294 **	0.8690 **
NORD	0.7763 **	0.5971 **	0.9231 **	0.5683 **
OISE	0.9164 **	0.8044 **	0.9490 **	0.8862 **
ORNE	0.5849 **	0.3152 **	0.7631 **	0.5059 **
PAS-DE-CALAIS	0.9076 **	0.8595 **	0.9181 **	0.8542 **
PUY-DE-DOME	0.7111 **	0.6563 **	0.9451 **	0.5268*
PYRENEES-ATLANTIQUES	0.8499 **	0.7612 **	0.8195 **	0.8910 **
HAUTES-PYRENEES	0.7640 **	0.1950	0.8019 **	0.6984 **
PYRENEES-ORIENTALES	0.8909 **	0.3071 **	0.8501 **	0.7698 **
BAS-RHIN	0.8950 **	0.8989 **	0.9225 **	0.8494 **
HAUT-RHIN	0.9258 **	0.9385 **	0.8655 **	0.8786 **
RHONE	0.8964 **	0.8304 **	0.9411 **	0.8996 **
HAUTE-SAONE	0.3015 **	0.3916*	0.7807 **	0.9321 **
SAONE-ET-LOIRE	0.8363 **	0.3649 **	0.9617 **	0.8913 **
SARTHE	0.8338 **	0.7383 **	0.8416 **	0.7346 **
SAVOIE	0.7277 **	0.4250 **	0.9549 **	0.8242 **
HAUTE-SAVOIE	0.9181 **	0.9461 **	0.9501 **	0.9349 **
PARIS	0.8468 **	0.7925 **	0.9108 **	0.8653 **
SEINE-MARITIME	0.9055 **	0.8252 **	0.7992 **	0.7662 **
SEINE-ET-MARNE	0.6583 **	0.8980 **	0.8223 **	0.8462 **
YVELINES	0.9718 **	0.9585 **	0.9753 **	0.9312 **
DEUX-SEVRES	0.7043 **	0.6844 **	0.6518 **	0.8337 **
SOMME	0.5119 **	0.6278 **	0.7834 **	0.8094 **
TARN	0.8929 **	0.9374 **	0.9495 **	0.7227 **
TARN-ET-GARONNE	0.6820 **	0.2921 **	0.9510 **	0.7258 **
VAR	0.5530 **	0.6611 **	0.9054 **	0.8277 **
VAUCLUSE	0.7715 **	0.7115 **	0.9387 **	0.8931 **
VENDEE	0.7806 **	0.3210*	0.8344 **	0.7974 **
VIENNE	0.7517 **	0.8561 **	0.8733 **	0.8298 **
HAUTE-VIENNE	0.8663 **	0.3005	0.8608 **	0.8876 **
VOSGES	0.5717 **	0.1181	0.8078 **	0.5624 **
YONNE	0.6256 **	0.0940	0.8911 **	0.5310 **
TERRITOIRE-DE-BELFORT	0.2479*	0.0481	0.6461 **	0.4075 **
ESSONNE	0.4008 **	0.8636 **	0.7158 **	0.7495 **
HAUTS-DE-SEINE	0.9518 **	0.7967 **	0.8528 **	0.8996 **
SEINE-SAINT-DENIS	0.7958 **	0.8085 **	0.8422 **	0.7982 **
VAL-DE-MARNE	0.8870 **	0.8913 **	0.8494 **	0.8059 **
VAL-D'OISE	0.9496 **	0.9105 **	0.9354 **	0.8684 **

** indicates significance at the 99% level

* indicates significance at the 95% level

Table 5: HSAR panel model Public inputs direct effects estimates

Region	Public inputs (publications in the field)			
	chemistry	pharmaceutical	mechanics	materials
AIN	0.1928 **	0.1599*	0.2220 **	0.1175
AISNE	0.0048	0.0243	0.1748*	0.0751
ALLIER	0.0503	0.1009	0.1802*	0.123
ALPES-DE-HAUTE-PROVENCE	-0.0338	0.0004	-0.0698	-0.1002
HAUTES-ALPES	-0.0229	-0.001	0.0141	-0.0057
ALPES-MARITIMES	0.2145 **	0.4914 **	0.2320 **	0.1736 **
ARDECHE	0.0734	-0.0018	0.2919 **	0.1965*
ARDENNES	0.016	-0.0071	-0.0936	0.014
ARIEGE	-0.0193	0.0802	0.0023	0.0868
AUBE	0.0478	-0.0359	-0.0911	0.094
AUDE	0.855	0.0418	0.0976	0.0847
AVEYRON	0.0259	0.0688	0.0673	0.065
BOUCHES-DU-RHONE	0.2532 **	0.4471 **	0.3446 **	0.3967 **
CALVADOS	0.1424	0.2292 **	0.1946*	0.1877 **
CANTAL	0.056	0.0568	0.0497	0.094
CHARENTE	0.0838	0.0466	-0.0479	0.0309
CHARENTE-MARITIME	0.0862	0.0718	0.0938	-0.0434
CHER	0.1763*	0.0702	0.2603 **	0.0218
CORREZE	0.0868	0.0439	0.0491	0.0439
COTE-D'OR	0.2031 **	0.4724 **	0.2907 **	0.1741*
COTES-D'ARMOR	0.1324	0.0423	0.2314*	0.3130 **
CREUSE	-0.0235	-0.0131	-0.0209	-0.03
DORDOGNE	0.0843	0.0886	0.1165	-0.0179
DOUBS	0.0766	0.0887	0.092	0.136
DROME	0.055	0.0687	0.0054	-0.0183
EURE	0.1852*	0.2220*	0.1544*	0.2708 **
EURE-ET-LOIR	-0.0307	0.1466	0.0111	0.0925
FINISTERE	0.2215 **	0.2418 **	0.0978	0.1359
GARD	0.0848	0.1685*	0.0422	0.1575 **
HAUTE-GARONNE	0.3344 **	0.5617 **	0.3980 **	0.4402 **
GERS	-0.0289	0.0252	0.0037	0.0589
GIRONDE	0.3707 **	0.4704 **	0.4623 **	0.4935 **
HERAULT	0.3448 **	0.4888 **	0.2972 **	0.3742 **
ILLE-ET-VILAINE	0.2587 **	0.4907 **	0.2236 **	0.2347 **
INDRE	-0.0328	0.0231	0.2376 **	0.1151
INDRE-ET-LOIRE	0.2399 **	0.3360 **	0.2216 **	0.2119 **
ISERE	0.3213 **	0.3199 **	0.2639 **	0.2427 **
JURA	0.062	0.0804	0.1304	0.0865
LANDES	-0.0067	0.0253	0.0056	0.0631
LOIR-ET-CHER	0.0535	0.0319	-0.0936	0.06
LOIRE	0.1192	0.114	0.1163	0.1442*
HAUTE-LOIRE	0.0837	0.0269	0.0871	0.0004
LOIRE-ATLANTIQUE	0.2733 **	0.4277 **	0.3141 **	0.2391 **
LOIRET	0.1339	0.2965 **	0.1752*	0.3571 **
LOT	-0.0022	0.0453	0.0163	0.0945
LOT-ET-GARONNE	-0.0233	-0.0024	0.0846	0.0085
LOZERE	0.0571	-0.0422	0.054	0.0582
MAINE-ET-LOIRE	0.149	0.1711*	0.0858	0.1076
MANCHE	-0.0452	0.0143	-0.0378	-0.0159
MARNE	0.3434 **	0.5999 **	0.4020 **	0.2096 **
HAUTE-MARNE	0.014	0.017	0.0166	-0.0123
MAYENNE	-0.0352	0.025	0.1850*	0.0725
MEURTHE-ET-MOSELLE	0.3397 **	0.5124 **	0.2582 **	0.2656 **
MEUSE	0.0015	-0.0308	0.0331	-0.0249
MORBIHAN	0.1388	0.0428	0.2500 **	0.1329
MOSELLE	0.1066	0.1072	0.2591 **	0.2299 **
NIEVRE	0.0656	0.0187	0.023	0.1954*
NORD	0.3633 **	0.5422 **	0.1936 **	0.3619 **
OISE	0.2539 **	0.1847*	0.2255 **	0.1709*
ORNE	0.0984	0.0012	-0.2114	0.027
PAS-DE-CALAIS	-0.0789	0.1509*	-0.0751	0.0503
PUY-DE-DOME	0.3281 **	0.4519 **	0.5811 **	0.2734 **
PYRENEES-ATLANTIQUES	0.3623 **	0.1811*	0.2674 **	0.3334 **
HAUTES-PYRENEES	0.0006	0.1094	0.1289	0.0495
PYRENEES-ORIENTALES	0.0998	0.0806	0.1276*	0.1107
BAS-RHIN	0.2449 **	0.4514 **	0.4523 **	0.2501 **
HAUT-RHIN	0.4389 **	0.4650 **	0.4313 **	0.1784*
RHONE	0.2725 **	0.4344 **	0.1507*	0.2121 **
HAUTE-SAONE	-0.054	0.0951	0.009	0.0061
SAONE-ET-LOIRE	0.0006	0.0371	-0.0523	0.081
SARTHE	0.1126	0.1423	0.1715*	0.1037
SAVOIE	0.1255	0.073	0.2481 **	0.2342 **
HAUTE-SAVOIE	0.1142	0.4073 **	0.1902*	0.1694 **
PARIS	0.1957 **	0.3000 **	0.1850 **	0.1720 **
SEINE-MARITIME	0.2153 **	0.3021 **	0.3221 **	0.2322 **
SEINE-ET-MARNE	0.2629 **	-0.0383	0.3039 **	0.0799
YVELINES	0.0259	0.0501	0.0262	-0.0085
DEUX-SEVRES	0.0322	0.0424	0.0862	-0.0324
SOMME	0.0591	0.0718	0.1844*	-0.0015
TARN	0.2753 **	0.4140 **	0.1910 **	0.1807*
TARN-ET-GARONNE	-0.0012	-0.025	0.0087	0.0023
VAR	0.1787*	0.0575	0.1019	0.0276
VAUCLUSE	0.2189*	0.0629	0.1143	0.1803 **
VENDEE	0.0652	-0.0122	0.1102	0.0838
VIENNE	0.1807 **	0.3375 **	0.0928	0.1716 **
HAUTE-VIENNE	0.2943 **	0.1449*	0.2265 **	0.4026 **
VOSGES	0.0941	0.023	0.1334	0.0598
YONNE	-0.026	0.0224	-0.0701	0.0083
TERRITOIRE-DE-BELFORT	0.0795	0.0345	-0.0189	0.135
ESSONNE	0.3259 **	0.0979	0.1777*	0.2063 **
HAUTS-DE-SEINE	0.1234	0.1765*	0.0696	0.1798*
SEINE-SAINT-DENIS	-0.0926	0.0709	-0.0516	0.0231
VAL-DE-MARNE	0.0801	0.1753*	0.0757	0.2246 **
VAL-D'OISE	0.036	0.0354	0.0692	-0.0813

** indicates significance at the 99% level

* indicates significance at the 95% level

Table 6: HSAR panel model Private inputs direct effects estimates

Region	Private inputs (R&D expenditures in the field)			
	chemistry	pharmaceutical	mechanics	materials
AIN	0.0162	0.0357	0.0499	0.1291
AISNE	0.0458	-0.0011	0.0729	0.0306
ALLIER	0.0225	0.139	0.1304	0.0033
ALPES-DE-HAUTE-PROVENCE	-0.001	-0.0017	0.0036	-0.0013
HAUTES-ALPES	0.0018	0.0004	0.0391	0.0107
ALPES-MARITIMES	0.2615 **	0.3327 **	0.1432	-0.0699
ARDECHE	0.0646	0.0104	0.2910 **	0.0594
ARDENNES	-0.0002	-0.0014	0.0993	0.1966*
ARIEGE	0.0326	0.0505	-0.0338	0.0601
AUBE	0.0619	-0.0035	0.0515	0.0524
AUDE	0.017	0.0355	-0.0079	0.0376
AVEYRON	-0.0007	0.0078	0.0807	0.0369
BOUCHES-DU-RHONE	0.2891 **	0.2362 **	0.0834	0.0916
CALVADOS	0.0652	0.0281	0.1421	0.0405
CANTAL	-0.0229	-0.0101	0.0047	0.0889
CHARENTE	0.1061	-0.0044	-0.0034	0.036
CHARENTE-MARITIME	0.0751	0.0207	0.1557*	0.0214
CHER	0.003	0.0475	0.0243	0.0121
CORREZE	0.0055	0.1088	0.0894	-0.0438
COTE-D'OR	0.1760*	0.3371 **	0.0544	0.0547
COTES-D'ARMOR	0.0174	0.0135	0.0967	0.0579
CREUSE	-0.0179	0.0039	-0.0191	-0.0282
DORDOGNE	0.0972	0.0924	0.0559	0.0674
DOUBS	0.0391	0.0501	0.2044*	0.1174
DROME	0.1964*	0.0132	0.3246 **	0.077
EURE	0.4809 **	0.2703 **	0.2843 **	0.3150 **
EURE-ET-LOIR	0.1810*	0.1407	-0.0078	0.0816
FINISTERE	-0.0284	0.0971	0.0032	0.0855
GARD	0.2064 **	0.0406	0.0419	0.1266
HAUTE-GARONNE	0.3132 **	0.3125 **	0.2734 **	0.2003*
GERS	-0.0248	-0.0395	0.0437	-0.0124
GIRONDE	0.3257 **	0.2727 **	0.1901*	0.2200*
HERAULT	0.2901 **	0.3126 **	0.1163	0.0019
ILLE-ET-VILAINE	0.1690*	0.1458	-0.014	-0.0558
INDRE	-0.0211	0.018	0.2974 **	0.0275
INDRE-ET-LOIRE	0.1860*	0.1125	0.0298	0.1213
ISERE	0.1515	0.2116*	0.0818	0.2054*
JURA	0.0669	0.0835	0.1725*	0.015
LANDES	0.0926	0.0506	0.0222	0.0103
LOIR-ET-CHER	0.0372	0.0491	-0.028	-0.0617
LOIRE	-0.0268	0.0667	0.1241	0.2340*
HAUTE-LOIRE	0.0538	-0.0014	0.0799	-0.0224
LOIRE-ATLANTIQUE	0.0725	0.0752	0.0458	0.2215*
LOIRET	0.2037*	0.2346 **	0.2963 **	0.3222 **
LOT	-0.0046	-0.0024	-0.0221	-0.0053
LOT-ET-GARONNE	0.0278	0.0173	0.0612	0.0059
LOZERE	-0.0078	-0.0156	-0.0019	0.0396
MAINE-ET-LOIRE	0.1146	0.0952	-0.0592	0.0823
MANCHE	0.1284	-0.003	0.0151	0.074
MARNE	0.2979 **	0.3245 **	-0.0118	0.1542
HAUTE-MARNE	-0.0131	-0.0106	0.0612	-0.0333
MAYENNE	0.037	-0.0062	0.1784*	0.04
MEURTHE-ET-MOSELLE	0.2514 **	0.1576*	0.0519	0.2073*
MEUSE	-0.0033	0.0094	0.046	-0.0003
MORBIHAN	0.1073	0.0613	0.1698	0.0578
MOSELLE	0.1175	0.0708	-0.0348	0.3249 **
NIEVRE	0.0722	0.0238	-0.047	0.1691*
NORD	0.2793 **	0.2101*	0.3661 **	0.2599 **
OISE	0.1976 **	0.1585	0.0707	0.1247
ORNE	0.0315	-0.0076	0.0352	0.0621
PAS-DE-CALAIS	0.2425 **	0.0579	0.0568	0.1385
PUY-DE-DOME	0.3307 **	0.2899 **	0.1326	0.2547 **
PYRENEES-ATLANTIQUES	0.3619 **	0.2623 **	0.0126	0.0447
HAUTES-PYRENEES	-0.0076	-0.0002	-0.0261	0.0633
PYRENEES-ORIENTALES	-0.0128	0.009	-0.0415	0.0488
BAS-RHIN	0.2611 **	0.1332	-0.2118	-0.0404
HAUT-RHIN	0.3020 **	0.3875 **	0.0616	0.1688*
RHONE	0.4460 **	0.3253 **	0.2531 **	0.2471*
HAUTE-SAONE	-0.0172	0.0577	0.1274	0.1373
SAONE-ET-LOIRE	0.1286	0.0385	0.1565*	0.1538
SARTHE	-0.0013	0.0863	0.0203	0.0318
SAVOIE	0.0727	0.0123	0.1371	0.2398 **
HAUTE-SAVOIE	0.3427 **	0.3549 **	0.2451 **	0.2876 **
PARIS	0.1321	0.1966*	-0.008	0.1295
SEINE-MARITIME	0.2626 **	0.1806*	0.2729 **	0.1963*
SEINE-ET-MARNE	0.1018	-0.0113	0.0541	0.052
YVELINES	0.1535*	0.0696	0.1207*	0.2399 **
DEUX-SEVRES	0.0928	0.0712	0.0466	0.0062
SOMME	0.0933	0.0423	0.0609	0.0984
TARN	0.3468 **	0.4604 **	0.0958	0.0413
TARN-ET-GARONNE	-0.0086	-0.0363	0.0298	0.0028
VAR	0.0662	0.1049	-0.0379	-0.1167
VAUCLUSE	0.0695	0.0461	0.0631	0.2599 **
VENDEE	-0.0062	-0.0088	0.1314	0.0229
VIENNE	0.1404	0.1365	-0.0051	0.074
HAUTE-VIENNE	0.0929	0.0287	0.1228	0.1835*
VOSGES	0.0379	0.0198	0.1569	0.0144
YONNE	0.0284	0.0019	-0.1114	0.0145
TERRITOIRE-DE-BELFORT	0.032	-0.0116	0.0462	0.1315
ESSONNE	0.2356 **	0.1303	0.1958*	-0.0005
HAUTS-DE-SEINE	0.0613	0.2199*	0.1897*	0.0667
SEINE-SAINT-DENIS	0.1438	0.1963*	0.0714	0.0327
VAL-DE-MARNE	0.0885	0.1273	0.083	0.0125
VAL-D'OISE	-0.0707	0.048	-0.0151	0.2121*

** indicates significance at the 99% level

* indicates significance at the 95% level

Table 7: HSAR panel model Public inputs spillover effects estimates

Region	Public inputs (Publications in the field)			
	chemistry	pharmaceutical	mechanics	materials
AIN	0.4164 **	0.1956*	0.7713 **	0.304
AISNE	0.0118	0.0475	0.7403*	0.1917
ALLIER	0.0777	0.0824	0.6145*	0.1897
ALPES-DE-HAUTE-PROVENCE	-0.0676	0.0005	-0.2343	-0.2171
HAUTES-ALPES	-0.06	-0.0013	0.0529	-0.016
ALPES-MARITIMES	0.3061 **	0.4562 **	0.4557 **	0.2708 **
ARDECHE	0.1511	-0.0009	0.9028 **	0.4569*
ARDENNES	0.0271	-0.0056	-0.3154	0.0324
ARIEGE	-0.0361	0.0756	0.0072	0.1376
AUBE	0.0725	-0.0213	-0.3373	0.1916
AUDE	0.1046	0.0464	0.2416	0.1266
AVEYRON	0.0276	0.0573	0.1401	0.0995
BOUCHES-DU-RHONE	0.5134 **	0.6695 **	0.9808 **	0.9309 **
CALVADOS	0.2676	0.2842 **	0.7081*	0.3420 **
CANTAL	0.046	0.0333	0.1198	0.128
CHARENTE	0.1525	0.0581	-0.1499	0.0712
CHARENTE-MARITIME	0.1381	0.0683	0.3245	-0.0842
CHER	0.2276*	0.088	0.8318 **	0.0268
CORREZE	0.069	0.0251	0.1264	0.0688
COTE-D'OR	0.2984 **	0.2543 **	1.1056 **	0.3917*
COTES-D'ARMOR	0.2473	0.058	0.7468*	0.5581 **
CREUSE	-0.0282	-0.0114	-0.0753	-0.0508
DORDOGNE	0.0953	0.0586	0.3371	-0.0293
DOUBS	0.1181	0.0863	0.2983	0.2881
DROME	0.1117	0.0814	0.0148	-0.0384
EURE	0.3195*	0.3952*	0.4631*	0.4976 **
EURE-ET-LOIR	-0.0716	0.2582	0.0401	0.209
FINISTERE	0.3624 **	0.2987 **	0.2483	0.235
GARD	0.1531	0.1561*	0.1123	0.2949 **
HAUTE-GARONNE	0.4499 **	0.5505 **	1.0070 **	0.6483 **
GERS	-0.0459	0.0256	0.0117	0.1029
GIRONDE	0.5145 **	0.4600 **	1.3367 **	0.8641 **
HERAULT	0.4351 **	0.3625 **	0.6536 **	0.5002 **
ILLE-ET-VILAINE	0.4958 **	0.6411 **	0.7198 **	0.4227 **
INDRE	-0.0534	0.0329	0.8248 **	0.193
INDRE-ET-LOIRE	0.3767 **	0.4587 **	0.8358 **	0.4326 **
ISERE	0.6754 **	0.4703 **	0.8399 **	0.5653 **
JURA	0.117	0.0981	0.472	0.2317
LANDES	-0.0094	0.0208	0.0138	0.1015
LOIR-ET-CHER	0.1002	0.0629	-0.3745	0.1185
LOIRE	0.2207	0.1356	0.3813	0.3185*
HAUTE-LOIRE	0.1608	0.0287	0.2785	0.0009
LOIRE-ATLANTIQUE	0.5412 **	0.6220 **	1.0664 **	0.4745 **
LOIRET	0.2016	0.2757 **	0.8037*	0.5903 **
LOT	-0.0019	0.038	0.0453	0.1486
LOT-ET-GARONNE	-0.0356	-0.002	0.258	0.015
LOZERE	0.0918	-0.0393	0.1779	0.1278
MAINE-ET-LOIRE	0.3064	0.2573*	0.3139	0.248
MANCHE	-0.0767	0.0249	-0.1229	-0.0292
MARNE	0.4578 **	0.2819 **	1.3084 **	0.4603 **
HAUTE-MARNE	0.0193	0.0147	0.058	-0.028
MAYENNE	-0.0777	0.0385	0.6779*	0.1626
MEURTHE-ET-MOSELLE	0.4289 **	0.3825 **	0.8127 **	0.5607 **
MEUSE	0.0005	-0.0321	0.1305	-0.0569
MORBIHAN	0.2742	0.0681	0.7853 **	0.2264
MOSELLE	0.141	0.1011	0.7013 **	0.4358 **
NIEVRE	0.1029	0.0153	0.0796	0.3678*
NORD	0.6929 **	0.9944 **	0.7012 **	1.0600 **
OISE	0.8252 **	0.7259*	1.0754 **	0.6232*
ORNE	0.238	0.0048	-0.7775	0.0678
PAS-DE-CALAIS	-0.1689	0.3505*	-0.3224	0.1531
PUY-DE-DOME	0.3288 **	0.3131 **	1.4494 **	0.4794 **
PYRENEES-ATLANTIQUES	0.3932 **	0.1162*	0.5969 **	0.3585 **
HAUTES-PYRENEES	0.001	0.1208	0.3142	0.0663
PYRENEES-ORIENTALES	0.0996	0.1038	0.2414*	0.1353
BAS-RHIN	0.3296 **	0.4296 **	1.1875 **	0.4603 **
HAUT-RHIN	0.5556 **	0.3649 **	1.1642 **	0.3238*
RHONE	0.5397 **	0.4919 **	0.4905*	0.4959 **
HAUTE-SAONE	-0.0895	0.0973	0.0299	0.0133
SAONE-ET-LOIRE	0.0016	0.0491	-0.1743	0.1759
SARTHE	0.1967	0.2161	0.6335*	0.2186
SAVOIE	0.2553	0.1172	0.7159 **	0.5276 **
HAUTE-SAVOIE	0.2171	0.4998 **	0.5828*	0.3713 **
PARIS	0.4685 **	0.9091 **	0.6607 **	0.4814 **
SEINE-MARITIME	0.4709 **	0.5984 **	1.2148 **	0.5869 **
SEINE-ET-MARNE	0.6707 **	-0.1005	1.1815 **	0.1889
YVELINES	0.0604	0.1462	0.0865	-0.0213
DEUX-SEVRES	0.06	0.0603	0.3476	-0.0707
SOMME	0.2185	0.2596	0.9614*	-0.0094
TARN	0.3192 **	0.3370 **	0.4553 **	0.2702*
TARN-ET-GARONNE	-0.0013	-0.0283	0.0215	0.0031
VAR	0.3546*	0.0661	0.2381	0.0542
VAUCLUSE	0.4718*	0.0811	0.3183	0.3797 **
VENDEE	0.1322	-0.0213	0.3862	0.183
VIENNE	0.2712 **	0.3395 **	0.3303	0.3461 **
HAUTE-VIENNE	0.2540 **	0.1188*	0.7007 **	0.5639 **
VOSGES	0.1296	0.0262	0.4111	0.1371
YONNE	-0.0376	0.0166	-0.251	0.0174
TERRITOIRE-DE-BELFORT	0.1355	0.0455	-0.0545	0.3297
ESSONNE	0.9767 **	0.2916	0.6887*	0.6041 **
HAUTS-DE-SEINE	0.2848	0.5343*	0.2426	0.4885*
SEINE-SAINT-DENIS	-0.2589	0.2536	-0.1941	0.0756
VAL-DE-MARNE	0.2004	0.5005*	0.2693	0.6334 **
VAL-D'OISE	0.0917	0.113	0.2799	-0.2508

** indicates significance at the 99% level

* indicates significance at the 95% level

Table 8: HSAR panel model Private inputs spillover effects estimates

Region	Private inputs (R&D expenditures in the field)			
	chemistry	pharmaceutical	mechanics	materials
AIN	0.0386	0.0444	0.1719	0.3312
AISNE	0.1006	0.0013	0.3054	0.0792
ALLIER	0.0352	0.1138	0.4444	0.0036
ALPES-DE-HAUTE-PROVENCE	-0.0014	-0.0007	0.0118	-0.0018
HAUTES-ALPES	0.0061	0.001	0.149	0.0326
ALPES-MARITIMES	0.3733 **	0.3094 **	0.2814	-0.1082
ARDECHE	0.1329	0.0139	0.9005 **	0.1398
ARDENNES	0.0007	-0.0017	0.3369	0.4201*
ARIEGE	0.0599	0.0485	-0.092	0.0964
AUBE	0.0943	-0.0023	0.1879	0.1079
AUDE	0.0212	0.0399	-0.0185	0.0562
AVEYRON	-0.001	0.0071	0.1666	0.0569
BOUCHES-DU-RHONE	0.5878 **	0.3530 **	0.237	0.2147
CALVADOS	0.1209	0.0344	0.519	0.0745
CANTAL	-0.0192	-0.006	0.0109	0.1211
CHARENTE	0.1929	-0.0041	-0.0124	0.0842
CHARENTE-MARITIME	0.1197	0.0194	0.5397*	0.0416
CHER	0.0047	0.06	0.0784	0.015
CORREZE	0.0046	0.0622	0.2313	-0.0672
COTE-D'OR	0.2594*	0.1816 **	0.2076	0.123
COTES-D'ARMOR	0.0318	0.0198	0.3119	0.1021
CREUSE	-0.0216	0.0039	-0.0679	-0.0464
DORDOGNE	0.1115	0.0608	0.1617	0.1122
DOUBS	0.0597	0.0485	0.6628*	0.2509
DROME	0.3985*	0.015	0.9384 **	0.1654
EURE	0.8285 **	0.4799 **	0.8541 **	0.5797 **
EURE-ET-LOIR	0.4292*	0.2492	-0.0264	0.1803
FINISTERE	-0.0443	0.1203	0.0095	0.1478
GARD	0.3719 **	0.0373	0.1108	0.2387
HAUTE-GARONNE	0.4212 **	0.3068 **	0.6924 **	0.2953*
GERS	-0.039	-0.0382	0.1277	-0.0221
GIRONDE	0.4523 **	0.2667 **	0.5486*	0.3849*
HERAULT	0.3664 **	0.2318 **	0.2564	0.0036
ILLE-ET-VILAINE	0.3247*	0.1908	-0.0457	-0.1006
INDRE	-0.0344	0.024	1.0313 **	0.0455
INDRE-ET-LOIRE	0.2919*	0.1539	0.1117	0.2483
ISERE	0.3181	0.3105*	0.2599	0.4786*
JURA	0.127	0.1011	0.6258*	0.0392
LANDES	0.1287	0.0397	0.0562	0.0176
LOIR-ET-CHER	0.07	0.0942	-0.1147	-0.1253
LOIRE	-0.0494	0.0784	0.4087	0.5160*
HAUTE-LOIRE	0.1028	-0.0016	0.2557	-0.0469
LOIRE-ATLANTIQUE	0.141	0.109	0.1561	0.4404*
LOIRET	0.3052*	0.2180 **	1.3565 **	0.5343 **
LOT	-0.0051	-0.0013	-0.0603	-0.009
LOT-ET-GARONNE	0.0412	0.0149	0.1858	0.0109
LOZERE	-0.0124	-0.0146	-0.0063	0.0862
MAINE-ET-LOIRE	0.237	0.1436	-0.2153	0.1889
MANCHE	0.2254	-0.005	0.0485	0.129
MARNE	0.3964 **	0.1521 **	-0.0386	0.3394
HAUTE-MARNE	-0.0172	-0.0083	0.2108	-0.078
MAYENNE	0.0814	-0.0099	0.6537*	0.091
MEURTHE-ET-MOSELLE	0.3168 **	0.1176*	0.1656	0.4369*
MEUSE	-0.0044	0.01	0.1825	-0.0024
MORBIHAN	0.2123	0.0949	0.5339	0.0994
MOSELLE	0.1579	0.0668	-0.0957	0.6139 **
NIEVRE	0.1135	0.0189	-0.1611	0.3184*
NORD	0.5338 **	0.3858*	1.3298 **	0.7608 **
OISE	0.6426 **	0.6231	0.341	0.4536
ORNE	0.0767	-0.0164	0.1281	0.1583
PAS-DE-CALAIS	0.5178 **	0.1352	0.2463	0.4231
PUY-DE-DOME	0.3323 **	0.2008 **	0.3294	0.4471 **
PYRENEES-ATLANTIQUES	0.3933 **	0.1688 **	0.0285	0.0496
HAUTES-PYRENEES	-0.0103	0	-0.0637	0.0847
PYRENEES-ORIENTALES	-0.0121	0.0116	-0.0763	0.0573
BAS-RHIN	0.3507 **	0.1265	-0.5549	-0.0739
HAUT-RHIN	0.3821 **	0.3039 **	0.1661	0.3054*
RHONE	0.8815 **	0.3688 **	0.8237 **	0.5771*
HAUTE-SAONE	-0.0307	0.0593	0.417	0.2808
SAONE-ET-LOIRE	0.2367	0.0508	0.5222*	0.3358
SARTHE	-0.0013	0.1317	0.075	0.0678
SAVOIE	0.1463	0.0199	0.3945	0.5389 **
HAUTE-SAVOIE	0.6495 **	0.4349 **	0.7500 **	0.6303 **
PARIS	0.3174	0.6049*	-0.0304	0.3611
SEINE-MARITIME	0.5734 **	0.3586*	1.0313 **	0.4962*
SEINE-ET-MARNE	0.2588	-0.0322	0.2092	0.1202
YVELINES	0.3536*	0.2003	0.4162*	0.6609 **
DEUX-SEVRES	0.1733	0.1002	0.1886	0.0149
SOMME	0.3426	0.153	0.3159	0.3669
TARN	0.4013 **	0.3746 **	0.2296	0.0611
TARN-ET-GARONNE	-0.0091	-0.0408	0.0731	0.0038
VAR	0.1307	0.1194	-0.0881	-0.2113
VAUCLUSE	0.15	0.06	0.1753	0.5477 **
VENDEE	-0.0115	-0.0167	0.462	0.052
VIENNE	0.2116	0.1369	-0.0176	0.1495
HAUTE-VIENNE	0.0802	0.0231	0.3785	0.2571*
VOSGES	0.0516	0.022	0.4812	0.0333
YONNE	0.0414	0.0015	-0.3996	0.036
TERRITOIRE-DE-BELFORT	0.0535	-0.015	0.1486	0.3246
ESSONNE	0.7090 **	0.3855	0.7638*	0
HAUTS-DE-SEINE	0.1407	0.6664*	0.6904*	0.1789
SEINE-SAINT-DENIS	0.3963	0.6902*	0.3233	0.1092
VAL-DE-MARNE	0.22	0.3646	0.3092	0.0348
VAL-D'OISE	-0.1814	0.1589	-0.0555	0.6776*

** indicates significance at the 99% level

* indicates significance at the 95% level

Table 9: HSAR panel model Public inputs spillin effects estimates

Region	Public inputs (Publications in the field)			
	chemistry	pharmaceutical	mechanics	materials
AIN	0.3473 **	0.4358 **	0.5060 **	0.3275 **
AISNE	0.2046 **	0.1027 **	0.3062 **	0.2579 **
ALLIER	0.1233 **	0.1486 **	0.3558 **	0.2358 **
ALPES-DE-HAUTE-PROVENCE	0.3172 **	0.3131 **	0.2557 **	0.3024 **
HAUTES-ALPES	0.0637 **	0.0269	0.1653 **	0.0583 **
ALPES-MARITIMES	0.2549 **	0.2136 **	0.4218 **	0.3147 **
ARDECHE	0.3137 **	0.1010 **	0.4229 **	0.2915 **
ARDENNES	0.1465 **	0.1068 **	0.4663 **	0.2540 **
ARIEGE	0.0609*	0.2020 **	0.2336 **	0.1338 **
AUBE	0.1128 **	0.0529	0.4728 **	0.2657 **
AUDE	0.1771 **	0.1715 **	0.2426 **	0.1677 **
AVEYRON	0.1103 **	0.0887 **	0.3222 **	0.1742 **
BOUCHES-DU-RHONE	0.3062 **	0.1151 **	0.3420 **	0.1948 **
CALVADOS	0.1570 **	0.2509 **	0.2913 **	0.2686 **
CANTAL	0.0241	0.0363	0.2281 **	0.2064 **
CHARENTE	0.0985 **	0.0763	0.5768 **	0.2310 **
CHARENTE-MARITIME	0.2987 **	0.2298 **	0.4224 **	0.4121 **
CHER	0.1390 **	0.1264 **	0.4597 **	0.1526 **
CORREZE	0.0630*	0.0801*	0.2765 **	0.1361 **
COTE-D'OR	0.1335 **	0.0544*	0.2833 **	0.1963 **
COTES-D'ARMOR	0.2603 **	0.2627 **	0.3538 **	0.1301*
CREUSE	0.0679 **	0.0554*	0.2461 **	0.0354*
DORDOGNE	0.0790*	0.0836 **	0.3552 **	0.1993 **
DOUBS	0.1939 **	0.1882 **	0.4204 **	0.2856 **
DROME	0.3795 **	0.2470 **	0.4981 **	0.3775 **
EURE	0.2474 **	0.2803 **	0.3811 **	0.2885 **
EURE-ET-LOIR	0.2069 **	0.3246 **	0.4611 **	0.2712 **
FINISTERE	0.2741 **	0.2566 **	0.5439 **	0.1027
GARD	0.3485 **	0.3006 **	0.5265 **	0.3812 **
HAUTE-GARONNE	0.0975*	0.1083 **	0.2952 **	0.1525 **
GERS	0.0633 **	0.1113 **	0.2915 **	0.1146 **
GIRONDE	0.1290 **	0.0676*	0.3246 **	0.1676 **
HERAULT	0.1612 **	0.1963 **	0.2960 **	0.2279 **
ILLE-ET-VILAINE	0.2460 **	0.2001 **	0.5423 **	0.3169 **
INDRE	0.0974 **	0.0733*	0.4957 **	0.1966 **
INDRE-ET-LOIRE	0.2094 **	0.2850 **	0.5315 **	0.2679 **
ISERE	0.3176 **	0.2759 **	0.4934 **	0.3448 **
JURA	0.2204 **	0.2089 **	0.3874 **	0.2239 **
LANDES	0.2314 **	0.1712 **	0.4383 **	0.2346 **
LOIR-ET-CHER	0.1627 **	0.2530 **	0.6426 **	0.2393 **
LOIRE	0.2960 **	0.1675 **	0.5458 **	0.3309 **
HAUTE-LOIRE	0.1112 **	0.0492	0.3530 **	0.3125 **
LOIRE-ATLANTIQUE	0.2641 **	0.2273 **	0.5222 **	0.2812 **
LOIRET	0.2542 **	0.2585 **	0.4207 **	0.0929 **
LOT	0.0539*	0.0571	0.2456 **	0.1484 **
LOT-ET-GARONNE	0.1165 **	0.1737 **	0.3469 **	0.2062 **
LOZERE	0.0277	0.0377	0.1215 **	0.0865 **
MAINE-ET-LOIRE	0.2305 **	0.3208 **	0.6218 **	0.3355 **
MANCHE	0.2796 **	0.1966 **	0.5047 **	0.3235 **
MARNE	0.0904*	0.0235	0.3127 **	0.1493 **
HAUTE-MARNE	0.1087 **	0.0455	0.4571 **	0.2355 **
MAYENNE	0.1480 **	0.2086 **	0.4117 **	0.2310 **
MEURTHE-ET-MOSELLE	0.1127 **	0.1166 **	0.3911 **	0.2066 **
MEUSE	0.1063 **	0.0745*	0.3064 **	0.2226 **
MORBIHAN	0.2660 **	0.2596 **	0.4223 **	0.2448 **
MOSELLE	0.3458 **	0.3876 **	0.6081 **	0.3375 **
NIEVRE	0.1225 **	0.0646	0.4691 **	0.2555 **
NORD	0.1074*	0.1231 **	0.3594 **	0.1439 **
OISE	0.2364 **	0.3480 **	0.4866 **	0.3227 **
ORNE	0.1648 **	0.1448 **	0.4618 **	0.2142 **
PAS-DE-CALAIS	0.3312 **	0.3541 **	0.5174 **	0.3600 **
PUY-DE-DOME	0.0953 **	0.0617*	0.2863 **	0.1210*
PYRENEES-ATLANTIQUES	0.1558 **	0.1999 **	0.3643 **	0.2777 **
HAUTES-PYRENEES	0.2190 **	0.0564	0.3611 **	0.2746 **
PYRENEES-ORIENTALES	0.2369 **	0.1242 **	0.3476 **	0.2689 **
BAS-RHIN	0.3018 **	0.3101 **	0.5196 **	0.3265 **
HAUT-RHIN	0.2546 **	0.3319 **	0.5185 **	0.3721 **
RHONE	0.3353 **	0.2229 **	0.5742 **	0.3770 **
HAUTE-SAONE	0.0832 **	0.0923*	0.4236 **	0.3217 **
SAONE-ET-LOIRE	0.3404 **	0.1535 **	0.6100 **	0.3879 **
SARTHE	0.2242 **	0.2962 **	0.4212 **	0.2780 **
SAVOIE	0.2505 **	0.1750 **	0.4361 **	0.2561 **
HAUTE-SAVOIE	0.3093 **	0.2522 **	0.5049 **	0.3404 **
PARIS	0.3599 **	0.3670 **	0.4805 **	0.3618 **
SEINE-MARITIME	0.2165 **	0.2701 **	0.2728 **	0.2567 **
SEINE-ET-MARNE	0.2805 **	0.5296 **	0.4250 **	0.3979 **
YVELINES	0.4667 **	0.5392 **	0.5768 **	0.4583 **
DEUX-SEVRES	0.2481 **	0.2341 **	0.3880 **	0.3417 **
SOMME	0.1668 **	0.3466 **	0.3536 **	0.3614 **
TARN	0.1244 **	0.1955 **	0.3201 **	0.1867 **
TARN-ET-GARONNE	0.1289 **	0.0891 **	0.4173 **	0.2102 **
VAR	0.2045 **	0.2991 **	0.4489 **	0.3342 **
VAUCLUSE	0.2853 **	0.2643 **	0.4776 **	0.3497 **
VENDEE	0.2973 **	0.1516*	0.5292 **	0.3292 **
VIENNE	0.2021 **	0.2241 **	0.5308 **	0.3002 **
HAUTE-VIENNE	0.1253 **	0.0557	0.3767 **	0.1699 **
VOSGES	0.2094 **	0.0518	0.5231 **	0.2514 **
YONNE	0.2057 **	0.0378	0.5198 **	0.2173 **
TERRITOIRE-DE-BELFORT	0.1059*	0.0267	0.5016 **	0.1826 **
ESSONNE	0.1494 **	0.4751 **	0.3882 **	0.3038 **
HAUTS-DE-SEINE	0.4255 **	0.4134 **	0.5010 **	0.3716 **
SEINE-SAINT-DENIS	0.4208 **	0.4430 **	0.5692 **	0.3942 **
VAL-DE-MARNE	0.4440 **	0.4124 **	0.5559 **	0.3241 **
VAL-D'OISE	0.4578 **	0.5071 **	0.5869 **	0.4474 **

** indicates significance at the 99% level

* indicates significance at the 95% level

Table 10: HSAR panel model Private inputs spillin effects estimates

Region	Private inputs (R&D expenditures in the field)			
	chemistry	pharmaceutical	mechanics	materials
AIN	0.4029 **	0.3242 **	0.4705 **	0.3324 **
AISNE	0.1963 **	0.0543*	0.2503 **	0.2723 **
ALLIER	0.1119 **	0.1024 **	0.2216 **	0.2265 **
ALPES-DE-HAUTE-PROVENCE	0.3014 **	0.2036 **	0.1754 **	0.1373*
HAUTES-ALPES	0.0590 **	0.0177	0.1208 **	0.0372 **
ALPES-MARITIMES	0.2060 **	0.1410 **	0.3039 **	0.2728 **
ARDECHE	0.2950 **	0.0548*	0.3195 **	0.2283 **
ARDENNES	0.1490 **	0.0535 **	0.2733 **	0.1946 **
ARIEGE	0.0472*	0.1244 **	0.0944*	0.0471
AUBE	0.1083 **	0.0329	0.2122 **	0.2118 **
AUDE	0.1561 **	0.1069 **	0.0966*	0.0571*
AVEYRON	0.0872 **	0.0620 **	0.1175*	0.0581
BOUCHES-DU-RHONE	0.2845 **	0.0750*	0.3133 **	0.1391 **
CALVADOS	0.2119 **	0.1628 **	0.2410 **	0.2162 **
CANTAL	0.017	0.0255	0.1213 **	0.1120*
CHARENTE	0.0791 **	0.0397	0.3173 **	0.1188 **
CHARENTE-MARITIME	0.2428 **	0.1122 **	0.2020 **	0.2015 **
CHER	0.1424 **	0.1100 **	0.3794 **	0.1062 **
CORREZE	0.0431*	0.0425*	0.1314 **	0.0860 **
COTE-D'OR	0.1517 **	0.0397	0.2268 **	0.1768 **
COTES-D'ARMOR	0.1258*	0.0942*	0.1643*	0.0730*
CREUSE	0.0427 **	0.0410*	0.1488 **	0.0195*
DORDOGNE	0.0550*	0.0456	0.2079 **	0.0778*
DOUBS	0.1854 **	0.1282 **	0.2126 **	0.2728 **
DROME	0.3244 **	0.1532 **	0.2885 **	0.2290 **
EURE	0.3305 **	0.1973 **	0.3668 **	0.2353 **
EURE-ET-LOIR	0.2692 **	0.2877 **	0.4599 **	0.2102 **
FINISTERE	0.1834 **	0.0862	0.2716 **	0.0419
GARD	0.2833 **	0.1854 **	0.3170 **	0.1695 **
HAUTE-GARONNE	0.1230 **	0.0675*	0.0979	0.0623
GERS	0.0699 **	0.0866 **	0.1062*	0.0428*
GIRONDE	0.1497 **	0.0405	0.1943*	0.0832
HERAULT	0.1309 **	0.1180*	0.1162	0.1140*
ILLE-ET-VILAINE	0.1372*	0.0761	0.2960 **	0.1731 **
INDRE	0.0671 **	0.0374*	0.2510 **	0.0970 **
INDRE-ET-LOIRE	0.1659 **	0.1610 **	0.3444 **	0.1352*
ISERE	0.3704 **	0.1798 **	0.4569 **	0.3573 **
JURA	0.2289 **	0.1420 **	0.2923 **	0.2328 **
LANDES	0.2201 **	0.1131 **	0.1764*	0.0936*
LOIR-ET-CHER	0.1609 **	0.1844 **	0.4679 **	0.1788 **
LOIRE	0.3218 **	0.1231 **	0.3999 **	0.2601 **
HAUTE-LOIRE	0.1013 **	0.0329	0.2423 **	0.2668 **
LOIRE-ATLANTIQUE	0.1825 **	0.1034*	0.2911 **	0.1053
LOIRET	0.1484 **	0.2414 **	0.2233 **	0.0735 **
LOT	0.0423*	0.0459	0.1357 **	0.0734*
LOT-ET-GARONNE	0.1103 **	0.0977 **	0.1755 **	0.0898 **
LOZERE	0.0252	0.0204	0.0732 **	0.0403 **
MAINE-ET-LOIRE	0.1532 **	0.1259*	0.3516 **	0.1815 **
MANCHE	0.1469 **	0.0679*	0.2630 **	0.1315 **
MARNE	0.0984*	0.0134	0.2687 **	0.1505 **
HAUTE-MARNE	0.0951 **	0.0268	0.2360 **	0.2034 **
MAYENNE	0.1163 **	0.0846*	0.2305 **	0.1176 **
MEURTHE-ET-MOSELLE	0.0906*	0.0662	0.1755*	0.2020 **
MEUSE	0.0890 **	0.0351*	0.1276 **	0.2124 **
MORBIHAN	0.1040*	0.0824	0.1725*	0.1129*
MOSELLE	0.2718 **	0.1818 **	0.1653	0.2119 **
NIEVRE	0.1230 **	0.0504	0.3149 **	0.1940 **
NORD	0.2475 **	0.0697	0.2900 **	0.1901 **
OISE	0.3546 **	0.2223 **	0.4504 **	0.3952 **
ORNE	0.2301 **	0.0904 **	0.3386 **	0.1464 **
PAS-DE-CALAIS	0.3811 **	0.2028 **	0.4554 **	0.3235 **
PUY-DE-DOME	0.052	0.0474	0.2187 **	0.0869*
PYRENEES-ATLANTIQUES	0.1832 **	0.1006*	0.1842*	0.1316*
HAUTES-PYRENEES	0.2523 **	0.0468	0.1588*	0.0866
PYRENEES-ORIENTALES	0.2279 **	0.0847 **	0.1583*	0.0908*
BAS-RHIN	0.2218 **	0.1798 **	0.2735 **	0.3511 **
HAUT-RHIN	0.2285 **	0.1275*	0.1579	0.2806 **
RHONE	0.2513 **	0.1378 **	0.4233 **	0.3377 **
HAUTE-SAONE	0.0649 **	0.0462*	0.2305 **	0.2541 **
SAONE-ET-LOIRE	0.3074 **	0.1058 **	0.4116 **	0.3381 **
SARTHE	0.2433 **	0.1448 **	0.3185 **	0.1740 **
SAVOIE	0.2567 **	0.1219 **	0.3653 **	0.2505 **
HAUTE-SAVOIE	0.2231 **	0.1457 **	0.3619 **	0.3060 **
PARIS	0.3938 **	0.3903 **	0.4714 **	0.3925 **
SEINE-MARITIME	0.3986 **	0.2381 **	0.3302 **	0.2489 **
SEINE-ET-MARNE	0.3008 **	0.5065 **	0.3920 **	0.3859 **
YVELINES	0.4266 **	0.5137 **	0.4386 **	0.3606 **
DEUX-SEVRES	0.1781 **	0.0933*	0.2151 **	0.1801 **
SOMME	0.2925 **	0.1710 **	0.4273 **	0.3611 **
TARN	0.1020*	0.0951*	0.1359	0.0799*
TARN-ET-GARONNE	0.1397 **	0.0620 **	0.2101 **	0.0855*
VAR	0.2214 **	0.1800 **	0.3629 **	0.2027 **
VAUCLUSE	0.3181 **	0.1569 **	0.3574 **	0.1400*
VENDEE	0.2119 **	0.0552*	0.2452 **	0.1675 **
VIENNE	0.1512 **	0.1016*	0.3156 **	0.1603 **
HAUTE-VIENNE	0.1027*	0.0342	0.2348 **	0.0837
VOSGES	0.1692 **	0.0277	0.1695*	0.2336 **
YONNE	0.1881 **	0.0286	0.3427 **	0.1747 **
TERRITOIRE-DE-BELFORT	0.0877*	0.0134	0.1343*	0.1333 **
ESSONNE	0.1750 **	0.4482 **	0.3112 **	0.3881 **
HAUTS-DE-SEINE	0.4611 **	0.3874 **	0.3738 **	0.4290 **
SEINE-SAINT-DENIS	0.3833 **	0.3459 **	0.4090 **	0.3892 **
VAL-DE-MARNE	0.3651 **	0.4257 **	0.3717 **	0.3645 **
VAL-D'OISE	0.5287 **	0.4360 **	0.4864 **	0.3933 **

** indicates significance at the 99% level

* indicates significance at the 95% level