Where do firms choose to locate their R&D?

A spatial conditional logit analysis on French data.

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Abstract:

The purpose of this paper is to empirically investigate how regional advantages and firms characteristics influence the location of R&D. Looking at 2024 decisions of R&D labs location in France, we implement an extended conditional logit with spatially lagged explanatory variables to evaluate the importance of each factor and to test the spatial dimension of knowledge spillovers. The results indicate that large market size, large amount of ideas, low level of competition, and low level of academic research in the target region increases the probability of setting up R&D labs while the diffusion of knowledge across regions induces a significant spatial dependence.

Keywords : Economic geography, Location choice, Knowledge spillovers, Spatial dependence

1. R&D labs location: Theoretical background

In the 'geography and growth' models[1], public knowledge diffusion explains both the high geographic concentration of innovation activities and its consequences on the economic growth. The innovative sector is submitted to a specific agglomeration force: the level of knowledge production characterising each region. Indeed, new knowledge produced by innovative firms is only partly appropriated. This public knowledge generates spillovers that reduce the cost in the innovative sector. Thus, the location choice of innovative firms is driven by the costs reduction in innovation induced by the amount of externalities available in each region.

Because of local knowledge spillovers, if a region has a small initial advantage, it accumulates experience in the innovative sector faster than the other region. This lowers the replacement cost of capital faster and this in turn attracts more resources to the innovative sector of this region. This regional disequilibrium may raise the economy to a higher growth path. Indeed, once all industry is agglomerated in one region[2], learning spillovers are as strong as possible and the cost of innovation as small as possible.

However, the strength of this agglomeration force, and its effect on the growth rate, depend on the extent to which spillovers are localized. If there is no geographical constraint to public knowledge diffusion, firms in the innovative sector benefit from the same amount of spillovers whatever their location. Several equilibria may arise, among which the symmetric one. Then geography does not impact the long term growth rate. Therefore, in these models, the hypothesis of a local dimension of spillovers is essential to account for the interrelations between two well-known stylized facts: the geographical concentration of innovation and the leading role of innovation in the growth process.

Several studies in the last fifteen years gave empirical evidence of such local spillovers[3]. However, they look at aggregated data[4], whereas 'geography and growth' models are based on individual rational choices. A more direct study of the decision process underlying firms location choice concerning innovative activities is still missing.

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[1] Englman and Walz (1995), Walz (1996), Baldwin and Forslid (2001), Martin and Ottaviano (1999), (2001), Baldwin, Martin and Ottaviano (2000). See Baldwin et al. (2003) or Baldwin and Martin (2005) for a review.
[2] If trade freeness is high enough.
[3] Jaffe (1989), Jaffe, Trajtenberg and Henderson (1993), Feldman (1994), Anselin,Varga and Acs (1997), Autant-Bernard (2001), Bottazzi and Peri (2003), Breshi and Lissoni (2003).
[4] The knowledge production function used in most of these studies relates the aggregated output of innovation in an area (county, metropolitan area, European region, etc.) to its aggregated R&D inputs.

This paper suggests to study the determinants of R&D labs location, looking at 2,024 decisions of location in France from 1,689 firms. A conditional logit is implemented to evaluate the relative importance of the main factors governing the choice of a location. A spatial dependence is introduced to estimate the spatial diffusion of knowledge spillovers.

This improves previous studies in two ways. First, it avoids the aggregation bias encountered in the 'geography of innovation' approach[5]. Indeed, a major problem in most studies in this field comes from the geographical level of observation. The unit is the metropolitan area or county for the United States and the region (NUTS 2 or 3) in Europe. By focusing on an aggregated level, these studies are constrained by the administrative segmentation of a geographical scale which is often quite large and fail to quantify in the spillovers enjoyed by each of these firms. They are measuring inter-agglomeration spillovers, whereas the major facts lie undoubtedly in the relationship between the firm and the agglomeration it belongs to (Lucas, 1988).

Second, in previous studies, knowledge spillovers are not estimated relatively to over agglomeration forces. While they account for non-market interactions, the studies of the 'geography of innovation' neglect the more traditional determinants of concentration. Consequently they give no evaluation of knowledge externalities relatively to more traditional agglomeration forces[6].

By examining the choices made by firms to locate their R&D, we intend to evaluate each of these forces and to better estimate the local dimension of knowledge diffusion. The next section details the econometric model. Data and results are presented in section 3. The last section summarises the main conclusions.

[5] See Autant-Bernard and Massard (2003) or Audretsch and Feldman (2004) for a review.

[6] As noticed by Rosenthal and Strange (2005), the evaluation of agglomeration forces driving firms location is not the subject of a unified literature. They review a series of estimations seeking to evaluate the importance of the various agglomeration forces found in the economic geography theories. But they note that these are separate evaluations as long as each of the studies is only assessing one or two distinct forces at most.

2. R&D labs location: An econometric model of firms location choice

An extended conditional logit model of individual choices

The method is based on a discrete choice model[7]. Each firm choosing between N potential locations, investors are assume to select a location if and only if this location gives higher profits than all the others.

Each firm chooses location j if the expected profits, noted Π_j are higher than all the expected profits associated to other locations:

$\Pi_j = \max\{\Pi_k\} \quad with \quad k = 1, \ldots N$ so if $P_j = P(\Pi_j > \Pi_k)$, $\forall k$, with $k \neq j$.

The profits of each firm, associated to location j, are given by:

$\Pi_j = V_j + \varepsilon_j$

where V_j is a function of all the characteristics of area j. ε_j is a random perturbation.

We choose a linear expression for V_j :

$V_j = \beta X_j$

where X_j is the vector of the observable characteristics of location j and β is the vector of the parameters to be estimated.

This conditional logit is extended to control for the individual specificities that may influence the choice of an area[8]. Indeed, the location choice of an SME may differ from the choice made by multinational firms.

Since a unique vector of parameters can't be estimated for these individual variables, one vector of parameter is estimated for each region. This will allow to evaluate, apart from their observed features, which king of laboratory regions are more likely to attract.

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[7] This method is quite usual in studies of multinational firms location (see for instance Head and Ries, 1996 ; Devereux and Griffith, 1998 ; Crozet, Mayer, Mucchielli, 2003). See Mucchielli and Mayer (2004) for a review.

[8] Such individual data are not observed in models of multinational firms location.

The probability for firm *i* to locate its R&D lab in location j is thus given by[9]:

$$P_j = \Pr ob(y_i = j) = \frac{\exp(X_{ij} b + Z_i \gamma_j)}{\sum_{k=0}^{N} \exp(X_{ik} b + Z_i \lambda_k)}, \quad \forall k \neq j$$

In this framework, the spatial dimension of knowledge spillovers may be measured by introducing a spatial dependence.

Discrete choice models and spatial dependence

As Flemming (2004) notices, the study of spatial dependence in discrete choice models has received little attention in the literature. The very few studies that have applied spatial econometric techniques to models with discrete dependent variable focus on binary choice.

Case (1992) applies a variance analysing transformation in maximum likelihood estimator to analyse the decisions by farmers to adopt new technologies. Marsh, Mittelhammer and Huffaker (2000), also applied this approach to correct for spatial autocorrelation in a probit model with geographic region while examining a data set pertaining to disease management in agriculture. Murdoch, Sandler and Vijverberg (2003) study the adoptions of environmental treaties by European countries using the RIS simulator developed by Beron and Vijverberg (2004). Extending Case's spatial probit by allowing spatial dependence to vary across regions, Coughlin, Garret and Hernandez-Murillo (2004) differentiate states with a lottery from those without a lottery.

As far as I know, the only paper that accounts for spatial dependence in multinomial models is from Nelson et al. (2004). They test the impact of transport infrastructures on the deforestation in developing countries. But they do not account for the heteroskedasticity and the autocorrelation

[9] For identification condition, explanatory variables and vectors of parameters are normalized. The numerator and denominator of expression (1) is divided by $\exp(x_{i0}).\exp(Z_i \gamma_0)$.

$$P_j = \Pr ob(y_i = j) = \frac{\exp[(X_{ij} - X_{i0})b + Z_i (\gamma_j - \gamma_0)]}{\sum_{k=0}^{N} \exp[(X_{ik} - X_{i0})b + Z_i (\lambda_k - \gamma_0)]}, \quad \forall k \neq j$$

$$= \frac{\exp(X^*_{ij} b + Z_i \gamma^*_j)}{1 + \sum_{k=1}^{N} \exp(X^*_{ik} b + Z_i \lambda^*_k)}, \quad \forall k \neq j$$

Consequently, the parameters of this model have to be interpreted cautiously: the parameters associated to individual variables (γ^*_j) express the difference between the original parameters (unconstraint) and those of the reference region (k_0), whereas the parameters b are associated to the differences between the variables relative to regions and the value of these variables in the reference case.

induced by the spatial dependence. The spatial dimension is accounted for by the introduction of the spatially lagged explanatory variables.

As we will mention at the end of this paper, this is largely insufficient. However, we adopt the same approach in this first draft of our study. This will give a first approximation of the spatial dependence between regions and its impact on R&D labs location.

The spatial dimension of knowledge spillovers is introduced as follow:

$$\Pi_{ij} = \rho W X_j + \beta X_j + \gamma_j Z_i + \varepsilon_{ij}$$

where W is a contiguity matrix. The latent variable is a function of the regional explanatory variables values at neighbours.

Estimations of this model will allow to evaluate the relative importance of the main factors governing the choice of one location. Moreover, the introduction of spatial dependence allows to test if a spatial diffusion of knowledge spillovers occurs. The significance of ρ will indicate whether R&D labs location choices are sensitive to the internal characteristics of the area only, or if they depend also on the characteristics of the neighbouring areas.

4. R&D labs location: Empirical evidence from French firms

The data set

The sample comes from an original data basis computed from the "2001 R&D Survey" and the "2001 Firms Survey" (of the French R&D Ministry and the French Industry Ministry respectively). Among the 22,000 industrial firms observed in the "Firms Survey", a sample of 1,689 innovative firms has been identified in the R&D survey, with a total of 2,024 decisions of R&D location. The two data bases give located information about these firms and their R&D laboratories and concerning the main features of their locations. The geographical unit is the administrative French Region (NUTS 2).

At the firm level, we get the following data:

- R&D expenditures carried out by the firm in each of its implantations (DIRD)
- The industrial field of research (19 sub-sectors are distinguished)

- A dummy variable indicating if the firm belongs to a foreign company (GR_ETR). It will allow to test if the location strategy of foreign enterprises differs significantly from the one of French firms.
- A dummy variable for firms with only one plant (MONOETS). In this case, the choice of R&D location is probably largely driven by the location of production.

At the regional level, the total number of workers (EFFREG) in the industry is used to account for the agglomeration forces due to circular causality. The production of the other innovative firms of the region (CAREG) measures the dispersion force produced by local competitors.
The global level of spillovers is accounted for by the following variables:
- The private R&D expenditures of the other labs present in the area, in the same industry as firm *i* (noted RDREG). [10]
- The level of knowledge production from publics labs, measured by the number of scientific publications in the related fields of firm *i* (noted PUBREG). These data come from the OST-SCI data basis[11].
These regional variables are smoothed other three years to account for the cumulative feature of knowledge and to avoid erratic variations associated with data collection.
Data are expressed in logarithms. W is the first order contiguity matrix, with row standardization. Then, each spatially lagged explanatory variable can be interpreted as the mean of this variable for the neighbours of region j.

The main features of these data are given in appendix. Except in few industries like aerospace, energy or computer, R&D labs are present in almost all regions. However, data exhibit a strong polarisation of R&D. Two regions concentrate more than 37% of R&D plants: Paris region (Ile de France) and Rhône-Alpes, receiving respectively 427 and 328 labs. Only two other regions (Centre and Pays de la Loire) have got more than one hundred R&D plants. This spatial concentration is particularly high in the computer and the pharmaceutical industries that localise 40% of their R&D labs in Ile de France.
The sectoral repartition is also characterized by a high level of concentration. 30% of R&D labs concern the Machinery and Equipment industry or the Chemistry (with respectively 341 and 260 plants). These sectoral disparities cannot be taken into consideration by the way of dummy variables. Since some industries do not have got R&D labs in each region, we can't estimate a vector of parameters for each region.

[10] Patents, frequently used in the literature to measure a stock of knowledge, are not the most relevant in this case. By definition, patents reflect codified knowledge, whereas the hypothesis of a local dimension of knowledge spillovers is based on its tacit nature.
[11] The data basis is computed by the French « Observatoire des Sciences et Techniques » from the information of the Science Citation Index in 1995, 1996 and 1997.

Preliminary results

Three models are estimated (results are reported in table 1 and 2). The first model includes only variables relative to the local characteristics. Results from this model confirm the observations of previous studies on aggregated data: the positive impact of private and public research carried out locally. Both RDREG and PUBREG have positive and significant coefficients. This agglomeration effect resulting from knowledge spillovers reinforces the more traditional agglomeration forces measured by the number of workers in the area. The dispersion effect resulting from competition between firms, and measured by the production of local innovative firms (CAREG), seems validated. A relatively high level of R&D carried out locally by other firms raises the probability that a firm chooses to locate its R&D in one region, while a relatively high level of production of these latter tends to reduce the settlement probability.

Table 1: Regional determinants of R&D labs location

	Model 1	**Model 2**	**Model 3**
RDREG	0.231*** (8.978)	0.250*** (8.919)	0.258*** (9.051)
PUBREG	0.063** (2.477)	-0.187** (-2.411)	-0.181** (-1.997)
EFFREG	0.669*** (14.103)	0.537*** (9.750)	0.539*** (9.732)
CAREG	-0.077*** (-7.576)	-0.093*** (-8.662)	-0.099*** (-8.979)
W-RDREG	-	-	0.095** (2.012)
W-PUBREG	-	-	-0.022 (-0.148)
W-EFFREG	-	-	-0.060 (-0.699)
W-CAREG	-	-	-0.002 (-0.071)
Individual features (see table 2)	No	yes	yes
McFadden R²	0.144	0.160	0.161
Adjusted-R²	0.144	0.159	0.159
Obs.	2024	2024	2024

The figures between brackets are t ratios.
*Significance thresholds are indicated by *, ** and *** which signify 10%, 5% and 1%, respectively.*

Table 2: Individual determinants of R&D labs location by region

	Model 2			Model 3		
	MONOETS	GR_ETR	DIRD	MONETS	GR_ETR	DIRD
Ilede France	0.090 (0.307)	0.613* (1.824)	0.107*** (4.041)	0.088 (0.298)	0.618* (1.837)	0.112*** (2.822)
Champagne-Ardennes	0.467 (1.220)	1.048** (2.417)	-0.064 (-1.550)	0.480 (1.251)	1.046** (2.413)	-0.059 (-1.354)
Picardie	-0.144 (-0.392)	1.054*** (2.709)	-0.039 (-1.131)	-0.137 (-0.372)	1.049*** (2.693)	-0.034 (-0.951)
Haute Normandie	0.143 (0.392)	0.879** (2.197)	-0.044 (-1.309)	0.151 (0.411)	0.880** (2.198)	-0.042 (-1.206)
Centre	0.198 (0.594)	1.264*** (3.409)	-0.035 (-1.093)	0.203 (0.605)	1.269*** (3.418)	-0.032 (-0.868)
Basse Normandie	0.132 (0.281)	0.335 (0.614)	-0.093** (-2.193)	0.134 (0.283)	0.334 (0.612)	-0.085 (-1.502)
Bourgogne	0.499 (1.410)	0.670 (1.624)	-0.041 (-1.209)	0.502 (1.416)	0.674 (1.632)	-0.040 (-1.113)
Nord-Pas-de-Calais	0.929*** (2.782)	0.667* (1.661)	-0.052* (-1.657)	0.911*** (2.662)	0.651* (1.619)	-0.042 (-0.722)
Lorraine	0.943*** (2.662)	1.182*** (2.868)	-0.073** (-2.129)	0.940*** (2.624)	1.173*** (2.844)	-0.056 (-1.168)
Alsace	1.243*** (3.678)	1.614*** (4.117)	-0.112*** (-3.276)	1.259*** (3.687)	1.608*** (4.098)	-0.098** (-2.139)
Franche-Comté	0.586 (1.536)	0.342 (0.735)	-0.062 (-1.626)	0.597 (1.559)	0.356 (0.764)	-0.053 (-1.199)
Pays-de-Loire	0.546* (1.681)	0.623 (1.612)	-0.004 (-0.124)	0.545* (1.652)	0.617 (1.594)	0.006 (0.138)
Bretagne	0.706** (1.975)	-0.085 (-0.182)	-0.034 (-1.107)	0.714** (1.977)	-0.064 (-0.138)	-0.021 (-0.463)
Poitou-Charentes	0.145 (0.331)	0.303 (0.589)	-0.056 (-1.430)	0.142 (0.320)	0.305 (0.592)	-0.047 (-0.837)
Acquitaine	0.634* (1.767)	0.554 (1.289)	-0.035 (-1.174)	0.634 (1.747)	0.550 (1.277)	-0.024 (-0.567)
Midi-Pyrénées	0.484 (1.351)	0.219 (0.492)	-0.004 (-0.148)	0.499 (1.374)	0.234 (0.525)	0.004 (0.107)
Limousin	0.516 (1.062)	0.432 (0.716)	-0.079 (-1.574)	0.513 (1.047)	0.439 (0.727)	-0.072 (-1.129)
Rhône-Alpes	0.681** (2.341)	0.726** (2.119)	0.072*** (2.996)	0.697** (2.375)	0.733** (2.138)	0.078*** (2.545)
Auvergne	0.511 (1.140)	0.419 (0.741)	-0.132*** (-2.931)	0.520 (1.156)	0.417 (0.737)	-0.125*** (-2.435)
Languedoc-Roussillon	0.664 (1.532)	-0.047 (-0.081)	-0.028 (-0.707)	0.667 (1.537)	-0.038 (-0.065)	-0.027 (-0.652)

The figures between brackets are t ratios.
*Significance thresholds are indicated by *, ** and *** which signify 10%, 5% and 1%, respectively.*

The second model introduces, together with the regional variables, the individual characteristics of the R&D lab and of the firm to which it belongs. This improves substantially the explanatory power of the model. The estimated coefficients for individual characteristics are reported in table 2. These effects are evaluated relatively to the reference region (PACA).

First, not surprisingly, when they belong to foreign companies, firms are more likely to locate their R&D in frontier regions (Nord-picardie, Haute-Normandie, Alsace-Lorraine) as well as in the main industrial regions (Rhône-Alpes and Ile de France).

Second, the attractiveness of an area seems to differ according to the size of the R&D plant. The higher the R&D expenditure, the higher the probability to locate in agglomerated areas. Indeed, regions with a positive and significant coefficient for R&D plant expenditure (DIRD) are Ile de France and Rhône-Alpes. Both concentrate the major part of French economic activities and all the more the major part of innovative activities (respectively 30% and 9% of the French GDP, and 48% and 12% of R&D expenditure).

Conversely, single plant firms have got a higher propensity to choose relatively more peripheral regions. Location for these latter is probably more influenced by the factors underlying the location of production. In that case, the competitive effect between productive structures may over balance the attraction effect induced by knowledge spillovers.

More unexpectedly, the introduction of these individual variables modifies the sign of PUBREG parameter (table 1). Once controlled for individual features driving location choices, the presence of a large amount of public research in the area seems to reduce the attractiveness of the region[12]. This result may come from the high level of concentration of the French public research. Private R&D labs appear to be relatively dispersed compare to public research. Moreover, this may confirm the idea of the importance of an absorptive capability to benefit from public research (Cockburn and Henderson, 1998). As noticed previously, the introduction of individual variables highlights that large R&D labs are more likely to be located in the main research centres. For small firms, relationships with public research are thinner. Since they would not benefit from public research, the dispersion forces associated to large agglomerations would incite small R&D labs to locate outside the areas with lots of scientific publications[13].

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[12] Using aggregated data, the models based on a knowledge production function cannot control for individual effects and conclude to a positive impact of public research on innovation. The result we obtain here invites to consider cautiously the observation drawn from aggregated data.

[13] Varga (1998) obtained similar results for the U.S. on aggregated data. A critical mass of private R&D must be reached to observe a local effect from public R&D spending. However this point should be studied more deeply. It is inconsistent with Beise and Stahl's results, for which small firms are more likely

This result does not mean that public research does not benefit to private R&D labs, but that these spillovers do not rely on geographic proximity[14]. This is confirmed by the estimations reported in column 3 where no spatial dependence is observed for public research.

The third model includes the spatially lagged explanatory variables. It highlights a rather weak spatial dependence that does not affect previous results. Traditional agglomeration and dispersion effects (measured by EFFREG and CAREG) seem geographically bounded. The only significant lagged variable is the R&D expenditure. Thus, the location decision does not only depend on internal characteristics of the region. It is driven by the knowledge spillovers available in the neighbouring areas also. The spatial parameter is three times as small as the coefficient of internal R&D, supporting the hypothesis of a local dimension of knowledge spillovers.

However, the spatial dependence is introduced in a very reducing way. Spatial spillovers are assumed to be 'local' in the sense of Anselin's classification (Anselin, 2003). Now, the uncertainty affecting the probability that a firm locates its R&D in one region depends on the unobservable characteristics of this region (image, climate for instance). But these characteristics are likely to affect also neighbouring areas. Consequently, spatial autocorrelation is probably not entirely accounted for by the spatially lagged explanatory variables and spatial dependence can appear in the random perturbation. If that is the case, the estimated coefficients remain unbiased, but they are no longer efficient.

Moreover, we do not account for the endogeneity resulting from the bi-directional dimension of the spatial dependence. If knowledge spillovers are not bounded inside regions, the profit associated to the location in one region depends positively on the profit that can be expected in a neighbouring region, and vice versa. Then, estimated parameters are both biased and inefficient.

Thus, a natural extension of these preliminary results relies on a true consideration of the spatial dependence, by introducing the spatially lagged dependent variable and allowing for spatial errors. This implies to extend the spatial probit model to the multinomial case.

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to establish local relations with public research centres (Beise and Stahl, 1999). Audretsch and Vivarelli (1994), also observed that small firms benefit more from academic research than large firms.

[14] Public research may also produce a local effect indirectly by inducing private R&D spending (Jaffe, 1989).

5. Conclusion

Looking at 2024 decisions of R&D labs location in France, this paper intends to better understand the mechanisms underlying the geography of innovation. A conditional logit is implemented to evaluate the relative importance of the main factors driving the location choice. Estimations indicate that individual characteristics, especially the scale of R&D, affect the location choice. However, the mains determinants are regional. Traditional agglomeration effects are reinforced by centripetal forces induced by knowledge spillovers stemming from private research. Estimations also confirm the local dimension of spillovers. The profit associated to the location in one region is primarily affected by the relative amount of knowledge available in this region, and to a lesser extent, by the relative amount of knowledge available in neighbouring areas. This question has important implications in terms of technological policy, especially in the European context dominated by the tension between regional equity and the building of technological poles of worldwide influence.

However, the way spatial dependence is accounted for needs to be improved. The estimations presented here assume that spatial spillovers are only local (in the sense of Anselin's classification). We have to carry on further research to find a proper way to implement a spatial multinomial model. This will allow to consider the decision to set up and develop R&D labs as an endogenous variable.

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APPENDIX:

Table A1: Number of R&D plants by regions

REGION	Number of plants
Ile-de-France	432
Rhône-Alpes	330
Centre	125
Pays de la Loire	120
Nord-Pas-de-Calais	94
Alsace	90
Picardie	89
Haute-Normandie	78
Bourgogne	74
Midi-Pyrénées	71
Aquitaine	68
PACA	68
Lorraine	67
Bretagne	64
Champagne-Ardenne	55
Franche-Comté	55
Poitou-Charentes	38
Languedoc-Roussillon	34
Auvergne	30
Basse-Normandie	29
Limousin	26

Table A2: Number of R&D labs by industry

INDUSTRY	Number of plants
Machines and equipment	341
Chemistry	260
Instrumentation	198
Radio, TV, com. equipments	151
Electricity	147
Pharmaceuticals	138
Work on metals	130
Rubber, plastics	123
Car	97
Textile, clothes	82
Other mining and metallurgy	65
Other industries	49
Aerospace	49
Building material and ceramic	44
Wood, paper, cardboard	42
Shipbuilding	30
Energy (including mining)	29
Office machines and computer	29
Glass	21

Table A3: Number of regions with R&D plants by industries

INDUSTRY	Number of regions
Electricity	21
Machines and Equipments	21
Work on metals	21
Rubber, plastics	21
Chemistry	21
Instrumentation	20
Radio, TV and com. equipements	20
Other mining and metallurgy	20
Pharmaceuticals	19
Textile, clothes	19
Car	17
Other industries	17
Wood, paper, cardboard	17
Shipbuilding and other transports	16
Building material and ceramic	15
Aerospace	11
Glass	11
Energy (including mining)	11
Office machines and computer	8