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Regional Alignment and Productivity Growth

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Abstract

We propose the concept of regional alignment to suggest that synergistic relations among the scientific expertise, technological specialization and industry composition of regions affect regional productivity growth. In this paper, we test an extended conditional β-convergence model using data on 94 French departments (NUTS3) for the period 2001-2011. Our results indicate that a conditional β-convergence is associated with a σ-divergence process in the total factor productivity (TFP) growth of French regions. This process is strongly affected by the level of regional alignment. Indeed, we find evidence that regional alignment both directly and indirectly influences regional productivity growth. The indirect effect of regional alignment materializes through its leverage on R&D investment, which is one of the most important drivers of productivity growth. Moreover, using a heterogeneous coefficients model, we show that the positive effect of regional alignment on TFP growth increases with the industrial and technological diversity of regions, which suggests that regional alignment increases the value of Jacobs externalities more than Marshall-Arrow-Romer (MAR) externalities.

JEL Classification: 030, 040, R11

Keywords: Regional Alignment, β-convergence, productivity growth, multi-regional model

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1 Introduction

In recent years, there has been increasing interest in persistent regional differences in the economic performance of regions in almost all studied countries. While the dispersion of GDP per capita among countries has narrowed over the last thirty years, within-country differences have widened almost everywhere (OECD, 2009, 2016). Unlike predictions popularized by Friedman's book "The World is Flat" (2005), the digital revolution and the decline in transportation and communication costs have not led the world toward a general convergence. The world has, in fact, never been so spiky (Florida, 2005, Moretti, 2013), which raises serious policy issues since national economic integration is an essential part of governments' agendas.

The view described above goes against the traditional view assuming an absolute (unconditional) β-convergence across countries and regions with growth rates declining with the level of GDP per capita (Solow, 1956, Barro and Salai-i-Martin, 1991, 1995; Sala-i-Martin, 1996). Empirical results confirm absolute β-convergence across OECD countries but do not find convergence across US states (e.g., see Evans and Karras, 1996; Sala-i-Martin, 1996; and Evans, 1997), US counties (Higgins et al. 2006; Young et al. 2008) or across European NUTS 3 regions (Paas et al. 2006; Simeonescu, 2014). However, absolute β-convergence only tells us whether and at what pace economies converge toward a steady state in time but not whether and to what extent there are disparities among regional economies. The steady state of a region may depend on characteristics that are specific within that region and therefore may vary and even diverge over time. Regions may converge, conditional on other region-specific variables being held constant, but to different steady states. To better account for the evolution of regional heterogeneity in countries, σ-convergence is more interesting and is generally measured as the temporal dynamic of the standard deviation of regional GDP per capita (Quah, 1993). Persistent within-country σ-divergence is striking because analysts generally assume that institutional conditions are homogeneous and that there is higher capital, labor and knowledge mobility within countries than between countries.

One convincing explanation of this phenomenon is that a positive relationship exists between agglomeration processes and growth, which are essentially spurred by spatially-mediated knowledge externalities (Baldwin and Martin, 2004)[1]. Knowledge spillovers induce complementarities in firms' R&D investment by facilitating access to external knowledge but often require social ties based on frequent face-to-face interactions. The literature suggests that there are two opposing views of localized knowledge spillovers (Glaeser et al., 1992). The Marshall-Arrow-Romer (MAR) framework and Porter's framework emphasize that industrial specialization in a single industry facilitates knowledge flows across firms sharing similar or related technological knowledge. In contrast, the opposite prescription promotes Jacob (1969)'s externalities resulting from the agglomeration of firms from different industries and where knowledge diversity increases the likelihood of cross-fertilization. This process may explain why industrial diversity contributes to the long-term growth of regions only when they rely on similar or related technologies (Frenken et al. 2007: Boshma, 2015).

[1] see Ciccone, 2002 for empirical evidence of the link between the job density and growth of European NUTS 3 regions. A series of studies have tested the sensitivity of knowledge spillovers to distance to determine whether they can explain agglomeration (e.g., see Jaffe et al., 1993; Ciccone and Hall, 1996; Audretsch and Feldman, 1996; Combes, 2000; Rosenthal and al., 2003; Carlino et al. 2012; Buzard and Carlino, 2013; Bloom et al. 2013; Lychagin et al., 2016; and Buzard et al. 2017).

However, divergence also arises among similar types of regions exhibiting significant growth-rate heterogeneity despite their similar initial conditions (Garcilazo and Martins, 2013). This divergence suggests that regional productivity differences may be due to heterogeneous access to specific resources and infrastructures or, more importantly, how regions organize, allocate, and develop their resources (Rosenthal and Strange, 2004; Aghion et al. 2009). This argument echoes Saxenian (1996)'s explanation of the different growth paths of the Silicon Valley and Boston Route 128, which is based on the ability of local industrial and innovation systems to promote interdependence and exchanges among individuals and institutions. Thus, the relations among localized knowledge spillovers, agglomeration and growth may rely on the underlying mechanisms in traditional growth models that have not yet been explored (Breschi and Lissoni, 2001).

We argue that regional alignment is a critical determinant of the differences in regional growth paths. Regional alignment reflects the level of synergies among the scientific domains, technological fields, and industrial sectors in which a region has expertise. In this article, we focus on science and technology synergies as an indicator of the effectiveness of interactions among universities, firms, and local political institutions or agencies. Universities have been shown to have a significant role in both producing basic research stimulating technological innovation through collaborations with firms, licensees or spinoffs and generating spillovers through the creation of high skilled workers who are trained by experts. However, spillovers should be more significant and impactful in aligned regions if local firms and startups can, either directly or indirectly, exploit the knowledge and human capital produced by universities.

This paper makes several contributions. First, it proposes a definition and measurement of regional alignment as an indicator of the effectiveness of synergies among complementary agents in a region, thus enabling systematic comparisons of regional characteristics. Second, we extend the conditional β-convergence model of total factor productivity (TFP) growth (Ha and Howitt, 2007) to take into account the existence of both localized knowledge spillovers between regions and the theoretical influence of regional alignment on productivity growth. Third, using French firm-level data aggregated at the NUTS 3-level for the period 2001-2011, we estimate an extended conditional β-convergence model of productivity growth. We use different econometric models (Simultaneous Equations Model and Heterogenous Coefficients Model) and consistent estimators (IV) to address the complexity of the interrelations among our explanatory variables and provide a better estimation of the influence of regional alignment on the dynamics of regional productivity growth.

Our results highlight the conditional β-convergence that is associated with a σ-divergence of the regional productivity/growth processes in France. In other words, we obtain evidence that the heterogeneity of French regions in terms of TFP increased during the last decade. We also find that regional alignment matters for explaining this heterogeneity. Regardless of the estimation method used, regional alignment positively influences regional TFP growth. Furthermore, our simultaneous equation model reveals that regional alignment has a significant indirect effect on R&D investment, which is a driver of TFP growth. Our last main empirical finding highlights that the nonlinear and heterogeneous effects of regional alignment are conditional on the industrial diversity of the region. Indeed, we show that the effect of regional alignment on productivity growth is negatively

related to industrial specialization, which seems to indicate that the positive effect of regional alignment plays a greater role in Jacobs' externalities than in MAR externalities.

The remainder of this paper is organized as follows. In Section 2, we present the concept of regional alignment and its statistical measure. Section 3 develops an extended conditional β-convergence model of regional productivity growth. In Section 4, we describe the data and the main descriptive statistics. Section 5 introduces the first estimations of the model, which highlight the process of regional productivity growth in France and the role of regional alignment. Then, using more advanced econometric techniques, we further investigate the influence of regional alignment in Section 6 and conclude in Section 7.

2 The regional alignment concept and its empirical measure

2.1 Literature background: R&D investment and knowledge spillovers as the main drivers of productivity growth

Investing in R&D is central for economic growth (Romer, 1986, 1990; Grossman and Helpman, 1991, Aghion and Howitt, 1992). The underlying assumption is that the level of R&D investment determines the likelihood of successfully exploiting technological opportunities, increasing the stock of knowledge, and generating productive innovation. As a quasi-public good, newly generated knowledge should spillover at a negligible marginal cost, reduce the overall cost of R&D, and contribute to both local and national economic growth. However, as noted by Lucas (1988) and evidenced by several empirical studies (e.g., von Hippel, 1994; Maskell and Malmberg, 1999; Breschi and Lissoni, 2001; Storper and Venables, 2004; and Laursen et al. 2014), spillovers rely on social or contractual interactions that are spatially bounded. Consequently, regional growth divergence appears when the size of regions differs due to localized knowledge spillovers; therefore, there are variations in the costs of R&D and growth paths (Baldwin, Martin & Ottaviano, 2001). Recent works analyzing the link between agglomeration and spillovers confirm the economic significance of knowledge spillovers and their sensitivity to the distance among innovative firms (Audrestch and Feldman, 1996; Rosenthal and al., 2003; Carlino et al. 2012, Buzard and Carlino, 2013; Murata et al. 2014; Kerr and Kominers, 2015; Lychagin et al., 2016; Buzard et al. 2017; Bloom et al. 2013; Lucking et al. 2018).

The economic literature identifies the types of knowledge spillovers that vary according to the economic structure of a territory. On one hand, according to the MAR view on spillovers, by co-locating in the same area, firms in a specific industry reduce their information and transaction costs as well as their R&D effort to build absorptive capacities and benefit from local knowledge spillovers. The spatial, economic and cognitive proximities of these firms facilitate the exchange of goods and services, human capital flows, and the pooling of specific resources, thus boosting spillovers and returns on R&D (e.g., see Glaeser et al., 1992 and Cohen and Levinthal,1990). MAR externalities provide a theoretical justification for the innovative benefits of the agglomeration of firms that are either in the same industry or in related industries (Porter, 1998, Frenken et al., 2007; Boschma and, Iammarino, 2009; Neffke et al. 2011). A series of empirical works shows that regions

exhibiting a high level of interdependence and relatedness among the knowledge bases of local firms tend to follow a common innovation path and therefore benefit more from knowledge externalities (North, 1990; Asheim and Coenen, 2005; Frenken et al., 2007; Martin and Sunley, 2012; Colombelli et al., 2014). However, regions with industries relying on similar or related knowledge bases may become trapped in a spiral of negative "lock-in", leading to technological obsolescence and economic decline (Marin and Sunley, 2012; Neffke et al. 2017).

On the other hand, according to the Jacobs (1969) view on spillovers, size matters because larger cities contain more variety and therefore provide more knowledge combination opportunities, thus yielding greater economic returns on local firms' innovative efforts. Indeed, cognitive diversity matters to avoid "lock-in" as firms develop new capabilities that generally result from interactions with heterogeneous and unrelated sources of knowledge (Miguelez, and Moreno, 2015; Neffke et al. 2017). Thus, the benefits of agglomeration not only depend on scale but also rely on the composition and organization of local economic and innovative activities[2]. Agglomeration studies consistently show that knowledge externalities arise from interdependencies or synergies across complementary actors (such as suppliers, customers, universities and public institutions) that either exchange resources, human capital, products or services or learn from each other (Marshal, 1920; Glaeser et al., 1992; Henderson et al. 1998; Cooke, 2001; Breschi et Lissoni, 2001). An important source of knowledge variety is interaction with universities (Gibbons and Johnston, 1974, Rosenberg, 1990; Nelson and Rosenberg, 1994; Bishop et al. 2011). Although academic knowledge can be accessed through scientific publications, patents or licenses, the proximity between scientists and engineers affects the intensity and quality of collaborations (Gibbons and Johnston, 1974; Mansfield and Lee, 1996; Arundel and Geuna, 2004; Bishop et al. 2011).

2.2 Regional alignment as a new input for productivity growth

In this paper, we argue that in addition to R&D investment and localized spillovers, regional innovative and growth performances are related to the alignment of the scientific expertise, technological capabilities and industrial specialization of regions. The concept "regional alignment" refers to the accumulation of assets and capabilities in various actors that can be mutually synergistic if effectively combined. This simple definition has three implications. First, regional alignment emphasizes the idea that in order to be productive, scientific knowledge must translate into concrete applications. This is similar to the idea of Arora and Gambardella (1994), who distinguish between general and abstract knowledge, which is found in the realm of science, and local and concrete knowledge, which belongs to the domain of technologies and industrial applications[3]. From these preliminary definitions, one can already infer that the region's endowment in both basic and applied knowledge is an essential characteristic of regional alignment. Second, a greater integration between scientific, technological and industrial expertise implies a greater accumulation of assets and their corresponding infrastructure. In other

[2]For example, the innovative and economic performances of regions vary with the diversity of industry composition (Vernon, 1960; Jacob; 1969; Porter, 1998; Duranton and Puga, 2001, Helsley and Strange, 2014), the intensity of competition among local firms (Porter, 1998, Bloom et al. 2013; Grebel and Nesta, 2017), the level of the maturity of industries (Neffke et al. 2011), the average or diversity of firm size (Rosenthal and al., 2003; Delgado et al. 2010; Agarwal et al., 2014), the intensity of entrepreneurship (Glaeser et al., 2015), and the overlap of resources across industries (Porter, 2003; Neffke et al. 2012; Delgado et al., 2010, 2014).

[3]Abstract knowledge means the ability to represent a range of phenomena by means of a limited number of variables. General knowledge is the ability to relate distant elements of knowledge. Conversely, local and concrete knowledge is applied to concrete experiments, a process which relies primarily upon tacit abilities and trial-and-error.

words, regional alignment emphasises the role of a minimum critical mass which translates into greater facilities, enhanced access to heavy experimental protocols, etc...For instance, universities play a significant role in creating more productive human capital and attracting talented students from other regions (Salter and Martin, 2001, Moretti, 2012). The literature has clearly established that university spillovers are geographically bounded and directly constribute to local firms' innovation (Jaffe, 1989; Acs et al., 1994 ; Anselin et al., 1997 Laursen et al. 2011, 2014). Indeed, academic researchers gain from collaborations with local firms providing potential research directions and access to additional resources (e.g., see Lee, 2000 and D'Este and Perkman, 2011), thus reinforcing the alignment process. Third, we believe that the concept of regional alignment may reveal potentially useful interactions among complementary agents such as public and private scientists, engineers, business communities, and policy makers, which may contribute to the innovation, the productivity and the growth of the local economy. Overall, we argue that regional alignment as defined here plays a critical role in the growth potential of regions.

2.3 The regional alignment measure

The objective of our regional aligment measure is to capture the potential synergistic relations among the scientific, technological and industrial resources in a region. The empirical estimation of regional alignment is a three-step process.

Step 1: Measuring the level of synergies among all the science domains and the technological fields at the national level

We use patent statistics and scientific publications to unravel regional alignment. We use scientific publications to unravel the scientific expertise of regions. Patent statistics span over a greater range of actors, namely public and private scientists and engineers. Therefore, we believe that patent can be used to qualify the technological and industrial expertise of the regions. We measure the level of synergies by the intensity of the combined use of technological fields and scientific domains in all French patents[4]. More precisely, the level of synergy between the technological field $j \in J$ and the scientific domain $k \in K$ is denoted as τ_{jk}, which results from the number of citations of scientific papers in domain k by patents associated with technological field j. We propose a parametric measure of τ_{jk} by using a random combination of j and k that follows a hypergeometric distribution[5] and define τ_{jk} as:

$$\tau_{jk} = \frac{C_{jk} - \mu_{jk}}{\sigma_{jk}} \tag{1}$$

where C_{jk} is the empirical number of co-occurrences observed between technology j and scientific domain k, μ_{jk} is the expected (mean) value of a random technological co-occurrence and σ_{jk} is its standard deviation. Thus, if $C_{jk} > \mu_{jk}$, then technology j and scientific domain k are highly related. Conversely, if $C_{jk} < \mu_{jk}$, then j and k are poorly related. More details on the computation of τ_{jk} are provided in Appendix B.

[4]The scientific domains and technological fields are presented in Appendix A

[5]The hypergeometric distribution, which stems from a binomial distribution, describes the probability of successfully drawing x out of N draws without replacement (while the binomial distribution assumes replacement).

Step 2: Measuring the regional technological expertise (RTE) and regional scientific expertise (RSE) in each technological field and scientific domain

We use the commonly-used indicators of technological and scientific specializations, i.e, the revealed technological advantage (RTA) indicator developed by Balassa (1961, 1969) and the revealed scientific advantage (RSA). The RTA of a specific technological field j is defined as the ratio of the share of regional applicants' patents associated with technological field j to the share of the country's patents associated with technological field j.

$$RTA_{ij} = \frac{P_{ij}/\sum_j P_{ij}}{\sum_i P_{ij}/\sum_{ij} P_{ij}}$$

where P_{ij} is the number of patents in technological field j granted in region i. We then define the RTE in technological field j for a region as a binary transformation of the RTA:

$$\begin{aligned} RTE_{ij} &= 1 \quad \text{if} \quad RTA_{ij} \geq 1 \\ RTE_{ij} &= 0 \quad \text{if} \quad RTA_{ij} < 1 \end{aligned} \tag{2}$$

The same ratio is used to define RSA in domain k and measures the share of regional patents citing scientific publications associated with scientific domain k to the share of the country's patents citing articles in journals associated with scientific domain k.

$$RSA_{ik} = \frac{P_{ik}/\sum_k P_{ik}}{\sum_i P_{ik}/\sum_{ik} P_{ik}}$$

where P_{ik} is the number of patents citing scientific domain k that were granted in region i.

$$\begin{aligned} RSE_{ik} &= 1 \quad \text{if} \quad RSA_{ik} \geq 1 \\ RSE_{ik} &= 0 \quad \text{if} \quad RSA_{ik} < 1 \end{aligned} \tag{3}$$

Step 3: Measuring regional alignment

We define the level of regional alignment (RA) as the mean of the level of regional alignment for each combination j and k. In other words, for each pair of technology field j and scientific domain k, the level of regional alignment is defined as the interactions among the RTE in j, the RTE in k and the level of synergy between j and k.

$$RA_{ijk} = \tau_{jk} * RTE_{ij} * RSE_{ik} \tag{4}$$

Where RA_{ijk} is the regional alignment of region i in technology j and scientific domain k. Next, we compute the index of regional alignment for region i as:

$$RA_i = \frac{\sum_{jk} RA_{ijk}}{(J_i * K_i)} \tag{5}$$

where J_i represents the number of technological fields for which region i is active, and K_i represents the number of scientific domains for which region i is active. Regional alignment increases with the effective number of related co-expertises jk (high τ_{jk}) but decreases with the potential number of co-expertises jk within the region (high J_i and K_i).

3 A regional productivity model

3.1 The TFP dynamic equation

Our theoretical framework is based on a variety R&D-based growth models proposed by Grossman and Helpman (1991, chap.3) and Jones (1995). In these models, TFP is measured as a stock of knowledge, and its accumulation over time drives economic growth. The main difference in different R&D-based growth models concerns an assumption made regarding the returns of this stock of knowledge, that is, the returns to the TFP stock. If we assume constant returns to scale, then we obtain endogenous growth with an immediate adjustment to the steady state. If we assume decreasing returns to scale, then we obtain semi-endogenous growth with an adjustment path to the steady state; i.e, the short-run growth rate differs from the long-run steady state growth rate.

We assume decreasing returns to the TFP stock and thus use the approach proposed by Jones (1995). Consequently, we can write the equation governing the dynamics of TFP for region i (noted $\dot{TFP}$) as:

$$\dot{TFP}_i = \eta_i RD_i^{\lambda} TFP_i^{\phi} \tag{6}$$

where RD refers to the level of R&D investment level of the region, and $\eta_i > 0$ is an exogenous productivity paremeter specific to the region. Following Jones, we assume that $\lambda < 1$, given the existence of potential duplications in R&D activities, and $\phi < 1$ refers to the decreasing returns of the TFP stock.

3.2 Regional alignment and the exogenous productivity parameter

In the previous section, we developed the concept of regional alignment and illustrated how it could be a central explanation for the productivity dynamics of regions. We argue that regional alignment could be the theoretical source of the exogenous productivity parameter. In other words, we believe that regional alignment is an interesting candidate that could endogenously explain the value of the productivity parameter of regions. We thus assume:

$$\eta_i \equiv RA_i^{\mu} \tag{7}$$

where RA is the level of regional alignment, and $\mu < 1$ is the returns of regional alignment. In (7), we assume that regional alignment is Hicks neutral for the dynamics of productivity. Obviously, we can also imagine that regional alignment more directly influences either the returns of R&D investment (Harrod neutral) or the

returns of the productivity stock (Solow neutral). In any case, this consideration is not the first importance for the purpose of this paper.

3.3 From a mono-regional to a multi-regional model of productivity

Previously, our theoretical framework considered regions such as Robinson Island. In reality, it is difficult to imagine that what happens in a particular region is totally independent of what happens in other regions, especially when they are in the same country where input mobility is strong. Indeed, due to the existence of (localized) knowledge spillovers, local trade and input mobility, it is obvious that the productivity dynamics of a particular region are driven not only by its productivity stock but also by the productivity stock of its neighboring regions. For a two-region (denoted as i and j) trade and growth model (Martin and Ottaviano, 1999), the existence of localized knowledge spillovers is modeled in the following way:

$$\dot{TFP}_i = \eta_i RD_i^{\lambda}[TFP_i + \delta TFP_j]^{\phi} \tag{8}$$

where $\delta \in [0, 1[$ measures the importance of interregional spillovers and thus their spatial boundary. We extend the concept proposed by Martin and Ottaviano (1999) to an N-regions model and rewrite (8) in the following way:

$$\dot{TFP}_i = \eta_i RD_i^{\lambda}[W_i TFP]^{\phi} \tag{9}$$

where $W_i = [\delta_{ii}, \delta_{ij}, ..., \delta_{in}]$ is a $1 \times n$ vector describing the strengh of the link between region i and the other regions. TFP is an $N \times 1$ vector of the productivity level such that $TFP^{'} = [TFP_i, TFP_j, ..., TFP_n]$. We follow new economic geography and growth (NEGG) theory by asumming that region i can fully benefit from its productivity stock, whereas it benefits to a lesser extent from the productivity stock of its neighboring regions. Consequently, in equation (8), we obtain $\delta_{ii} = 1$ and $\delta_{in} \leq \delta_{ii}$, $\forall m \neq i$. As a short example, assume that region i has a significant link with three regions denoted respectively as j,k and l; then, the total stock of productivity that benefits region i is given by $W_i TFP = TFP_i + \delta_{ij} TFP_j + \delta_{ik} TFP_k + \delta_{il} TFP_l$. Thus, in our model, the productivity growth of the region is influenced by its "usuable" productivity stock ($W_i TFP$), which is composed of its own productivity level (TFP_i) plus a share of other regions' productivity stock.

By inserting proposition (7) into expression (9) and dividing through by TFP_i, we obtain the following equation for the productivity dynamics of a particular region i:

$$g_i = RA_i^{\mu} RD_i^{\lambda} TFP_i^{-1} (W_i TFP)^{\phi} \tag{10}$$

where $g_i = \dot{TFP}_i / TFP_i$ is the growth rate of the productivity of region i. Next, it is necessary to rewrite (10) as TFP_i is included in $W_i TFP$. After some manipulations, which are provided in appendix C, we are able to

determine the growth rate of the productivity of a multi-region framework as:

$$\begin{aligned} g_i &= \zeta_i RA_i^{\mu} RD_i^{\lambda} (W_i TFP)^{\phi-1} \\ \zeta_i &\equiv [(W_i - \tilde{W}_i)(W_i^{'} W_i)^{-1} W_i^{'}]^{-1} \end{aligned} \tag{11}$$

where $\tilde{W}_i = [0, \delta_{ij}, ..., \delta_{in}]$ is a $1 \times n$ vector describing the strength of the link between region i and the other regions. The only difference in vector W_i is that in $\tilde{W}_i$, we have $\delta_{ii} = 0$. Consequently, $(W_i - \tilde{W}_i)$ is a non-negative $(1 \times n)$ vector of the form $[1, 0, 0..., 0]$. The interesting result of this simple equation is that the TFP growth rate of a region depends not only on its distance to the frontier (TFP_i) but also its distance to the frontier of its neighboring (or influencing) regions. As we assume decreasing returns of the productivity stock $(\phi < 1)$, for a region, all else being equal, the higher the neighboring levels of productivity stock are, the lower its growth rate.

3.4 From theory to empirical specification

We now assume that there is a shock ε_{it} to the growth rate in each period. This shock is generated by a stationary process with a mean of zero. Then, following Ha and Howitt (2007), the log-linear approximation of a discrete-time version of the generalized productivity-growth function (11) for region i yields:

$$\triangle \ln TFP_{it} = \ln \zeta_i + \mu \ln RA_{it} + \lambda \ln RD_{it} + (\phi - 1) \ln[W_i TFP_t] + \eta_t + \varepsilon_{it} \tag{12}$$

In what follows, we discuss the expected value of the main parameters from a theoretical point of view. As we assume decreasing returns of the TFP stock, i.e, $\phi < 1$, we also assume that there is a conditional β-convergence of the regional TFP growth where $\beta \equiv (1-\phi) < 0$. Based on the discussion in the previous section, we can expect a positive value for μ as a better regional alignment should increase the effects of both R&D and productivity stock. We also assume that $0 < \lambda < 1$, implying that non-cooperative R&D investment decisions generate some duplications at the regional level.

4 Data and descriptive statistics

4.1 Data sources

The data collection required to evaluate the influence of regional alignment on regional productivity growth was very important and time consuming. Indeed, we needed to use various microeconomic data sources. In what follows, we describe the main databases we used to construct the empirical measures for the key variables of Model (12).

Data sources for the regional alignment measure: Patstat and the Web of Science (WOS)

As described in Section 2, the regional alignment measure aims to estimate the potential synergies between scientific domains and technological fields as well as the scientific and technological expertise of regions. Therefore, we relied on information obtained from patents and scientific publications.

We retrieved patent data from the Patstat database compiled by the European Patent Office (EPO). We collected information from all patents granted in France for which the priority year was between 1995 and 2011 (n= 574,515). To avoid problems due to irregular patenting activity in regions, every year reports the aggregation of a backward five-year window of patenting. Using the IPC codes that each patent is associated with, we used the correspondence table provided by the EPO to allocate each patent to one of the 35 technological fields in the database (see Appendix A). To measure RTE, the usefulness of patents is measured as the number of forward citations of patents associated with each technological class.

To estimate the scientific expertise of regions, we retrieved 753,046 journal articles that were indexed by the Institute of Scientific Information's (ISI's) WOS and published between 1995 and 2011 by researchers located in France. We collected the year of publication, the name of the journal and the address of the researchers using the zip code to determine the French region they were associated with. Using the WOS's classification of journals that separates journals into scientific categories, we identified 22 scientific domains (see Appendix A). Then, the researchers' addresses enabled us to allocate each publication to a region and measure the expertise of each region on a yearly basis.

We measured the level of interdependence between each pair of scientific domain-technological field by using the so-called "non-patent literature references" (NPLR) and selected references to scientific journal literature (Narin et al. 1997, Perko and Narin, 1997; Cockburn et al., 1998; Fleming and Sorenson, 2004). In other words, we retrieved all scientific publications that have been used in French patents. Scientific publications can be identified in NPLR by extracting titles between quotation marks in patents. However, titles are often incomplete, preventing us to find the right reference systematically. We used Google Scholars to find the full title of the article, as well as the name of the journal publishing the article, which allowed us to allocate each article to a WOS scientific category. We obtained 13,838 articles published between 2000 and 2011.

Data sources for the TFP measure: FICUS and FARE

The FICUS and FARE databases contain the financial statements of all enterprises (with the exception of microenterprises and agricultural holdings) with turnover that exceeded 75000 euros and that were active between 1997 and 2011. All nominal variables are deflated using various deflators made available online by INSEE, the National statistical office in France, including deflators for production, value added, intermediate consumption, investment, and hours worked. It is from these deflated data, and therefore by volume, that the levels of TFP are calculated. Although they contribute to GDP, companies with no employees are excluded from the analysis because it is not possible to compute their productivity index. Of the 32 million observations for the study period, the database includes approximately 16 million observations after the exclusions. This significant reduction in the number of observations is equivalent to excluding a mass of companies representing 7% of the total value added.

One important potential bias that occurs when using firm-level data is related to location. Indeed, the location of firms is not necessarily equivalent to the location of production activities; the latter pertains to the establishments themselves. Although the vast majority of companies have only one establishment (93.5% of the companies in our sample), in our base, multi-establishment firms represent 53% of total value added and 56% of total employment. Hence, these multi-establishment companies represent a sizeable bias toward heavily agglomerated territories. Larger companies tend to settle their headquarters close to major administrative, political and economic centers. By way of consequence, we would tend to overestimate the economic activities of agglomerated areas and underestimate the economic activities of more rural areas. To correct for this geographical bias, we use establishment-level data (the annual Declarations of Social Data, i.e., DADS data). Such data make it possible to know, for each company, the location of manpower by establishment. Since these establishments are geographically identified by municipality and assuming that there is a proportional relationship between the proportion of staff per establishment and all other production variables (turnover, value added, investment, capital stock, and intermediate consumption), it is possible to correct the aggregation bias mentioned above.

Overall, the regional TFP measure is based on data gathered on more than 3.5 million establishments from 1997 to 2011 and includes more than 18 million observations. Finally, the establishments are aggregated at the departmental level. The methodology used in this paper to calculate the TFP at the firm level is described in appendix D.

Data sources for the R&D measure: the R&D survey

Growth theory explains TFP growth by means of R&D investments. Although the translation of R&D investments into observed TFP growth may be diffused over time, it is necessary to account for the intangible investments that must eventually translate into product or process innovation, that is, into TFP growth. Therefore, we use the French R&D survey that is collected each year by the French Ministry of Higher Education, Research and Innovation. This database provides firm-level information on R&D activities and, particularly, on domestic R&D expenditures (DERD) and the sources of R&D financing. This survey database is organized into three files: the first provides firm-level information allowing us to characterize the firms, the second provides R&D sector-level information on the financial sources used by the firms to develop their R&D activities and the third provides NUTS 3-level information on the R&D executed in each department in each firm (expenditure and staff). The sample used to calculate aggregate R&D expenditures at the regional level includes 11,000 firms.

4.2 Descriptive statistics and a spatial analysis

In this section, we conduct a descriptive analysis of the variables we use to estimate our extended conditional β-convergence Model (14). Table 1 below shows that, on average, productivity growth in the French regions during the last decade has been negative ($-0,4\%$ per annum) with strong heterogeneity as the minimum value is -15.8% (Savoie region in 2008) and the maximum value is 9.4% (Paris region in 2007). Moreover, the empirical

distribution of productivity growth is skewed to the left with excess kurtosis, implying a high proportion of negative productivity growth within the French regions. We also see important heterogeneity in the productivity stock (TFP) of the French regions. The lowest productivity stock value is obtained for the Lozere region in 2009 (0.349), and the highest is obtained for the Paris region in 2007 (20.117). The distribution of productivity stock is strongly skewed to the right with a high level of excess kurtosis, which means that most of the productivity stock observed is well over the average productivity stock (2.752).

Variable	Obs.	Mean	S.D	Min	Max	Skewness	Kurtosis
$\Delta \ln TFP$	1034	-0.004	0.036	-0.158	0.094	-1.235	5.656
TFP	1034	2.752	2.475	0.349	20.117	3.371	20.469
$WTFP$	1034	4.939	3.216	1.401	25.908	2.757	15.355
RD	1034	251 381	527 109	0	3 738 882	4.181	22.220
RA	1034	9.173	10.346	-0.049	152.6547	4.525	46.761

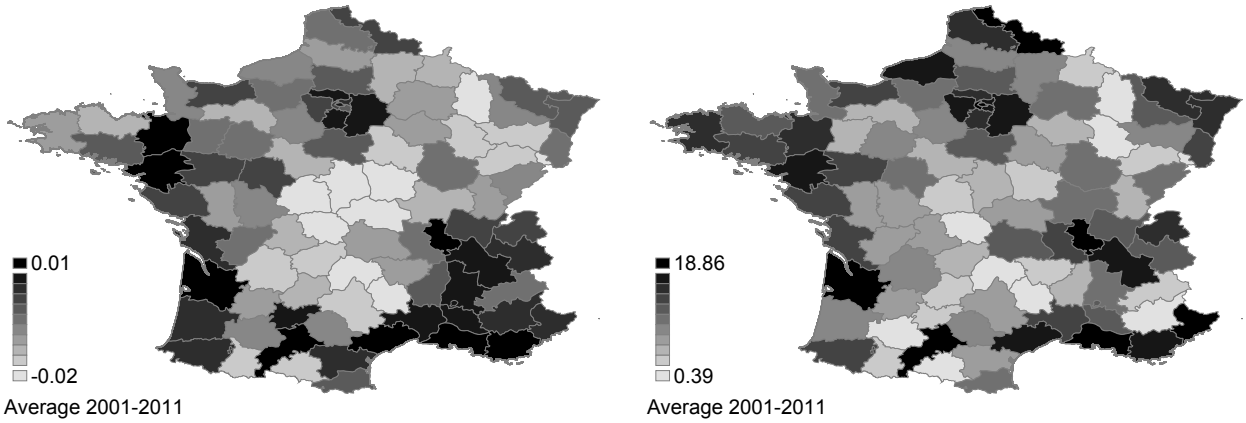
Table 1: Descriptive Statistics

To produce our "usuable" productivity stock variable (W TFP), we construct a spatial matrix describing the links among the French regions. This spatial matrix uses two criteria to weight the link between the two regions. First, we generate a matrix of economic similarity between regions. The economic similarity between region i and region j is measured by the inverse of the euclidean distance of their share of valued added in agriculture, industry and services. Second, we generate a contiguity matrix, and we multiply the two matrices. Consequently, in our final spatial matrix, two regions are linked if they are geographically contiguous, and the weight of this link depends on the economic similarity between these two regions. Consequently, if a region has three contiguous regions, then we add the weighted average productivity stock of these three regions to the region's own productivity stock. This calculation explains why the descriptive statistics for the "usuable" stock of productivity (W TFP) are higher than those for the stock of productivity (TFP). The main characteristics of the distribution of "usuable" productivity stock (W TFP) are similar to those of productivity stock. Nevertheless we note that by taking into account the spatial dependence between the regions and their capacity to benefit from external knowledge, we slightly reduce the heterogeneity of the distribution.

Concerning R&D investment, the distribution is also highly heterogeneous, with a minimum of 0 for the Lozere region in 2005 and 2008 and a maximum of 3.74 billion euros for the Hauts-de-Seine region in 2011. We can see considerable heterogeneity in R&D investment as the standard deviation is more than two times higher than the mean. Finally, and most importantly, we focus on our measure of regional alignment. Again, our data on the French regions indicate there is considerable heterogeneity as the minimum value is -0.049 for the Creuse region in 2001, and the maximum value is 152.655 for the Lot region in 2004. The distribution of regional alignment is highly skewed to the right with considerable excess Kurtosis, implying that most levels of regional alignment are above the mean of 9.173. Due to the small size of certain French regions, some did not report any patents and thus have a value of 0 for regional alignment. Among our 1,034 observations, 10% (103 observations) have a zero value. These 103 observations are split among 37 regions, but 40% of those with

zero values concern only 7 French regions: Cantal, Aude, Lozere, Creuse, Meuse, Alpes-de-Haute-Provence and Haute-Alpes. Nevertheless, no region has a zero value over the entire study period.

Figure 1 below provides two maps representing the means of TFP growth and TFP stock for the period 2001-2011. These two maps highlight a strong geographical concentration of both TFP growth and TFP stock

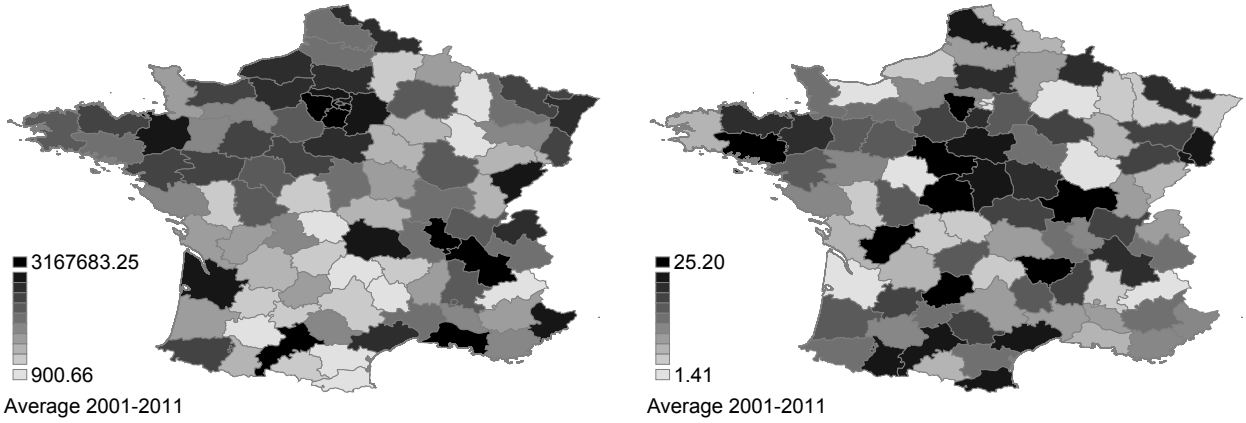


(a) TFP growth (%) (b) TFP stock

Figure 1: TFP levels and dynamics in the French regions

with leading TFP regions surrounded by low TFP regions. If the unconditional convergence theory applies, we should observe high TFP growth dynamics in regions with low TFP stock, and vice-versa. If a small number of French regions with low TFP stock have indeed experienced high TFP growth over the period, then we should see that most of the high (low) TFP regions have also a high (low) TFP growth rate over the period. These two maps clearly highlight the absence of an unconditional convergence of French regions and the strong probability of an increase in TFP heterogeneity over time.

Figure 2 provides two maps representing the geographical disribution of average R&D investment and regional alignment for the period 2001-2011.



(a) R&D (b) Regional Alignment

Figure 2: TFP, R&D and RA in French regions

Maps (c) and (d) represent the geographical disribution of R&D investment and regional alignment, respectively. Although the interpretation of such maps is a matter of taste, we do observe that the map of regional alignment (Figure 2(b)) differs from the three other maps, which do exhibit some degree of overlap.

5 The link between productivity growth and regional alignment

5.1 The conditional β-convergence of TFP growth and regional Alignment

To estimate a conditional β-convergence model, estimators that can address endogeneity must be used as the productivity stock is in the right-hand side of equation (12). In addition, the causal relationships existing among productivity levels, R&D investment and regional alignment could be sources of additional endogeneity. Indeed, as Myrdal (1957) notes, the dynamics of regions, and especially their inequalities, are driven by circular cumulative causation between the variables. Consequently, the ordinary least squares (OLS) estimator is inconsistent and inefficient for estimating a conditional β-convergence model.

To address these endogeneity problems, our econometric strategy includes two processes: 1) directly estimating equation (12) using consistent IV estimators and 2) estimating equation (12) using a simultaneous equation model (SEM) with a three-stage least squares (3SLS) estimator. Both methods are able to address endogeneity problems related to temporal dependence and causality, but the advantage of the SEM approach is that it provides results on the complex interrelationships existing among productivity stock, R&D investment and regional alignment.

We start with the first part of our econometric strategy by presenting the estimation of equation (12) with three different estimators: least squares dummy variables (LSDV) (OLS on panel), IV-2SLS and IV-GMM. The LSDV estimation is inconsistent but provides a benchmark compared with the two IV consistent estimators.

	LSDV			IV-2SLS			IV-GMM		
Variable	Coeff.	s.e.	P-Value	Coeff.	s.e.	P-Value	Coeff.	s.e.	P-Value
$\ln[W_iTFP]$	-0.089	0.027	0.001	-0.145	0.043	0.001	-0.174	0.042	0.000
$\ln[RD]$	0.002	0.002	0.389	0.014	0.006	0.017	0.015	0.005	0.003
$\ln[RA]$	0.002	0.001	0.001	0.014	0.004	0.000	0.017	0.003	0.000

Table 2: Conditional β-convergence model

The results presented in Table 2 provide evidence of a β-convergence process in the French regions' productivity growth. More precisely, the efficient estimators (IV-2SLS and IV-GMM) estimate the speed of convergence to be between 14.5% and 17.4%. Table 2bis in Appendix E provides the estimation of the same equation using the productivity stock of the region (TFP) instead of its usable productivity stock (W_iTFP). For this estimation, the speed of convergence is estimated to be between 10.3% and 12.1%, which is significantly lower than the results presented in Table 2. Thus, the results imply that the β-convergence process is influenced by spatial

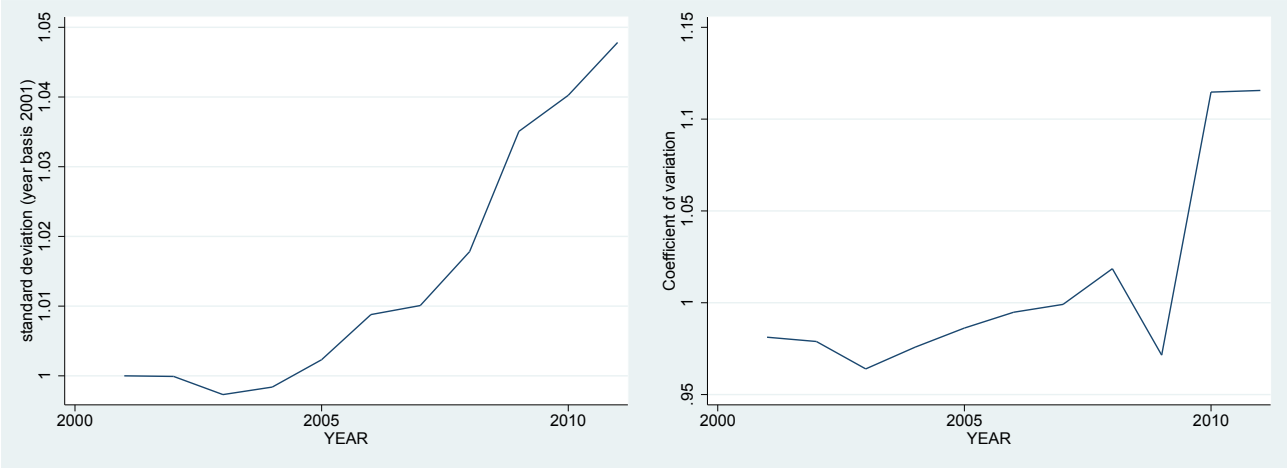
dependence among regions. Consequently, geography matters for explaining local productivity dynamics and implies that the empirical estimation using an a-spatial framework, i.e, using the productivity stock of a region instead of its "usuable" stock, is likely to understimate the true speed of convergence. The same results occur if we do not control for endogeneity as the LSDV estimator clearly underestimates the speed of convergence (less than 9%; see Table 2).

Table 2 also confirms that the β-convergence process is conditional on the level of R&D investment and regional alignment. Indeed, the consistent estimators presented in Table 2 show that both R&D investment and regional alignment positively and significantly influence the productivity growth of a region. Consequently, French regions naturally converge toward different steady states according to their behavior in terms of R&D investment and regional alignment. The heterogeneity in French regions' R&D profiles (see map (a) in Figure 2) can thus explain why regions with the highest productivity experienced a high productivity growth, and vice-versa. Indeed, as R&D investment is highly concentrated in a few regions that are also the leading productivity regions, naturally, these regions have high productivity growth potential. Nevertheless, the differences in R&D investment cannot explain why some regions with relatively high productivity stock and low R&D profiles experienced high productivity growth, such as the Aude, Lot-et-Garonne and Pyrénées-Orientales regions. It seems that regional aligment is able to provide one explanation for the dynamics of these regions, and this is a very important implication. Indeed, if the level of R&D investment is strongly correlated with industries (and thus cannot be strongly influenced by political strategies), then the level of regional alignment can be more easily influenced by public authorities especially because government and local authorities strongly support scientific activities. Consequently, regional alignement could be very important in the political strategy of local authorities (especially for low-intensive R&D regions) to boost TFP growth in both the short and long run.

5.2 The sigma divergence of productivity growth and regional alignment

Since the previous subsection highlights the existence of a conditional convergence process in the TFP growth of French regions, a natural question is whether the β-convergence is associated with a σ-convergence, i.e, if heterogeneity in TFP among the French regions has increased over time. To test the presence of the σ-convergence, we use two different indicators measuring the cross variations in TFP stocks: the cross standard deviation of TFP stock and the cross coefficient of variation (which corresponds to the standard deviation divided by the mean).

These two graphs clearly highlight that the conditional β-convergence is associated with a strong σ-divergence of productivity among the French regions. Indeed, the cross standard deviation increased by 5% over the study period (basis year: 2001), and the coefficient of variation increased from 98% in 2001 to 111% in 2011. It is also important to note that the 2008 financial crisis seems to have increased the σ-divergence process. These results suggest that the variables conditioning the β-convergence process, i.e., R&D investment and regional alignment, are at the heart of this process of increasing heterogeneity among the French regions. We thus decide to study the time evolution of the cross standard deviation of R&D investment and regional alignment (Figure



(a) Cross Standard Deviation (b) Cross Coefficient of Variation

Figure 3: Evolution of the TFP heterogeneity of the French regions

4). Using year 2001 as the base level, Figure 4 shows that the cross standard deviation of regional alignment has

(a) Regional Alignment (b) R&D expenditures

Figure 4: Cross standard deviation of regional alignment and R&D investment

increased by nearly 30% in 2011 compared to 2001, whereas the cross standard deviation of R&D investment has increased by 2% between these two dates. Thus, if heterogeneity in R&D investment and in regional alignment both affect an increase in the heterogeneity of TFP heterogeneity across French regions, it suggests that the heterogeneous dynamics of regional alignment play a predominant role in the observed σ-divergence process.

6 A deeper discussion of the influence of regional alignment

6.1 The indirect effect of regional alignment on productivity growth

As explained in the previous section, the estimation of our conditional β-convergence Model (12) with complex interrelationships among the explanatory variables suggests that it is necessary to develop a simultaneous equation model. This model will allow us to better understand the direct and indirect effects of regional

alignment on TFP growth by taking into account potential reverse causality and the cumulative causation mechanisms of the variables.

As we do not want to impose any restrictions regarding the causality existing among productivity stock, R&D investment and regional alignment, we start by defining a general simultaneous equation system for each explanatory variable of the core equation (12). In what follows, F refers to a linear function, and all variables are expressed in logarithm. A detail explanation of the variables used in the SEM approach is provided in Appendix F.

$$\begin{cases} \triangle TFP_{it} &= F(RA_{it}, RD_{it}, W_iTFP_t, u_{it}) \\ W_iTFP_t &= F(W_iTFP_{t-1}, RD_{it}, RA_{it}, HI_{it}, HT_{it}, HS_{it}, EN_{it}, EX_{it}, u_{it}) \\ RD_{it} &= F(RD_{it-1}, RA_{it}, W_iTFP_t, SUB_{it}, HI_{it}, HS_{it}, HT_{it}, u_{it}) \\ RA_i &= F(RA_{it-1}, RD_{it}, W_iTFP_t, SUB_{it}, HI_{it}, HS_{it}, HT_{it}, u_{it}) \end{cases}$$

where $u_{it} = \alpha_i + \eta_t + \varepsilon_{it}$ includes both the idiosyncratic error term and the individual and time fixed effects. The first equation of the system is the TFP growth equation we defined in (12). The second equation corresponds to the usuable TFP stock for the region that we explain by a set of variables. The first (W_iTFP_{t-1}) is a temporal lag that takes into account the strong time dependency of TFP stock. The second (RD) and third (RA) are the R&D investment and regional alignment of the region, respectively, which are the main drivers of conditional TFP growth convergence. We also include three different Herfindahl indices that measure the specialization of the region in terms of industries (HI), technologies (HT) and sciences (HS). Finally, in this second equation, we include the dynamics of the entry (EN) and exit (EX) of firms in the region. The third equation of our system explains the level of R&D investment in regions. As R&D investment is strongly time dependent, we include the temporal lag of R&D investment as the first explanatory variable (RD_{it-1}). We add the level of regional alignment (RA), usable productivity stock ($WTFP$), the amount of R&D subsidies received (SUB) and our three Herfindhal specialization indices. Finally, the last equation of the system explains RA. As explanatory variables, we include the temporal lag of regional alignment, R&D investment and usuable productivity stock ($WTFP$). We also take into account R&D subsidies (SUB) to see if public support for R&D drives regional alignment. Finally, our three Herfindhal specialization indices are used as controls.

In what follows, we present the 3SLS results obtained from the SEM that was previously developed. To check for robustness, we also present, for each equation, the results we would obtain if nonsignificant causality among productivity stock, R&D investment and regional alignment were not considered. In the following tables, the estimations of the entire SEM is called the "full system", whereas the estimations of the SEM without significant causality is called the "restricted system".

The results for the core equation (Table 3) are consistent with our previous findings using IV-2SLS and IV-GMM estimators and are presented in Table 2. Indeed, we find evidence of a β-convergence process of TFP growth that is conditional on a positive effect of both regional alignment and R&D investment. The speed of

convergence is estimated at 12.6%, which is slightly lower than the results obtained with other IV estimators. The quality of our model is relatively good with an R^2 of 0.67.

Equation 1: Δ TFP								
	Full System				Restricted System			
Variable	Coeff.	S.E.	t-Stat	P-Value	Coeff.	S.E.	t-Stat	P-Value
$WTFP$	-0.126	0.038	-3.35	0.001	-0.123	0.030	-4.05	0.000
RD	0.010	0.003	3.03	0.000	0.010	0.003	3.70	0.000
RA	0.020	0.002	8.40	0.000	0.021	0.02	8.52	0.000
	R^2: 0.6710				R^2: 0.6674			

Table 3: Conditional β-convergence with the SEM approach

As the SEM approach provides similar results for our core equation of productivity growth, we focus our analysis on the three other equations of the system. We start with the usuable TFP stock equation ($WTFP$) for which we obtain the following results (Table 4):

Equation 2: WTFP								
	Full System				Restricted System			
Variable	Coeff.	S.E.	t-Stat	P-Value	Coeff.	S.E.	t-Stat	P-Value
$L.WTFP$	0.803	0.015	52.88	0.000	0.804	0.015	52.96	0.000
RD	0.001	0.000	2.76	0.006	0.001	0.000	2.80	0.005
RA	0.000	0.000	1.35	0.178				
HI	0.002	0.003	0.69	0.489	0.002	0.003	0.69	0.492
HT	-0.000	0.000	-0.50	0.614	-0.000	0.000	-0.66	0.510
HS	0.001	0.000	1.55	0.121	0.001	0.000	1.69	0.091
EN	0.086	0.005	17.50	0.000	0.085	0.005	17.47	0.000
EX	-0.025	0.005	-5.44	0.000	-0.025	0.005	-5.55	0.000
	R^2: 0.9998				R^2: 0.9998			

Table 4: Productivity model with the SEM approach

Our model for the usable TFP stock equation is very good with an R^2 of 99.98%. Most of the results obtained are comparable to those in the literature. Indeed, the usuable TFP stock is serially correlated in time with a coefficient related to its lag value of 0.803. We find evidence that the level of TFP stock of a region is positively related with its level of R&D investment. In contrast, the level of regional alignment does not seem to significantly influence the usable TFP stock. This last result is due to the fact that the usuable stock of productivity also takes into account the productivity stock of neighboring regions. Indeed, if we replicate the SEM using the productivity stock instead of the "usable" stock, then we find that regional alignment has a positive and significant effect on the productivity stock. Nevertheless, dropping this nonsignificant relation between regional alignment and usable productivity stock does not change the other results (see the results for

the restricted system). Concerning the control variables, the dynamics of the entry and exit of firms matter and suggest that regional barriers to firms' mobility hinders the development of regional productivity stock. Concerning our Hefindahl indices, the usable TFP stock seems to be influenced by only the regional specialization in science. Indeed, specialization in terms of technologies and industries is not satistically significant.

We now discuss the third equation of our system related to the R&D investment level of regions. We obtain the following results for the R&D equation (Table 5):

Equation 3: RD								
	Full System				Restricted System			
Variable	Coeff.	S.E.	t-Stat	P-Value	Coeff.	S.E.	t-Stat	P-Value
$L.RD$	0.343	0.035	9.73	0.000	0.338	0.032	10.71	0.000
RA	0.810	0.141	5.74	0.000	0.841	0.122	6.91	0.000
$WTFP$	-0.899	1.206	-0.75	0.456				
SUB	0.035	0.017	2.09	0.037	0.038	0.017	2.29	0.022
HI	-0.756	0.212	-3.56	0.000	-0.765	0.216	-3.35	0.000
HT	-0.072	0.021	-3.42	0.001	-0.073	0.021	-3.42	0.001
HS	0.292	0.077	3.76	0.000	0.278	0.072	3.88	0.000
	R^2: 0.7993				R^2: 0.7872			

Table 5: R&D investment model with the SEM approach

Our model for R&D investment fits well with our data with an R^2 of nearly 80%. Most of the results obtained are comparable to those in the literature. Indeed, we find evidence that R&D investment is serially correlated in time with a coefficient related to the lagged value of approximately 0.34. We also find that R&D subsidies have a positive influence. A more important result concerns the influence of the usable productivity stock and regional alignment. First, we do not find a significant relationship between the productivity stock and the level of R&D investment, which implies that the causal relationship between R&D investment and productivity stock is clear: investment in R&D drives productivity, but the inverse does not hold. Second, we find that RA has a strong positive effect on the level of R&D investment. This result reveals that regional alignment has a more complex influence on productivity growth. Indeed, all the previous estimates show that regional alignment can be seen as a regional input that directly drives productivity growth. This last equation highlights that regional aligment has an indirect effect on productivity growth through its leverage effect on R&D investment (which is the other input of productivity growth). Consequently, this last result implies that regional alignment is at the heart of the σ-divergence process of productivity that we observe among the French regions. Concerning the controls, our results show that the specialization of regions in terms of industries and technologies limits R&D investment, whereas specialization in science has a positive effect.

Finally, another reason for using the SEM approach is that it allows us to better understand what creates regional alignment. We obtain the following results from the regional alignment equation (Table 6):

Equation 4: RA								
	Full System				Restricted System			
Variable	Coeff.	S.E.	t-Stat	P-Value	Coeff.	S.E.	t-Stat	P-Value
$L.RA$	0.027	0.021	1.24	0.214	0.028	0.020	1.38	0.166
RD	0.003	0.065	0.05	0.962				
$WTFP$	0.758	1.738	0.44	0.663				
SUB	-0.024	0.026	-0.92	0.358	-0.021	0.024	-0.88	0.379
HI	0.510	0.281	1.82	0.070	0.507	0.281	1.80	0.071
HT	0.048	0.027	1.82	0.069	0.049	0.026	1.84	0.065
HS	-0.115	0.082	-1.41	0.159	-0.110	0.020	-1.35	0.177
	R^2: 0.3719				R^2: 0.3706			

Table 6: Regional alignment model with the SEM approach

Our model for regional alignment, which takes into account both time and regional fixed effects, is clearly not satisfactory because it has an R^2 of approximately 37%. Indeed, only the industrial and technological specialization of regions seem to positively drive the regional alignment, but the significance remains low (p-value $> 5\%$). This result clearly highlights the complexity of explaining the (res)sources that create the regional alignment. Unfortunately, our dataset does not allow us to test a richer model, and it is clear that a better understanding of the elements at the source of regional alignment is needed.

6.2 The heterogenous effect of regional alignment

In the previous subsection, we highlighted that regional alignment has an indirect effect (which is cumulative with its direct effect) on regional productivity growth. Another important question that arises is whether the impact of regional alignment is homogenous or heterogeneous among French regions. To investigate this question, we need to estimate equation (12) by including a heterogenous coefficient; i.e, the impact of the explanatory variables are region specific. To retain the logic of the conditional β-convergence model, we still assume that there is a common β parameter for the usable productivity stock, but we allow for the heterogeneous impacts of both regional alignment and R&D investment. Thus, we estimate the following model

$$\triangle \ln TFP_{it} = \alpha_i + \mu_i \ln RA_{it} + \lambda_i \ln RD_{it} + (\phi - 1) \ln W_i TFP_t + \eta_t + \varepsilon_{it} \tag{13}$$

Therefore, we use the common correlated effects estimator (CCE) proposed by Peasaran (2006) that takes into account the unobserved common factors of the regions, i.e, a cross-section correlation. Due to the small temporal dimension of our data, we apply two corrections for the mean group estimates: jacknife and recursive. The results of the estimations are provided in the table 7.

	Jacknife Correction				Recursive Correction			
Variable	Coeff.	S.E.	t-Stat	P-Value	Coeff.	S.E.	t-Stat	P-Value
Pooled								
$WTFP$	-0.168	0.986	-0.17	0.865	-0.416	0.149	-2.78	0.005
Mean Group Estimates								
RD	0.013	0.004	3.35	0.001	0.010	0.004	2.49	0.013
RA	0.013	0.003	4.79	0.000	0.007	0.002	3.88	0.000

Table 7: Conditional β-convergence with the CCE approach

As we can see, the estimated pooled and mean group values are similar to those obtained with the IV and SEM methods when we apply the jacknife correction, whereas they are very different when we apply a recursive correction. We thus decide to focus our analysis on (1) the results provided by the jacknife correction and (2) the heterogenous effect of regional alignment.

In the previous section, we highlight that regional alignment has a positive indirect effect on R&D investment. As discussed in Section 2, localized knowledge spillovers induced by R&D activities are important drivers of productivity growth. Thus, a natural question arises as to whether the positive (direct and indirect) effect of regional alignment on productivity growth plays a role in Jacob or MAR externalities. To provide some answers to this question, we analyze whether the reaction of regions with respect to regional alignment (μ_i) is influenced by their level of specialization at three different levels: industry, technology and science. This level of specialization is computed using the Herfindahl index. If Marshallian externalities dominate, concentration of either scientific (HS), technological (HT) or industrial (HI) activities would increase the effectiveness of regional alignment (μ_i) on productivity growth. If instead Jacobian externalities dominate, such concentration measures (HS, HT, HI) would have a negative effect on μ_i.

To start this analysis, we compute and test the Pearson's correlation coefficient between the heterogeneous effects of regional alignment and our three measures of specialization. We find a systematic negative correlation coefficient between the effect of regional alignment and the the value of the Herfindhal indices. Nevertheless, the negative correlation is only (strongly) significant for the Herfindhal index related to technology ($\rho = -0.2128$ with a p-value of 0.039), whereas it is less significant for the Herfindhal indices related to industry ($\rho = -0.0997$ with a p-value of 0.339) and science ($\rho = -0.121$ with a p-value of 0.246). To delve deeper into the analysis and because one limitation of the Pearson's correlation coefficient is its linearity, we decide to run a simple OLS regression. The Table 8 shows our main findings.

Dependent Variable: μ_i (see equation (13))										
		Model 1			Model 2			Model 3		
Variable	Obs	Coeff.	S.E.	P-Value	Coeff.	S.E.	P-Value	Coeff.	S.E.	P-Value
H	94	-0.112	0.316	0.723	-3.326	1.466	0.026	-3.388	1.445	0.021
HT	94	-0.048	0.028	0.092	-0.114	0.078	0.150	-0.031	0.027	0.261
HS	94	-0.012	0.019	0.528	-0.021	0.089	0.818			
H^2	94				28.363	12.391	0.025	29.053	12.305	0.020
HT^2	94				0.188	0.121	0.124			
HS^2	94				0.020	0.131	0.876			
cons	94	0.027	0.013	0.036	0.114	0.037	0.003	0.105	0.036	0.004
		R^2: 0.049			R^2: 0.1319			R^2: 0.1080		

Table 8: Effect of regional alignment and the specialization of regions

When we test for the linear effect of our Herfindhal measures (Model 1), we find that technology specialization has a significant negative effect on the effect of regional alignment on productivity growth but only at the 10% level of significance. Specialization in terms of industry and science do not seem to have a significant influence. Nevertheless, we can easily imagine that a non-linear relation exists. Model 2 introduces non-linear effects, and this change strongly affects our findings. Indeed, Model 2 indicates that there is a negative convex relation between industrial specialization and the effect of regional alignment on productivity growth. The two others measures of specialization (technology and science) have no significant impact. Model 3 confirms the results of Model 2. Using results from Model 3, we compute $\partial\mu_i/\partial HI = 0$ in order to identify the value HI^* which provides us with the threshold below (above) which Jacobs (MAR) externalities dominate. We find a value $HI^* = 0.058$, and empirically observe that for 91% of regions, the Jacobs externality dominates (diversity enhances the effect of regional alignment) whereas in the remaining 9% of regions, the MAR externalities dominates (specialization enhances the effect of regional alignment). Consequently, we find evidence that in most cases, industrial specialization reduces the positive effect of regional alignment on productivity growth. This result suggests that regional alignment plays more of a role in Jacob's spillovers rather than MAR externalities. Thus, the diversified regions could strongly increase their potential growth by increasing their regional alignment between science and technology. In the figure below, we represent the convex relationship between industrial specialization and the effect of regional alignment. Figure 5 (except for the three most specialized regions) clearly indicates that regional alignment has a greater impact on the productivity growth of regions that are more industrially diversified. In a sense, this is not a surprising result because increased alignment between the scientific and technological capabilities in diversified regions will have a more positive effect positive effect on productivity growth due to Jacobs spillovers. In less diversified regions, potential Jacobian spillovers are lower, implying that regional alignment has less of an effect on productivity growth, all else being equal.

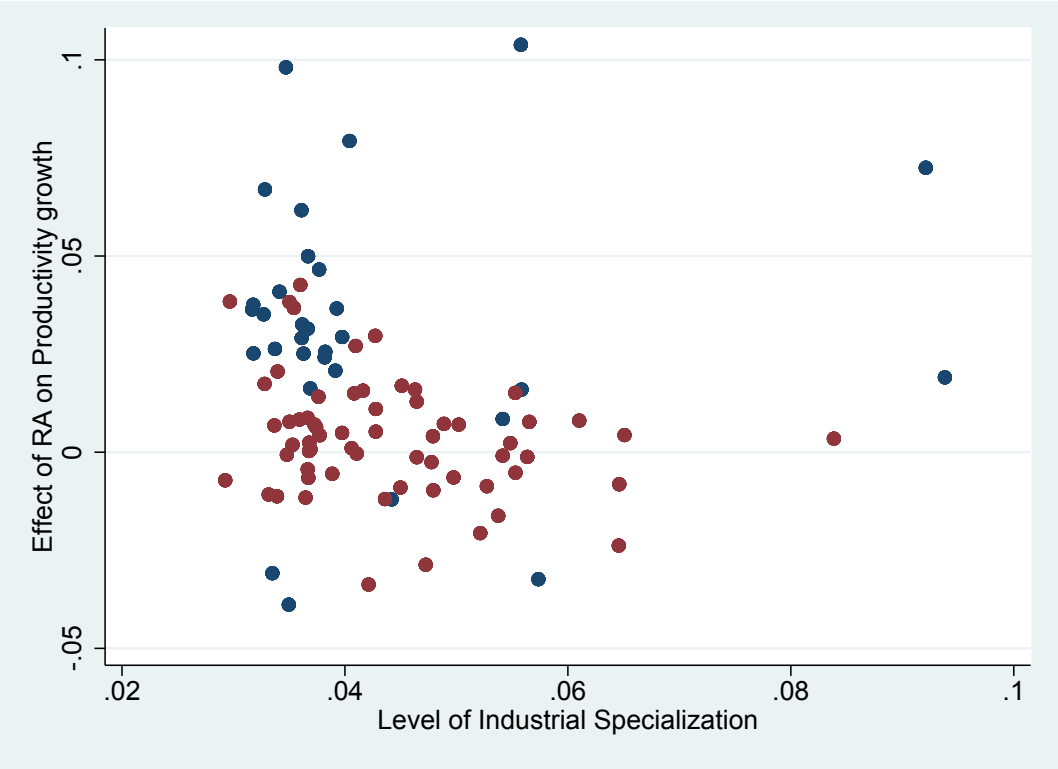


Figure 5: Link between the effect of regional alignment and industrial specialization

7 Conclusion

Since the pioneering works of Barro and Sala-i-Martin (1995), the economic literature has widely discussed the concept of regional convergence. A large consensus on conditional convergence suggests that there are persistent or increasing regional differences in terms of economic performance. Although the literature can clearly explain why "weak" regions become weaker and strong regions become stronger, economists remain unable to explain why regions with similar conditional factors (such as the level of R&D investment and human capital) experience different growth paths. The aim of this paper is to provide a theoretical and empirical explanation.

This paper makes several contributions. First, we propose the concept of regional alignment as a measure of the level of synergies among the scientific fields, technological domains, and industrial sectors in which a region has expertise. We argue that regional alignment can theoretically reflect regions' specific characteristics and contributes to the development of a productivity parameter in growth theory. Therefore, regional alignment is a critical determinant of differences in regional growth paths. Second, we develop a spatial extension of the traditional convergence model of productivity growth (Ha and Howitt, 2007) by including both localized knowledge spillovers and regional alignment as an input of productivity growth. Third, using French firm-level data aggregated at the NUTS 3 level over the period 2001-2011, we estimate our extended conditional convergence model and test our hypothesis about the influence of regional alignment. Using consistent IV estimators, we develop a simultaneous equations model and a heterogeneous coefficient model to better understand the influence and causality of regional alignment in the dynamics of regional productivity growth.

Our results confirm most of our hypotheses about the importance of regional alignment as an essential driver of the productivity growth of a region. First, we obtain evidence that regional productivity growth in France follows a conditional convergence process (regions tend to converge toward different steady states), which is associated with increasing heterogeneity across regions. All the results indicate that regional alignment matters for explaining this productivity growth process. Indeed, regional alignment has a direct effect on productivity growth and can be seen as a regional input. Moreover, our simultaneous equations model shows that regional alignment has an indirect effect by leveraging the role of private R&D investment in local productivity growth. The last empirical finding emphasizes the heterogeneous effect of regional alignment across the French regions. We find evidence that a negative relationship exists between the effect of regional alignment on productivity growth and the level of industrial specialization of regions. In other words, regional alignment matters more for the productivity growth in diversified regions than that in specialized regions. This result suggests that regional alignment tends to increase the value of Jacob's externalities and thus materializes if the regional industrial structure is sufficiently diversified.

In addition to the simple synergies between science and technology, we argue that regional alignment contributes to productivity growth because it actually reveals the efficiency of coordination mechanisms, which Aghion et al. 2009 (p. 2) call "the intimate and multiple connections of technological change and innovation with advances in science, on the one hand, and the set of socio-economic institutions operating in a given context, on the other." (Aghion et al. 2009, p. 2). Synergistic relations between scientists and engineers can only be effective if there are spaces for dialogue contributing to a shared understanding among different communities, which allow knowledge to be shared despite high cognitive distance (Sabel, 2001; Lester and Piore, 2004, Lowe and Feldman, 2008, Cohendet et al., 2014). This study may explain why, everything else being equal, despite a low level of R&D investment, aligned regions can change their steady state growth path better than other regions. Further works should analyze the micro-processes that lead to effective regional alignment.

It follows that regional alignment could be an important guide for policy makers (especially for low-intensive R&D regions) who are willing to boost TFP growth in both the short and long run. The question, then, is to discuss possibilities to generate and reinforce alignment. In this respect, regional alignment is not orthogonal to smart specialization policy design (Foray et al., 2009; 2011; McCann and Ortega-Argilés, 2015). They both recognize the importance of taking into account the heterogeneity of regional trajectories based on industrial, institutional, cultural and historical specificities. However, unlike the related variety interpretation of smart specialization (Balland et al., 2018), regional alignment does not focus on a technology driven policy. Rather, synergies between technological fields and scientific domains only reveal systemic dynamics, the effectiveness of decisions made by heterogeneous actors and the level of efficiency in resource allocation processes. It would be interesting to understand better the mechanisms underlying the emergence of those synergies, in particular to design policies dedicated to laggard regions.

Appendix A: List of scientific domains and technological fields

List of Scientific domain

Number	Name	Number	Name
1	Agriculture Fisheries and Forestry	12	General Arts & Humanities
2	Biology	13	General Science & Technology
3	Biomedical Research	14	Historical Studies
4	Built Environment Design	15	Information & Communication Technologies
5	Chemistry	16	Mathematics & Statistics
6	Clinical Medicine	17	Philosophy & Theology
7	Communication & Textual Studies	18	Physics & Astronomy
8	Earth & Environmental Sciences	19	Psychology & Cognitive Sciences
9	Economics & Business	20	Public Health & Health Services
10	Enabling Strategic Technologies	21	Social Sciences
11	Engineering	22	Visual & Performing Arts

List of Technological field

Number	Name	Number	Name
1	Electrical machinery, apparatus, energy	19	Basic materials chemistry
2	Audio-visual technology	20	Materials, metallurgy
3	Telecommunications	21	Surface technology, coating
4	Digital communication	22	Micro-structural and nano-technology
5	Basic communication processes	23	Chemical engineering
6	Computer technology	24	Environmental technology
7	IT methods for management	25	Handling
8	Semiconductors	26	Machine tools
9	Optics	27	Engines, pumps, turbines
10	Measurement	28	Textile and paper machines
11	Analysis of biological materials	29	Other special machines
12	Control	30	Thermal processes and apparatus
13	Medical technology	31	Mechanical elements
14	Organic fine chemistry	32	Transport
15	Biotechnology	33	Furniture, games
16	Pharmaceuticals	34	Other consumer goods
17	Macromolecular chemistry, polymers	35	Civil engineering
18	Food chemistry		

Appendix B: The parametric measure of synergies λ_{jk}

Number of patents with technology j

To smooth the importance of patents associated with a particular technology j (or a scientific domain k), all patents are counted using a five year moving sum.

Let $P_{nj}^t = 1$ if patent n is assigned to technology j and 0, otherwise. The total number of patents assigned to technology j in t is thus $C_j^t = \sum_n P_{nj}^t$. Let $P_{nk}^t = 1$ if patent n mentions an article published in a journal associated with the scientific domain k in the non-patent citations section and 0, otherwise. The total number of patents assigned to scientific domain k in t is thus $C_k^t = \sum_n P_{nk}^t$. Since technology j and scientific domain k may be assigned to the same patent document, then $C_j \cap C_k \neq \oslash$ and thus the number C_{jk} of the observed co-occurences of j and k is $C_{jk}^t = \sum_n P_{nj}^t P_{nk}^t$. Applying the latter to all possible pairs of technologies, we obtain a matrix $\Omega_{(J*K)}$ with $J = 35$ technological fields and $K = 22$ scientific domains.

This number of joint occurrences is used to construct our measure of synergy by relating it to some measure of its expected frequency $\hat{C}_{jk}$ under the hypothesis of random joint occurrence. There is no authoritative measure of $\hat{C}_{jk}$, but we propose a parametric-based measure in this paper. More precisely, we assumre that the number C_{jk} of patents assigned to j and k is a hypergeometric random variable. Thus, the probability of drawing C patents with both technology j and scientific domain k follows the hypergeometric density function.

$$P(X_{jk} = x) = \frac{\begin{pmatrix} C_j \\ x \end{pmatrix} \begin{pmatrix} N - C_j \\ C_k - x \end{pmatrix}}{\begin{pmatrix} N \\ C_k \end{pmatrix}}$$

where is X_{jk} is the number of patents assigned to both technology j and scientific domain k, x is the hypergeometric random variable and N is the total number of patents. The mean value (expected frequency) and variance of random co-occurrence are:

$$\hat{C}_{jk} = \mu_{jk} = E(X_{jk} = x) = \frac{C_j C_k}{N}$$

$$\hat{\sigma}_{jk}^2 = \mu_{jk} \left(\frac{N - C_j}{N} \right) \left(\frac{N - C_k}{N - 1} \right)$$

If the actual number C_{jk} of co-occurrences observed between j and k greatly exceeds the expected value μ_{jk} of random co-occurrences, then j and k are synergistic; that is, they are more productive than a random association. Conversely, when $C_{jk} < \mu_{jk}$, then technologies j and k are poorly synergistic (their combined use produces fewer patents than expected when drawing a random combination). Hence, the level of synergy between j and k is defined as:

$$\tau_{jk} = \frac{C_{jk} - \mu_{jk}}{\sigma_{jk}}$$

Equation (4) has two interesting features. First, τ_{jk} is a real number that can be either positive or negative, with no lower or upper bounds: $\tau_{jk} \in \mathbb{R} :]-\infty; +\infty[$ the sign is a straightforward and intuitive interpretation.

Second, τ_{jk} is similar to a t-student, so that if $\tau_{jk} \in]-1.96; +1.96[$, then the null hypothesis H0 (no synergistic relations exist between technology j and k) can be safely accepted. Third, τ_{jk} is a matrix of science technological relations that can be seen as an approximation of scientific and technological knowledge represented as a hierarchical tree (Popper, 1972).

Appendix C: The productivity growth rate in a multi-regional model

We start with equation (10)

$$g_i = RA_i^{\mu} RD_i^{\lambda} (TFP_i)^{-1} (W_i TFP)^{\phi}$$

Rewriting $(W_i TFP) = TFP_i + \tilde{W}_i TFP$, we thus have

$$TFP_i = [W_i - \tilde{W}_i] TFP$$

Next, we rewrite the level of productivity in region i as:

$$TFP_i = [W_i - \tilde{W}_i][(W_i^{'} W_i)^{-1} W_i^{'} W_i] TFP = [W_i - \tilde{W}_i][(W_i^{'} W_i)^{-1} W_i^{'}][WTFP]$$

Inserting this last expression of TFP_i into equation (10) leads to:

$$\begin{aligned} g_i &= RA_i^{\mu} RD_i^{\lambda} \left[[W_i - \tilde{W}_i][(W_i^{'} W_i)^{-1} W_i^{'}][W_i TFP] \right]^{-1} (W_i TFP)^{\phi} \\ &= RA_i^{\mu} RD_i^{\lambda} \left[[W_i - \tilde{W}_i][(W_i^{'} W_i)^{-1} W_i^{'}] \right]^{-1} (W_i TFP)^{-1} (W_i TFP)^{\phi} \\ &= RA_i^{\mu} RD_i^{\lambda} \left[[W_i - \tilde{W}_i][(W_i^{'} W_i)^{-1} W_i^{'}] \right]^{-1} (W_i TFP)^{\phi - 1} \end{aligned}$$

Appendix D. The TFP measure

The productivity measure

We compute total factor productivity (TFP) by using the so-called *multilateral productivity index*, which was first introduced by Caves and al.(1982) and extended by Good and al. (1997). Contrary to Olley-Pakes (1996) measure, this is a non-parametric measure of TFP that does not impose a functional form for the production function. This methodology consists of computing the TFP index for firm z at time t as follows:

$$\begin{aligned} \ln TFP_{zt} = \ln\ Y_{zt} - \overline{\ln\ Y_t} + \sum_{\tau=2}^{t} \left(\overline{\ln\ Y_{\tau}} - \overline{\ln\ Y_{\tau-1}} \right) \\ - \left[\begin{array}{l} \sum_{n=1}^{N} \frac{1}{2} \left(S_{nzt} + \overline{S_{nt}} \right) \left(\ln\ X_{nzt} - \overline{\ln\ X_{nt}} \right) \\ + \sum_{\tau=2}^{t} \sum_{n=1}^{N} \frac{1}{2} \left(\overline{S_{n\tau}} + \overline{S_{n\tau-1}} \right) \left(\overline{\ln\ X_{n\tau}} - \overline{\ln\ X_{n\tau-1}} \right) \end{array} \right] \end{aligned} \tag{14}$$

where Y_{zt} denotes the real gross output produced by firm z at time t using the set of n inputs X_{nzt}, where input X is alternatively capital stocks (K) and labor, in terms of hours worked (L) and intermediate inputs (M). S_{nzt} is the cost share of input X_{nzt} in the total cost. Subscripts τ and n are indices for time and inputs, respectively. Symbols with an upper bar correspond to the measures for the reference point (the hypothetical firm), which are computed as the means of the corresponding firm level variables, over all firms in year t. Note that (14) implies that the reference points $\overline{\ln Y}$ and $\overline{\ln X}$ are the geometric means of the firm's output quantities and input quantities respectively, whereas the cost shares of inputs of the representative firms $\overline{S}$ is computed as the arithmetic mean of the cost share of all firms in the dataset.

Equation (14) allows us to estimate the productivity stock of each firm in our sample. To produce a regional measure of productivity, we calculate the average level of productivity for firms located in region i:

$$\overline{TFP}_{it} = \frac{\sum_{z=1}^{z=N} TFP_{zt}}{N} \tag{15}$$

and then apply the following formula:

$$TFP_{it} = \left(\overline{TFP}_{it} \times \frac{L_{it}}{L_t} \right) \tag{16}$$

where L_{it} is the employment level in region i at time t, and L_t is the employment in France at time t.

All nominal output and inputs variables are available at the firm level. Industr-level data are used for price indexes, hours worked and depreciation rates.

Output

Gross output deflated using sectoral price indexes published by INSEE (French system of national accounts).

Labor

Labor input is obtained by multiplying the number of effective workers (i.e., the number of employees plus the number of outsourced workers minus workers taken from other firms) by average number of hours worked. The annual series for hours worked are available at the 2-digit industry level and provided by *the Groningen Growth Development Center (GGDC)*). This choice was made because there are no data on hours worked in the EAE survey.

Capital input

Capital stocks are computed from the investment and book value of tangible assets following the traditional perpetual inventory method (PIM):

$$K_t = (1 - \delta_{t-1})\, K_{t-1} + I_t \tag{17}$$

where δ_t is the depreciation rate, and I_t is real investment (deflated nominal investment). Both the investment price indexes and depreciation rates are available at the 2-digit industrial classification level from the INSEE data series.

Intermediate inputs

Intermediate inputs include the purchase of materials, merchandise, transport, traveling, and miscellaneous expenses. Intermediate inputs are deflated using sectoral price indexes for intermediate inputs published by INSEE.

Appendix E: Estimated β-convergence in a mono-regional model

	LSDV			IV-2SLS			IV-GMM		
Variable	Coeff.	S.E.	P-Value	Coeff.	S.E.	P-Value	Coeff.	S.E.	P-Value
$\ln[TFP_{t-1}]$	-0.093	0.022	0.000	-0.103	0.033	0.002	-0.121	0.031	0.000
$\ln[RD_t]$	0.002	0.002	0.386	0.013	0.005	0.20	0.013	0.005	0.004
$\ln[RA_t]$	0.002	0.001	0.001	0.014	0.004	0.000	0.017	0.003	0.000

Table 2bis: Conditional β-convergence of TFP growth (using TFP_i instead of $WTFP$)

Appendix F. Details on the variables used

In this appendix, we provide details on the variables used in the simultaneous equation model (SEM).

Entry (EN) and exit (EX) rates of establishments at the NUTS 3 level

We compute these measures using the FICAS and FARE databases. The measures of industry churning account for the capacity of a region to rejuvenate, that is, to devote private resources to new entrepreneurial projects. We do this by measuring firm entry into and exit from the local area. The entry rate is simply the ratio of the number of establishments new to a NUTS 3 region over the overall number of establishments in that region. For each year, we count the number of new establishments in a given NUTS 3 region using the SIRET administrative number. Entry in the database may not accurately trace entry in the region, due to the fact that inclusion in the FICUS and FARE databases implies that company revenues exceed the minimum threshold of 75,000 euros. Likewise, the exit rate is the ratio of the number of establishments exiting a NUTS 3 region over the overall number of establishments in that region. Exit from the database may not accurately trace liquidation or relocation, due to the threshhold of 75,000 euros.

Concentration indices for industry, technology and science (H, HT and HS): the computation of HHI

In this paper, we also account for the industry, technological and scientific structure of region i by computing the Hirschman-Herfindahl Index (HHI).

To compute the HHI index for indusry (denoted H), we use the FICUS and FARE databases and calculate the following statistics:

$$H_i = \sum_z s_{iz}^2$$

where s is firm z's market share in the NUTS 3 region i, including all sectors. A value close to unity indicates market concentration, the polar case being unity, where all the market is supplied by a unique monopolistic company. Hence, the HHI is usually used to account for the degree of competition in an industry, most often within a country or geographic unit. In our case, however, we aim to determine the weight of large firms within a region across all productive activities. Hence, this measure of competition considers the local industrial structure rather than the degree of competition that most often spans over single NUTS 3 regions.

To compute the HHI index for technologies (denoted as HT), we use the PATSTAT database and calculate the following statistics:

$$HT_i = \sum_j s_{ij}^2$$

where s is technology field j's share in the NUTS 3 region i, including all the patents that have been granted. A value close to unity indicates strong technology concentration, the polar case being unity, where all the patents granted in a region belong to one technological field. Hence, the HHI for technology indicates the local technological structure of NUTS 3 regions.

To compute the HHI index for sciences (denoted HS), we use the WOS database and calculate the following statistics:

$$HS_i = \sum_k s_{ik}^2$$

where s is scientific domain k's share in the NUTS 3 region i, including all publications. A value close to unity indicates a strong scientific concentration, the polar case being unity, where all the publications produced in a region belong to one scientific domain. Hence, the HHI for science indicates the local scientific structure of NUTS 3 regions.

R&D subsidies (SUB)

We use the second and third files of the R&D survey to calculate the level of public R&D subsides received by firms at the NUTS 3 level.The second file of the R&D survey describes the financial sources used by firms to develop their R&D activities. From this file, we can calculate the share of R&D expenditures financed by public funds by firm and sector. However, this file only includes 11,000 R&D firms. To correctly geo-localize the R&D subsidies in each NUTS 3 region, we had to match the information calculated from the second file of the R&D survey with the information contained in the third file, i.e, the R&D executed by firms at the NUTS 3 level. Thus, we are able to redistribute the subsidies proportionally to the R&D executed in each NUTS 3 region (taking into account the size and sectorial composition of the firms in the region) .

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