

# An Expanded Knowledge Production Function: Evidence from Brazil with a Dynamic Spatial Panel Approach

Adirson Maciel de Freitas Júnior (ESALQ-USP)

Pedro Henrique Batista de Barros (FEA-USP)

**Abstract:** This paper sought to provide a theoretical motivation for an Expanded Knowledge Production Function (EKPF) that encompasses both path dependence and spatial spillovers. In addition, search for evidence from Brazil using a Dynamic Spatial Panel Data approach. The purpose is to identify the determinants of knowledge production in the country as well as its temporal evolution, using innovation patents as proxy. Regarding its spatial distribution, we identified a North-South disparity for the knowledge production in Brazil, with Southeast and South producing a large part of the country's patents. Based on the EKPF, we confirmed the path dependence and knowledge spillovers importance to explain the Brazilian innovation. The number of researchers in universities and export of high and mid-high technology products are also relevant to knowledge production in the country while urbanization and population density, which generates Jacobin externalities and economies of agglomeration, are important structural features.

**Keywords:** Knowledge Production Function (KPF); Path Dependence; Spatial Spillover; Dynamic Spatial Panel.

**Resumo:** Este artigo objetiva prover uma motivação teórica para uma Função de Produção de Conhecimento Expandida (FPCE) que incorpore simultaneamente o processo de *path-dependence* e de transbordamentos espaciais. Além disso, buscar evidências para o Brasil utilizando um Painel Dinâmico Espacial. O intuito é identificar os determinantes da produção de conhecimento no país assim como a sua evolução temporal, tendo as patentes de inovação como *proxy*. Como corolário, identificou-se uma disparidade Norte-Sul para produção de conhecimento, com a atividade inovativa se concentrando no Sudeste e Sul do país. Com base na FPCE, verificou-se a importância do *path dependence* e dos transbordamentos espaciais do conhecimento para explicar a inovação brasileira. O número de pesquisadores em universidades e a exportação de produtos de alta e média tecnologia também são relevantes para explicar a criação de conhecimento no Brasil enquanto a urbanização e densidade demográfica, geradoras de externalidades jacobinas e economias de aglomeração, são características estruturais importantes.

**Palavras-Chave:** Função de Produção de Conhecimento (KPF); Trajetória Prestabelecida; Transbordamentos Espaciais; Painel Dinâmico Espacial.

**JEL Classification:** O3, O31, C23.

## Área 9 - Economia Industrial e da Tecnologia

### 1. Introduction

The economic development of a country is associated, among other factors, to its ability to generate scientific and technological knowledge, as they are likely to become innovations, which enable increases in productivity and competitiveness for the economy. The identification of technological innovation as a driving force of economic growth dates back to Solow (1956) and the emergence of long-term development theories. Despite showing its importance, Solow (1956) treated technology as exogenous, not establishing its possible determinants. Subsequently, Romer (1990) worked this limitation, making technological innovation an endogenous variable, assuming a key role in the process of long-term economic growth. In this context, knowledge improves technology, and the generation of a new idea can induce new

combinations of certain inputs, creating better goods and services, which leads to an increase in material well-being. Technological progress, by intensifying productivity, is, therefore, an economic growth booster.

However, the creation of knowledge and innovations often entails high costs and, according to Romer (1993), since they are non-rival goods, the returns obtained with the invention are usually insufficient to generate incentives for their development. On the other hand, Douglas North (1981) argues that the development of intellectual property rights, the legal basis for the patent system, is a major contributor to modern economic growth. Therefore, the consolidation of institutions that guarantee intellectual property rights in a given country is an essential condition for their economic development.

Recognizing the importance of innovation, Brazil created, in 2005, the Brazilian Innovation Law (Law nº10,973 of 2005). Its main purpose was to establish specific legal guidelines for the licensing of patents of public entities and to create greater legal certainty in patenting. In other words, it consolidated the intellectual property rights in the country by allowing security in the appropriation of part of the benefits generated with the knowledge created. The monopoly power induced by intellectual property makes it possible to increase the return on investment in innovations, thus encouraging the generation of knowledge.

Legal insecurity due to the lack of a clear legislation on the subject, in the period prior to the creation of the innovation law, inhibited the strengthening of technological development in the country (STAL and FUJINO, 2005). This fact explains the relative backwardness of Brazil in terms of knowledge generation. For these reasons, Law Nº. 13,243, in its Article 1, sought to establish "[...] measures to encourage innovation and scientific-technological research in the productive environment [...] under the terms of arts. 23, 24, 167, 200, 213, 218, 219 and 219-A of the Federal Constitution. "

In this context, the present paper aims to contribute in two directions to the literature on technological development and knowledge creation. The first is a theoretical motivation in explaining the determinants of knowledge production, with special focus on the process of path dependence and spatial spillover, based on works developed by Griliches (1979), Jaffe (1989), Fischer et al. (2009) and Autant-Bernard and LeSage (2011). There is no theoretical explanation in the literature for the simultaneous occurrence of the two cited effects, which are treated separately by the authors mentioned. The second contribution is an empirical application of the Dynamic Spatial Panel method developed by Yu et al. (2008), which is capable of verifying the validity of the theoretical proposition for Brazil.

The best proxy to capture innovation and knowledge production, according to Griliches (1990) is the number of patents created by a particular country or region, which has been widely used by researchers of the subject (GRILICHES, 1990; ALBUQUERQUE et al., 2002; GONÇALVES, 2007; GONÇALVES and ALMEIDA, 2009; FREITAS et al., 2010; MONTENEGRO et al., 2011; MIRANDA and ZUCOLOTO, 2015; GONÇALVES et al., 2018). This is the case, according to Miranda and Zucoloto (2015), because patents are an important indicator of the presence of "knowledge with an innovative profile". Therefore, when analyzing the number of patents in the microregions, it is possible to infer the contribution of each of these regions to the production of knowledge in Brazil.

This article is structured in four more sections besides this one. The second deals with the theoretical proposition of an Expanded Knowledge Production Function, as well as an investigation in the literature on the determinants of knowledge production. In the third section, we present the empirical approach and the database used. The results found and their analysis are performed in the fourth section. Finally, the fifth section presents the final considerations.

## 2. An Expanded Knowledge Production Function with Path Dependence and Spatial Spillovers

The Knowledge Production Function (KPF) was formulated and empirically tested in Griliches (1979; 1984). Subsequently, Jaffe (1989) expanded the model to apply it to geographic units, increasing the scope of knowledge production analysis. Since then, several papers have applied the KPF to understand the determinants of the innovative process (ANSELIN et al., 1997; GONÇALVES and ALMEIDA, 2009; MONTENEGRO et al., 2011). The model proposed by Griliches (1979) are defined as

$$Y = F(X, K, u) \quad (1)$$

where  $F(\cdot)$  is the production function that relates the product,  $Y$ , to the inputs  $X, K$  and  $u$ ;  $X$  is a vector of the capital and labor inputs.  $K$  is a measure of the current state of scientific and technological knowledge, which to a certain extent is determined by the level of recent and past research and development (R&D);  $u$  captures all other factors that influence the level of productivity and production of knowledge. Then, let  $A = Y/X$  be the total factor productivity and  $\tau = y - x = (dY/dt)/Y - (dX/dt)/X$  the growth rate.

Griliches (1979) supports the basic hypothesis that there is a relation between the scientific and technological development level,  $K$ , and an index that captures recent and past levels of R&D investment, denoted by  $W(B)R$ . The  $W(B)$  is a polynomial lag, that describes the relative contribution of past and future research to the current level of  $K$ , with  $B$  being a lag operator. Therefore,  $K$  is

$$K = G[W(B)R, v] \quad (2)$$

and

$$W(B)R_t = (w_0 + w_1B + w_2B^2 + \dots)R_t = w_0R_t + w_1R_{t-1} + w_2R_{t-2} + \dots \quad (3)$$

where  $v$  is a parameter that captures influences on the level of accumulated knowledge. Griliches (1979) seeks to define  $F(\cdot)$  through the Cobb-Douglas functional form while assuming that  $u$  can be considered as random after the introduction of a time indicator  $t$  in the equation in order to represent other immeasurable systematic components that can influence  $Y$ . Therefore,  $F(\cdot)$  are

$$Y = DC^\alpha L^\beta K^\gamma e^{\lambda t + u} \quad (4)$$

where  $D$  is a constant;  $C$  and  $L$  are capital and labor respectively;  $t$  is a time indicator;  $e$  is the basis of the natural logarithm; and  $\alpha, \beta, \gamma$  are the parameters to be estimated empirically.

In a later formulation, Griliches (1984) uses the number of patents created as an indicator of knowledge production. The author defined in a reduced form the patenting model as

$$p_{i,t} = dt + \beta \dot{k}_{i,t} + v_{i,t} \quad (5)$$

in which  $\beta$  is the elasticity of patents in relation to an increase of knowledge;  $d$  is a measure of temporal tendency with respect to the determinant factors in the propensity to create patents;  $v$  is the part of the patents that cannot be explained by the increment of knowledge or temporal tendency.

In a theoretical advance, Jaffe (1989) modified the model proposed by Griliches (1979; 1984) in an attempt to capture effects of spillovers in knowledge creation. The modification defined by Jaffe (1989) is

$$\log(P_{ikt}) = \beta_{1k} \log(I_{ikt}) + \beta_{2k} \log(U_{ikt}) + \beta_{3k} [\log(U_{ikt}) \log(C_{ikt})] + \epsilon_{ikt} \quad (6)$$

$i$  refers to the observation unit (municipalities, microregions, states);  $k$  is the technological area;  $t$  is a time index;  $P$  is the number of patents;  $I$  is the R&D carried out by the industries;  $U$  is the R&D undertaken by universities. Lastly,  $C$  is a geographic measure that seeks to capture the coincidence between activities of university and industrial research, variable introduced in the purpose of capturing possible spillovers that impact on the creation of patents.

Fischer et al. (2009), on the other hand, explicitly incorporated the regional perspective, into the knowledge production function. The author defined KPF as

$$Q_{it} = A_{it} g(L_{it}, C_{it}) \quad (7)$$

where  $i = 1, \dots, N$  are the regions; while  $t = 1, \dots, T$  is a time denotation;  $L$  and  $C$  are the factors of production, labor and capital, respectively.  $g(\dots)$  is a homogeneous function of degree one with decreasing returns of scale for capital inputs ( $C$ ) and labor ( $L$ ). Lastly,  $Q$  is the value of production and  $A$  is an index of technological efficiency defined as

$$A_{it} = A(K_{it}, K_{it}^*) \quad (8)$$

$K$  and  $K^*$  are the knowledge stocks inside and outside the region, respectively. Fischer et al. (2009) argues that even when the patenting occurs, there is the possibility of a portion of that knowledge be appropriate by the agents located in neighboring regions. According to the author, this process is given through personal

contacts, seminars and scientific conferences, legal transfers, reverse engineering, etc. Therefore, in a country with  $N$ -regions, the global stock of knowledge is

$$\sum_{j=1}^N K_{jt} \quad (9)$$

$j$  denote the  $j$ -th region and assumes that the level of knowledge  $K_{jt}$  is accumulated through activities specified in the Knowledge Production Function, as well as depreciates each period at a pace  $r_k$ . Therefore, Fischer et al. (2009) establishes a law of movement for the stock of knowledge

$$K_{jt} = (1 - r_k)K_{jt-1} + S_{jt-1} = K_{jt-1} \left( 1 - r_k + \frac{S_{jt-1}}{K_{jt-1}} \right) \quad (10)$$

this law implies that the activities carried out to produce knowledge in  $t - 1$ ,  $S_{jt-1}$ , only become productive in the period  $t$ , in other words, there are a path dependence in the production of knowledge.

Fischer et al. (2009) argues that due to the occurrence of knowledge spillover in neighboring regions, the variable  $K_{it}^*$  should be defined taking into account this non-complete appropriation, as follows

$$K_{it}^* = \sum_{j \neq i}^N w_{ij} K_{jt-m} \quad (11)$$

where  $w_{ij}$  represents the capacity of the region  $i$  in absorb the knowledge generated in the region  $j$ , which is defined according to some criterion of neighborhood or geographical distance;  $K_{jt-m}$  is the stock of knowledge in the region  $j$  in the period  $t - m$  with  $m \in \mathbb{N}$ . The author defends the need to include the time lag of the knowledge spillovers of the neighboring regions because its effects often do not occur in the same period. Therefore, the spillover effect must be temporally and spatially lagged. The author considers the Cobb-Douglas functional form for the KPF, replacing equation (8) in (7), for each region  $i$ , as

$$Q_{it} = Q(K_{it}, K_{it}^*, L_{it}, C_{it}) = K_{it}^{\gamma_1} K_{it}^{*\gamma_2} L_{it}^{\alpha} C_{it}^{1-\alpha} \exp(\varepsilon_{it}) \quad (12)$$

in which  $\gamma_1, \gamma_2, \alpha, 1 - \alpha$  are the elasticities of knowledge production in relation to the internal knowledge stock of region  $i$ , as well as external stock, labor and capital, respectively.

Autant-Bernard and LeSage (2011), in turn, developed a theoretical model for KPF that incorporates not only the knowledge spillover generated in a given region, but also the externality of its own inputs and determinants. In general, the authors defined the equation relating such factors as

$$\mathbf{I} = \alpha_1 \mathbf{r} + \mathbf{r}^* \quad (13)$$

where  $\mathbf{I}$  represents a (logarithmic) vector of observations from innovations performed by the  $n$  regions considered;  $\mathbf{r}$  is a vector representing the measurable inputs of the production of knowledge;  $\mathbf{r}^*$  are important inputs to explain the innovative process, but that are difficult to measure. Considering that the spatial dependence process in the generation of knowledge is something recurrent in the literature <sup>1</sup>, the authors sought to incorporate this dependency explicitly, as follows

$$\mathbf{r} = \phi \mathbf{W} \mathbf{r} + \mathbf{u}, \quad \mathbf{r}^* = \psi \mathbf{W} \mathbf{r}^* + \mathbf{v} \quad \text{and} \quad \mathbf{v} = \gamma \mathbf{u} + \varepsilon \quad (14)$$

so that,  $\mathbf{W}$  is a  $n \times n$  spatial lag matrix that seeks to capture the structural configuration between the regions;  $\phi$  and  $\psi$  are parameters that capture the force of spatial dependence of variables  $\mathbf{r}$  and  $\mathbf{r}^*$ , respectively;  $\gamma$  reflects a Pearson correlation between the shocks of  $\mathbf{u}$  and  $\mathbf{v}$  in relation to measurable and immeasurable inputs of production when  $\gamma \neq 0$ . In addition, the errors have constant variance and zero mean

$$\mathbf{u} \sim N(\mathbf{0}, \sigma_u^2 \mathbf{I}_n), \quad \mathbf{v} \sim N(\mathbf{0}, \sigma_v^2 \mathbf{I}_n) \quad \text{and} \quad \varepsilon \sim N(\mathbf{0}, \sigma_\varepsilon^2 \mathbf{I}_n) \quad (15)$$

<sup>1</sup> For example: Autant-Bernard (2001), Autant-Bernard et al. (2007), Parent and LeSage (2008). For Brazil, spatial dependence has also been a recurrent process: Gonçalves (2007), Gonçalves and Almeida (2009), Montenegro et al. (2011), Araújo (2013).

Finally, Autant-Bernard and LeSage (2011) considering (9), (10) and (11), proposes the following relation

$$\mathbf{I} = \psi \mathbf{W} \mathbf{I} + \mathbf{r}(\beta + \gamma) + \mathbf{W} \mathbf{r}(-\psi\beta - \phi\gamma) + \varepsilon \quad (16)$$

or

$$\mathbf{I} = \psi \mathbf{W} \mathbf{I} + \mathbf{r}\beta_1 + \mathbf{W} \mathbf{r}\beta_2 + \varepsilon, \text{ with } \beta_1 = (\beta + \gamma) \text{ and } \beta_2 = (-\psi\beta - \phi\gamma) \quad (17)$$

equation (16) and (17) represent the *Spatial Durbin Model* by Anselin (1988). Therefore, Autant-Bernard and LeSage (2011) developed a theoretical motivation for the incorporation of spatial lag both for the dependent variable ( $\mathbf{W} \mathbf{I}$ ) and for the explanatory variables ( $\mathbf{W} \mathbf{r}$ ).

Based on the works mentioned, the present paper seeks to contribute theoretically to the understanding of the production of knowledge, proposing a model that combines the approaches, especially Fischer et al. (2009) and Autant-Bernard and LeSage (2011). We initially propose the following equation that relates the knowledge produced by a given region according to the inputs needed to generate it, as

$$K_{it} = f(L_{it}, C_{it}, r_{it}) \quad (18)$$

where the regions are denoted by  $i = 1, \dots, N \in R \subset \mathbb{N}$ , in which  $R$  is a natural well-order and upper bounded set of the regions; while  $t = 1, \dots, T$  refers to the time period;  $L$  and  $C$  is the stock of labor and capital employed in knowledge production, respectively; and  $r_{it}$  are the other factors not explicitly considered that influence the creation of knowledge in the region  $i$  in period  $t$ . In addition,  $f: K_{it} \rightarrow \mathbb{N}$  is a homogeneous function of degree one with decreasing returns of scale to capital ( $C$ ) and labor ( $L$ ):  $\partial^2 K_{it} / \partial C_{it}^2 < 0$  and  $\partial^2 K_{it} / \partial L_{it}^2 < 0$ , respectively. Lastly,  $K_{it}$  is the amount of knowledge produced by the region  $i$  in period  $t$ . Assuming that  $f: K_{it} \rightarrow \mathbb{N}$  is a Cobb-Douglas functional form, as in Fischer et al. (2009), we have

$$K_{it} = f(L_{it}, C_{it}, r_{it}) = L_{it}^{\beta_1} C_{it}^{\beta_2} r_{it}^{\beta_3} \exp(\varepsilon_{it}) \quad (19)$$

where  $\beta_1, \beta_2$  and  $\beta_3$  are the elasticities of knowledge production in relation to the labor, capital and other factors that influence the creation of knowledge, respectively; all for region  $i$  in period  $t$ . Making a transformation in (19) based on that realized by Jaffe (1989), we get

$$\log(K_{it}) = \beta_1 \log(C_{it}) + \beta_2 \log(L_{it}) + \beta_3 \log(r_{it}) + \varepsilon_{ikt} \quad (20)$$

Which the present paper adopt the approach used by Autant-Bernard and LeSage (2011). Therefore, the spillovers are captured with a spatial lag matrix,  $\mathbf{W}$ ,  $n \times n$  which represents the structural configuration between the regions. Considering, for simplification, the inputs in (20) as a vector  $\mathbf{I} = [\beta_1 \log(C_{it}) + \beta_2 \log(L_{it}) + \beta_3 \log(r_{it})]$ , we can represent the equation (20) with the knowledge spillovers as

$$\log(K_{it}) = \rho \mathbf{W} \log(K_{it}) + \mathbf{I} \beta + \mathbf{W} \mathbf{I} \tau + \varepsilon_{ikt} \quad (21)$$

where  $\rho$  and  $\tau$  are parameters that capture the force of spatial dependence of variables  $\log(K_{it})$  and the input vector  $\mathbf{I}$ , respectively. This formulation results, as in Autant-Bernard and LeSage (2011), in the *Spatial Durbin Model*, as in Anselin (1988).

However, this theoretical formulation, despite being effective to evidence the existence of spillovers in the production of knowledge, as well as in the inputs used, is not able to capture the intertemporal relationship proposed by Fischer et al. (2009). This author states that not only the generation of knowledge in  $t$  creates spillovers on neighboring regions, but also those generated in the previous period,  $t - 1$ . Moreover, considering equation (10) and (11), the knowledge generated by the region  $i$  in  $t - 1$  not only affect the neighboring regions  $j$  in  $t$ , but also the region  $i$  that created it. Thus, the present paper proposes a theoretical model that incorporates both the spillovers effects proposed by Autant-Bernard and LeSage (2011), as well as the path dependence and intertemporal spillover from Fischer et al. (2009). Thus, such a model can be represented as

$$\log(K_{it}) = \gamma \log(K_{it-1}) + \rho \mathbf{W} \log(K_{it}) + \omega \mathbf{W} \log(K_{it-1}) + \mathbf{I} \beta + \mathbf{W} \mathbf{I} \tau + \varepsilon_{ikt} \quad (22)$$

where  $\log(K_{it-1})$  represents the time lag of the dependent variable that seeks to capture temporal dependence, the influence of knowledge production in the region  $i$  in  $t - 1$ , in itself in a later period  $t$ .

$W \log(K_{it-1})$  seeks to capture the spillover of knowledge production in  $t - 1$  from region  $i$  on the creation in  $t$  of its neighbors  $j$ , according to a spatial configuration matrix represented by  $W$ ;  $\gamma$  is the coefficient that captures the force of path dependence on knowledge production in the region  $i$  while  $\rho$  and  $\omega$  are coefficients that capture the space-time spillover between regions.

## 2.1 Determinants of Knowledge Production

Here, we seek to identify in the literature the main determinants of knowledge production and innovation. The main purpose is to identify the variables that can represent the vector  $I = [\beta_1 \log(C_{it}) + \beta_2 \log(L_{it}) + \beta_3 \log(r_{it})]$  that is, labor, capital and other positive influences in knowledge production.

Lucas (1988) and Romer (1990), in the endogenous growth theory, have shown that innovation is among the "deep" causes of economic progress. This is due the existence of positive externalities of knowledge; and its generation occurs mainly through expenditures on Research and Development (R&D), whether public or private. According to Cassiolato (1999), innovation and the development of new technologies do not occur in isolation in the intra-firm environment, since the institutions of the countries and regions in which the company is inserted are fundamental. Freeman (1988) emphasizes the importance of articulation between the educational system and the productive sector in the generation of knowledge, especially universities that supply skilled labor to firms, besides the realization of basic and applied research, which can be transformed into technological developments, raising the productivity and competitiveness of the firms. In this context, Freeman (1988) and Nelson (1996) argues that internal R&D performed in private companies, combined with those spent in universities and research institutes are key elements in the production of knowledge.

The production of knowledge and innovation, however, does not take place in an isolated and independent way, since reflects attitudes and paths taken previously in a historical construction (NELSON, 1996). According to Arthur (1989), technological development tends to assume a pre-established trajectory, a relation called path-dependence. Hence, the amount of innovation created in the  $t - 1$  is an important determinant of knowledge produced in the current period  $t$ . Ejermo (2005) emphasizes the need to include the temporally lagged dependent variable in the knowledge production function. Otherwise, the econometric model may suffer from omission of relevant variable, invalidating the statistical inferences, although the author did not address it in a theoretical perspective. Therefore, we can infer that initial advantages help to determine the future development of knowledge production, causing, in the long run, inequalities between regions. In the context of the present paper, such a path-dependence relationship was formally incorporated in the Knowledge Production Function with the term  $K_{it-1}$ .

In addition, Krugman (1991) argues that scientific and technological knowledge, as a source of increasing returns to scale, can unleash attractive forces for similar activities, resulting in a process of agglomeration or geographical concentration. Thus, location is an important factor in explaining the differences in economic growth rate, as well as in the process of development and dissemination of innovation. In other words, there is a need to incorporate spatial and geographic location in regional analyzes, especially those related to inventive activities related to scientific and technological knowledge in order to avoid mistaken or incomplete conclusions.

Jacobs (1969) supports the importance of agglomeration and geographic proximity, which make it possible to increase the diffusion, transmission and exchange of knowledge. This phenomenon, in most cases, is linked to the urbanization, which leads to the concentration of economic activities known as agglomeration economies. From this perspective, Griliches (1992) emphasizes the importance of knowledge spillovers related to geographical concentration and urbanization, which result from positive externalities inherent to the innovative process. These spillovers, according to the author, only occur when there is geographic proximity, and can induce the increase of the spatial concentration of this activity.

Considering Brazil, according to Albuquerque (1996) and Villaschi (2005), Brazil presents an inadequate infrastructure for scientific and technological development, as well as a low interaction of the agents. In relation to the analysis of the spatial distribution of the innovative activity in the country,

Gonçalves (2007) identified the existence of spatial autocorrelation in the production of knowledge, with regions with high level of technological activity having neighbors with similar characteristics. In addition, the author found a North-South spatial pattern for the Brazilian innovation distribution, with the southeast and south regions being characterized as having high technological activity while the Northeast, North and Central West regions with low.

Freitas et al. (2010) sought to investigate the inequality between Brazilian states from 1990 to 2001 and also found evidence of spatial concentration of the Brazilian innovation, with the existence of significant spatial clusters of inventive activity in the country, especially in the Southeast and South. They also identified evidence of a convergence process between Brazilian states, that is, regions less developed presenting a higher growth rate than more consolidated regions. Similar results were obtained by Oliveira et al. (2016) and Rodriguez and Gonçalves (2017) that also identified a spatial concentration of the innovative activity in Brazil, indicating the importance of the spatial component, besides the occurrence of a catching up process between the regions.

Gonçalves and Almeida (2009), in turn, estimate a Knowledge Production Function for the Brazilian microregions for the year 2000 with a Spatial Autoregressive Model (SAR). The authors found that knowledge spillover is an important determinant of Brazilian innovation. In addition, factors such as R&D performed by universities and companies, demographic density (urban scale) and industrial infrastructure were important for determining the knowledge generated in Brazil. Also for the microregions in Brazil, Araújo (2013) estimated a KPF using the SAR-Tobit method. The author found that higher levels of regional industrial R&D and academic research imply greater innovation measured by patents. Moreover, denser and diverse cities tend to present a better innovative performance what indicates Jacobian advantages for regional innovation in Brazil. Finally, the author highlights the importance of interregional knowledge spillovers associated to innovative activities.

Montenegro et al. (2011) and Gonçalves et al. (2018) are the only papers in the literature to seek to estimate a KPF through a Dynamic Panel, in order to verify the importance of path dependence for Brazil. However, the authors used the Generalized Method of Moment (GMM) estimator, different from the one employed in this paper, and did not considered possible impacts from spillover of knowledge production in  $t - 1$  in neighbors regions. Considering the geographic and temporal cut, Montenegro et al. (2011) did the research only for the microregions of São Paulo in the 1996-2003 period while Gonçalves et al. (2018) considered all microregions in Brazil in the 2000-2011 period. Both authors confirmed the importance of path dependence for the production of knowledge in the country. In addition, Gonçalves et al. (2018) found evidences of knowledge spatial spillovers that reinforce the path-dependence process.

### 3. Methodology

#### 3.1 Exploratory Spatial Data Analysis (ESDA)

The ESDA capture effects of spatial dependence and heterogeneity, association patterns (spatial clusters) and indicate how the data are distributed. The Moran's I statistics seeks to capture the degree of spatial correlation between a variable across regions. Mathematically,

$$I = \frac{n}{S_0} \frac{\sum_i \sum_j w_{ij} z_i z_j}{\sum_{i=1}^n z_i^2} \quad (23)$$

where  $n$  is the number of regions,  $S_0$  is a value equal to the sum of all elements of matrix  $W$ ,  $z$  is the normalized value for deforestation. However, the Moran's I statistic only capture global autocorrelation, not identifying association at a local level. In this context, we use the LISA (statistic, which are capable to capture local spatial autocorrelation and clusters,

$$I_i = z_i \sum_{j=1}^J w_{ij} z_j \quad (24)$$

where  $z_i$  represents the variable of interest of the standardized region  $i$ ,  $w_{ij}$  is the spatial weighting matrix element ( $W$ ) and  $z_j$  is the value of the variable of interest in the standardized region  $j$ . The local Moran I (LISA) can represent four spatial clusters: High-High (AA), Low-Low (BB), High-Low (AB) and Low-High (BA). The most analyzed is the High-High cluster, which indicates that a region with a high value for the analyzed variable is surrounded by regions with similar values.

### 3.2 Dynamic Spatial Panel

The Dynamic Spatial Panel Model, besides incorporating the spatial lag of the dependent variable, also incorporates a temporal dependent variable. In addition, it is possible to incorporate a space-time lag of the dependent variable. Therefore, it is a methodology capable of empirically grasping the theoretical model proposed in this article. The estimation of such a model will follow the approach proposed by Yu et al. (2008). The general specification are

$$Y_{nt} = \lambda_0 W_n Y_{nt} + \gamma_0 Y_{nt-1} + \rho_0 W_n Y_{nt-1} + X_{nt} \beta_0 + c_{n0} + V_{nt}, \quad t = 1, 2, \dots, T \quad (25)$$

where  $Y_{nt} = (Y_{1t}, Y_{2t}, \dots, Y_{nt})'$  and  $V_{nt} = (V_{1t}, V_{2t}, \dots, V_{nt})'$  are column vectors with dimension  $n \times 1$ ,  $V_{nt}$  is *i. i. d* with  $i$  and  $t$  with mean zero and variance  $\sigma^2_0$ ;  $W_n$  is a spatial weight matrix  $n \times n$  that captures the spatial dependence between the cross-section variables  $y_{it}$ ;  $X_{nt}$  is a matrix  $n \times k_x$  of non-stochastic regressors; and  $c_{n0}$  is a column vector  $n \times 1$  of fixed effects. Therefore, the number of parameters in the model will be equal to the number of individuals  $n$  plus the other common parameters to be estimated,  $(\gamma, \rho, \beta', \lambda, \sigma^2)$ , ie,  $k_x + 4$ .

Denoting  $S_n \equiv S_n(\lambda_0) = I_n - \lambda_0 W_n$  and  $A_n = S_n^{-1}(\gamma_0 I_n + \rho_0 W_n)$ , where  $S_n$  is invertible, (25) can be rewritten as  $Y_{nt} = A_n Y_{nt-1} + S_n^{-1} X_{nt} \beta_0 + S_n^{-1} c_{n0} + S_n^{-1} V_{nt}$ . Assuming that infinite sums, by continuous substitution, are well defined, we have

$$Y_{nt} = \sum_{h=0}^{\infty} A_n^h S_n^{-1} (c_{n0} + X_{n,t-h} \beta_0 + V_{n,t-h}) = \mu_n + \mathfrak{X}_{nt} \beta_0 + U_{nt} \quad (26)$$

In which  $\mu_n = \sum_{h=0}^{\infty} A_n^h S_n^{-1} c_{n0}$ ,  $\mathfrak{X}_{nt} = \sum_{h=0}^{\infty} A_n^h S_n^{-1} X_{n,t-h}$  and  $U_{nt} = \sum_{h=0}^{\infty} A_n^h S_n^{-1} V_{n,t-h}$ . The next step is to define the maximum likelihood function that should be maximized. For this, it we denoted  $\theta = (\delta', \lambda, \sigma^2)'$  and  $\zeta = (\delta', \lambda, c'_n)'$ , where  $\delta = (\gamma, \rho, \beta')'$ , being the true value  $\theta_0 = (\delta'_0, \lambda_0, \sigma^2_0)$  and  $\zeta_0 = (\delta'_0, \lambda_0, c'_{n0})$ , which results in the following maximum likelihood function:

$$\ln L_{n,T}(\theta, c_n) = -\frac{nT}{2} \ln 2\pi - \frac{nT}{2} \ln \sigma^2 + T \ln |S_n(\lambda)| - \frac{1}{2\sigma^2} \sum_{t=1}^T V'_{nt}(\zeta) V_{nt}(\zeta) \quad (27)$$

where  $V_{nt}(\zeta) = S_n Y_{nt} - \gamma_0 Y_{nt-1} - \rho_0 W_n Y_{nt-1} - X_{nt} \beta_0 - c_n$ , ie,  $V_{nt} = V_{nt}(\zeta)$ . If  $V_{nt}$  is normally distributed, we will have the maximum likelihood estimators (MLEs)  $\hat{\theta}_{nT}$  and  $\hat{c}_{nT}$ , derived from the maximization of (27). In the other hand, if  $V_{nt}$  is not normally distributed, we have the quasi-maximum likelihood estimators (QMLEs).

However, a problem with equation (27) is that the number of parameters tends to infinity as  $n$  tends to infinity. Therefore, Yu et al. (2008) proposes a concentrated function of maximum likelihood, concentrating  $c_n$  out, focusing the asymptotic analysis only in the estimator  $\theta_0$  by the concentrated function, since it does not change the parameter size when  $n$  and/or  $T$  change. With the purpose of simplification, the author denoted  $\tilde{Y}_{nt} = Y_{nt} - \bar{Y}_{nT}$  and  $\tilde{Y}_{nt-1} = Y_{nt-1} - \bar{Y}_{nT-1}$ , for  $t = 1, 2, \dots, T \in \mathbb{N}$  where  $\bar{Y}_{nT} = \frac{1}{T} \sum_{t=1}^T Y_{nt}$  and  $\bar{Y}_{nT-1} = \frac{1}{T} \sum_{t=1}^T Y_{n,t-1}$ . Similarly,  $\tilde{X}_{nt} = X_{nt} - \bar{X}_{nT}$  and  $\tilde{V}_{nt} = V_{nt} - \bar{V}_{nT}$ ; denoting  $Z_{nt} = (Y_{nt-1}, W_n Y_{nt-1}, X_{nt})$ , therefore the equation (27), using the first order condition  $\frac{\partial \ln L_{n,T}(\theta, c_n)}{\partial c_n} = \frac{1}{\sigma^2} \sum_{t=1}^T V_{nt}(\zeta)$ , the concentrated estimator of  $c_{n0}$  given  $\theta$  is  $\hat{c}_{n0}(\theta) = \frac{1}{T} \sum_{t=1}^T (S_n(\lambda) Y_{nt} - Z_{nt} \delta)$  and the concentrated maximum likelihood function is



$$\ln L_{n,T}(\theta) = -\frac{nT}{2} \ln 2\pi - \frac{nT}{2} \ln \sigma^2 + T \ln |S_n(\lambda)| - \frac{1}{2\sigma^2} \sum_{t=1}^T \tilde{V}'_{nt}(\zeta) \tilde{V}_{nt}(\zeta) \quad (28)$$

with the first order condition

$$\frac{1}{\sqrt{nT}} \frac{\partial \ln L_{n,T}(\theta)}{\partial \theta} = \begin{pmatrix} \frac{1}{\sigma^2} \frac{1}{\sqrt{nT}} \sum_{t=1}^T \tilde{Z}'_{nt} \tilde{V}'_{nt}(\zeta) \\ \frac{1}{\sigma^2} \frac{1}{\sqrt{nT}} \sum_{t=1}^T ((W_n \tilde{Y}_{nt})' \tilde{V}_{nt}(\zeta) - \text{tr} G_n(\lambda)) \\ \frac{1}{2\sigma^4} \frac{1}{\sqrt{nT}} \sum_{t=1}^T \tilde{V}'_{nt}(\zeta) \tilde{V}_{nt}(\zeta) = n\sigma^2 \end{pmatrix} \quad (29)$$

while the second order condition is

$$\frac{1}{\sqrt{nT}} \frac{\partial^2 \ln L_{n,T}(\theta)}{\partial \theta \partial \theta'} = -\frac{1}{\sqrt{nT}} \begin{pmatrix} \frac{1}{\sigma^2} \sum_{t=1}^T \tilde{Z}'_{nt} \tilde{Z}_{nt} & \frac{1}{\sigma^2} \sum_{t=1}^T \tilde{Z}'_{nt} W_n \tilde{Y}_{nt} & \frac{1}{\sigma^2} \sum_{t=1}^T \tilde{Z}'_{nt} \tilde{V}_{nt}(\zeta) \\ * & \frac{1}{\sigma^2} \sum_{t=1}^T ((W_n \tilde{Y}_{nt})' W_n \tilde{Y}_{nt} + \text{tr}(G_n^2(\lambda))) & \frac{1}{\sigma^4} \sum_{t=1}^T (W_n \tilde{Y}_{nt})' \tilde{V}_{nt}(\zeta) \\ * & * & -\frac{nT}{2\sigma^4} + \frac{1}{\sigma^4} \sum_{t=1}^T \tilde{V}'_{nt}(\zeta) \tilde{V}_{nt}(\zeta) \end{pmatrix} \quad (30)$$

where  $\tilde{V}_{nt}(\zeta) = S_n(\lambda)Y_{nt} - Z_{nt}\delta$  and  $\tilde{Z}_{nt} = (Y_{nt-1} - \bar{Y}_{nT-1}, W_n Y_{nt-1} - W_n \bar{Y}_{nT-1}, X_{nt} - \bar{X}_{nT})$ . The QMLE  $\hat{\theta}_{nT}$  maximizes the function (28), satisfying the conditions of first and second order, and the estimator of quasi-maximum likelihood of  $\mathbf{c}_{n0}$  is  $\hat{\mathbf{c}}_{n0}(\hat{\theta}_{nT})$ . Therefore, concluding the necessary estimates for the Dynamic Spatial Panel.

### 3.3 Database

The variable used as proxy for knowledge production is the number of innovation patents created in the 558 microregions of Brazil, based on Griliches (1992). Patent deposit data were acquired in the Statistical Database of Intellectual Property, generated by INPI (*Instituto Nacional de Propriedade Intelectual*). Information on Brazilian inventors' deposits is considered according to their region of residence. With regard to the population of the microregions, the data is from the Instituto Brasileiro de Geografia e Estatística (IBGE). With this database, an indicator of innovation patents per 100,000 inhabitants are constructed for the country's microregions,

$$K_{it} = \frac{\text{Innovation}.P_{it}}{(\text{Population}_{it}/100.000)} \quad (31)$$

where  $K_{it}$  represents the indicator of patents per 100,000 inhabitants for microregion  $i$  in period  $t$ , which will represent the *Knowledge Production* in the EKPF;  $\text{Innovation}.P_{it}$  is the number of innovation patents created;  $\text{Population}_{it}$  represents the size of the population of the microregion  $i$  in period  $t$ . Therefore, microregions with a low population gain more weight in knowledge production, when compared directly

with those that have large populations. This enable measure more effectively the productivity of these regions. The explanatory variables, inputs in the EKPF, are described in Table 1.

Table 1 - Explanatory variables used in the Expanded Knowledge Production Function.

VARIABLE	DESCRIPTION	SOURCE
Knowledge Production	Innovation patents per 100,000 inhabitants.	INPI e IBGE
Researchers	Number of researchers in public and private universities.	CAPES
Private R&D	Proportion of technical-scientific workers in total employment.	RAIS
Higher Education	Portion of workers with higher education.	RAIS
Firms	Establishments with more than one employee per capita.	RAIS e IBGE
Large Firms	Proportion of companies with more than 500 employees in the total of the microregion.	RAIS
Export	Exports of high and mid-high technology intensities products.	COMEX STAT
Per Capita GDP	Per Capita Gross Domestic Product of the microregions.	IBGE
Science and Technology	Expenditure of the microregion on science and technology.	IPEA e FINBRA
Population Density	(Demographic Density) number of inhabitants per km <sup>2</sup> .	IBGE

Source: research data.

The choice of variables are based on works already mentioned in this article, especially those who sought to investigate innovation in the Brazilian context. In any case, some variables need further explanation. For example, there is no data available in relation to private R&D; therefore, the proportion of professionals employed in technical and scientific activities in the microregion was used as proxy, following recommendations of Araújo, Cavalcante e Alves (2009)<sup>2</sup>. According to Freitas et al. (2010) and Montenegro et al. (2011), this variable is a suitable proxy, due to the high correlation between them, being therefore the best variable to represent private R&D, given the lack of data in Brazil.

On the other hand, the Employment Density and Population Density seeks to capture economies of agglomeration and Jacobian externalities. According to Jacobs (1969), the concentration and geographical proximity of individuals makes possible an increase in the diffusion, transmission and exchange of ideas and information, both in their tacit and codified form, resulting in the amplification of knowledge production. This phenomenon, for the most part, is linked to the urbanization of a certain locality, a result of the concentration of economic activities. In addition, several papers empirically corroborate the importance of agglomeration economies and Jacobian externalities for the innovative process. (GONÇALVES and ALMEIDA, 2009; FELDMAN and AUDRETSCH, 1999; HARRISON et al., 1996; GLAESER et al, 1992).

However, according to Jacobs (1969), the excessive increase in population density may lead to agglomeration diseconomies, resulting in negative externalities. Therefore, Population Density may have a non-linear relationship with innovation. Such a fact can be captured with the inclusion of a term in the linear form and another in the quadratic form in KPF. If the linear is positive and the quadratic is negative, both significant, we have the presence of agglomeration diseconomies, acting together with the positive externalities. The overlapping of the two effects will depend on the magnitude of the population density, with negative externalities standing out in densely populated areas. In fact, Gonçalves and Almeida (2009) identified this phenomenon as important for the production of knowledge in Brazil.

The Export variable, in turn, capture the exports of high and mid-high technology intensities products, which were aggregated following Raiher et al. (2017). In the high intensity products, we have the aerospace, pharmaceutical, computational, electronic and telecommunications sectors. On the other hand, in the mid-high intensity products, we have the electrical material; automotive vehicles; chemistry; railroad and transportation equipment; machinery and equipment. High and mid-high intensity sectors are both

<sup>2</sup> The professionals included are from the following areas: biotechnology, biomedical, engineers, researchers (in firms), mathematics and statistics professionals, computer systems analysts, physicists, chemists, space and atmosphere professionals and architects.

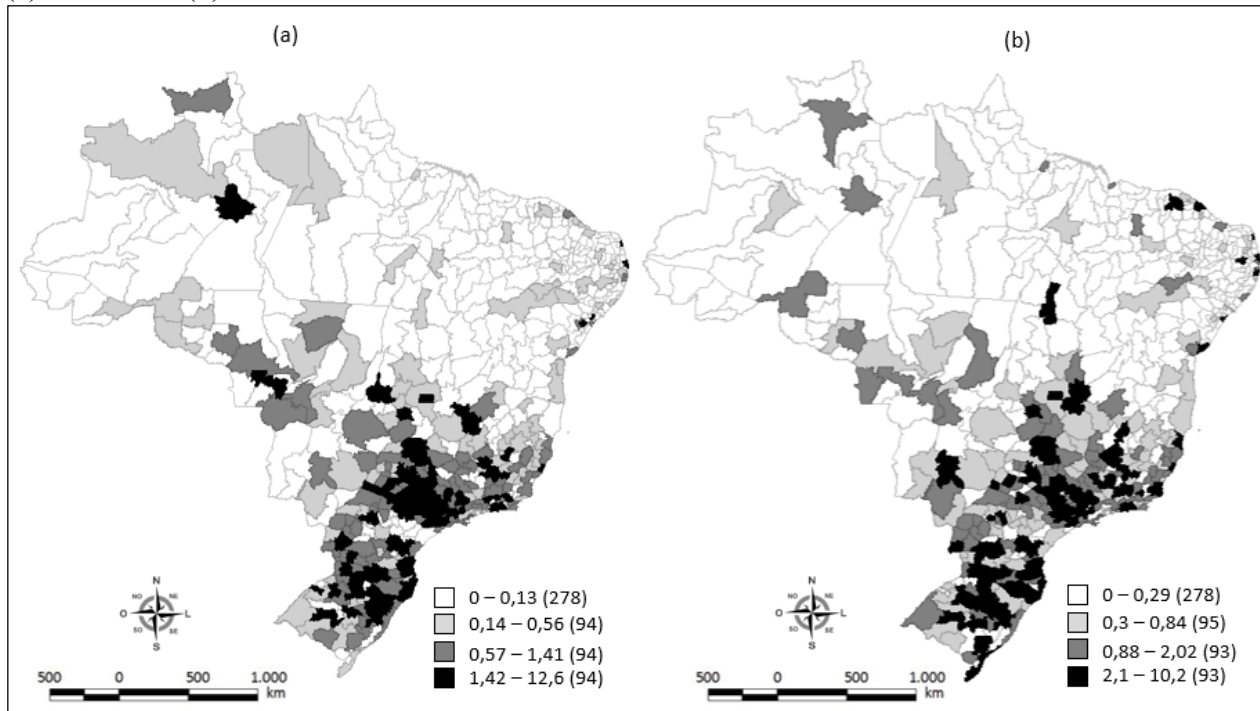
intensive in capital and technology, which can influence the innovation process and in the creation of knowledge, both directly and indirectly, through spillovers.

Finally, we also check for possible correlations between the variables (Appendix A) in order to avoid multicollinearity problems. From them, we can notice no extremely high correlations that could compromise the model estimation.

#### 4. Spatial Distribution of Knowledge Production and its Determinants in Brazil

Innovation and technological development have important repercussions on the economic structure of a country, because it creates and makes new combinations of factors of production, generating alternative productive processes, with greater productivity, and / or new goods. Therefore, different authors defend the production of knowledge as the foundation for the economic dynamics of a space. A preliminary descriptive analysis of the data are performed, in relation to creation of patents by the microregions, in order to verify the dynamics presented by this production in Brazil (see Figure 1).

Figure 1: Distribution of innovation patents per 100,000 inhabitants in the Brazilian microregions in 2005<sup>3</sup> (a) and 2015<sup>4</sup> (b).



Source: INPI, with data organized by the research

For 2004, the country presented 3740 innovation patents, while in 2016 this number rose to 5193, an increase of approximately 38.85%. However, such growth does not occur homogeneously throughout the country. When considering regional levels, for example, a small number of microregions are responsible for most knowledge produced (patents) in the period 2004 to 2014. It is also evident the concentration of this innovative process in the country, located mainly in the Center-South portion of the country, which was called by Gonçalves (2007) and Araújo (2013), a North-South polarization regime. When comparing the initial period (a) versus the final (b), the production of patents per 100,000 inhabitants maintained the same spatial distribution and concentration of the amount of knowledge produced. Therefore, it is evident

<sup>3</sup> Average of 2004, 2005 and 2006. Procedure adopted to avoid random effects of the knowledge-producing process, which will also be adopted for the next exploratory analyzes.

<sup>4</sup> Average of 2014, 2015 and 2016.

the existence of an inertial process in the creation of patents, which indicates the possible existence of path dependence for the production of knowledge in Brazil.

In addition, the spatial concentration of microregions in relation to patents deposited in both periods is visible (Figure 1). This is proved by the Moran's I coefficients in Table 2, whose values were positive and statistically significant independent of the weight matrix applied. Thus, microregions with a high number of patents per 100,000 inhabitants tended to be surrounded by microregions with also high values for this variable. In addition, there is a fall in the magnitude of the coefficients, signaling a decrease of spatial concentration in the period.

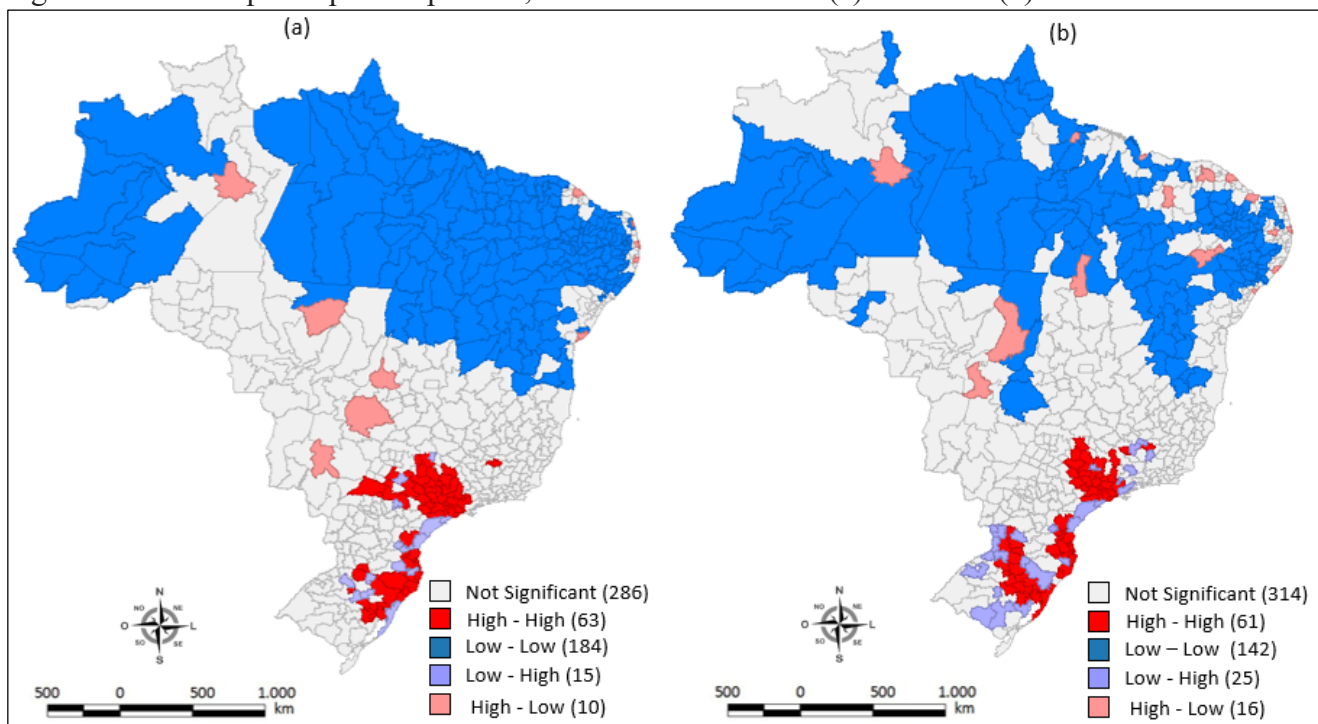
Table 2 - Moran's I for Patents per 100,000 inhabitants in the Brazilian microregions in 2005 and 2015.

	Weights Matrix			
	Three neigh.	Five neigh.	Seven neigh.	Ten neigh.
Patents/100,000 inhabitants 2005	0,40*	0,38*	<b>0,41*</b>	0,39*
Patents/100,000 inhabitants 2015	0,34*	0,33*	<b>0,35*</b>	0,33*

Source: research data. *Note:* Empirical Pseudo-significance based on 99999 random permutations. \* Significance of 1%.

By using the local spatial association indicators (Lisa maps), the existence of innovation clusters throughout Brazil was identified. Between the periods, there is the consolidation of two High-High (HH) clusters (Figure 2), which represents microregions with high innovation surrounded by neighbors with equal innovative productivity.

Figure 2: LISA maps for patents per 100,000 inhabitants - 2005 (a) and 2015 (b).



Source: INPI, with data organized by the research

The first HH cluster is located in the state of São Paulo and is configured as the largest spatial HH cluster due to the number of microregions and the territorial extent of the spatial agglomeration. This polygon of high technological activity, in period one (a), extends from São Paulo and closer neighbors such as Guarulhos, Osasco and Santos, passing by Campinas, Piracicaba, São Carlos, Araraquara, Ribeirão Preto, to the north and northwest of the state, in Franca, Barretos and São José do Rio Preto. According to Montenegro et al. (2011), the high technological development of the region is because it has a diversified industrial base, as well as specialized sectors that encourage innovation.

However, in the second period (b), some microregions in the north and northwest were no longer significant, thus making this cluster of high technological activity more concentrated closer to microregions such as São Paulo and Campinas. According to Fernandes et al. (2016), the technology-based companies in the state of São Paulo suffered from the country's economic crisis, which possibly impacted on their respective innovative capabilities. Finally, this HH cluster of high technological activity coincides in general with that found by the Gonçalves (2007), Montenegro and Betarelli Júnior (2009), Montenegro et al. (2011), Araújo (2013) and Góis Sobrinho and Azzoni (2016).

The second HH spatial cluster, in the first period (a), is located mainly in the eastern portion of the state of Santa Catarina (SC) and Rio Grande do Sul (RS). In SC, two local groups of the HH type, both on the coast of the state, stand out. Joinville, Blumenau and Itajaí compose one of them while the second agglomeration refers to the microregions of Florianópolis, Tubarão and Criciúma. These regions are characterized in the information technology sector and in industrial activities in the area of mechanics and electrical. In addition, the proximity of these localities may indicate the presence of technological spillovers between the microregions, impelling the production of knowledge. In the second period (b), the number of micro of type HH was widened in the state, consolidating the spatial cluster of the region. The SC cluster starts at the border with RS, passing through the entire regional coast of SC, to the northeast region of Curitiba in Paraná, the latter being an important industrial complex of the south of Brazil, especially with regard to its automotive complex (GONÇALVES, 2007; GÓIS SOBRINHO and AZZONI, 2016).

The state of Rio Grande do Sul, in turn, presents most of the southern cluster in both periods considered. Moreover, from 2005 to 2015, there was an enlargement of this agglomeration, extending from the region of Porto Alegre, Caxias do Sul to Passo Fundo, also including adjacent regions such as Gramado, Montenegro, Guaporé and Não-Me-Toque, forming a corridor of technological development in the State. According to Araújo (2013), these regions have physical and technical-scientific infrastructure suitable for knowledge production, with a skilled labor market and a dense industrial network.

Identified the basic characteristics of technological development and the production of knowledge in Brazil, in terms of the distribution of the creation of innovation patents in the micro, the next step is to find its basic determinants from the perspective of the theoretical proposition of section 2. Therefore, Table 3 brings the results of the Expanded Knowledge Production Function with path dependence and spatial spillovers, estimated with the Dynamic Spatial Panel method for the period from 2004 to 2016.

Prior to the estimation, we applied the Hausman test in order to verify the adequacy of the method to the sample used. From this, it was possible to reject the null hypothesis that there is no systematic difference between the estimated coefficients<sup>5</sup>. Therefore, the estimation by fixed effect is in fact the most adequate. In addition, we chose the spatial lag matrix that generated the largest Moran's I coefficient for the fixed effect (2) model residues (Appendix B) to estimate the Dynamic Spatial Panel Model, opting for the three neighbors matrix. We identified the presence of heteroscedasticity and to control the problem, we estimated the spatial models using the robust standard error by Huber/White/Sandwich (HUBER, 1967).

Subsequently, we tried to define which spatial model is the one that best represents and captures the dynamics of the phenomenon under study. Using the Akaike information criterion, the Dynamic Spatial Autoregressive Model (DSAR) are the one that presented the lowest value for this adjustment criterion. Considering the spatial dependence in the dynamic spatial models residuals (Appendix C and D), the DSAR also are the best model, since it minimize the spatial effects on the residuals. This fact indicates that knowledge creation in Brazil is not affected by spillovers of independent variables as proposed by Autant-Bernard and LeSage (2011). Therefore, further analyzes are performed using the DSAR, which is disposed in column (I) of Table 3.

Among the results, we have that the time-lagged dependent variable,  $K_{t-1}$ , presented a coefficient ( $\gamma$ ) statistically significant at the 1% level and with a positive impact on knowledge produced. Therefore, the assumption of Fischer et al. (2009), that the production of knowledge in  $t$  is positively influenced by the quantity produced in  $t - 1$ , was true for the microregions of Brazil. In others words, the innovation in the country has an inertial component, assuming a pre-established trajectory, or path dependence, as in

<sup>5</sup> Chi<sup>2</sup> statistics: 76.46, with a probability of 0,000.

Arthur (1989). This fact explains the dynamics presented by the innovative activity in Figures 1 and 2, where it is evident that the regions that were the largest producers of knowledge in 2005 continued to be in 2015, with few visible changes.

Table 3 – The Expanded Knowledge Production Function (EKPF) for Brazil, 2004 to 2016.

VARIABLES	DYNAMIC SPATIAL PANEL	
	DSAR (I)	DSDM (II)
$Knowledge (\gamma)_{t-1}$	<b>0.2514**</b>	0.2505**
$W Knowledge (\omega)_{t-1}$	<b>0.0349</b>	0.0321
$W Knowledge (\rho)_t$	<b>0.0712**</b>	0.0677**
$Researchers_t$	<b>0.0002**</b>	0.0002**
$Private R \& D_t$	<b>7.46e-06</b>	0.0001
$Firms_t$	<b>1.6701</b>	2.1669
$GDP_t$	<b>1.96e-06</b>	1.11e-06
$Population Density_t$	<b>0.0090**</b>	0.00836**
$Population Density^2_t$	<b>-8.60e-07**</b>	-8.37e-07**
$Science and Technology_t$	<b>-0.00000</b>	-2.71e-10
$Exports_t$	<b>0.0001*</b>	-0.0001*
$Higher Education_t$	<b>-0.0429</b>	-0.1315
$Large Firms_t$	<b>1.6367</b>	1.6352
$W Researchers_t$	-	0.0001
$W Private R \& D_t$	-	-0.0004
$W Firms_t$	-	-17.8035
$W GDP_t$	-	0.0001
$W Population Density_t$	-	-0.0013
$W Population Density^2_t$	-	2.61e-07
$W Science and Technology_t$	-	-2.88e-09
$W Exports_t$	-	-9.96e-06
$W Higher Education_t$	-	2.0887
$W Large Firms_t$	-	-2.0915
Akaike Information Criterion	<b>14426</b>	14335

Source: research results. Note: \*\* Significant at a significance level of 1%; \* Significant at a significance level of 5%.

On the other hand, the coefficients that aim to capture the knowledge spillovers in  $t$ ,  $(\rho)$ , did present statistical significance while the coefficient to capture in  $t - 1$ ,  $(\omega)$ , did not. Therefore, only the current spatial spillovers component of the Extended Knowledge Production Function, based on Autant-Bernard and LeSage (2011),  $WK_{it}$ , are relevant to explain innovation in Brazil, indicating that regions with high knowledge production influence positively their neighbors and can be one of reasons for the spatial concentration of knowledge in Figure 1 and 2. The spatial concentration phenomena occurs because certain activities are agglomerated in a given locality due to the presence of attractive (centripetal) forces. This result corroborates Gonçalves and Almeida (2009) and Araújo (2013) who found significant knowledge spillovers in the country.

An important determinant of knowledge production in Brazil are the population density in both linear and quadratic form. They were significant at the 1% level and with expected signs, that is, with positive and negative, respectively. This relationship confirms for Brazil the hypothesis of Jacobs (1969), Krugman (1991) and Griliches (1992) on the importance of agglomeration economies and urbanization in the production of knowledge. Therefore, the increase in the number of people in a certain locality of the country is able to facilitate the diffusion, transmission and exchange of ideas among the economic agents, factors capable of increasing the returns of the knowledge produced, due to the positive (Jacobian) externalities. However, as indicated by the negative sign of the squared version of Population Density, these

benefits of agglomeration occur until a certain urban scale, from which they begin to act as inhibitors in the production of knowledge. Gonçalves and Almeida (2009) and Araújo (2013) also found a similar result for Brazil. Therefore, this work corroborates the importance of Jacobian externalities and agglomeration economies to explain the innovative process in the Brazilian microregions.

Another important variable for the production of knowledge in the country is the number of university researchers in the microregions, which obtained a positive sign for its coefficient and statistical significance of 1%, a similar result to Gonçalves and Almeida (2009) and Araújo (2013). This variable is part of the labor force,  $L_t$ , employed in the search for new ideas, being intrinsically related to scientific and technological research, which, according to Nelson (1996), are important vectors of knowledge production and innovation. However, other components of the labor input in the EKPF, such as Private R&D (which had as proxy, the professionals related to this activity) and workers with Higher Education are not significant, which indicate a low return, in terms of innovation, for R&D in the Brazilian firms. Finally, the Export of high and mid-high technologic intensity products presented statistical significance, confirming that sectors intensive in capital and technology influence positively the innovation process.

## 5. Final Remarks

This paper sought to provide a theoretical motivation for an Expanded Knowledge Production Function (EKPF) that encompasses both path dependence and spatial spillovers. In addition, search for evidence from Brazil using a Dynamic Spatial Panel Data approach, using the microregions as a basic geographic cut. The purpose was to identify the determinants of knowledge production in the country as well as its temporal evolution, using innovation patents as proxy. The years analyzed correspond to the period from 2004 to 2016.

The main evidence found regarding the distribution of knowledge production are the existence of a North-South disparity for the innovative activity in Brazil, with São Paulo and the South of Brazil having the two largest high-high clusters in the country. Some elements are preponderant for the determination and explanation of the innovation in the period under analysis, with special importance for the path dependence phenomenon and spatial spillovers from knowledge production. Therefore, the distribution of the innovative activity in the country presents an inertial element, with regions that started before their technological development having considerable advantages in the production of knowledge. Hence, the unchanged North-South disparity for innovation in the country between 2004 and 2016 may be due to the presence of path dependence, which makes it difficult to reduce regional differences. In addition, spatial spillovers from knowledge reinforce the spatial agglomeration, since it influence the production of knowledge in neighbors regions. Such evidence indicates the importance of targeted public policies for some localities to be able to initiate a technological development trajectory, without which some microregions will not reach the leading regions in knowledge production in Brazil.

Other elements are also relevant to explain the production of knowledge in the country, in addition to path dependence. The Population Density, for example, presented an inverted "U" influence with innovation, capturing a nonlinear relation from agglomeration externality. Put another way, these benefits of agglomeration occur until a certain urban scale, from which they begin to act as inhibitors in the production of knowledge. This fact corroborates the importance of urbanization and the urban scale for Brazilian technological activity. In addition, the number of university researchers, a proxy for R&D conducted by universities, and the exports of high and mid-high technology products also proved to be significant in explaining the production of knowledge in the country, as expected.

From these evidences, we identified the key elements that boost innovation activity and the production of knowledge in Brazil. However, the lack of significance of the other factors included in the EKPF leaves open the reasons why these variables are not relevant for the country's knowledge production. As an example, we can mention the cases of private R&D and investments in science and technology that are expected to assist in the production of knowledge. However, such variables have not behaved as expected for the country, evidencing a malfunction of these basic inputs, a fact that deserves attention by public agents and researchers.

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## Appendix

### Appendix A - Correlation for the variables use in the econometric estimation.

	Knowledge	R&D	Research	Firm	Sci.Tech	High.Ed	Larg Firm	Exports	GDP	Pop.Dens
Knowledge	1.000									
R&D	-0.013	1.000								
Research	0.213	-0.002	1.000							
Firms	0.425	-0.046	0.054	1.000						
Sci. Tech.	0.081	0.000	0.090	0.025	1.000					
Higher Ed.	0.264	0.076	0.159	0.215	0.070	1.000				
Large Firms	-0.183	0.075	-0.030	-0.544	-0.007	-0.056	1.000			
Exports	0.126	-0.004	0.012	0.056	0.013	0.049	-0.027	1.000		
GDP	0.376	-0.027	0.087	0.529	0.059	0.237	-0.244	0.306	1.000	
Pop.Dens	0.285	0.001	0.358	0.053	0.239	0.300	-0.023	0.033	0.204	1.000

Source: research results.

### APPENDIX 2.B - Moran's I for Fixed Effect Panel Data residuals - convention matrix decision.

	Weights Matrix			
	Three neigh.	Five neigh.	Seven neigh.	Ten neigh.
2004	<b>0.2899*</b>	0.2682*	0.2579*	0.2208*
2005	<b>0.3062*</b>	0.2780*	0.2528*	0.2048*
2006	<b>0.3076*</b>	0.2786*	0.2533*	0.2005*
2007	<b>0.2811*</b>	0.2506*	0.2406*	0.1844*
2008	<b>0.3110*</b>	0.2764*	0.2614*	0.2015*
2009	<b>0.3144*</b>	0.2933*	0.2804*	0.2212*
2010	<b>0.3259*</b>	0.2804*	0.2675*	0.2066*
2011	<b>0.2663*</b>	0.2409*	0.2543*	0.2113*
2012	<b>0.3046*</b>	0.2673*	0.2482*	0.1979*
2013	<b>0.2813*</b>	0.2420*	0.2256*	0.1885 *
2014	<b>0.2973*</b>	0.2740*	0.2611*	0.2159*
2015	<b>0.3081*</b>	0.2873*	0.2499*	0.1969*

Source: research data. *Note:* \* Level of significance of 1%.

### APPENDIX 2.C - Moran's I for DSDM.

	Weights Matrix			
	Three neigh.	Five neigh.	Seven neigh.	Ten neigh.
2005	<b>0.0436</b>	0.0078	0.0176	0.0090
2006	<b>0.0802*</b>	0.0507	0.0323	0.0123
2007	<b>-0.0438</b>	-0.0353	-0.0252	-0.0268
2008	<b>0.0046</b>	0.0295	0.0237	0.0099
2009	<b>-0.0595</b>	0.0139	0.0057	-0.0007
2010	<b>0.0568</b>	0.0143	0.0198	0.0076
2011	<b>-0.0622</b>	-0.0434	0.0954*	0.1045*
2012	<b>-0.0341</b>	-0.0341	-0.0219	-0.0136
2013	<b>0.0354</b>	-0.0033	-0.0065	0.0347

2014	<b>-0.1169</b>	-0.0438	-0.0092	0.0090
2015	<b>0.0127</b>	0.0266	0.0070	0.0140

Source: research data. *Note:* \* Level of significance of 1%.

#### APPENDIX 2.D - Moran's I for DSAR.

	Weights Matrix			
	Three neigh.	Five neigh.	Seven neigh.	Ten neigh.
2005	<b>0.0404</b>	0.0059	0.0168	0.0080
2006	<b>0.0814</b>	0.0515	0.0331	0.0131
2007	<b>-0.0430</b>	-0.0350	-0.0248	-0.0263
2008	<b>0.0037</b>	0.0290	0.0232	0.0095
2009	<b>-0.0591</b>	0.0140	0.0060	-0.0000
2010	<b>0.0572</b>	0.0146	0.0199	0.0073
2011	<b>-0.0614</b>	-0.0424	0.0963*	0.1052*
2012	<b>-0.0336</b>	-0.0341	-0.0222	-0.0140
2013	<b>0.0344</b>	-0.0002	-0.0057	0.0349
2014	<b>-0.1171*</b>	-0.0439	-0.0092	0.0096
2015	<b>0.0107</b>	0.0253	0.0067	0.0129

Source: research data. *Note:* \* Level of significance of 1%.