Department of Economics- FEA/USP

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Otávio J. G. Sidone
Eduardo A. Haddad
Jesús P. Mena-Chalco

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Otávio J. G. Sidone (otavio.sidone@usp.br)

Eduardo A. Haddad (ehaddad@usp.br)

Jesús P. Mena-Chalco (jesus.mena@ufabc.edu.br)

**Research Group:** (NEREUS)

## Abstract:

Brazilian scholarly outputs have had rapid growth that was accompanied by an expansion of domestic research collaboration. In this paper, we identify spatial patterns of research collaboration in Brazil, as well as measure the role of geographical proximity in determining the interaction among Brazilian researchers. Using a database comprised of over one million researchers and seven million publications registered in the Brazilian Lattes Platform, we collect and consolidate information on inter-regional research collaboration in terms of scientific co-authorship networks among 4,615 municipalities over the period between 1992 and 2009, which enabled a range of data analysis unprecedented in literature. The effects of geographical distance on collaboration are measured for different knowledge areas under the estimation of spatial interaction models. The main results suggest strong evidence of geographical deconcentration of collaboration in recent years with an increased participation of authors in scientifically less traditional regions, such as South and Northeast Brazil. Additionally, the distance still is significant in determining the intensity of knowledge flows in scientific collaboration networks in Brazil since the increase of 100 kilometers between two researchers implies the average reduction on 16% of the probability of collaboration and there is no evidence that its effect has diminished over time, although the magnitude of such effects varies among networks of different knowledge áreas.

**Keywords:** Scientific collaboration; spatial analysis; spatial interaction models; diffusion process.

**JEL Codes:** O33; C21; R12

# Scholarly Publication and Collaboration in Brazil: The Role of Geography

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**Abstract**. Brazilian scholarly outputs have had rapid growth that was accompanied by an expansion of domestic research collaboration. In this paper, we identify spatial patterns of research collaboration in Brazil, as well as measure the role of geographical proximity in determining the interaction among Brazilian researchers. Using a database comprised of over one million researchers and seven million publications registered in the Brazilian Lattes Platform, we collect and consolidate information on inter-regional research collaboration in terms of scientific co-authorship networks among 4,615 municipalities over the period between 1992 and 2009, which enabled a range of data analysis unprecedented in literature. The effects of geographical distance on collaboration are measured for different knowledge areas under the estimation of spatial interaction models. The main results suggest strong evidence of geographical deconcentration of collaboration in recent years with an increased participation of authors in scientifically less traditional regions, such as South and Northeast Brazil. Additionally, the distance still is significant in determining the intensity of knowledge flows in scientific collaboration networks in Brazil since the increase of 100 kilometers between two researchers implies the average reduction on 16% of the probability of collaboration and there is no evidence that its effect has diminished over time, although the magnitude of such effects varies among networks of different knowledge areas.

## 1. Introduction

Recent efforts to develop new visualization techniques for spatial maps of scientific networks among municipalities and research institutes to facilitate the geographic localization of knowledge flows (Leydesdorff and Persson 2010) evidence the crescent concern related to the role of geography in scientific activities. Spatial scientometric analyses have the main purpose of studying the geographical disposition of knowledge flows (among individuals, organizations, or geographic entities), i.e., of the linkages among researchers in knowledge creation and diffusion processes (Frenken et al. 2009). This approach is essential due to the unequal distribution of scientific activity among countries and throughout their territory, which is usual evidence of localization patterns characterized by spatial heterogeneity (Grosseti et al. 2013), although scientific production has other determinant factors (Gantman 2012).

Understanding the relationships among researchers in the knowledge creation process, especially by means of social relationship networks, has become a recurrent empirical subject of research in scientometrics, because research collaboration has played a significant role in fostering knowledge production in modern science, specifically due to its capacity to promote the transfer of knowledge and skills and to decrease the time spent and error occurrences (Royal Society 2011). In this context, research collaboration has become a central element of science, technology, and innovation (STI) policies. Research expenditures may result in different intensities of knowledge flows, depending on the scientific network structures and integration level, and the articulation of collaborative networks can exercise a decisive influence over research quality, visibility, and productivity (Royal Society 2011; Ponds et al. 2007; Sahu and Panda 2014).

In a spatial perspective, the current literature is moving towards an explanation and interpretation of geography on the interaction among researchers in scientific collaboration networks. This is an important aspect, because interactions among researchers are expected to be characterized by spatial localization, with the progress of research activities usually needing face-to-face interactions through meetings and discussions between the partners (Pan et al. 2012; Frenken et al. 2009). Nevertheless, a small body of empirical research has aimed to examine the role of geography in the inter-regional scientific collaboration networks in some specific places: United Kingdom (Katz 1994), China (Liang and Zhu 2002; Scherngell and Hu 2011), Sweden (Danell and Persson 2003), France (Okubo and Zitt 2004), Netherlands (Ponds et al. 2007), United States (Jones et al. 2008), Europe (Hoekman et al. 2010, 2013; Acosta et al. 2011), Africa (Boshoff 2010), and worldwide (Pan et al. 2012). Such research has also found evidence that geographical proximity plays an important role in determining inter-regional collaboration, because such proximity favors relationships among researchers.

There are practical reasons to incorporate the spatial dimension in scientific collaboration networks. First, doing so may provide solid information for decisions related to choosing partners in the academic community to optimize research impact and visibility. Second, it may purposefully leverage the effects of public policies aimed at encouraging inter-regional research projects and, thus, the improvement of research quality (Pan et al. 2012).

The recent evolution of Brazilian science has gained international prominence. On the one hand, despite its being still far from having the growth pattern of China, Brazil has acquired an increasing relevance in the international scientific community, with publication growth substantially above the world average. For instance, Brazil presented the third highest average annual growth of scientific publication between 1996 and

2008. Intensification of this trend of growth took place between 2002 and 2008, when the growth of Brazilian scholarly publications was approximately 110% (Glänzel et al. 2006; Cruz and Chaimovich 2010; Leta 2011; Royal Society 2011). On the other hand, the increase of the collaborative profile in modern science occurs in all areas, with approximately 70% of the currently produced articles worldwide being associated with authors from different institutions. Among these articles, approximately 44% were developed in collaborative work among researchers from different countries and about 56% of collaborations were among researchers located within their national territories. This implies an increasing attention to co-authorship domesticity in China (Wang et al. 2005), Turkey (Gossart and Ozman 2009), Colombia (Buchelli et al. 2012), and Finland (Puuska et al. 2014). Especially in the case of scientifically emerging countries, such as China, Brazil, and India, the accelerated growth production is directly associated with the intensification of domestic collaborative efforts (Royal Society 2011). Because the size of their country allows some scale advantages related to the existence of specialized research institutes, national researchers have more opportunities to collaborate with local partners (Glänzel and Schubert 2005; Chinchilla-Rodríguez et al. 2010).

Beyond the necessities of stimulating spending in research and development (R&D) by the private sector and promoting the internationalization of universities, one of the biggest challenges faced by policies of STI in the Brazilian case consist in the necessity to stimulate the diffusion of scientific excellence from research centers in the Southeast to research centers in other less privileged regions (Cruz and Chaimovich 2010), as well as to associate the growth of scientific activity with increasing quality (Helene and Ribeiro 2011). These challenges could be faced more properly and efficiently by perceptions that are inextricably linked to the establishment and operation of scientific collaboration in Brazil. Research collaboration is the main mechanism for dissemination of knowledge and is closely associated with a higher quality of scientific production.

The importance of geography in knowledge production, primarily its role in mediating interactions among Brazilian researchers in scientific collaborations, is still an unexplored topic in the literature. Understanding the functioning of scientific networks may assist in formulating policies on STI in Brazil, because the functioning of these networks plays an essential role in the development of incentives regarding the geographical closeness between innovative firms and the main sources of knowledge production. From this perspective, we analyze the spatial distribution of production growth and scientific collaboration networks among Brazilian researchers localized in 4,616 municipalities for all areas of knowledge over the period 1992-2009. Furthermore, we discuss the importance of geographical distance as an impediment factor to the interactions among researchers in scientific collaboration networks. It is worth noting that, to our knowledge, this is the first study related with spatial scientometrics that treats an extremely large amount of data associated with more than one million Brazilian researchers registered in the Lattes Platform. More specifically, we aimed to verify some hypothesis about the spatial configuration of scientific production and collaboration in Brazil:

**Hypothesis 1** (*H.1*): The scientific production growth in Brazil was accompanied by a geographical deconcentration process and by an expansion of spatial scientific collaboration networks across the national territory.

**Hypothesis 2** (*H.2*): Geographical proximity still plays an important role in determining the relationships among Brazilian researchers, but its effect varies among the networks of different knowledge areas.

**Hypothesis 3** (*H.3*): The recent technological development in transportation and communication media has implied the decrease of the effects of geographical distance in Brazilian scientific collaboration networks over time.

Beyond this introduction, the paper begins with a detailed description of data collection on Brazilian scientific collaboration (section 2). Then we present the main characteristics of the spatial evolution of knowledge production and scientific collaboration networks among Brazilian municipalities (section 3). The extent of the role played by geographical distance in the spatial network configuration is evaluated by means of a gravity model approach (sections 4 and 5). Finally, some of the main conclusions are discussed (section 6).

## 2. Brazilian Scientific Collaboration Database

Among the mechanisms responsible for the articulation of social relationships in the scientific community, co-authorship networks are particularly significant because they are indicators of knowledge flows among researchers. However, such networks represent only one facet of collaboration. The collaboration process does not necessarily result in coauthored publications, due to the possible rejection of the work by the technical reviewers, to time constraints, or to the cost of submission (Katz and Martin 1997; Hoekman et al. 2010).

Although data relating to accounting for co-authorship in publications are an imperfect indicator, research on scientific collaboration networks typically use such data as a quantitative measure of scientific collaboration (Wang et al. 2005). From the perspective of spatial scientometrics, it becomes necessary to aggregate the co-authorship among individuals into geographical units. Thus, it is possible to elaborate inter-regional scientific collaborations, composed of the observed flow amounts among regions (e.g., municipalities) and measured by counting co-authorship among researchers located in these regions.

The main purpose of this section is to describe the source of information on scientific collaboration (co-authorship), the definition of the spatial unit used, and the characterization of data collecting and accounting procedures, data frequency, and their main limitations.

Co-authorship data were extracted from some available information of the Lattes curriculum vitae (CV), a part of the CNPq Lattes Platform, which consists of a Brazilian information system, deployed and maintained by the Brazilian government to manage information related to researchers, institutions, and research activities across the country (CNPq 2012).[1] The public availability of curriculum information and research groups via the web and the utilization of such information by universities stimulate the correct insertion and veracity of published data, which became the national standard system to the registry of scientific community academic and professional activities. Therefore, the establishment of a real incentive mechanism to fill and correctly update information provided credibility and international recognition to the Lattes system, a successful model to be internationally followed (Lane 2010).

[1] The CV Lattes (CL) system consists of a comprehensive system of curriculum information of researchers, teachers, students, and professionals from all knowledge areas, and has crucial importance in the planning, management, and operation of federal funding agencies, the foundations of science support, universities, and research institutions, mainly to provide reliable information for the analysis of researchers' merit and competence, evaluation of postgraduate programs, and analysis of claims for funding (CNPq 2012).

The CVs are publicly available on the Lattes platform web portal (CNPq 2012). However, although access to individual information is immediate, access to a systematic database is not possible. The effort in gathering information is the main obstacle to the analysis of a large amount of data, thus making it necessary to automate this process. As we shall see, the procedure described below enabled the processing of information from 1,131,912 CVs.[2]

For our purposes, a modified version of ScriptLattes was used to establish links among researchers if there is a shared scientific production among them publicized in their CVs. Basically, the procedure is based on a search of similarities from a direct comparison between the titles of publications registered in the CVs.[3] More precisely, the co-authorship identification and counting were performed from information contained in only four specific fields of the CV: *papers published in journals*, *papers published in annals of congresses*, *published books*, and *chapters of published books*, amounting to the analysis of 7,351,957 distinct academic material published between 1992 and 2009.

After co-authorship identification, the links among researchers were accounted by means of the full-counting process, in which each unit of analysis (authors or regions) receives one unit of collaboration for its participation in publications (Scherngell and Barber 2011). For instance, for a publication among coauthors I, II, and III, located in the regions A, A, and B, respectively, the value 1 is given to the pair (A, A) and the value 2 to the pair (A, B). By symmetry, the pair (B, A) also receives the value 2 (see Figure 1). Alternatively, the fractional counting method performs a weighted count so that the values of the connections between the two regions are divided by the number of connections between the researchers' regions (the co-authorship credit is divided proportionally among the coauthors). More common in citation analysis, this method underestimates the effective impact of inter-regional collaboration, whereas the complete count method overestimates this count. We chose the method of complete count, which is usually utilized in empirical studies on scientific collaboration.

[2] To achieve a large representation of the database, the CLs were tracked through their identification codes. The complete procedure of data mining is described in Digiampietri et al. (2011).
[3] In the social network analysis, each researcher is represented by a node, and the detection of co-authorship relations among them is represented by a connection between nodes (edge).

*<< Insert Figure 1 here >>*

Determining the geographic location of researchers is important in spatial scientometrics and thus deserves special mention.[4] We consider the Brazilian municipalities as our geographical unit of analysis. However, instead of locating the co-authors from their addresses informed in the publications (or with the aid of complementary databases), we used the direct information about the professional addresses of researchers reported in each CV. Initially, a program for the extraction of information about municipal location in the CVs was developed. However, the autonomy given to users in filling the field "professional address" created difficulties, because it revealed problems related to typos, regional abbreviations, and the erroneous attribution of municipalities to their respective states. Thus, a standardization of the municipalities' names and the correct identification of their corresponding states was required, by which means the relationships among the 4,615 Brazilian municipalities were determined.[5]

To allow the differentiation of scientific collaboration patterns, the co-authorship was identified for each major knowledge area: agricultural sciences (AGR), biological sciences (BIO), exact and earth sciences (EXT), humanities (HUM), applied social sciences (SOC), health sciences (SAU), engineering (ENG), and linguistics, letters, and arts (LLA).[6] The extraction of information allowed the association among researchers and the major knowledge areas they declared. As shown in Table 1, about 76.7% of identified researchers were associated with a particular area of knowledge.

*<< Insert Table 1 here >>*

[4] The determination of the spatial unit has several methodological problems, since the scientific networks consist of complex systems of interlacing and rupture of the formal frontiers, and it is hardly a coincidence between the frontiers perceived by researchers and the official administrative boundaries of countries, states, or municipalities. Nevertheless, the inherent arbitrariness in any classification makes usual the utilization of the official spatial units (Frenken et al. 2009).

[5] The examined CVs without any geographic localization information were associated to a fictitious municipality named "undetermined".

[6] In cases of more than one declared knowledge area, we adopted the association between the researcher and all the declared areas. Beyond the cited knowledge area there also exists another area named "Other" consisting of knowledge areas not classified among the eight previous areas.

The association among the researcher, municipality, and knowledge area allowed the development of inter-municipal co-authorship matrices: each cell (*i*, *j*) has the amount of co-authorship among researchers from the municipalities *i* and *j*, respectively.

The information statement about the publication year (contained in the publication complete titles) allowed the annual periodization of co-authorship matrices. Therefore, we consolidated the co-authorship dataset consisting of 210 inter-municipal co-authorship matrices (associated with the total and each particular area, and with the years between 1992 and 2009) with a dimension of 4,615, composed of 10,651,420 elements.[7] We noted that the CVs were associated with 4,615 municipalities, but 3,268 municipalities had no co-authored publications. The matrices could then be reduced to the size of 1,347 elements.[8]

Some characteristics of the data used are worth noting, because they allowed an overcoming of several problems typically arising from the literature. First, the comprehensiveness of the sample used must be highlighted, in terms of both the number of researchers and the extended data collection period, because the volume of data analyzed is much higher than commonly examined.[9]

Second, spatial scientometrics deals with the problem that the collected information about the addresses often refers to research institutes and is not related to authors. This can lead to erroneous association in the case of publications with multiple addresses, because the authors may have multiple affiliations or may have eventually moved to other institutes (Frenken et al. 2009).[10] Such problems are to a certain extent contoured, because the geographical location was obtained from the address information reported by the authors.

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[7] For each matrix, the symmetry implies that the total of distinct entries is given by: $n + (n-1) + (n-2) + \cdots + 2 + 1 = \frac{[n.(n+1)]}{2}$. Thus, for n = 4615 we have 10,651,420 distinct entries.

[8] For more recent years, it is possible that the accounting is underestimated, because it depends on the latest update of CL.

[9] Scherngell and Hu (2011) accounted 758,682 co-authorships in roughly half of Chinese researchers' publications in 2007. Hoekman et al. (2010) accounted 524,155 co-authorships among European regions in 2007.

[10] Researchers in a temporary visit may choose to register their institutes or the funding organizations instead of the effective institute where the research is really conducted. Regarding the research institutes and firms, the headquarters' locations may be registered instead of the subsidiaries' locations where the research was actually executed.

Third, the quality of the source data for Brazilian science analysis is noteworthy, in so far as the vast majority of scientometric studies make use of international databases, which could lead to two main limitations in our particular case. First, these databases have a particular bias for covering journals in English. Thus, its utilization requires the assumption that the journals that are not indexed have only a local or domestic scope and publish their research in the native language. Second, the scientific production coverage in social sciences and humanities is quite low (Hoekman et al. 2010). This situation is due mainly to the intrinsic characteristics of these areas. Their scientific production occurs predominantly in the form of books and chapters in books, and the translation to English is often unfeasible because of the difficulty of getting an accurate translation of specific terms and expressions. Thus, these areas have a bias for publication in the local language. Therefore, the utilization of international databases does not allow a complete evaluation of the Brazilian scientific productivity, because in developing countries the state-of-the-art knowledge is published and publicized by the local journals, a large number of which do not have an international circulation. Moreover, although English is the *lingua franca* of scientific research, the linguistic universalization process still faces many obstacles, and Portuguese is a predominant language in Brazilian journals, mainly in the applied social sciences and humanities areas (Royal Society 2011).

In the face of these peculiarities, the procedure adopted here highlights the comprehensive coverage of the Brazilian scientific publication enabled by the data collection of CVs, since it has allowed co-authorship accounting in the articles published in national circulation journals and scholarly publications under the form of books and chapters in books chapters, resulting in a better evaluation of scientific production in the social sciences and humanities areas. Among the limitations of the procedure, our main restriction is the accounting of domestic co-authorship, i.e., it is not possible to identify and count the collaborations among Brazilian and foreign researchers. Thus, a publication produced together with foreign researchers is accounted only when a collaboration among Brazilian researchers occurs simultaneously.

The inherent nature of the data also imposes some limitations. First, the utilization of address information for the geographic location of researchers is based on the assumption that the registers correspond to the effective location where the research was carried out. Second, it is assumed that the observed geographical location is the researchers' true location throughout the analyzed period.[11] Thus, the data collection structure does not consider a researcher's possible migration across the country. However, these problems do not invalidate our database, because the problems pointed out are, to some extent, contoured or reduced by the large sample size considered.

## 3. Geographic Patterns of Brazilian Scholarly Publication and Collaboration

Approximately 43.2% of the analyzed CVs did not have any information about geographical location. However, such fact should be quantified more accurately by the relative importance of these researchers in scientific activities, i.e., in terms of the number of co-authorships.[12] As shown in Table 2, the loss of information is not negligible, but it does not involve a large loss with respect to the structural analysis of the patterns of scientific production and collaboration.

*<< Insert Table 2 here >>*

The determination of spatial patterns of scientific activity has as a significant characteristic the manner by which the product is allocated among the spatial units, a process frequently permeated by many difficulties, because the association between a publication and a specific location is not amenable to be determined by a direct and unique way.[13] In our work, we adopted the strategy of measuring co-authorship, instead of measuring the total number of effective publications. For each publication co-authored between two researchers from different municipalities, a unit for each municipality involved was accounted, so that the total (two participations) overestimated the actual publication (one publication). Thus, the parsed values do not correspond to total effective publications, but to the absolute total number of coauthoring in publications by researchers associated with each municipality. Although

[11] For instance, the accounting of co-authorship among authors of a publication relating to 1996 is assigned to the municipalities based on the information about the geographic location of the researchers extracted in 2011.
[12] In Brazil, virtually all the people involved in scientific research, both active researchers and graduate students, have a CL. Whereas the first are the most responsible for scientific publication, there are many cases of CL without any information of bibliographic production, a typical situation in the case of graduate students who are just beginning their studies.
[13] The main problem in determining municipal scientific production is the existence of co-authorships among researchers from different municipalities, as it is not possible to directly associate the publication with a single municipality.

fractional accounting[14] seems to be a more intuitive choice at first glance (as a result of maintaining the total number of effective publications), there is consensus that the ranking of the most productive regions does not depend on the accounting method chosen and that the regional efforts in collaborative publications are underestimated by using the fractional accounting method (Osborne and Holland 2009; Grossetti et al. 2013). To improve a spatial analysis of Brazilian scholarly publication (and not a precise quantification of its evolution), we chose to consider the absolute participation in publications as an indicator of the municipal scientific production, in so far as its growth can be associated with an increase in the real production and correlated to an increase of the collaborative profile.

Despite the inter-municipal co-authorship matrices built for each year between 1992 and 2009, six triennia were considered (according to the period used by CAPES in the assessment of Brazilian scientific activities): I: 1992-1994; II: 1995-1997; III: 1998-2000; IV: 2001-2003; V: 2004-2006; VI: 2007-2009. On the one hand, the determination of the optimal time window in scientometric analysis is a subject of debate in the literature, and the utilization of periods between two and five years is predominant. On the other hand, the evaluation model of Brazilian scientific activities in recent decades has been based on the determination of international standards to be pursued by the researchers, which operates as a veritable incentive mechanism for them (Leta 2011).[15]

Figure 2 shows the share of total scholarly publications and the growth rate for each of major knowledge areas. Note that the relative contribution of each area to total production showed no great transformations throughout the period. A rapid growth of the total production over triennia occurred, but with the area growth rates approaching a general trend of slowing down of the total production.

*<< Insert Figure 2 here >>*

[14] In this method, the accounting is given by the relative contribution of each author in a particular publication, i.e., in the case of co-authors from *n* municipalities is allocated the value (1/n) for every link among the involved municipalities.

[15] In the Brazilian case the choice of the triennial time window seems to be quite reasonable, because there are incentives for researchers to try to finish their research efforts made in the determined triennium, transforming them into publications until the end of the period to avoid the situation where the efforts are not valued until the next assessment period.

*<< Insert Table 3 here >>*

As regards the individual analysis, Table 3 presents the top ten municipalities associated with scientific production in Brazil for each triennium. It is important to note that the values correspond to the sum of the scientific publication participations of geographically located researchers and not to the total of effective publication, since a unit was assigned to each author in the co-authorships cases. The values show an enormous spatial heterogeneity of scientific activities across the country, with a higher concentration in the Southeast region. We noticed that 38 municipalities in the Southeast region were among the 50 largest knowledge producers in 2007-2009. Only two municipalities not belonging to this region (Recife/PE and Brasilia/DF) are listed among the leading producers of knowledge.

In general, a small variation occurs among the first municipalities, where the presence of quite populous municipalities and headquarters of public universities (state and federal) predominates, such as São Paulo/SP (USP, UNIFESP), Rio de Janeiro/RJ (UFRJ, UERJ), Porto Alegre/RS (UFRGS), Belo Horizonte/MG (UFMG), Campinas/SP (Unicamp), Curitiba/PR (UFPR), Recife/PE (UFPE), Florianópolis/SC (UFSC), Brasília/DF (UnB), Ribeirão Preto/SP (USP), and São Carlos/SP (USP, UFScar), among others.[16] The small variation among the major producers is expected, since the research centers established in these municipalities are historically consolidated and have an intense activity level and prominent scientific production in the national and international scientific scenarios (Leta et al. 2006).[17] For instance, the city of São Paulo accounts for about 20% of the Brazilian scientific production. During the past decade, the city rose 21 positions in the list of top cities of worldwide knowledge production (Royal Society 2011) and stood out among the world cities that presented an accelerated growth in scientific production and an improvement in the citation pattern (Matthiessen et al. 2010).

[16] Legend: UERJ: Universidade do Estado do Rio de Janeiro; UFMG: Universidade Federal de Minas Gerais; UFPE: Universidade Federal de Pernambuco; UFPR: Universidade Federal do Paraná; UFRGS: Universidade Federal do Rio Grande do Sul; UFRJ: Universidade Federal do Rio de Janeiro; UFSC: Universidade Federal de Santa Catarina; UFSCar: Universidade Federal de São Carlos; UnB: Universidade de Brasília; Unicamp: Universidade Estadual de Campinas; UNIFESP: Universidade Federal de São Paulo; USP: Universidade de São Paulo.

[17] Besides the public universities, several research institutes such as Embrapa (agriculture), Fiocruz (health), INPA (biodiversity), Butantan Institute (biology and biomedicine), and Adolfo Lutz Institute (public health), among others, develop relevant research activities with recognition at national and international scientific scenarios.

The Brazilian spatial heterogeneity highlights the necessity for a geographical decentralization process of scientific research activities across the country, because this process may potentiate the regional development of less privileged areas and allows the targeting of efforts for dealing with important local problems. In this context, it becomes critical to understand how the growth in Brazilian scholarly publication occurred in the geographical space.

Figure 3 presents the municipal scholarly publication in the 1992-1994 and 2007-2009 triennia. Observe that knowledge production is better spatially distributed in the second period.[18] For the 2007-2009 triennium, we presented the structure of existing public university campuses (federal and state) in 2009, where there is a clear association among their locations and municipal scholarly publication.[19]

The finding of a systematic process of spatial deconcentration during the period is confirmed by constructing the localization curves of publication for the 200 most productive municipalities in each triennium (Figure 4). In 1992-1994, 90% of the Brazilian publication was concentrated in only 48 municipalities, whereas this same proportion was distributed in 102 municipalities in 2007-2009. Therefore, according to our *H.1*, there is solid evidence of a spatial decentralization process conjoint with Brazilian publication growth throughout the analyzed period, similar to the pattern observed in other countries, such as Russia, France, Spain, and China, where the development of their scientific production systems seems to follow a spatial deconcentration trend, primarily based on the production growth of the secondary cities, which are characterized by an intermediate level of scientific production (Grossetti et al. 2013).[20] The spatial deconcentration process is common to all knowledge areas, but in different intensities, as observed by the comparison between the localization curves in Figure 5.

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[18] A high number of municipalities have passed from the low production range (11-100) in 1992-1994 to the intermediate production range (101-10,000) in 2007-2009.

[19] Although not shown, we find evidence for spatial deconcentration in the maps of all knowledge areas.

[20] It is noteworthy that the observed process of spatial deconcentration of scientific activity is underestimated due to the accounting of municipal production by means of participation in scientific publications. This method favors the municipalities of greater production because these are involved in a systematic way in scientific collaboration networks (Grossetti et al. 2013). We also note that the generalized process of spatial deconcentration occurred in all knowledge areas until the 2004-2006 triennium, but in the next triennium (2007-2009) there was strong evidence of the deconcentration process slowing down, even its reversion in the cases of agricultural sciences and biological sciences.

*<< Insert Figure 3 here >>*

*<< Insert Figure 4 here >>*

*<< Insert Figure 5 here >>*

The analysis of the inter-regional co-authorship matrices reveals some general trends regarding the evolution of the Brazilian scientific collaboration networks. First, there is a strong upward trend in collaboration, in terms of both the total quantity of inter-municipal and intra-municipal collaborations and their mean values. The amount of scientific collaborations, measured by co-authorships, jumped from 547,249 in the 1992-1994 triennium to 9,445,399 in the 2007-2009 triennium (intra-municipal collaborations increased from 317,810 to 1,037,274; inter-municipal collaborations increased from 229,439 to 8,408,125). In this growth process, the acceleration period in the 2001-2003 and 2004-2007 triennia stands out, being substantial evidence of the primary relevance of domestic collaboration as an engine of the Brazilian publication growth acceleration over time.

Table 4 presents the evolution of the main inter-municipal knowledge flows in Brazil, where the highest observed link is the accounting of 76,716 collaborations among researchers from Campinas/SP and São Paulo/SP in 2007-2009. In general, we observe a systematic location of flows in the Southeast region (similar to the pattern found in the spatial analyses of publication), with the main inter-municipal and intra-municipal links given primarily among the Southeast state capitals and the State of São Paulo municipalities that host traditional universities. Out of this context, there is an intensification of intra-municipal collaboration in Recife/PE, Fortaleza/CE, Goiânia/GO, Brasilia/DF, Viçosa/MG, and Santa Maria/RS, municipalities that also host traditional public universities.

*<< Insert Table 4 here >>*

To facilitate the visualization of knowledge flows across the country, Figure 6 shows maps with the 100 main knowledge flows from the agricultural sciences and health sciences areas for the complete period (1992-2009). The figure highlights the difference among the geographical patterns of collaboration for each major knowledge area.

Finally, the analysis of the evolution of scientific collaboration networks global metrics also allows some interesting results. Figure 7 shows the number of connected municipalities (network size) and the municipality average degree (network integration) in the scientific collaboration of each knowledge area. We observe both the expansion of collaboration networks (with the incorporation of new municipalities to the networks) and the strengthening of network relationships (growth of the municipality average degree) over time, which corroborates totally our hypothesis *H.1*.

*<< Insert Figure 6 here >>*

*<< Insert Figure 7 here >>*

## 4. Spatial Interaction Modeling

The expansion of spatial scientific collaboration networks and the intensification of their relationships motivate the interesting discussion about the role of geographical distance in the determination of interactions among researchers along the national territory.

An accurate evaluation of the effect of a particular proximity form, for instance, geographic proximity, must be reached more accurately by means of a multivariate framework due to the possibility of isolation and control of the other dimensions of proximity effects.[21] In this context, we model the spatial structure of scientific collaboration flows by the spatial interaction model approach,[22] a procedure commonly and properly used in spatial scientometric studies.[23] Basically, the spatial interaction model of the gravity type is characterized by a formal distinction between three kinds of

[21] The usual definition of the dimensions of proximity is presented in Boschma (2005).
[22] The gravity models are fundamental in identifying the sources of regional disparities in phenomena arising from human interactions, as these models allow the verification of the hypothesis that geographic distance is the main responsible or if there are other determinants that explain the observed patterns of interaction.
[23] The gravity models were used to explain the intensity of scientific collaborations among regions in the Netherlands (Ponds et al. 2007), China (Wang et al. 2005; Scherngell and Hu 2011), and Europe (Hoekman et al. 2010).

functions that could explain the variation of inter-regional interactions in a regression model:

$$Y_{ij} = X_{ij} + \varepsilon_{ij} \qquad ; \qquad i,j = 1,\dots,n \tag{1}$$

$$X_{ij} = O_i \,.\, D_j \,.\, S(u_{ij}) \qquad ; \qquad i,j = 1,\dots,n \tag{2}$$

The functions $O_i$ and $D_j$ characterize the interaction regions *i* and *j*, respectively, and could be specified using "power functions" with regard to the classical theory of spatial interaction (Sen and Smith 1995). The traditional specification of the spatial separation term $S(u_{ij})$ occurs by the multivariate exponential functional form. Therefore, the functions take the following forms:[24]

$$O_i = O(o_i, \alpha_1) = o_i^{\alpha_1} \qquad ; \qquad i = 1,\dots,n \tag{3}$$

$$D_j = D(d_j, \alpha_2) = d_j^{\alpha_2} \qquad ; \qquad j = 1,\dots,n \tag{4}$$

$$S(u_{ij}) = S(u_{ij}, \beta) = \exp\left[\sum_{k=1}^{K} \beta_k . u_{ij}^{(k)}\right] \qquad ; \qquad i,j = 1,\dots,n \tag{5}$$

where $o_i$ and $d_j$ are variables that measure the specific characteristics of regions *i* and *j*, respectively, and the variables $u_{ij}^{(k)}$ represent *k* measures of spatial separation between regions *i* and *j*. The terms $\alpha_1$ and $\alpha_2$ are parameters to be estimated in two specifications,[25] and the $\beta_k$ term refers to the set of *k* unknown parameters associated with each of the *k* measures of spatial separation between *i* and *j*. By replacing the specifications in the initial model, we obtain the empirical model to be estimated:

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[24] As our interest lies in measuring the relative importance of the region characteristics of origin and destination and the distance measures on the determination of collaboration flows, we chose the specification of $X_{ij}$ as a general gravity model.

[25] The indeterminacy of the direction of the scientific collaboration flows among regions (interactions are the result of collaborations without direction), the variables of origin and destination are symmetrical, and thus $\alpha_1 = \alpha_2$, where it is expected that the estimates are statistically significant and close to unit. Therefore, the product of $O_i$ and $D_j$ may be simply interpreted as the total number of possible collaborations between the two distinct regions *i* and *j* (Scherngell and Barber 2011).

$$Y_{ij} = \alpha + o_i^{\alpha_1}.\ d_j^{\alpha_2}.\exp\left[\sum_{k=1}^{K}\beta_k.u_{ij}^{(k)}\right] + \varepsilon_{ij} \quad ; \qquad i,j = 1,\dots,n \tag{6}$$

It is significant to notice the nature of co-authorship data, characterized by integers and non-negative values, because it makes inappropriate the typical application of a log-normal specification over the model equation (6) and the subsequent parameter estimation using the traditional ordinary least squares (OLS) method (Long and Freese 2001).[26] However, the deficiencies of the log-normal specification and the strong assumptions required for an OLS application could be contoured by interpreting the model as a count data model and assuming that the data generation process produces only integers and non-negative numbers. From this, it is usual to assume that the amount of collaborations follows a Poisson distribution, given by the following expression:[27]

$$\Pr(Y_{ij} = \gamma_{ij} \mid X_{ij}) = \frac{e^{-\mu_{ij}}.\mu_{ij}^{\gamma_{ij}}}{\gamma_{ij}!}; \qquad i,j = 1,\dots,n; \quad \gamma_{ij} = 0,1,2,\dots \tag{7}$$

where $\mu_{ij}$ represents the set of dependent variables in the empirical model (6):

$$\mu_{ij} = X_{ij} = exp\left[\alpha_0 + \alpha_1.\log(o_i) + \alpha_2.\log(d_j) + \sum_{k=1}^{K}\beta_k.u_{ij}^{(k)}\right] \tag{8}$$

The Poisson distribution function has the statistical property of equidispersion defined by the equality among the conditionals mean and variance.[28] If this hypothesis is not rejected by the observed data, it is possible to assume that such data are generated from a Poisson process, and the specified model could be consistently estimated by the standard maximum likelihood method. Nevertheless, the counting of regional scientific collaborations may deviate from a standard Poisson data generation, because the

[26] Besides the inadequacy of the OLS method, the biggest problem with the previously described procedure is the fact that the data-generating process is too far from the assumption that the count of co-authorships is generated from a log-normal distribution around its mean and with a constant variance (Hoekman et al. 2010).

[27] In general, the family of Poisson models solves the technical shortcomings of OLS, explicitly recognizes the nature of integers and non-negative numbers of the dependent variable, and allows the maximum likelihood estimates of the parameters to be interpreted as elasticities (Winkelmann 2008).

[28] $\mu_{ij} = V[Y_{ij} \mid X_{ij}] = E[Y_{ij} \mid X_{ij}]$

distribution of these values commonly does not satisfy the equidispersion property,[29] a situation typically occasioned by the problem of unobserved heterogeneity once the specified independent variables are not completely able to capture the data heterogeneity by the conditional mean function. The overdispersion leads to biased estimates of the parameters and the invalidity of the usual hypothesis tests because the standard errors are underestimated (Winkelmann 2008; Hilbe 2011).

In this context, a typical alternative of empirical studies on scientific collaboration is the use of a negative binomial model (Hoekman et al. 2010; Scherngell and Barber 2011; Scherngell and Hu 2011), which is able to deal with unobserved heterogeneity by the inclusion of an additional parameter (parameter of heterogeneity) that allows the accommodation of overdispersion on observed data. The expressions of the density of negative binomial distribution and the conditional variance are as follows:[30]

$$\Pr(Y_{ij} = y_{ij} \mid X_{ij}) = \frac{\Gamma(y_{ij} + \alpha^{-1})}{y_{ij}!\,\Gamma(\alpha^{-1})} \cdot \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_{ij}}\right)^{\alpha^{-1}} \cdot \left(\frac{\mu_{ij}}{\alpha^{-1} + \mu_{ij}}\right)^{y_{ij}} \tag{10}$$

$$V[Y_{ij} \mid X_{ij}] = \mu_{ij}(1 + \alpha.\mu_{ij}) \qquad ; \qquad \mu_{ij} = E[Y_{ij} \mid X_{ij}] \tag{11}$$

where $\Gamma(\cdot)$ is the gamma function, and $\alpha$ is the parameter of heterogeneity.[31]

The Poisson model has a particular specification of the negative binomial model concerning the state in which the heterogeneity parameter is equal to zero. Thereby the verification of statistical significance of the parameter heterogeneity estimate $\alpha$ (estimated from the binomial model negative) allows the decision between the two models (Long and Freese 2001).

[29] Unlike other parametric distributions, the disruption of the equidispersion hypothesis is sufficient for violation of the hypothesis of a Poisson data-generating process. Thus, the verification of the presence of overdispersion (conditional variance greater than the conditional mean) is usual in empirical analyses on the appropriate choice of model (Winkelmann 2008; Hilbe 2011).

[30] The expression presented refers to Negbin II specification (Winkelmann 2008, p. 134), which is the most frequently used in empirical research (Hilbe 2011).

[31] Note that a more general form of heterogeneity is allowed (alternative to equality between the mean and conditional variances imposed by the Poisson distribution). Thus, the main element in the specification decision between the two models is the evaluation of presence of unobserved heterogeneity (Winkelmann 2008).

Another problem of specification refers to the excessive number of zeros in the observed data, which may appear as an additional source of unobserved heterogeneity, in so far as the occurrence of zero values could be quite superior to that accommodated by the Poisson and negative binomial models. However, the utilization of the zero-inflated Poisson model (ZIP) and the zero-inflated negative binomial (ZINB) model allows correction of this problem by a structure of the conditional mean that differentiates the zero and positive values (Hilbe 2011).

## 5. Results

The variables of origin ($o_i$) and destination ($d_j$), described in equation 6, were measured by the total scientific publications in each municipality. It is expected that the total of collaborations among researchers of municipalities *i* and *j* ($y_{ij}$) positively depends on the total publications in each municipality, because the higher scientific production of a municipality must imply a larger probability of collaboration.

Regarding the separation variables, two measures were used. First, we constructed a matrix of geographical distance measured by a continuous manner where each element $u_{ij}^{(1)}$ has the calculation of the distance in kilometers (km) between two municipalities *i* and *j*.[32] Distance is expected to play an impediment role in the interactions among researchers, but it is possible that its effect has decreased over time due to the recent process of communication facilitation. Furthermore, a second separation variable was introduced with the purpose of measuring the institutional relationship among the municipalities. Based on the assignment of the value $u_{ij}^{(2)} = 1$ to the municipalities *i* and *j* when both have public university campuses (and zero otherwise), we constructed a matrix that represents the institutional distance among the municipalities.[33] Therefore, the fact that two municipalities possess public universities is expected to increase the probability of scientific collaboration among researchers in these municipalities.

[32] Due to the absence of consolidated data on the distances between the Brazilian municipalities, we opted to measure the shortest distance between them by applying the geodesic distance formula to the data latitude and longitude of the municipality centroids. The intra-municipal distances $u_{ii}^{(1)}$ (the diagonal terms of the distance matrix) were calculated as a function of the municipality area *i* ($A_i$), using the formula of Bröcker (1989): $u_{ii}^{(1)} = \left(\frac{2}{3}\right).\left(\frac{A_i}{\pi}\right)^{0,5}$

[33] The matrix of institutional distance for each triennium results from identification of Brazilian municipalities with public (state or federal) universities campuses in the first year of each triennium analyzed.

A reduced sample of 105 municipalities was utilized for the estimation of the Poisson, negative binomial, ZIP, and ZINB models (corresponding to the set of municipalities related to 77.4% and 87.6% of collaboration and production totals, respectively, in 2007-2009), because the complete matrix of collaborations with 1,347 municipalities presented 97.8% as zero values, an amount as elevated that it would invalidate the estimates. Therefore, the observation of flow collaboration among 105 counties totaled 11,025 observations. Table 5 shows the estimates of the models. As expected, the estimates of the mass terms (origin and destination) are statistically significant and close to 1 for all triennia, an indication of the adequate specification of these models. A statistically significant and positive sign of estimates related to the institutional distance over the triennia is also observed. This result was expected and sustains the fact that two municipalities having public universities increases the probability of scientific collaboration among researchers in these municipalities.

Although the presented results are significant, our main interest lies in estimating the effect of geographic distance on the probability of collaboration. It is observed in Table 5 that these estimates are statistically significant and with a negative sign for all selected triennia, which corroborates the hypothesis that increasing the distance between two researchers reduces the probability of collaboration between them (*H.2*). Nevertheless, the interpretation of the estimates in count models (non-linear) is not as immediate as in the classical linear regression model. Thus, the value found in 2007-2009 (-0.0017769) means that an increase in 100 kilometers (km) of distance between two researchers reduces the probability of collaboration by 16.3% on average. As the effect is not linear, an increase in 300 (600) km of distance reduces the probability of collaboration by 41.3% (65.6%) on average.[34] However, the expected hypothesis (*H.3*) that the effect of geographical distance would have diminished over time has not been corroborated by the results. We obtained cogent evidence that geographical distance still plays a decisive role in the articulation of Brazilian scientific collaboration networks, similar to the result found in Hoekman et al. (2010) for Europe.

[34] The effect on the dependent variable from an increase in the count explanatory variable, in percentage terms (keeping constant the other variables), is calculated from the following expression (Long and Freese 2001): $100.\left(E(y \mid x, x_1k + \delta) - E(y \mid x, x_1k)\right)/\left(E(y \mid x, x_1k)\right) = 100.[\exp(\beta_1 k.\delta] - 1$

Finally, we observe in Figure 8 that the effect of geographic distance on the probability of collaboration is not proportional to the distance in a linear manner. It varies considerably among the scientific collaboration networks of different knowledge areas. For instance, the distancing of 400 km between two researchers reduces by 40% the probability of collaboration if they work in the linguistics, letters, and arts area, whereas the impact reaches 65% in the case of agricultural sciences or exact and earth sciences. According to the figure, distancing two researchers at 100 km causes a 16% reduction on average of the probability of collaboration. The distancing from 400 km reduces by almost half (50%) the probability of collaboration. It is also interesting to note that total proximity (null geographic distance) is associated with verification of 100% probability of collaboration, i.e., the null distance has no impact on the probability of collaboration. It is worth noting, however, that the model excludes this situation, because it always admit some geographical distance between two researchers, even though both are within a single municipality.

*<< Insert Table 5 here >>*

*<< Insert Figure 8 here >>*

## 6. Final remarks

Understanding the spatial patterns of Brazilian scholarly publication and scientific collaboration over six triennia (1992-2009) revealed some important issues. First, we see a swift growth of both production and scientific collaboration in all knowledge areas, but with evidence of slowing down. Second, the geography of production and scientific collaboration across the country is characterized by an intense spatial heterogeneity. There is a systematic concentration of scientific production and knowledge flows in the Southeast and South regions, with prominence of state capitals municipalities. Nevertheless, we found strong evidence of geographical deconcentration associated with the growth process of scientific production.

Considering the role played by geographic distance in articulating scientific collaboration networks, the results highlight its importance in the interaction among the Brazilian researchers; an increase of 100 kilometers between two researchers implies an average reduction of 16% on the probability of collaboration. Finally, we found that the effect of distance varies among the networks of the different major knowledge areas, and there is no evidence that its effect has diminished over time.

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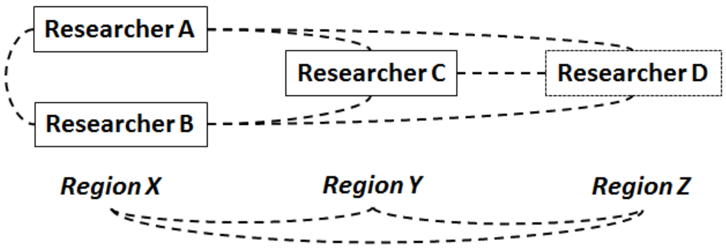
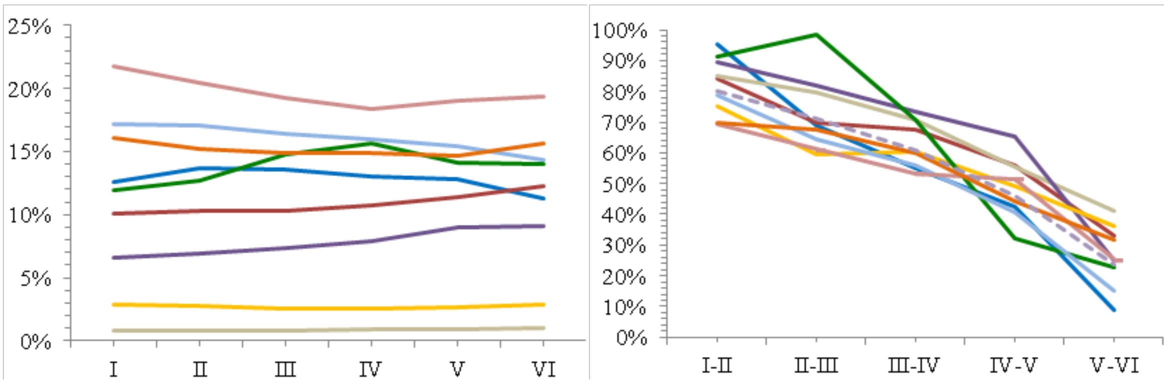
**Figure 1. Full-counting method of inter-regional co-authorships**




| | *Region X* | *Region Y* | *Region Z* |
|---|---|---|---|
| *Region X* | 1 | 2 | 2 |
| *Region Y* | 2 | 0 | 1 |
| *Region Z* | 2 | 1 | 0 |

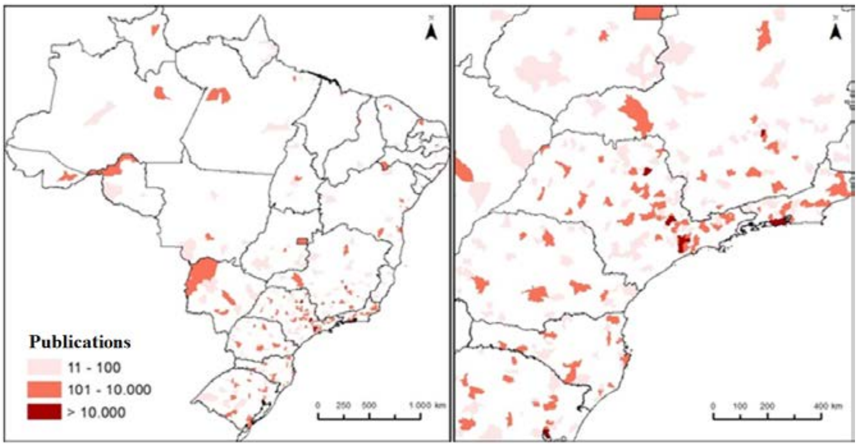
**Figure 2. Participation and growth rates of scholarly publications of knowledge areas**




Triennia: I: 1992-1994; II: 1995-1997; III: 1998-2000; IV: 2001-2003; V: 2004-2006; VI: 2007-2009

**Figure 3. Municipal scholarly publication in Brazil in selected triennia**

**1992-1994**




**2007-2009**

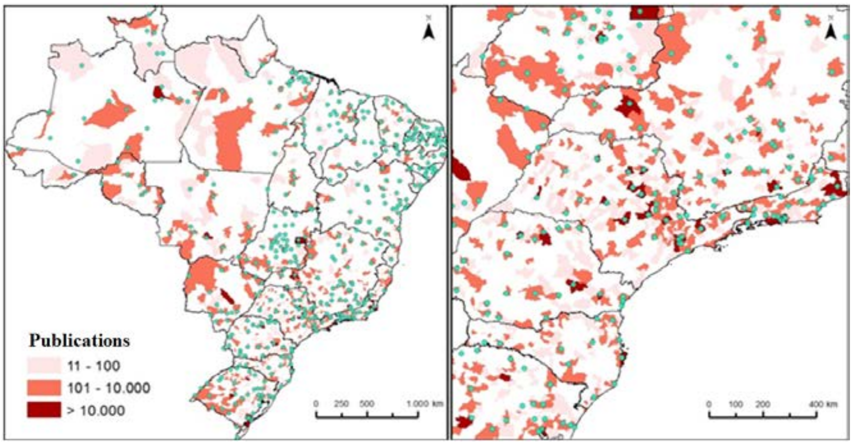


**Figure 4. Evolution of location curves of municipal production**

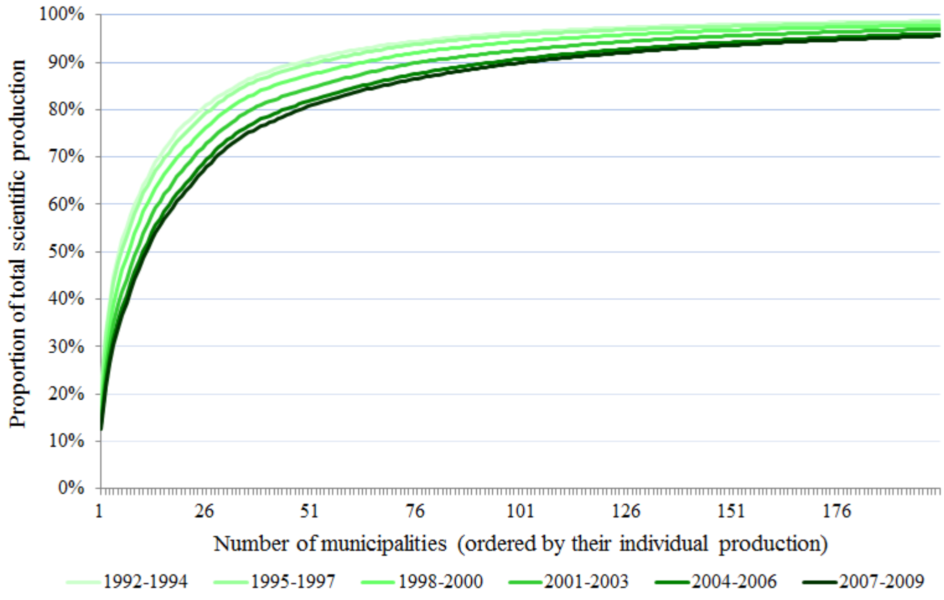


**Figure 5. Evolution of location curves of municipal production, by major knowledge area**

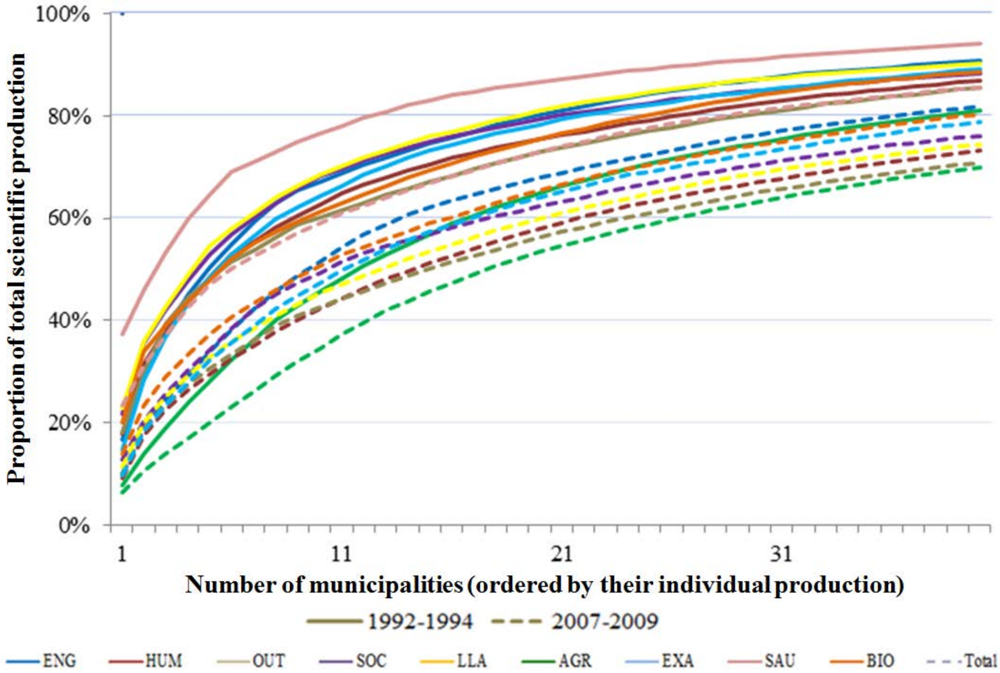
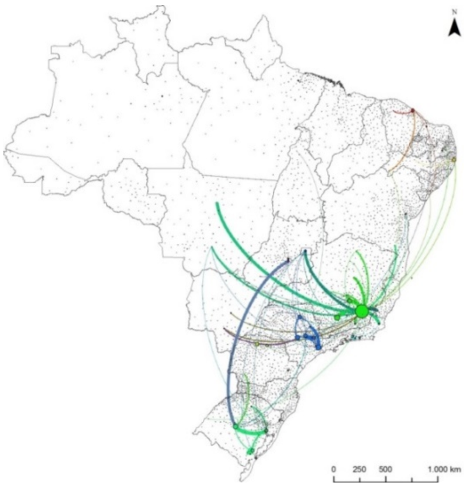


**Figure 6. Main scientific collaboration flows in agricultural sciences and health sciences: 1992-2009**

*Agricultural sciences*




*Health Sciences*

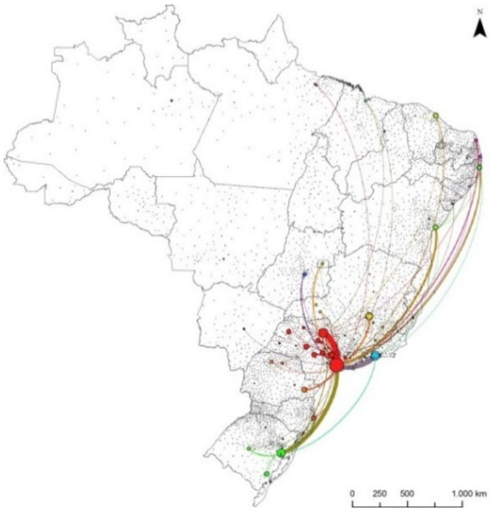


**Figure 7. Evolution of the number of municipalities and average degree in scientific collaboration networks**

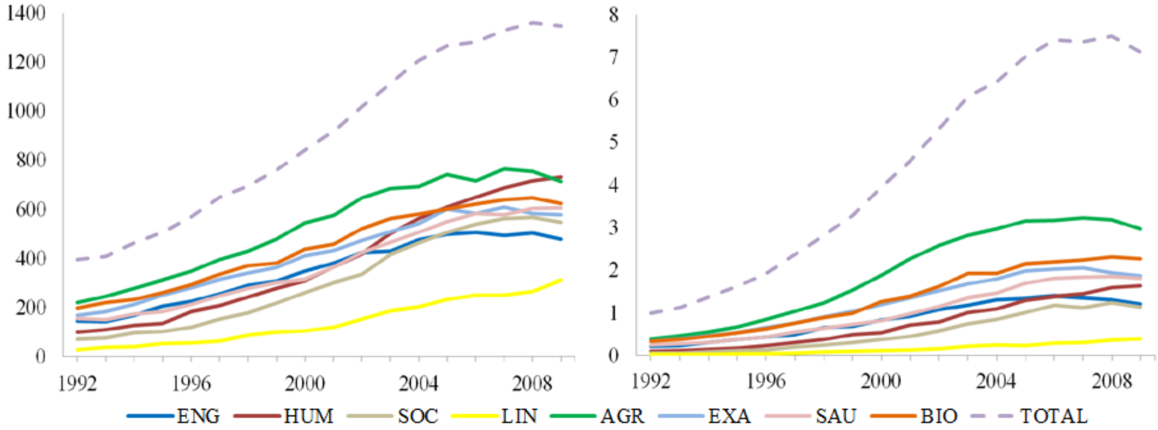


**Figure 8. Effect of geographic distance on the probability of scientific collaboration in 2007-2009**

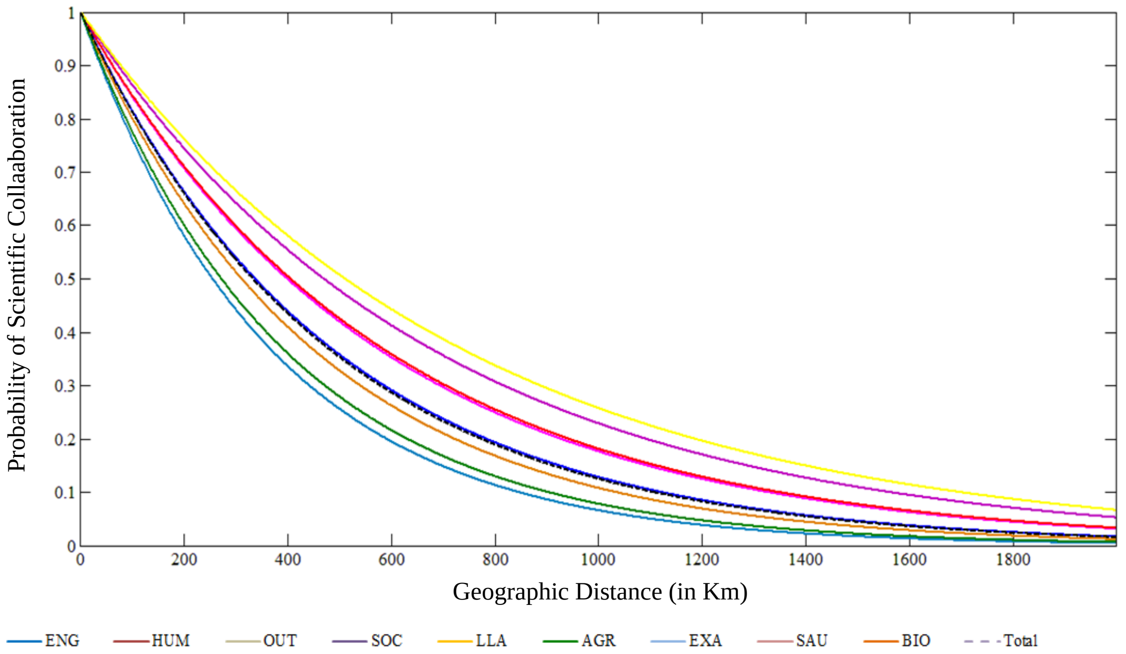


**Table 1. Number of researchers associated to each major area of knowledge**

| | *Total of researchers* | *Researchers associated to a single major area* |
|---|---|---|
| AGR | 92,927 | 59,484 (64.0%) |
| BIO | 128,104 | 65,593 (51.2%) |
| ENG | 120,993 | 70,075 (57.9%) |
| EXT | 176,114 | 102,372 (58.1%) |
| HUM | 270,149 | 141,376 (54.2%) |
| LLA | 99,129 | 53,151 (53.6%) |
| SAL | 272,783 | 206,772 (75.8%) |
| SOC | 264,230 | 164,037 (62.1%) |
| **Total** | **1,131,912** | **868,250 (76.7%)** |

**Table 2. Percentage of production and collaboration without municipal location**

| | *1992-1994* | *1995-1997* | *1998-2000* | *2001-2003* | *2004-2006* | *2007-2009* |
|---|---|---|---|---|---|---|
| *Production* | 7.1% | 7.0% | 7.0% | 7.9% | 9.2% | 10.6% |
| *Collaboration* | 8.1% | 8.0% | 8.8% | 10.2% | 11.9% | 13.5% |

**Table 3. Evolution of top municipalities associated to scholarly publication in Brazil, by all major knowledge areas**

| | *Total* | | *Total* | | *Total* |
|---|---|---|---|---|---|
| **1992-1994** | | **1995-1997** | | **1998-2000** | |
| São Paulo/SP | 71,013 | São Paulo/SP | 112,539 | São Paulo/SP | 161,991 |
| Rio de Janeiro/RJ | 37,100 | Rio de Janeiro/RJ | 64,109 | Rio de Janeiro/RJ | 102,309 |
| Campinas/SP | 20,045 | Porto Alegre/RS | 32,944 | Porto Alegre/RS | 52,446 |
| Porto Alegre/RS | 18,228 | Campinas/SP | 31,283 | Campinas/SP | 47,949 |
| Belo Horizonte/MG | 14,420 | Belo Horizonte/MG | 25,432 | Belo Horizonte/MG | 44,633 |
| Ribeirão Preto/SP | 10,388 | São Carlos/SP | 18,501 | São Carlos/SP | 28,430 |
| São Carlos/SP | 9,034 | Florianópolis/SC | 15,077 | Brasília/DF | 25,925 |
| Brasília/DF | 8,540 | Brasília/DF | 15,054 | Florianópolis/SC | 25,713 |
| Recife/PE | 7,583 | Ribeirão Preto/SP | 14,925 | Recife/PE | 24,500 |
| Florianópolis/SC | 7,334 | Recife/PE | 14,035 | Curitiba/PR | 24,253 |
| **2001-2003** | | **2004-2006** | | **2007-2009** | |
| São Paulo/SP | 226,688 | São Paulo/SP | 313,910 | São Paulo/SP | 352,541 |
| Rio de Janeiro/RJ | 146,139 | Rio de Janeiro/RJ | 193,348 | Rio de Janeiro/RJ | 215,550 |
| Porto Alegre/RS | 82,101 | Porto Alegre/RS | 115,614 | Porto Alegre/RS | 132,622 |
| Belo Horizonte/MG | 64,294 | Campinas/SP | 90,575 | Belo Horizonte/MG | 113,487 |
| Campinas/SP | 64,194 | Belo Horizonte/MG | 89,293 | Campinas/SP | 95,089 |
| Brasília/DF | 43,711 | Curitiba/PR | 61,462 | Curitiba/PR | 75,125 |
| Curitiba/PR | 41,102 | Brasília/DF | 61,003 | Recife/PE | 72,119 |
| São Carlos/SP | 40,628 | Recife/PE | 56,519 | Florianópolis/SC | 70,322 |
| Recife/PE | 38,781 | São Carlos/SP | 56,372 | Brasília/DF | 65,963 |
| Florianópolis/SC | 37,763 | Florianópolis/SC | 54,094 | Ribeirão Preto/SP | 65,252 |

**Table 4. Top inter-municipal scientific collaboration links in Brazil**

| | | | |
|---|---|---|---|
| **1992-1994** | | **1995-1997** | |
| Campinas/SP – São Paulo/SP | 5,682 | Campinas/SP – São Paulo/SP | 9,890 |
| Rio de Janeiro/RJ – São Paulo/SP | 3,883 | Rio de Janeiro/RJ – São Paulo/SP | 9,500 |
| Niterói/RJ – Rio de Janeiro/RJ | 3,793 | Niterói/RJ – Rio de Janeiro/RJ | 7,199 |
| Ribeirão Preto/SP – São Paulo/SP | 2,607 | Porto Alegre/RS – São Paulo/SP | 4,682 |
| Florianópolis/SC – São Paulo/SP | 2,107 | Ribeirão Preto/SP – São Paulo/SP | 4,097 |
| Araraquara/SP – São Paulo/SP | 1,971 | Belo Horizonte/MG – São Paulo/SP | 4,085 |
| Belo Horizonte/MG – São Paulo/SP | 1,765 | São Carlos/SP – São Paulo/SP | 3,984 |
| Porto Alegre/RS – São Paulo/SP | 1,597 | Curitiba/PR – São Paulo/SP | 3,738 |
| Botucatu/SP – São Paulo/SP | 1,457 | S, J, dos Campos/SP – São Paulo/SP | 3,643 |
| **1998-2000** | | **2001-2003** | |
| Ribeirão Preto/SP – São Paulo/SP | 40,727 | Ribeirão Preto/SP – São Paulo/SP | 48,657 |
| Campinas/SP – São Paulo/SP | 30,672 | Campinas/SP – São Paulo/SP | 41,538 |
| Botucatu/SP – São Paulo/SP | 22,587 | Goiânia/GO – Brasília/DF | 37,518 |
| Rio de Janeiro/RJ – São Paulo/SP | 15,839 | Rio de Janeiro/RJ – São Paulo/SP | 36,168 |
| Piracicaba/SP – São Paulo/SP | 14,249 | Niterói/RJ – Rio de Janeiro/RJ | 26,363 |
| Niterói/RJ – Rio de Janeiro/RJ | 12,563 | São Carlos/SP – São Paulo/SP | 22,649 |
| Porto Alegre/RS – São Paulo/SP | 10,139 | Botucatu/SP – São Paulo/SP | 20,108 |
| São Carlos/SP – São Paulo/SP | 9,532 | Santa Maria/RS – Porto Alegre/RS | 17,987 |
| Belo Horizonte/MG – São Paulo/SP | 9,173 | Porto Alegre/RS – São Paulo/SP | 17,057 |
| **2004-2006** | | **2007-2009** | |
| Campinas/SP – São Paulo/SP | 72,698 | Campinas/SP – São Paulo/SP | 76,716 |
| Ribeirão Preto/SP – São Paulo/SP | 72,375 | Ribeirão Preto/SP – São Paulo/SP | 74,078 |
| Rio de Janeiro/RJ – São Paulo/SP | 56,346 | Niterói/RJ – Rio de Janeiro/RJ | 75,224 |
| Niterói/RJ – Rio de Janeiro/RJ | 41,536 | Rio de Janeiro/RJ – São Paulo/SP | 72,500 |
| Goiânia/GO – Brasília/DF | 35,948 | Seropédica/RJ – Rio de Janeiro/RJ | 65,348 |
| Porto Alegre/RS – São Paulo/SP | 33,655 | Porto Alegre/RS – São Paulo/SP | 47,343 |
| Botucatu/SP – São Paulo/SP | 31,152 | Santa Maria/RS – Porto Alegre/RS | 39,252 |
| Santa Maria/RS – Porto Alegre/RS | 30,151 | Santo André/SP – São Paulo/SP | 35,694 |
| São Carlos/SP – São Paulo/SP | 26,444 | Curitiba/PR – São Paulo/SP | 32,692 |

**Table 5. Estimates of Poisson, Negative Binomial, ZIP and ZINB, by major knowledge areas**

| | | *1992-1994* | *1995-1997* | *1998-2000* | *2001-2003* | *2004-2006* | *2007-2009* |
|---|---|---|---|---|---|---|---|
| *Poisson* | Origin – Destination ( ) | 0.82127*** | 0.77950*** | 0.82201*** | 0.78581*** | 0.79731*** | 0.78859*** |
| | | (0.07994) | (0.06784) | (0.06838) | (0.0579629) | (0.0544) | (0.05789) |
| | Geographic Distance ( ) | -0.00195*** | -0.00192*** | -0.00174*** | -0.00153*** | -0.00154*** | -0.00177*** |
| | | (0.0003065) | (0.00025) | (0.00020) | (0.00016) | (0.00015) | (0.00017) |
| | Institucional Distance ( ) | 0.36443*** | 0.41621*** | 0.16094*** | 0.31369*** | 0.29401*** | 0.42871*** |
| | | (0.1769) | (0.14363) | (0.12549) | (0.10611) | (0.10686) | (0.11636) |
| | Constant ( ) | -7.8571*** | -7.2514*** | -7.8745*** | -7.3404*** | -7.5977*** | -7.3564*** |
| | | (1.3045) | (1.1495) | (1.2150) | (1.0601) | (1.0349) | (1.1167) |
| *Negative Binomial* | Origin – Destination ( ) | 0.85214*** | 0.81110*** | 0.74925*** | 0.72744*** | 0.73588*** | 0.64376*** |
| | | (0.02546) | (0.02155) | (0.02520) | (0.02193) | (0.02193) | (0.2798) |
| | Geographic Distance ( ) | -0.00080*** | -0.00086*** | -0.00077*** | -0.00077*** | -0.00083*** | -0.00088*** |
| | | (0.00006) | (0.00004) | (0.00003) | (0.00001) | (0.0004) | (0.0003) |
| | Institucional Distance ( ) | 0.20469*** | 0.1340*** | 0.25959*** | 0.18238*** | 0.07382*** | 0.20527*** |
| | | (0.09759) | (0.07653) | (0.06870) | (0.06341) | (0.05982) | (0.05890) |
| | Constant ( ) | -8.8486*** | -8.2565*** | -7.2966*** | -6.7090*** | -6.8110*** | -5.0248*** |
| | | (0.25238) | (0.24356) | (0.3405) | (0.27935) | (0.31460) | (0.45363) |
| | Heterogeneity ( ) | 6.082* | 5.0892* | 4.5624* | 3.8480* | 3.6189* | 3.7508* |
| | | (0.19144) | (0.1167) | (0.09137) | (0.06647) | (0.06441) | (0.06666) |
| *ZIP* | Origin – Destination ( ) | 0.78074*** | 0.75185*** | 0.80186*** | 0.76963*** | 0.7812*** | 0.77849*** |
| | | (0.00092) | (0.0006) | (0.00041) | (0.00030) | (0.00023) | (0.00020) |
| | Geographic Distance ( ) | -0.0019*** | -0.00188*** | -0.00172*** | -0.00152*** | -0.00153*** | -0.00176*** |
| | | (4.00. ) | (2.59. ) | (1.51. ) | (9.39. ) | (7.19. ) | (6.51. ) |
| | Institucional Distance ( ) | 0.35437*** | 0.39968*** | 0.15269*** | 0.30125*** | 0.28582*** | 0.41281*** |
| | | (0.00334) | (0.00231) | (0.00139) | (0.00100) | (0.00359) | (0.00064) |
| | Constant ( ) | -7.0511*** | -6.0088*** | -7.4462*** | -6.9826*** | -7.300*** | -7.1203*** |
| | | (0.01261) | (0.0088) | (0.00612) | (0.00449) | (0.00359) | (0.00315) |
| | Vuong (ZIP x Poisson) | 17.29*** | 17.07*** | 20.38*** | 20.45*** | 22.92*** | 23.29*** |
| *ZINB* | Origin – Destination ( ) | 0.53245*** | 0.56452*** | 0.57718*** | 0.59961*** | 0.62453*** | 0.56556*** |
| | | (0.1361) | (0.01171) | (0.01119) | (0.01128) | (0.01146) | (0.01171) |
| | Geographic Distance ( ) | -0.00068*** | -0.00075*** | -0.00071*** | -0.00073*** | -0.00077*** | -0.00083*** |
| | | (0.00002) | (0.00002) | (0.00002) | (0.00002) | (0.00010) | (0.00002) |
| | Institucional Distance ( ) | 0.06398*** | 0.03475*** | 0.13497*** | 0.09068*** | 0.02596*** | 0.12313** |
| | | (0.04710) | (0.04102) | (0.03725) | (0.03516) | (0.03403) | (0.03586) |
| | Constant ( ) | -3.4376*** | -3.8969*** | -4.0241*** | -4.2271*** | -4.5902*** | -3.3780*** |
| | | (0.14343) | (0.13169) | (0.13119) | (0.13833) | (0.14309) | (0.14616) |
| | Heterogeneity ( ) | 1.6661* | 1.7251* | 1.8355* | 1.8653* | 1.8665* | 2.0805 |
| | | (0.03434) | (0.02983) | (0.02733) | (0.02503) | (0.02419) | (0.02615) |
| | Vuong (ZINB x Bin. Neg.) | 83.05*** | 99.67*** | 92.65*** | 73.58*** | 61.97*** | 53.86*** |
| | Likelihood Ratio | ZINB*** | ZINB*** | ZINB*** | ZINB*** | ZINB*** | ZINB*** |

Notes: *i)* =11,025 observations; *ii)* standard errors are within parentheses; *iii*) ***, ** and * refer to statistically significant estimates of significance levels of 0.001, 0.01 e 0.05, respectively