UNIVERSIDADE ESTADUAL DE CAMPINAS
INSTITUTO DE ECONOMIA

SARAH CRISTINA RIBEIRO FERREIRA

ACADEMIA AND INDUSTRY INNOVATION: ESSAYS ON PATENTING AT REGIONAL AND INDIVIDUAL LEVEL

INOVAÇÃO NA ACADEMIA E INDÚSTRIA: ENSAIOS SOBRE O PATENTEAMENTO NO NÍVEL REGIONAL E INDIVIDUAL

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Este trabalho corresponde à versão final da dissertação defendida por Sarah Cristina Ribeiro Fereira e orientada pelo Prof. Dr. Renato de Castro Garcia.

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RESUMO

A academia e a indústria têm normas e incentivos diferentes para participar no processo inovativo, refletindo diferentes focos e especializações. Estas diferenças ocorrem em diferentes níveis de análise; assim, esta dissertação tem como objetivo avaliar os determinantes da atividade de patenteamento da Academia e da Indústria nos níveis individual e regional. Para atingir esse objetivo, esta dissertação tem dois ensaios. Primeiro, a partir de uma Função Produção de Conhecimento Regional avalia-se patentes industriais e universitárias separadamente para o Brasil de 1998 a 2018 usando um painel espacial para 133 regiões. Este trabalho visa definir o papel desempenhado pelos diferentes determinantes citados na literatura sobre patenteamento universitário e industrial de inovação em países em desenvolvimento. Os resultados incluem diferenças entre inovações acadêmicas e industriais em relação aos esforços de P&D, aglomeração urbana e conexões de rede. Além disso, há uma grande fonte de heterogeneidade e diferenças em inovação. Esses resultados são essenciais para compreender o real efeito de cada tipo de patente, ajudando a direcionar políticas públicas de inovação específicas para indústrias em desenvolvimento e conhecimento universitário em regiões periféricas. O segundo ensaio analisa o patenteamento em nível individual. Para isso, investiga-se a produtividade dos inventores, com foco nas conexões de trabalho e nos laços relacionais com universidades e empresas, além dos efeitos de vínculos de trabalho simultâneos com universidades e indústria. Por fim, investiga-se quais conexões exercem efeito dominante no desempenho individual. A estimação é realizada a partir de modelo de Pseudo Máxima Verossimilhança de Poisson para contagens de patentes individuais entre 1997 e 2018 com diferentes especificações e efeitos fixos. Os principais resultados mostram que indivíduos com vínculos de trabalho simultâneos com a indústria e a academia podem se beneficiar em alguns contextos. Além disso, os indivíduos que utilizam as suas redes utilizam estas ligações para promover o seu patenteamento individual. Finalmente, indivíduos que conseguem ligar a indústria e a academia através de ligações profissionais e relacionais podem ser mais produtivos, com maior importância para os laços relacionais. Estes resultados permanecem mesmo após vários testes de robustez. Analisamos as implicações dos nossos resultados para as políticas públicas e apresentamos algumas sugestões para futuras agendas de pesquisa sobre este tema.

Palavras-chave: Patentes, Transferência de conhecimento, Universidade e Indústria, Inventores, Regiões.

ABSTRACT

Academia and industry have different norms and incentives to participate in the innovative process, reflecting different focuses and specializations. These differences occur at different analysis levels; thus, this dissertation aims to evaluate the determinants of patenting activity from academia and industry at the individual and regional levels. To accomplish this objective, this dissertation is divided into two essays. First, we use a Regional Knowledge Production function to evaluate industrial and university patents separately for Brazil from 1998 to 2018 using a spatial panel for 133 regions. This work aims to define the role played by the different determinants cited in the literature on university and industrial patenting of innovation in developing countries. The results include differences between academic and industrial innovations regarding R&D efforts, urban agglomeration, and network connections. Additionally, there is a great source of heterogeneity and differences in innovation. These results are essential to understanding the real effect of each type of patent, helping to direct public innovation policies specific to developing industries and university knowledge in peripheral regions. In the second essay, we analyze the patenting activity on an individual level. We analyze inventors' productivity by focusing on working linkages and relational ties with universities and firms. Additionally, we investigate the effects of simultaneous working linkages with universities and industry. Finally, we verify which connections exert a dominant effect on individual performance. We use a Poisson Pseudo Maximum Likelihood model for individual patent counts between 1997 and 2018 with different specifications and fixed effects. Our main results show that individuals with simultaneous working ties with industry and academia can benefit in some contexts. In contrast, individuals who use their networks use these connections to foster innovative productivity. Finally, we find that individuals can connect industry and academia through both working and relational linkages can be more productive, with a major importance for relational ties. These results remain even after several robustness checks. We analyze the implications of our results for public policy and present some suggestions for future research agendas on this topic.

Keywords: Patents, Knowledge Transfer, University and Industry, Inventors, Regions.

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INTRODUCTION

Innovation varies across different dimensions, such as individual characteristics, organizational and institutional attributes, regional dynamics, and the structure of collaboration networks. Furthermore, industries and universities have distinct innovative profiles, each making different contributions to the innovation landscape. In this context, the two essays within this dissertation aim to investigate the factors influencing innovation and differences between academia and industry at regional and individual levels, using patent data from the Brazilian Intellectual Property Office.

The first essay, entitled 'On university patenting and its effects on Regional Knowledge Production Function', analyzes the differences between Industrial and University R&D, Agglomeration, and Knowledge Spillovers in industrial and university patents in Brazilian intermediate regions using a spatial panel regression. The second essay, entitled 'Bridging University and Industry: Learning by Hiring, Collaboration with Gatekeepers and its Effects on Patenting' aims to observe the differences between academic, industrial, and hybrid inventor productivity given their copatenting networks and ability to act as gatekeepers between university and industry using a Poisson Pseudo Maximum Likelihood model.

The subject of this dissertation holds significant importance in the current context of innovation research since the role of universities in innovation is expanding (Martínez; Sterzi, 2019; Anna Villarroya; Menéndez, 2022). Thus, understanding the dynamics of knowledge creation and diffusion that can create innovation is crucial. Moreover, the interplay between academia and industry has significant economic development and competitiveness implications. By examining the determinants of innovation at the regional and individual levels, this dissertation contributes valuable insights to policymakers, researchers, and industry stakeholders. It sheds light on how collaborative efforts between academia and industry can foster innovation, stimulate regional growth, and drive individual productivity.

This dissertation is structured as follows. The first chapter introduces some brief theoretical remarks and the main theoretical foundations that underpin both essays of this dissertation. The second and third chapters present the two essays and their contributions and results.

1 THEORETICAL ASPECTS OF INNOVATION

1.1 INNOVATION

Schumpeter (1934) defined innovation as new combinations of productive means to create new products, new methods of production, new sources of supply, new markets, and new ways to organize a business. Additionally, the author distinguished between innovation and invention. While innovations are motivated by competitive forces to achieve excessive profits, inventions can occur in various settings without any immediate commercialization intent. Thus, for Schumpeter, innovations are novel combinations of knowledge subject to attempts at commercialization (Fagerberg, 2009).

Moreover, it is essential to note that inventions and innovations often exhibit a close and intricate interplay and are hard to distinguish. However, there is a considerable time lag between the two. These lags reflect the different requirements for carrying ideas and translating them into practical applications (Rogers, 1962; Hall; Jaffe; Trajtenberg, 2002). To turn an invention into an innovation, a firm typically must combine several types of knowledge, capabilities, skills, and resources (Fagerberg, 2006).

The process of allocating resources to foster the generation of new ideas is the core of the growth dynamics in modern market economies, as conceived by Schumpeter (1942). The diffusion of innovations can serve as an equalizer within the global economy, offering developing nations the prospect of elevating their living standards. Innovation can also be used for changes new to the local context, even if the contribution to the global knowledge frontier is negligible. Consequently, innovation is as essential for developing countries as for the developed part of the world (Fagerberg; Srholec; Verspagen, 2010).

Since innovation is intrinsically unobservable, patents are often used to measure innovative output (Audretsch; Acs, 1989; Jaffe, 1986; Griliches, 1990). Patents symbolize the outcomes of the inventive process, specifically inventions anticipated to have a business impact. They are a particularly appropriate indicator to capture technological change's proprietary and competitive dimensions. In addition, obtaining patent protection is time-consuming and costly. Consequently, patent applications are typically filed for innovations that, on average, provide benefits that compensate for these costs (Archibugi, 1992).

However, not all inventions are patented, and not all innovation requires intellectual property protection, which may lead to an underestimation of the innovation capacity. Despite these shortcomings, patent data have the advantage of being immediately available, measurable, and comparable both over time and across space (Ascani et al., 2020).

Inventors can use legal protection in countries with patent laws to establish exclusivity in any industry. Consequently, the trajectory of technical progress is influenced by factors beyond the effectiveness of secrecy. Establishing intellectual property rights through patents may incentivize inventors to share information about their patented inventions, facilitating cumulative innovation and learning by doing (Moser, 2013; Furman; Nagler; Watzinger, 2021). Patents effectively serve as an extensive repository of codified knowledge, and patents can constitute a knowledge input for other inventors (Baruffaldi; Simeth, 2020; Scotchmer, 1991).

1.2 INVENTORS

Innovation has great importance for economic development (Fagerberg; Srholec; Verspagen, 2010). Inventors are a primary input of innovation due to their skills and knowledge. Understanding human factors of innovation is essential since the accumulation of knowledge by inventors is the foundation for new ideas (Akcigit et al., 2018).

Many elements within the innovation process, including innovation performance, career preferences, task selections, and collaborative networks, exhibit distinct patterns and trajectories influenced by the individual characteristics of innovators (Toivanen; Väänänen, 2012). Furthermore, inventors are motivated by different reasons, such as financial rewards, reputational and career rewards, or intrinsic satisfaction (Blind; Filipović; Lazina, 2022). Individual productivity is also influenced by personal, working, and regional linkages (Boschma, 2005; Tubiana; Miguelez; Moreno, 2022).

The literature has examined the personal attributes of inventors, with a particular focus on understanding the driving factors of inventors' productivity. In his seminal work, Lotka (1926) formulated the law of productivity for scientific production. According to Lotka's Law, the distribution of scientific contributions among researchers follows a right-skewed distribution. Price (1965) demonstrated that productivity tends to be highly concentrated among a few scientists. Subsequently, (Narin; Breitzman, 1995) demonstrated Lotka's Law in the distribution of patents, revealing that a relatively small cohort of inventors is responsible for ten or more patents, while most inventors account for only a single patent (Hoisl, 2007).

1.3 REGIONS

Innovative activity is geographically concentrated (Feldman; Audretsch, 1999; Moreno; Paci; Usai, 2005). Thus, knowledge spillovers tend to be geographically bounded within the region where the new economic knowledge was created (Feldman; Audretsch, 1999; Jaffe; Trajtenberg; Henderson, 1993; Feldman; Kogler, 2010). Moreover, innovation significantly impacts regional performance and growth, as highlighted by Baumol (2003). Although innovation is not the only factor influencing economic development and performance, it is essential for regional development (Klomp; Roelandt, 2004).

The literature on the geographical determinants of innovation has focused on the role of agglomeration as a pivotal source of innovation. Inspired by Marshall (1920), scholars have stated that agglomeration economies arise from labor-market dynamics, backward and forward linkages of firms, and knowledge spillovers. Labor-market interactions contribute significantly to agglomeration due to the demand for specialized skills and more agile labor markets characterized by higher turnover rates. Additionally, workers gain access to a broader array of potential employers within agglomerated areas (Storper; Venables, 2004).

Moreover, linkages between suppliers of intermediate and final goods facilitate the exchange of critical information among firms. When conducted over longer distances, this process may entail substantial costs or logistical challenges. Knowledge spillovers emerge due to spatial proximity, which enhances the flow of information vital for fostering innovations (Storper; Venables, 2004). In this context, knowledge spillovers primarily occur among firms operating within the same industry, whereas intraindustry knowledge spillovers are commonly referred to as localization or specialization externalities (Panne, 2004).

Jacobs (1969) argued that knowledge can spillover into complementary sectors since ideas originating in one industry can find valuable applications in other related industries. The exchange of such complementary knowledge among diverse firms and economic agents enhances innovation's search and experimentation process. Therefore, a locally diversified production structure fosters increased returns and enhances urbanization or diversification externalities (Panne, 2004).

In addition, Duranton and Puga (2004) identified sharing, matching, and learning as the primary drivers of agglomeration. The authors argue that firms and individuals benefit from sharing indivisible resources and facilities, the advantages stemming from diversity, and the gains from individual specialization. Agglomeration further improves the quality of matches between individuals and firms, increasing the likelihood of successful matches and mitigating problems. Last, agglomeration economies play a pivotal role in facilitating the processes of knowledge generation, diffusion, and accumulation.

In addition to agglomeration, Crescenzi, Rodríguez-Pose, and Storper (2007) listed the quantity and quality of innovation inputs and the innovative infrastructure as critical factors of regional innovativeness. The authors also highlight the importance of resources allocated to innovative activity, a substantial R&D workforce, and institutions and policies governing new technologies' invention, development, and adoption. These factors directly shape innovative performance and lead to different patterns of innovation spatial organization.

1.4 INNOVATION AND THE ROLE OF INDUSTRIES AND UNIVERSITIES

Universities have an established role in conducting research. However, this role expanded, making them innovation centers through collaborative efforts with public and private research entities and institutes (Martínez; Sterzi, 2019; Anna Villarroya; Menéndez, 2022). Over recent decades, the university's function as a primary source of new scientific and technological knowledge has become more critical due to rising knowledge requirements in modern economies (Mowery; Sampat, 2006; Cohen; Nelson; Walsh, 2002; Klevorick et al., 1995). Consequently, the knowledge generated in universities has the potential to foster social and technological development, elevating the technological standards within local industries (Guerrero; Cunningham; Urbano, 2015).

While usually characterized as an "ivory tower" primarily dedicated to pursuing knowledge for its intrinsic value, the university has increasingly assumed a more active role. The university has emerged as a relevant actor in supporting economic and technological development processes, particularly as a driver for promoting catch-up in developing countries. In addition, the university can catalyze changes driven by knowledge-intensive technologies (Mowery; Nelson, et al., 2004; Garcia; Suzigan, 2021).

Due to this change, several governments have initiated efforts to promote stronger ties between academic research conducted at universities and business innovation (Garcia; Suzigan, 2021). Some countries have even created legislation to incentivize collaboration between research institutions and companies. The Bayh-Dole Act is widely recognized for intensifying university-business relations in the United States (Mowery; Nelson, et al., 2001, 2004). Similarly, the Brazilian Innovation Law introduced a novel legal framework for innovation, establishing mechanisms to foster interaction between research institutions and businesses (Póvoa; Rapini, 2010).

In addition, the proximity of academic research institutions and industry is an essential source of positive knowledge externalities. Personal networks of academic and industry researchers, university spin-off companies, and graduate students are the main essential channels for the diffusion of new knowledge from the university to local firms. Moreover, the proximity of academic research institutions and industry is an essential source of positive knowledge externalities. Personal networks of academic and industry researchers, university spin-off companies, and graduate students are the main essential channels for the diffusion of new knowledge from the university to local firms (Varga, 2000).

Furthermore, universities create a pool of young scientists, entrepreneurs, and skilled laborers who contribute significantly to the local labor market. Intellectual human capital tends to concentrate close to universities that carry out high-quality scientific research (Zucker; Darby; Brewer, 1998). Additionally, universities engage in research activities within specific domains and technologies that can foster business innovation. Workforce training and academic research constitute foundational pillars underpinning business innovation across various sectors in numerous countries (Nelson, 1996). Finally, universities that produce scientific and technological knowledge close to the state of the art tend to attract more renowned scientists, students, and firms that aim to access human and scientific capital (Florida, 1999).

Arguably, the focus on innovation in the university could generate problems from the university's perspective. The economic benefits of collaboration could shift academic researchers' focus away from research and undermine academic productivity. Moreover, the focus on industrial research could weaken researchers' commitment to scientific principles, encouraging adverse effects such as data retention, secrecy, and publication delay, as industrial competition requires intellectual property and limited exchange of information and knowledge (Partha; David, 1994).

Nonetheless, Breschi, Lissoni, and Montobbio (2008) found that academic inventors, specifically university professors listed as inventors on at least one patent application, exhibit a higher publication rate and produce greater quality research than their nonpatenting peers. These findings suggest that pursuing innovation can complement academic output. Additionally, findings from Garcia, Araujo, et al. (2019) indicate that scientists engaged in long-term collaborations with industry partners demonstrate better scientific performance. Thus, long-term partnerships between universities and firms can positively influence academic productivity.

2 ON UNIVERSITY PATENTING AND ITS EFFECTS ON REGIONAL KNOWLEDGE PRODUCTION FUNCTION

2.1 INTRODUCTION

Almost 35 years ago, Jaffe (1989) published his seminal article “Real Effects of Academic Research”, introducing the Regional Knowledge Production Function (RKPF) as an empirical framework to analyze the effect of university research on regional innovation. The author sought to understand the effect of the local innovation ecosystem on regional innovation using patents as a proxy for innovation output. In that context, there was no strong empirical evidence regarding the role performed by universities in fostering industrial innovation. Jaffe’s (1989) paper laid the foundation for a new branch of literature on regional innovation that persisted, and to date, it guides empirical studies that help policy-makers and researchers understand the relationship between local research ecosystems and innovation.

However, over time, universities have been engaging more in applied knowledge and have increased their patenting levels[1]. University patents currently represent a substantial share of the total patent count across several countries[2]. Notably, universities differ in their motivation to patent and the type of knowledge generated compared to industry (Baldini; Grimaldi; Sobrero, 2007). Thus, to achieve Jaffe’s original aim of assessing regional innovation, it is necessary to consider the relevance of university patents and their specificities.

Therefore, we aim to evaluate how industrial and university patents are differently shaped by the regional drivers proposed by the RKPF framework. To achieve this, we estimate an RKPF spatial panel for 133 Brazilian regions between 2003 and 2018, distinguishing between industrial and university patents. By focusing on industrial patents, we ensure the examination of commercial innovation as originally proposed by Jaffe and enable comparisons with previous studies that consider total patents. Although our study is primarily empirical, we also present arguments to explain the differences in determinants affecting industrial and university regional patenting.

There is a growing literature on patent singularities dealing with industrial (Adams, 2002) and university patents (Lissoni, 2012) and even some studies that analyze both industrial and university patents (Cowan; Zinovyeva, 2013). However, there is a gap in the literature regarding the understanding of the different determinants of industrial and university regional innovation. Thus, the main contribution of our study is to provide new empirical evidence regarding the different drivers of industrial and university patenting, providing insights into the regional

[1] In many countries, this change is associated with law and regulation changes such as the Bayh Dole Act in the U.S. (Mowery; Nelson, et al., 2001) and the Innovation Law in Brazil (Póvoa; Rapini, 2010). These laws provided universities with resources, simplified procedures, and facilitated the conditions of intellectual protection of university inventions.

[2] University patenting increased in several countries such as EU countries, UK or the USA (Martínez; Sterzi, 2019; Anna Villarroya; Menéndez, 2022)

determinants of commercial innovation. In addition, comparing the results of industrial and university patent estimations, we can indicate how the presence of university patents in the previous RKPF results could be biased and misguide innovation policy and research agenda. Despite the empirical nature of our study, we believe that our findings can help to understand the theoretical arguments regarding the regional determinants of university and industrial patenting.

Our results reveal distinct determinants of regional innovation for university and industrial patents. We find that local industrial R&D is associated with a higher number of patents in all cases, whereas local university R&D exhibits a positive association only for university patenting. We also find positive effects for agglomeration, regional coinventor networks, and spatial spillovers. Together, our results indicate that the separation between university and industrial patents ensures a better estimation of local innovation determinants using RKPF. We perform several robustness checks to ensure the quality of our estimations. We also present some policy implications and a research agenda related to these results.

This paper is structured as follows. The next section provides a conceptual background on the RKPF and discusses the main theoretical reason for expecting differences in the regional determinants of university and industry patenting. The third section offers an overview of the Brazilian regional innovation system. Next, we provide a brief description of our model and the data employed in our analysis. Section 5 presents the results of our econometric exercises, followed by robustness checks. The final section concludes with remarks, limitations, and implications for innovation policies, along with suggestions for future research.

2.2 THE REGIONAL KNOWLEDGE PRODUCTION FUNCTION

In his seminal article, Jaffe (1989) established what became known as the Regional Knowledge Production Function (RKPF) relating regional innovative inputs — industrial and university R&D investment — to local new knowledge outputs measured by patents. The author found that university research is related to local innovation. This had major implications since improving the university research system could increase local innovation by attracting industrial R&D, augmenting its productivity, and generating new patents (Varga; Horváth, 2015).

Historically, universities have often played a supporting role in innovation in firms, whether by training skilled workers, providing research infrastructure, or generating new knowledge. However, the transfer of knowledge between universities and industry with a focus on innovation has increased in recent years. This process has been the subject of extensive studies that sought to analyze formal university-industry cooperation and qualified personnel training, indirect relations such as contacts, talks and meetings, and informal channels as local knowledge spillovers (Perkmann et al., 2013; Póvoa; Rapini, 2010; Barra; Maietta; Zotti, 2019).

In addition to supporting innovation in firms, universities have been engaging more in applied sciences and assuming a direct role in innovation. The university organizational culture moved toward a positive framing of market-related innovations, using inventive activity as patenting as a criterion for academic staff hiring and promotion and as a source of academic prestige (Baldini; Grimaldi; Sobrero, 2007). Therefore, the role played by universities in regional innovation is associated with greater participation in patenting, which implies a greater percentage of university patents, greater participation in copatenting networks, and a different technological profile. Despite this, the empirical literature that uses the RKPF has not yet addressed heterogeneity in industrial and university patents.

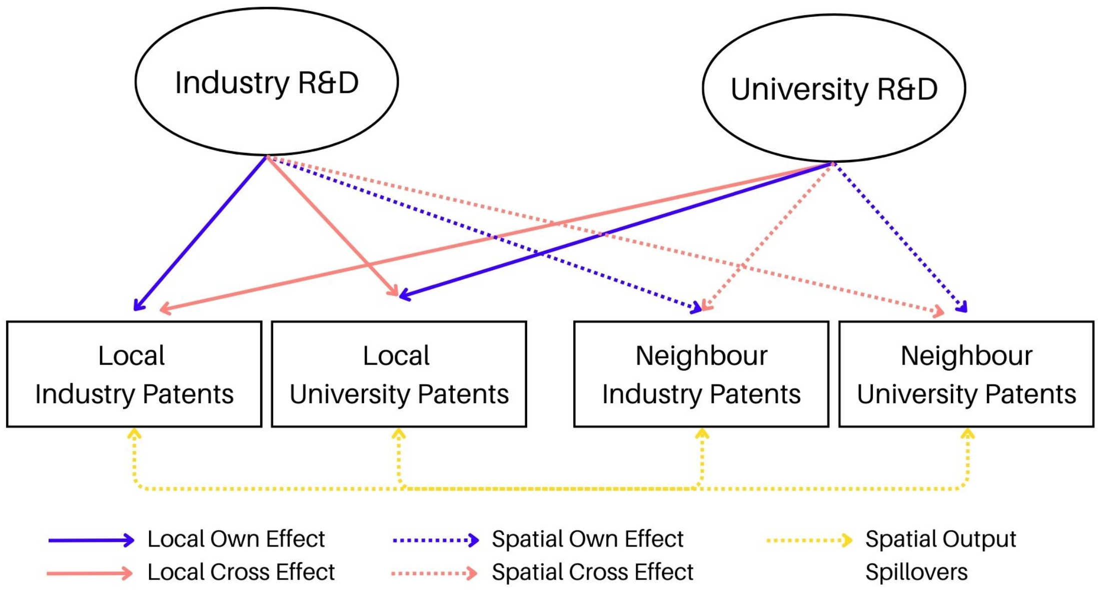
2.2.1 UNIVERSITY AND INDUSTRY: DIFFERENCES AND SIMILARITIES

RKPF models use total patents as an innovation output and commonly include two separate variables for industrial and university R&D since they are the main regional innovation inputs (Acs; Anselin; Varga, 2002; Gonçalves; Oliveira; Almeida, 2020). The model specification progressively included other factors, such as agglomeration, coinventor networks, and knowledge spillovers, as regional innovation determinants. Agglomeration terms are used to assess innovation gains in denser areas (Carlino; Kerr, 2015; Crescenzi; Rodriguez-Pose; Storper, 2012). Moreover, relationships between inventors are important sources of knowledge for innovation. Regions with more interconnected inventors can enhance their innovative performance; thus, it is common to control for regional copatenting networks (De Noni; Ganzaroli; Orsi, 2017; Miguélez; Moreno, 2013). Furthermore, knowledge tends to spillover between neighboring regions. These spillovers are usually measured using spatial autocorrelation models (Acs; Anselin; Varga, 2002; Gonçalves; Almeida, 2009). Therefore, these empirical models consider different dimensions of analysis for local innovation that may have different effects on industrial or university patenting. In this sense, we seek to theoretically delve into the possible similarities and differences of these dimensions' effects on industrial and university regional patenting.

A result of differentiating industrial and university patenting in a regional analysis is the need to separate the R&D effects (Figure 2.1). First, it is necessary to consider the R&D effect from local firms and universities on industrial and university local patent counts, which we call local R&D own-effect. The literature points to a direct and positive reason for local R&D's own-effects on patenting, since a firm or university performing R&D may patent the innovation output result itself. In addition, there are local knowledge spillover positive externalities that can be absorbed by other local firms or universities, generating more patents (Kantor; Whalley, 2014).

Second, there are also indirect effects arising from local university R&D to industrial patents and from industrial R&D to university patents in the same region, which we call local R&D cross-effects. We can find evidence in the literature for both effects; however, the empirical evidence is stronger for the role played by local university research on firms' innovation. Jaffe (1989) considered university R&D a main input to local firms' innovation. This relation can occur through multiple channels, such as the association between basic and applied research, university-industry collaboration, local knowledge spillovers, and staff training (Perkmann et al., 2013; Zucker; Darby; Brewer, 1998). Firms' R&D effect on university patents is a much more recent topic, and Karlsson and Andersson (2009) pointed out two possible channels for a positive effect: industry might use part of their R&D funds to finance local universities' R&D, and universities in regions with a certain level of industrial R&D might find it easier to attract R&D funds due to cooperation with industry.

Figure 2.1 – R&D effects on patenting



Source: Own elaboration

Concerning agglomeration, there are clear benefits for local industrial innovation in denser areas (Carlino; Kerr, 2015; Autant-Bernard; Lesage, 2011; Moretti, 2021). However, these agglomeration effects may affect industry and university patents differently. Indeed, university location is often associated with public policies (Rosenthal; Strange, 2004). Moreover, there is evidence that universities in more agglomerated regions could take advantage of the best conditions to generate, accumulate, and disseminate knowledge arising from knowledge-based agglomeration benefits (Kantor; Whalley, 2014).

Regional coinventor networks are very relevant for the diffusion of knowledge and are fundamental elements for local innovation cohesion (Strumsky; Thill, 2013). Furthermore, Ejermo and Karlsson (2006) pointed out that invention networks are closely linked to university and private R&D structures in a region and can help to overcome local limitations and allow more and better innovations. In this sense, interregional coinventor network connections allow more innovation in both environments. However, the incentives and norms in industry and universities imply different collaboration patterns. For instance, universities are expected to be more open to collaboration than industry since academics have larger inventor communities (Forti; Franzoni; Sobrero, 2013).

Concerning interregional innovation dynamics, there is plenty of theoretical motivation and empirical evidence for the occurrence of spatial heterogeneity and autocorrelation in both cases, but it is not clear whether the same spatial effect will occur for industrial and university patents (Autant-Bernard; LeSage, 2019).

Some studies separate industrial and university R&D local and spatial effects, considering university and industrial patents together (Autant-Bernard; LeSage, 2019). To the best of our knowledge, there are no studies that separate university and industrial patents and consider the own and cross-effects of R&D spatial spillovers. In this sense, there is little theoretical basis to predict *ex-ante* spatial spillover results, but it is possible to recognize that a positive result can indicate synergies, as postulated by Camagni, Capello, and Caragliu (2016) for borrowed size and borrowed functions from neighboring regions. On the other hand, a negative result can indicate shadow effects from neighbors on local innovation (Yang et al., 2022).

Regarding agglomeration spatial effects, Camagni, Capello, and Caragliu (2016) argue that a region can benefit from proximity in different ways. Regions benefit from borrowed size by exploiting the larger neighboring markets for their firms and can borrow functions from other localities in the same regional context. However, Adams (2002) argues that the knowledge that flows among academics is more attached to the local context, and therefore, the academic spillover benefits are more local, reducing potential agglomeration advantages from neighboring regions for university patenting.

In a sense, there are multiple theoretical motivations to assess how the regional innovation ecosystem affects industrial and university patenting differently and the effect of this difference in RKPF. We seek to evaluate these determinants using an RKPF model for Brazil with a longer and more recent panel ($2003 - 2018$).

2.3 BRAZILIAN REGIONAL PATENTING

Patenting activity has been growing in Brazil, not only in patent counts but also in their quality and inventor network density. The annual number of patents filed by Brazilian inventors grew 2.69% yearly between 2003 and 2018. This growth occurred for both industrial and university patents; however, it was more expressive in the latter. In 2003, these patents accounted for 6.7% of all patents filed in Brazil. In 2018, this share rose to 30.1%, closer to countries with more developed university systems (Martínez; Sterzi, 2019).

Table 2.1 presents the top 10 regions by industrial and university patents per capita. The top industrial and academic regions show, on average, approximately double the number of patents per capita compared to Brazil. We can only see a weak association among regions since only 4 of 10 regions appear in both ranks: Florianopolis, Curitiba, Araraquara, and Campinas. Indeed, the Pearson correlation between industry and university patents per capita in Brazilian regions is only 0.48[3]. This pattern could be related to a weak relationship between industrial and academic innovation and to regional specialization in both cases. Three of the top industrial

[3] The differences present in the colocation of industrial and university patents may be associated with the fact that Brazil is a country with continental dimensions, similar to Li and Xing (2020) and Rudkin, He, and Chen (2020) findings for China.

regions have virtually no university patents. A similar trend occurs from a university point of view since more than half of the patents in Pelotas, Joao Pessoa, Campina Grande, and Aracaju are from universities.

Regarding geographical distribution, it is noted that all top regions for industry patents are in the South and Southeast regions. For university patents, there are three in the Northeast, pointing to a less concentrated spatial distribution (Figure 2.1). Industry activity is strongly concentrated in the South–Southeast region, the main Brazilian university research centers are public, and their locations are associated with industrial and technological policy. These stylized facts help to illustrate the spatial dynamics of innovation and reinforce the need to address this heterogeneity using spatial models[4].

In summary, in Brazil, there is a relevant colocation between industrial and university innovation. However, there are also different regional specializations with locations more focused on industrial or university patents. This heterogeneous distribution also occurs in other countries and is consistent with Brazil's continental dimensions. Therefore, our case presents a heterogeneous spatial and innovative structure, similar to other countries and regions, which reinforces the relevance of this study.

Table 2.1 – Top 10 innovative regions for industries and universities (2003-2018)

	Region	Industry Patents	%		Region	University Patents	%
	Brazil Average	27.2	84%		Brazil Average	5.1	16%
S	Joinville	130.5	98%	SE	Araraquara	31.8	31%
S	Caxias do Sul	92.2	91%	S	Pelotas	19.7	62%
S	Florianopolis	80.2	82%	S	Florianopolis	17.1	18%
S	Curitiba	74.3	85%	SE	Campinas	16.4	20%
SE	Araraquara	69.4	69%	NE	Joao Pessoa	15.0	56%
SE	Campinas	66.0	80%	SE	Belo Horizonte	14.0	22%
SE	São Paulo	62.1	94%	NE	Campina Grande	13.7	71%
S	Blumenau	57.3	98%	S	Curitiba	13.4	15%
S	Chapecó	55.4	97%	SE	Uberlandia	12.7	45%
S	Porto Alegre	51.2	84%	NE	Aracaju	11.8	64%

Source: Own elaboration
Notes: The Pearson correlation of industry and university patents regional distribution is 0.4798. S stands for the South region, SE for the Southeast, and NE for the Northeast region.

2.4 MODEL, METHODOLOGY AND DATA

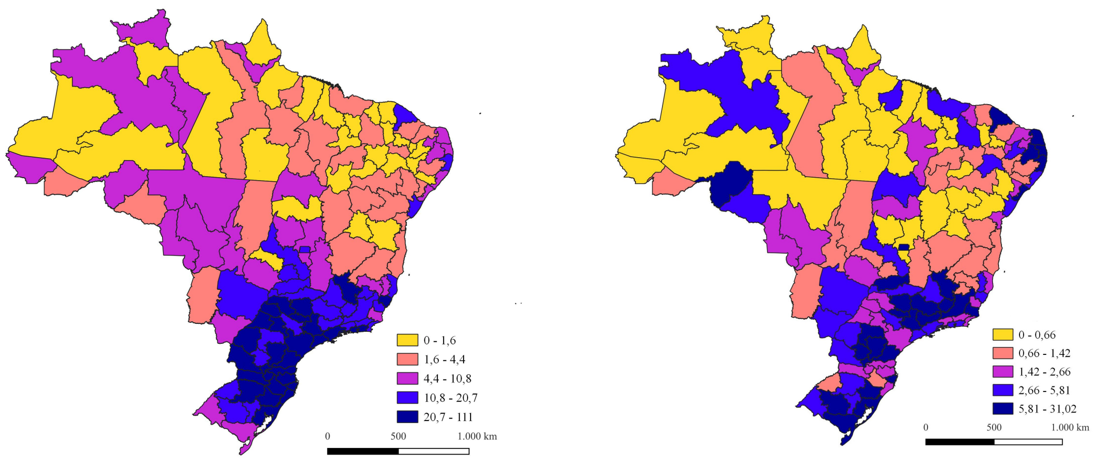
In his seminal article, Jaffe (1989) established the RKPF. The author found that regional innovation measured by patents was mainly associated with industrial and university R&D. Since this study, there has been great interest in assessing the determinants of local innovation. The literature on RKPF often estimates an equation that can be expressed as:

$$I_{r,t} = g(\beta_1 \ R\&D_{r,t-1} + \beta_2 X_{r,t-1} + \beta_3 W R\&D_{r,t-1} + \beta_4 W X_{r,t-1} + u_t) \quad (1)$$

[4] We also performed the Moran I index for University and Industrial Patents. Moran I is always statistically significant, rejecting the null hypothesis of zero spatial correlation

Figure 2.2 – University and industrial patents per 100,000 inhabitants by intermediate region (2003-2018)

(a) Industrial patents (b) University patents



Source: Own elaboration

where I is the regional innovation output intensity, often measured using patents of a region r at time t. g is a function, often assumed to be Cobb-Douglas (Charlot; Crescenzi; Musolesi, 2015). $R\&D$ is the vector for R&D efforts in region r in period $t-1$, which is the main input for innovation; X represents a vector for the observable regional characteristics; $WR\&D$ and WX are the spatially lagged R&D and observable characteristics, respectively; and u represents all unobservable factors that influence regional innovative performance.

Studies progressively included more regional controls in the RKPF (Audretsch; Feldman, 1996) and adopted spatial econometric models (Acs; Anselin; Varga, 2002; Ó hUallacháin; Leslie, 2007). Among these elements, it is worth highlighting agglomeration effects (Carlino; Kerr, 2015; Crescenzi; Rodriguez-Pose; Storper, 2012), regional copatent networks (De Noni; Ganzaroli; Orsi, 2017; Miguélez; Moreno, 2013) and interregional spillovers (Charlot; Crescenzi; Musolesi, 2015).

Finally, it is important to consider that innovative activity is concentrated in space. However, knowledge can flow between regions through formal activities such as collaborative research and consulting; they also include informal activities such as providing advice and networking and even unintended flows in the form of knowledge spillovers. The literature has been able to quantify knowledge spillovers, measure their spatial extent, and explore the underlying mechanisms (Autant-Bernard; Lesage, 2011; Perkmann et al., 2013).

2.4.1 ECONOMETRIC MODEL

Interregional knowledge flows are fundamental to assessing regional innovation spatial dynamics. Therefore, we estimate an RKPF using patents per capita as our dependent variable and regional innovation effort and socioeconomic context as our independent variables. The panel has 133 regions, and the periods are aggregated into 15 moving average triennials. We use the following spatial Durbin model (SDM)[5]:

$$I_{r,t} = \eta W I_{r,t-1} + \beta_1 R\&D_{r,t-1} + \beta_2 X_{r,t-1} + \beta_3 W R\&D_{r,t-1} \beta_4 W X_{r,t-1} + \beta_5 Z_{r,t-1} + \phi_r + u_t \quad (2)$$

where $I_{r,t}$ is the per capita patent count in a given region r at period t. Since we are estimating a spatial model, W is the spatial weight matrix and η accounts for the spatial autocorrelation. The $R\&D_{r,t-1}$ vector indicates the local innovative effort, the $X_{r,t-1}$ vector indicates agglomeration, and the $Z_{r,t-1}$ vector indicates the copatent networks[6], in addition to controls. We apply a time-lagged structure for our independent variables for two main reasons. First, it takes time to generate innovation outputs (Hall; Jaffe; Trajtenberg, 2002). Second, implementing a lag structure may also be useful to address potential endogeneity issues in a given region. We also add fixed effects for regions (ϕ_t) to control for regional unobserved characteristics (Elhorst, 2014).

Regarding our spatial weight matrix, W is a normalized inverse distance spatial weight matrix with a 500-kilometer cutoff, which was selected by the Akaike information criteria test following Kubara and Kopczewska (2023). We also use an alternative formulation in which spatial correlations in both the observation and error components have the same spatial effect parameter (Kapoor; Kelejian; Prucha, 2007).

In models containing spatial lags, the interpretation of the parameters becomes richer and more complex. Models such as SDM include dependent and independent variable spatial spillovers from neighboring regions. The results incorporate the effect of feedback loops where observation i affects observation j and observation j also affects observation i as well as longer paths that might go indirectly from and back to i through other regions (LeSage; Pace, 2009). Since the estimated coefficients cannot be interpreted as elasticities or partial derivatives, they do not have a direct economic interpretation. Thus, they must be separated into direct effects, based on their partial derivative, indirect effects, representing spatial spillovers corresponding to cross partial derivatives and the total effects that aggregate both (Autant-Bernard; Lesage, 2011).

Additionally, it is common for RKPF models that present spatial autocorrelation of the dependent/independent variables to report not only the estimated coefficients but also the total effects resulting from the estimates (Autant-Bernard; Lesage, 2011). Furthermore, from the

[5] As for the conceptual reasons, the existence of spatial spillovers is well established in the RKPF literature. The SDM specification captures different spatial spillover sources and neighboring dynamics (in which there is spatial feedback from region r to the dependent variable of its neighboring regions, neighbors of neighboring regions, etc.). Elhorst (2014) also points out that the spatial Durbin model produces unbiased coefficient estimates if the true data-generation process is a spatial lag or a spatial error model without imposing prior restrictions on the potential spatial spillover effects magnitude. In contrast to other spatial regression specifications, these spillover effects can be global or local and be different for different explanatory variables.

[6] We do not include the spatially lagged variables for closeness and betweenness because it is unlikely that a region would rely on the relational connectivity of its neighbors to innovate rather than its network connections. However, in the robustness check section, we included these variables and the overall results remained the same.

perspective of policy-makers, it is a primary concern, whereas spillover and, thus, total effects reflect the broader outlook of society at large (LeSage; Pace, 2009). Therefore, we also present the total effects of our estimations.

2.4.2 DATA AND SOURCES

We gathered patent data from the patent data set filed with the Brazilian National Patent Office (INPI) between 2003 and 2018. From each patent, we extracted the inventors, their location, their applicants and the technological classifications. Fractional patent counts were generated from the inventors' data after a process of geo-location and fractional attribution to the patent coinventors' network. The number of geo-localized patents during this period is $62,482$[7].

Our dependent variable is the number of fractional patents per capita of the region in log form. To measure the differences between industry and university, we split patents into two subsamples: university and industrial patents. We follow Lissoni (2012) and define university patents as university-owned patents[8].

We use R&D, agglomeration, and coinventor networks as independent variables. We measure local R&D efforts using traditional proxies for industrial and university R&D. Industrial R&D is calculated using workers in research-related occupations in the region[9] (Fritsch; Slavtchev, 2007). University R&D is measured by the regional scientific publication counts indexed in the Web of Science per capita[10] (Cowan; Zinovyeva, 2013). We use population density as our proxy for agglomeration. Since an excessive increase in population density may lead to agglomeration diseconomies, resulting in negative externalities, we use population density in linear and quadratic forms (Gonçalves; Almeida, 2009).

We use closeness and betweenness as our copatent network variables. Closeness is calculated by the centrality level of the region in the copatenting network, and betweenness accounts for the position as a regional broker in the whole network. Broker regions bridge otherwise unconnected parts of the network and thus can foster knowledge sharing (Tóth; Lengyel, 2021; Breschi; Lenzi, 2015). We also follow Ter Wal (2013) and generate data using a five-year moving window procedure. This implies that a network of a particular year contains all coinventor-ship linkages of that year and the preceding four years. Assume that social links between inventors persist over time (Agrawal; Cockburn; McHale, 2006). Since we are using separate estimations for

7 We geo-localized 84.2% of the patents during this period.

8 We disregard patents that are owned by industry and university at the same time.

9 We use the classification from Ministry of Labor and Employment for jobs that are directly associated with R&D activity: Researchers of Biological Sciences; Researchers of Natural and Exact Sciences; Engineering and Technology Researchers; Health Sciences Researchers; Agricultural Sciences Researchers; Social and Human Sciences Researchers; R&D Directors and Managers

10 We used information about the scientific publication by institutions provided by WoS. Since some institutions are present in more than one region, we weighted the scientific publications by graduate students' data from GeoCapes.

industrial and university patents, we generated coinventors' networks for these cases, ensuring that we are not using the average effect but evaluating our networks correctly.

Finally, we use controls for the regional industrial and economic context using the Hirschman-Herfindahl Index for employment in regions and imports by the GDP of the region. We also control for prevailing technological fields of patents in a given region and use fixed effects for regions.

In addition, regarding the territorial division adopted, we use REGIC intermediate divisions that are designed from a hierarchical-functional structure (IBGE, 2017). The intermediate level was designed using local labor inflows, public and private services, and the existence of more complex urban functions. They present sufficient granularity to assess regional innovation that allows comparison with studies for other countries[11].

Table 2.2 reports the description and Table 2.3 reports the summary statistics of the variables included in the models.

Table 2.2 – Definition of the Variables

Variable	Description	Source
$I_{r,t}$	Number of fractional patents per 100,000 inhabitants of the region in log form	INPI
Industry $R\&D_{r,t-1}$	Number of workers in research-related jobs per million inhabit. of the region in log form	Ministry of Labor and Employment
University $R\&D_{r,t-1}$	Number scientific publications per million inhabit. of the region in log form	WoS
Population $density_{r,t-1}$	Population density for the region in linear and quadratic form	IBGE
$Closeness_{r,t-1}$	Centrality level of the region in the copatenting network	INPI
$Betweenness_{r,t-1}$	Position of the region in the whole network as a broker	INPI
$HHI_{r,t-1}$	Hirschman–Herfindahl index for the region employment in manufacturing	Ministry of Labor and Employment
$Import_{r,t-1}$	Import in FOB dollars by GDP of the region	ComexStat and IBGE

Source: Own elaboration

Table 2.3 – Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
$I_{r,t}$	0.621	0.553	0.000	2.364
Industry $R\&D_{r,t-1}$	1.007	0.709	0.000	3.444
University $R\&D_{r,t-1}$	0.470	0.610	0.000	3.233
Population $density_{r,t-1}$	72.835	199.947	0.482	2039.141
$Closeness_{r,t-1}$	0.320	0.215	0.000	0.746
$Betweenness_{r,t-1}$	0.009	0.025	0.000	0.238

Source: Own elaboration
Notes: Number of observations: 1,995.

[11] These regions' size are similar to European NUTS-2 regions.

2.5 RESULTS AND DISCUSSION

We perform our estimation results using patent data as dependent variables, covering the period 2003 to 2018 for the 133 Brazilian regions (Table 2.4). We estimate a model for whole patents in regions (Model 1 - Total Patent) and two additional models for separate samples of industrial (Model 2 - Industrial Patents) and university patents (Model 3 - University Patents). These models allow us to assess and compare the main regional drivers for industrial and university patenting. Our benchmark models are Models 2 and 3.

Regarding total patents (Model 1), our findings show that R&D efforts, agglomeration, networks, and spatial effects are relevant, confirming theoretical expectations and previous empirical results (Jaffe, 1989; De Noni; Ganzaroli; Orsi, 2017). We find a positive and significant coefficient for Industry R&D in all three models, as expected (Jaffe, 1989). Regions with higher industrial R&D expenditures present better innovative performance. Furthermore, our findings show the existence of spatial local R&D cross-effects from industry for university patents, which may be an indicator of the presence of complementary relations between local firms' innovation efforts and university patents. Regarding industrial R&D spatial effects, we find both own and cross R&D effects, so universities' academic capabilities, which are expressed in university patents, can represent important support for local firms' innovative activities. It is possible that in the absence of local industry expertise, universities can borrow functions with industrial partners in neighboring regions, as suggested by Camagni, Capello, and Caragliu (2016).

Regarding university R&D, we find positive and significant coefficients for total and university patents, but we do not find the same results for industrial patents. This result suggests that academic R&D efforts have important positive effects on regional innovation and the patenting activities of local universities. Therefore, our results point to the importance of local academic activities for innovation, confirming theoretical expectations and previous empirical studies (Jaffe, 1989; Gonçalves; Oliveira; Almeida, 2020). However, our findings also suggest that there are no local cross-effects of university R&D on industrial patents. There are two main reasons for this result since it could not necessarily indicate the absence of local cross-effects of university R&D on industrial patents. The first reason is related to the uneven territorial distribution of university innovative activities. Regions with lower absorptive capacity have more difficulties benefiting from local knowledge spillovers generated by academic activities (Rosenthal; Strange, 2004). This is the usual case in emerging countries such as Brazil, but it can also be seen in lagging-behind regions in developed countries (Rodríguez-Pose; Wilkie, 2019). The second reason could be related to the fact that the relationship between industrial innovation and university research can be enabled through other knowledge-sharing mechanisms, such as university-industry collaboration, which are not equally present in all regions (Perkmann et al., 2013). Nevertheless, this finding requires further studies on this subject.

Concerning agglomeration, we find a positive and nonlinear direct relation between population density and innovation in a given location, as expected (Gonçalves; Almeida, 2009).

Table 2.4 – Regression results. Patents as dependent variable

	(1) Total Patents	(2) Industrial Patents	(3) University Patents
Industry R&D$_{r,t-1}$	0.059***	0.034***	0.039***
	(0.014)	(0.011)	(0.011)
University R&D$_{r,t-1}$	0.195***	-0.007	0.278***
	(0.020)	(0.017)	(0.017)
Population density$_{r,t-1}$	0.002***	0.003***	0.003***
	(0.001)	(0.001)	-0.001
Population density$^2_{r,t-1}$	-8.65e-07***	-9.51e-07***	-1.23e-06***
	(2.70e-07)	(2.13e-07)	(2.16e-07)
Closeness$_{r,t-1}$	0.015	0.070**	0.0002
	(0.040)	(0.031)	(0.036)
Betweenness$_{r,t-1}$	2.041***	-0.062	2.099***
	(0.498)	(0.375)	(0.323)
W Industry R&D$_{r,t-1}$	0.056	0.087*	0.090*
	(0.063)	(0.051)	(0.053)
W University R&D$_{r,t-1}$	-0.313***	-0.139***	-0.246***
	(0.054)	(0.045)	(0.044)
W Population density$_{r,t-1}$	0.009***	0.005**	0.003
	(0.003)	(0.002)	(0.002)
W Population density$^2_{r,t-1}$	-3.69e-06***	-2.50e-06**	-7.87e-07
	(1.24e-06)	(9.91e-07)	(1.08e-06)
W Y$_{r,t}$	0.640***	0.521***	0.650***
	(0.038)	(0.048)	(0.038)
Constant	0.396***	0.231***	0.220***
	(0.048)	(0.038)	(0.040)
N	1,995	1,995	1,995
n	133	133	133
T	15	15	15
Controls	Yes	Yes	Yes
Tech Fields FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
AIC	-1471.78	-2223.91	-2151.49
R2	0.9146	0.9289	0.7365

Source: Own elaboration

Notes: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Estimates for the 133 intermediate regions using an inverse distance spatial weight matrix with a 500 kilometer cutoff from 2003 to 2018. We use fractional patents per 100,000 inhabitants of the region in log form as our dependent variable for total, industry, and university patents. We use a three-year moving average specification. Omitted controls: Employment Hirschman-Herfindahl Index and import participation in GDP. We also include region and patent technological field fixed effects. Controls are omitted due to space restrictions and are available upon request.

This finding suggests increasing innovation benefits with urban scale, in line with previous studies that empirically analyze the impact of agglomeration on patenting (Carlino; Kerr, 2015). The indirect effects of agglomeration are similar for total patents and for industrial patents, which could mean that the advantages of agglomeration can be obtained locally by borrowed size effects from neighboring regions (Camagni; Capello; Caragliu, 2016). However, we find no indirect spatial agglomeration effects for university patenting. Taken together, these results may indicate that regional spillovers from universities tend to be more localized than those from firms, as pointed out by Adams (2002).

Concerning regional coinventor networks, we find positive and significant coefficients for closeness and industrial patents and betweenness and both total and university patents. The closeness results mean that industrial coinvention networks depend more on the ability to reach knowledge bases in other regions. The result for betweenness may indicate that more university patents in regions bridge knowledge between other regions and transcode and diffuse external knowledge internally, fostering local innovation (Tóth; Lengyel, 2021). In addition, it is necessary to consider that universities tend to have stronger network connections with their industrial peers, as noted by Forti, Franzoni, and Sobrero (2013).

Finally, we find spatial interregional spillovers for all three specifications. The innovation effect may spread through knowledge spillovers that can propagate and reinforce themselves (LeSage; Pace, 2009). This finding reinforces the existence of a knowledge-spreading dynamic both for industrial and university patenting and reinforces the suitability of spatial models for our analysis.

Since we estimate spatial models with a lagged spatial dependent term, the coefficients cannot be directly interpreted, and it is necessary to estimate the total effects of a dependent variable on the independent one. These effects are reported in Table 2.5 and are quite similar to the estimated coefficients, which reinforces the main findings. The only exception is the result for university R&D, which becomes nonsignificant for total patents and negative and significant for industrial patents[12].

Analyzing regional innovation separately using industrial and university patents pointed to differences between the local innovation determinants for RKPF. Among these, the role of university R&D in industrial innovation, neighboring region borrowed functions and size, and different roles in the structure of coinventor networks stand out. These results have two consequences for the RKPF literature. First, it draws attention to a potential bias in the RKPF results of previous empirical studies that seek to analyze industrial innovation, but it does not exclude university patents. In this case, the effects will be more expressive in countries where university patenting is more relevant, as in the case of many developed and developing countries. Therefore, the correct evaluation of regional industrial innovation dynamics using the RKPF depends on the separation between industry and university patents.

Another concern is the necessity to validate the present results in other scenarios and to inquire into the different determinants and their underlying mechanisms. Specifically, it would be convenient to carry out new RKPF analyses in other countries to deepen these specificities. This is even more relevant considering that previous results do not take these differences into account and may misguide industrial public policies.

[12] This result may be associated with the university-industry collaboration dynamics. The innovation generated in collaboration with universities in a large neighboring university area may end up attracting firms to relocate or create startups and joint ventures in the university location, increasing industrial patents in that location and not in the area of origin.

Table 2.5 – Total Effects. Patents as dependent variable

	(1) Total Patents	(2) Industrial Patents	(3) University Patents
Industry R&D$_{r,t-1}$	0.223**	0.175***	0.246***
	(0.106)	(0.067)	(0.091)
University R&D$_{r,t-1}$	-0.134	-0.200***	0.160**
	(0.084)	(0.054)	(0.075)
Population density$_{r,t-1}$	0.020***	0.011***	0.013***
	(0.004)	(0.003)	(0.004)
Population density$^2_{r,t-1}$	-8.28e-06***	-4.98e-06***	-4.07e-06**
	(2.18e-06)	(1.38e-06)	(1.96e-06)
Closeness$_{r,t-1}$	0.031	0.119**	0.001
	(0.083)	(0.054)	(0.078)
Betweenness$_{r,t-1}$	4.323***	-0.105	4.550***
	(1.110)	(0.638)	(0.798)

Source: Own elaboration
Notes: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Estimates for the 133 intermediate regions using an inverse distance spatial weight matrix with a 500-kilometer cutoff from 2003 to 2018. We use fractional patents per 100,000 inhabitants of the region in log form as our dependent variable for total, industry, and university patents. We use a three-year moving average specification. Coinventor network variables do not include spatially lagged terms.

2.5.1 ROBUSTNESS CHECK AND HETEROGENEITY

We perform several robustness checks, and the main findings stand for all of them. First, considering that our variable of interest is total patents, it is possible to argue that it is a very strict proxy for innovations and that the results may be sensitive to this choice. In this sense, we regress an alternative version using patents and utility models together as our dependent variable (Table A1). Utility models are "minor inventions" since they require conformity with less rigorous requirements, and they are a relevant way to spread new knowledge in emerging countries, mainly for industry. Therefore, one can argue that its omission may give a limited view of the effect on industrial innovation. Our main results remain similar for this case.

Second, to ensure that outliers are not leading our main results, we also estimated a regression without the 5% less and 5% more productive regions in terms of patenting[13] (Table A2). Third, we consider university patents only those with full university ownership and drop partially owned university patents. To avoid disregarding these inventions that could be relevant, we again estimate our results considering partially owned inventions as university patents (Table A3). In all specifications, our results remain similar.

Our results could also be sensitive to the spatial weights matrix (W) definition. In the main specifications, we used an inverse distance spatial weight matrix with a 500 km cutoff, so we also performed a robustness check with different cutoffs. We also estimate regressions with all our independent variables spatially lagged. These results are quite the same (and available

[13] The 5% less productive regions are Tefe in Amazonas, Rorainopolis/Caracarai, Altamira and Breves in Para, Oiapoque/Porto Grande in Amapa, Sao Raimundo Notato in Piaui, and Crateus in Ceara. The 5% most productive regions are Sao Paulo, Araraquara and Campinas in Sao Paulo, Curitiba in Parana, Florianopolis and Joinville in Santa Catarina, and Caxias do Sul in Rio Grande do Sul.

upon request).

Finally, the relationship between industry and university R&D can affect regional innovation; some studies have sought to understand this association and its impact on patenting in regions by adding the interaction term among these R&D (Sanyal, 2003). Therefore, we seek to explore this heterogeneity by adding the interaction term between the two regional R&D in our spatial model (Table A4). The Industrial and University R&D interaction term coefficient is positive in all cases. Therefore, we found a complementary relationship between industrial and university R&D in the generation of industrial innovations. Other results remain quite similar. This result reinforces that evaluating total patents masks details of the local innovation dynamics, such as the connection between R&D that can only be found with the correct separation of industrial and university patents. Moreover, we show that our results hold even after performing many robustness checks.

2.6 FINAL REMARKS AND POLICY IMPLICATIONS

Jaffe (1989) proposed the RKPF to assess the local effects of universities' R&D on industrial innovation on regional innovation, often using patents as the innovation proxy. In Jaffe's original background, there was a lack of empirical evidence regarding the role played by universities in fostering industrial innovation. Over time, universities have been engaged more in applied knowledge and have increased their patenting. Currently, university patents represent a substantial share of the total patent count across several countries (Martínez; Sterzi, 2019; Anna Villarroya; Menéndez, 2022). However, university patents' shared importance is often disregarded in the RKPF literature.

Our aim in this paper is to evaluate how industrial and university patents are differently shaped by the regional drivers proposed by the RKPF literature. We estimate an RKPF spatial panel for 133 regions in Brazil between 2003 and 2018, distinguishing industrial and university patents. We fill the gap in the literature regarding the understanding of the different determinants of industrial and university regional innovation, providing new empirical evidence regarding the different drivers of industrial and university patenting.

Our results reveal different determinants of regional innovation for university and industrial patents. First, we find that industrial R&D local own and cross-effects are associated with a higher number of patents in all cases, whereas we find only local university R&D own-effects. In part, results such as these have not been found in the literature due to the nonseparation of university and industrial patents. However, it is necessary to delve deeper into the literature to understand local and cross-effects, mainly regarding the understanding of the mechanisms behind these spillovers.

We also find that agglomeration effects vary, being more spatially bounded for universities and broader for industry, which includes agglomeration effects from neighbors that can point to borrowed size and function benefits (Camagni; Capello; Caragliu, 2016). Regional coinventors' network effects also vary in our results. Regions with a higher number of direct connections (closeness) matter for industrial patenting, and regions acting as brokers among other regions (betweenness) diffusing external knowledge could benefit university patenting. Finally, we find spatial knowledge spillovers for both cases. Together, our results indicate that the separation between university and industrial patents could avoid bias and ensure a better estimation of local innovation determinants using RKPF, helping to properly guide innovation policy and research agenda.

Regarding limitations, our results are restricted to patent counts, as data for patent citations are not available in our dataset and context. In this sense, it could be relevant to make an additional analysis with patent citations. We expect that our results could be generalized to other countries since the expansion of university patents is a general trend, and previous RKPF results for Brazil are in line with the literature (Gonçalves; Oliveira; Almeida, 2020; Garcia; Araujo, et al., 2019).

In addition, our results set a research agenda to assess the extent to which RKPF determinants could vary in different contexts and countries. For instance, it could be relevant to verify how some of the previous RKPF results in which university R&D leads to more patent changes after excluding university patents from the sample, helping to better understand when and how university knowledge can improve local industrial innovation. This assessment is especially important to the effects of university-industry collaborations on local innovation.

The policy implications of our results are even more relevant in the context of university patenting expansion in both developed and developing countries (Martínez; Sterzi, 2019; Anna Villarroya; Menéndez, 2022). Since the results vary for industry and university patents, policymakers need to carefully propose local innovation policies based on empirical results from total patent records. In addition, there are important institutional and technological differences between industrial and university patents that need to be considered in policy formulation, especially at the regional level. Another relevant policy implication is to not take the R&D cross-effects as granted since regional industrial and university R&D will not necessarily lead to more patents for both. Therefore, policy-makers should stimulate university-industry interactions and other formal and informal mechanisms of collaboration to ensure that a given region has the right endowment to promote synergies between university and industry research. Without this separation, a policy could be designed to seek to produce industrial patents but stimulating mechanisms that are closely linked to university patents and vice versa.

3 BRIDGING UNIVERSITY AND INDUSTRY: LEARNING BY HIRING, COLLABORATION WITH GATEKEEPERS AND ITS EFFECTS ON PATENTING

3.1 INTRODUCTION

Innovation is an uncertain, costly, and complex process fuelled by knowledge. However, this valuable resource is often scattered across unconnected environments (Raff; Wentzel; Obwegeser, 2020). Particularly for radical innovations, it is fundamental to bridge complex knowledge. Consequently, knowledge derived from external sources is essential to generate new ideas (Boschma, 2005). In this sense, several mechanisms are used to overcome these barriers and connect distant actors, such as contracted research and development (R&D), collaborative ventures, and university-industry collaboration (Perkmann et al., 2013).

When considering knowledge transfer between universities and industry, it is necessary to understand their different knowledge profiles, incentives, and motivations (Baldini, 2011; D'Este; Perkmann, 2011). Furthermore, individuals are the primary source of embedded knowledge and the main agents facilitating knowledge transfer between universities and firms (Cranefield; Yoong, 2007). Hence, there is extensive literature concerning the advantages of participation in such arrangements, particularly in terms of knowledge generation by inventors, with a specific focus on patent production. Some inventors effectively use their working connections to access new resources and enhance their innovative performance (Arts; Veugelers, 2020; Buenstorf; Heinisch, 2020). Moreover, individuals can use their relationships to improve their inventive productivity (Hayter, 2016; Lissoni, 2010).

At an individual level, some mechanisms can be used to bridge knowledge between university and industry, such as working linkages or copatenting networks. In this study, we define hybrid inventors as those employed by a university and a firm simultaneously. Gatekeepers, conversely, establish connections between disconnected actors in university and industry communities, as evidenced by their involvement in copatenting collaborations with inventors from both worlds. Both hybrid inventors and gatekeepers assist organizations in surpassing barriers to acquiring knowledge, as they facilitate transcode processes and enhance knowledge dissemination (Colombo; Garcia, 2022; Breschi; Lenzi, 2015; Le Gallo; Plunket, 2020).

In this context, we aim to understand the impact of inventors' working and relational ties on individual innovative performance. We use a Poisson Pseudo Maximum Likelihood model to estimate whether inventors' working and relational ties and their interaction impact individual patenting activity. This approach enables us to understand the effects of being a hybrid or a gatekeeper inventor while controlling for a broad set of observable and unobservable characteristics, such as inventors' characteristics, organization size, patent portfolio and absorptive capacity, and regional agglomeration and patenting.

This paper makes two contributions. First, we expand upon the existing research on individual knowledge generation. Our primary focus revolves around inventors and their collaborative relations, enabling us to assess the effects of their simultaneous working linkages with universities and firms in patenting. While prior studies have primarily explored this topic from the firm perspective (Lam, 2007; Parmentola; Ferretti; Panetti, 2021), we believe ours to be the first study to investigate the effects of these concurrent working ties on individual innovative performance. Second, we examine working and relational ties and explore their interaction in enhancing individual productivity. While we anticipate a positive influence from both types of connections, we can not predict which one will exert a dominant effect.

Additionally, our empirical approach includes three distinct levels: the individual, the organization, and the regional, following Tubiana, Miguelez, and Moreno (2022). This option allows us to control for several factors that define individual productivity and helps to mitigate potential errors stemming from unobserved characteristics. Also, our database covers $56,778$ patents from $27,347$ inventors over 22 years, and we match inventors with their working records, recovering data on their characteristics, working affiliation, and location. Furthermore, our analysis focuses on Brazil, a developing country with continental dimensions that can complement the existing empirical insights on individual innovative performance.

Our results reveal insights into the performance of different types of inventors. Hybrid inventors often perform better or on the same level as academic and industrial inventors in specific contexts. On the other hand, gatekeepers consistently perform better than non-gatekeepers, a phenomenon that persists even when accounting for various heterogeneities. When examining the interaction, gatekeepers consistently display a positive and statistically significant effect across all models, emphasizing their ability to use relational ties to foster their patenting. However, hybrid inventors who do not act as gatekeepers tend to underperform compared to their counterparts. At the same time, those with relational ties benefit from access to resources and knowledge from both working connections, effectively bridging disconnected inventors and fostering knowledge sharing. Most importantly, our findings demonstrate the importance of relational ties over working linkages in promoting individual innovation performance.

This paper is structured as follows. The next section offers a review of the relevant literature upon which our study is built, and we present our hypothesis. The third section presents the methodological approach and the data employed in our analysis. Section 4 presents the results of our econometric exercises, followed by robustness checks. The final section concludes with remarks, limitations, implications for innovation policies, and suggestions for future research.

3.2 LITERATURE REVIEW

3.2.1 INNOVATION AND KNOWLEDGE CREATION

The innovation process is complex, uncertain, rare, and depends on several elements, such as infrastructure, laboratory resources, or specialized services. However, above all, it depends on knowledge. In general, this knowledge is not available in codified form; instead, it is often attainable in its tacit form and embedded in people (Nonaka; Takeuchi, 1995). The fact that workers' knowledge is the basis for competitive advantages and the tacit knowledge nature is central to several topics in the innovation literature, mainly to some streams such as coinventor networks, and learning by hiring (Buenstorf; Heinisch, 2020; Hayter, 2016). Inventors who are more able to access, transcode, and diffuse external knowledge are central to the success of this process, being more prolific and generating more innovation.

However, the factors impacting innovation and patenting in industry and academia are significantly different, which has a distinct effect on how individual inventors perform in these two settings (Lissoni, 2012; Baldini, 2011). These differences are relevant when examining the specific mechanisms of formal and informal knowledge exchange among inventors belonging to both worlds, such as university-industry collaborations, contracted research, or academic spin-offs (Perkmann et al., 2013). These factors are also relevant to analyze the effects on the patenting of individuals who bridge knowledge between these two communities. Institutional and relational factors can shape individuals' performance and capacity to bridge both worlds.

Regarding institutional factors, differences in patenting can be attributed to several underlying causes. These include distinct technology trajectories within industries and different propensities to patent (Albuquerque, 2000). Moreover, the institution's position as an innovation leader among its peers and the distance of its innovation portfolio to the frontier can influence individuals' patenting. At the individual level, the ability to establish connections, transcode knowledge, foster collaborative research, and overcome information barriers through coinvention networks affect patenting. Thus, it is important to account for the characteristics of an individual's current network, including factors such as network size and the inventor's position within that network, as well as the nature of their connections (Hayter, 2016). Similarly, potential interactions can affect their patenting, suggesting that the inventor's social and cultural proximity to others can establish conditions for increased inventive productivity (Boschma, 2005).

Therefore, inventors play a crucial role in successful knowledge transfers between academia and industry (Zucker; Darby; Torero, 2002; Cranefield; Yoong, 2007), and their institutional and relational framework shapes the knowledge flows between these two worlds. On the one hand, institutional elements can affect the performance of an inventor who has professional links with both institutions. These actors involved in knowledge transfer must understand the distinct institutional settings, norms, and incentives related to academic and industrial environments (Baldini, 2011; D'Este; Perkmann, 2011). On the other hand, relational factors such as having coinventors spanning both academic and industrial communities can be key for their ability to generate new knowledge. In this sense, actors that connect distinct institutions can engage in a more prolific knowledge generation process, ultimately enhancing inventor productivity (Lissoni, 2010; Hayter, 2016).

3.2.2 RESEARCH HYPOTHESES

Several studies have sought to understand how work links can affect patenting. Evidence in the literature illustrates how working for a large firm, in companies with prior patenting, in an applied field, or having a technological occupation implies greater patenting by individuals (Zwick et al., 2017). In particular, the literature has tried to understand how academic and industrial inventors have different patenting profiles (Lissoni, 2012; Baldini, 2011). Inventors may benefit from their institutional proximity to academia and industry. However, few works have been devoted to understanding the effect of simultaneous links with academia and industry on inventors' patenting (Parmentola; Ferretti; Panetti, 2021; Lam, 2007). We define hybrid inventors as those individuals with two simultaneous work links with universities and firms.

Academia and industry have different paradigms regarding basic versus applied research, invention secrecy, and resource access. Individuals with dual ties have opportunities to combine knowledge and financial resources from both institutions and overcome information barriers, bridging differences in norms and modes of operation and reducing the cultural gap between both communities (Colombo; Garcia, 2022; Dasgupta; David, 1987).

Regarding work links, hybrid inventors can transcode different types of knowledge and combine them to generate new knowledge. Some studies find that firms that hire academic researchers or recent graduates show increased patenting or a change in their portfolio (Arts; Veugelers, 2020). These works point out that hiring researchers and university graduates has enabled firms to innovate, explore new technologies, and benefit from the knowledge and skills these researchers have acquired in prior experience (Buenstorf; Heinisch, 2020; Rosenkopf; Almeida, 2003). On the other hand, having industry experience can contribute to academics. They may access funding, equipment, new or improved products, devices, or processes. It can also generate intellectual benefits related to industrial applications, insights for research agendas, and reputation gains (Garcia; Araujo, et al., 2018). Academics collaborating with industry can use a common language to reduce distrust, solve conflicts, and deal better with limited in-house technical capabilities or time constraints (Colombo; Garcia, 2022).

We argue that hybrid inventors can access knowledge, infrastructure, and resources from industry and academia. Such work relations affect their innovative capabilities and increase their patenting. Based on these theoretical arguments, we present our first hypothesis:

Hypothesis 1 *Being a hybrid inventor positively affects individual patenting.*

However, the university-industry knowledge bridge can occur in other ways and does not depend on formal working contracts. Direct relations between inventors can occur more quickly than formal employment contracts and are more focused on specific innovation projects, thus based on opportunities and having a shorter duration in general (Boschma, 2005). Therefore, social relations are essential in fostering knowledge sharing between universities and firms. One common way to connect different sources of knowledge is copatenting with inventors, who are able to easily access knowledge from universities and industry through their coinventors.

Inventors mediating two other actors from different groups are often defined as gatekeepers (Lissoni, 2010; Le Gallo; Plunket, 2020). In our case, we define gatekeepers as actors that connect disconnected inventors in academia and industry through copatenting networks.

Gatekeepers contribute to increasing institutional proximity by combining their knowledge mediation role of transcoding and diffusing external knowledge with their ability to coordinate and reduce transaction costs through their embeddedness (Le Gallo; Plunket, 2020). They typically differ from other actors due to their higher absorptive capacity, distinct technological profile, and influential position in their respective networks (Françoso; Vonortas, 2023). Furthermore, gatekeepers hold the necessary skills to overcome obstacles in collaborative efforts and are familiar with procedures in both contexts.

Inventors often connect with their peers through social networks to share knowledge and create a joint research effort. However, since closely related individuals often characterize social networks, it may generate lock-in and lead to a lack of ideas (Boschma, 2005). In this sense, gatekeepers bridge disconnected actors from distant social circles or communities, promoting knowledge sharing. Interinstitutional knowledge collaboration is a difficult task, demanding the establishment of solid relationships across distinct environments. This process requires specific capabilities and entails significant transaction costs (Françoso; Vonortas, 2023; Meissner; Shmatko, 2017). In this sense, we present the following hypothesis:

Hypothesis 2 *Being a gatekeeper and connecting knowledge through interinstitutional coinventor networks positively affects individual patenting.*

We expect that both gatekeepers and hybrid inventors perform better than the average. Additionally, it is essential to explore whether the roles of hybrid inventors and gatekeepers complement or substitute each other. A gatekeeper is recognized by their peers in academia and industry. Thus, if they have formal work links with both worlds, they can use institutional support to enhance their privileged position in the networks to innovate more. On the other hand, a hybrid inventor who assumes the gatekeeper position already has all the institutional support from both worlds to innovate and has developed capabilities to access strategic points in the network and could generate more new patents. A gatekeeper with simultaneous work links and developing a new invention can make his firm's economic and laboratory resources available to his academic coinventors while mobilizing graduate students and researchers from his research institution.

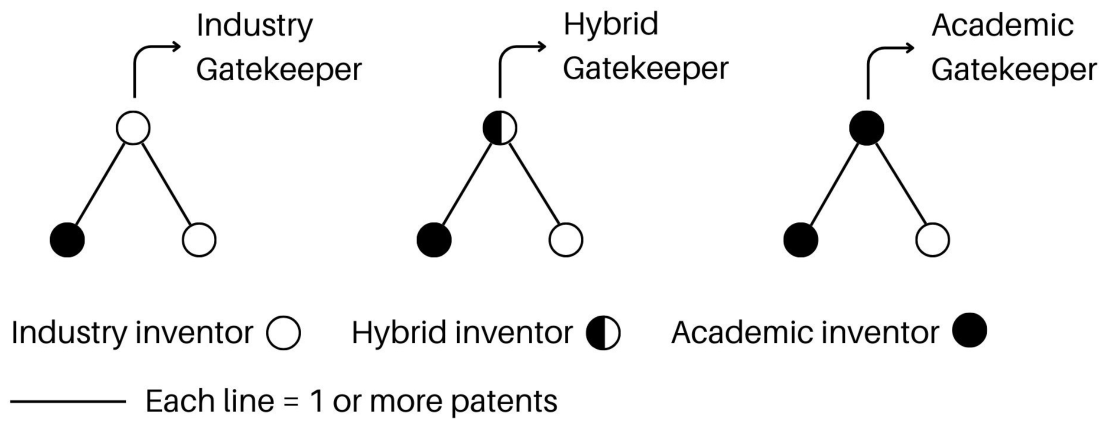
Despite our theoretical approach being new to the literature, it converges with some achievements in the literature previously pointed to a higher publication or citations to academics due to the so-called Matthew Effect (Merton, 1968) or even for innovation since some inventors are naturally more productive such as the star inventors (Zucker; Darby, 2001), even recent studies for gatekeepers (Le Gallo; Plunket, 2020).

The effect of being a gatekeeper and a hybrid can be complementary. Thus, individuals who are both hybrid and gatekeepers perform better than the simple sum of both effects. In this sense, we present the following hypothesis:

Hypothesis 3 *Being simultaneously a gatekeeper and a hybrid inventor can enhance knowledge transfer through interinstitutional social networks, positively affecting individual patenting.*

Figure 3.1 reports our definitions regarding hybrid and gatekeepers.

Figure 3.1 – Hybrid inventors and Gatekeeper definitions



Source: Own elaboration

3.3 EMPIRICAL STRATEGY

3.3.1 MODEL

Our empirical model that estimates individual inventor productivity takes the following form:

$$I_{i,t} = \beta_0 + \beta_1 Acad_{i,t-1} + \beta_2 Acad_{i,t-1} * Ind_{i,t-1} + \beta_3 X'_{i,t-1} + \mu_i + \mu_t + \mu_f + \mu_s + \mu_r \qquad (3)$$

where $I_{i,t}$ is the counts of patents filed by inventor i in year t, $Acad_{i,t-1}$ is a dummy assuming 1 if an inventor has a work contract with a university and industry is a dummy assuming 1 if the inventor has a working contract outside of academia in the previous year $(t-1)$. Since an inventor can have multiple working contracts in the same period, we interact with our variables to identify hybrid inventors. Since it is not possible to include $Acad_{i,t-1}$, $Ind_{i,t-1}$ and their interaction in the same regression, we adopt two specifications with the interaction and a different reference.

The vector $X'_{i,t-1}$ encompasses our control variables for individuals' characteristics, including their educational attainment, engagement in technological occupations, and participation in copatenting networks. Additionally, it incorporates variables related to their main occupation[14],

[14] We delineate the main occupation as the one wherein the individual allocates a more significant number of hours per week and receives a higher remuneration.

such as the firm's patent stock, workforce size, and the ratio of employees holding advanced degrees. Furthermore, we add regional variables to this vector, such as the local patent stock and population density. We also use controls for technological fields of patents. As usual in this literature, we use all of these characteristics with a temporal lag of a year since the innovative effort to patent could take time to occur (Hall; Jaffe; Trajtenberg, 2002). Finally, we include individual, year, firm, sector, and region fixed effects.

We also estimate a second model:

$$I_{i,t} = \beta_0 + \beta_1 Gatekeeper_i + \beta_2 X'_{i,t-1} + \mu_t + \mu_f + \mu_s + \mu_r \tag{4}$$

Again, our dependent variable is $I_{i,t}$. Now, our attention turns to the gatekeeper, a dummy variable assuming 1 if an inventor has patents with academic and industrial peers at some point. We also evaluate the effect of being a gatekeeper for academic and industrial inventors, including the previous $Acad_{i,t-1}$ and $Ind_{i,t-1}$ dummy variables and an interaction term.

Since our dependent variable is a count dependent variable, without negative value and many zeros, without distributional assumption, we employ a Poisson Pseudo Maximum Likelihood (PPML) estimation (Silva; Tenreyro, 2006). This approach follows other econometric studies of innovation and science (Berkes et al., 2023; Cristelli; Lissoni, 2020; D'Ambrosio et al., 2019). We use Stata's package PPMLHDFE, which allows for fast estimation with multiway fixed effects even for large samples (Correia; Guimarães; Zylkin, 2020).

3.3.2 DATA

We gather our data from the count of patents applied in Brazil. The National Patent Office (INPI) aggregates patent application data in a database. This dataset includes information on local and international patents filed in Brazil and PCT patents filed at WIPO. We merge these data with employment records from the Ministry of Employment. Thus, our primary dataset is an inventor panel with individual and organizational characteristics covering $56,778$ patents from $27,347$ inventors between 1997 and 2018.

3.3.2.1 DEPENDENT VARIABLE

The dependent variable of our baseline model is the count of patent applications signed by an inventor in a year. We match inventor-patent information through their employment or patent count records to capture the inventors' performance over time. We have an unbalanced panel since an inventor is included in our dataset in a given year if they hold an official work contract or have filed a patent[15].

[15] Informality is uncommon for people with higher education in Brazil according to Maurizio and Monsalvo (2021), which represents 73.3% of our sample

3.3.2.2 EXPLANATORY VARIABLES

An individual is a hybrid inventor if they maintain concurrent employment contracts with a firm and a university in a given year. This classification identifies those who could bridge academia and industry through learning by hiring mechanisms[16].

There are several definitions of gatekeepers in the literature (Graf; Krüger, 2011; Le Gallo; Plunket, 2020). We establish our definition whereby gatekeepers encompass inventors who engage in copatenting activities with both academic and industry counterparts, whether on the same patent or not (Lissoni, 2010; Capellari; De Stefano, 2016). These individuals can use their social network ties to bridge industry and university, fostering knowledge transfer and generating new patents.

3.3.2.3 CONTROLS

To assess the individual characteristics of inventors we used years of education as a proxy for human capital and technological occupations[17] (Zwick et al., 2017). We also measure the inventor network's linkages[18] using closeness, which indicates how close nodes are to the other nodes of the inventor.

To capture the organization's characteristics, we calculated the organization's size by the number of employees (Zwick et al., 2017). We also use the stock of patents of the firm to absorb cumulative effects since firms with more patents may hold higher quality patents and attract more inventors (Ferrucci; Lissoni, 2019). Finally, we measure absorptive capacity by the ratio of employees with high education to measure the ability to recognize, assimilate, and exploit external knowledge (Hussinger, 2021).

We included population density in linear and quadratic forms to measure agglomeration effects on a region (Moretti, 2021). The regional stock of patents is measured by the total number of patents in the region. Again, regions with more patents may hold higher quality patents and attract more inventors (Ferrucci; Lissoni, 2019). Finally, Crescenzi, Filippetti, and Iammarino (2017) point out that academic and industrial inventors are highly heterogeneous across technological profiles. Thus, we used controls for patent technological fields[19]. We also add fixed effects for time, individual, firm, sector, and region.

[16] We are using formal working contracts. Thus, we do not have access to scholarship data that are usually assigned to graduate students.

[17] We follow Araujo, Cavalcante, and Alvez (2009) and define as technological occupations as occupational groups potentially employed in science and technology and R&D activities: researchers, engineers, R&D directors and managers, and "scientific" professionals: mathematicians, statisticians, IT professionals, physicists, chemists, and biologists. This variable has an approximate 90% correlation between aggregate R&D measures.

[18] We follow Ter Wal (2013) and generate copatent networks in a five-year moving window procedure. We assume that a network of a particular year contains all coinventor-ship linkages of that year and the preceding four years.

[19] We use the IPC-technology concordance table to convert 35 corresponding technological fields into Electrical engineering, Instruments, Chemistry, Mechanical engineering, and Other Fields.

3.3.3 DESCRIPTIVE STATISTICS

Table 3.1 reports the description, and Table 3.2 reports the summary statistics of the variables included in the models. Finally, Table 3.3 reports the distribution of inventors for working ties and relational ties.

Table 3.1 – Definition of the Variables

Variable	Description	Source
$I_{i,t}$	Patent count of inventor i in year t	BADEPI
$\text{Academic}_{i,t-1}$	Dummy for academic inventors	BADEPI & RAIS
$\text{Industry}_{i,t-1}$	Dummy for industry inventors	BADEPI & RAIS
Gatekeeper_{i}	Dummy for gatekeeper individual	BADEPI
$\text{Education}_{i,t-1}$	Years of formal education of inventor i	RAIS
Technological $\text{Occupation}_{i,t-1}$	Dummy for inventors that have technological occupations	RAIS
$\text{Closeness}_{f,t-1}$	Centrality level of the inventor in the copatenting network	BADEPI
Stock of patents of the $\text{organization}_{o,t-1}$	Stock of patents in the inventor's main working linkage from 1997 until the year of analysis in log form	BADEPI
Number of $\text{workers}_{o,t-1}$	Number of workers in the inventor's main working linkage in log form	RAIS
Ratio of higher $\text{education}_{f,t-1}$	Ratio of employees with high education in the inventor's main working linkage	RAIS
Stock of patents of the $\text{region}_{r,t-1}$	Number of patents applied in the region from 1997 until the year of analysis in log form	BADEPI
Population $\text{density}_{r,t-1}$	Number of inhabit. per km^2 in the inventor's region in linear and quadratic form	IBGE

Source: Own elaboration

Table 3.2 – Descriptive Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
$I_{i,t}$	307,392	0.185	0.579	0	38
$\text{Academic}_{i,t-1}$	284,306	0.271	0.445	0	1
$\text{Industry}_{i,t-1}$	284,306	0.744	0.436	0	1
Gatekeeper_{i}	307,392	0.186	0.389	0	1
$\text{Education}_{i,t-1}$	293,454	15.249	2.625	0	20
Technological $\text{Occupation}_{i,t-1}$	293,660	0.202	0.401	0	1
$\text{Closeness}_{f,t-1}$	311,240	0.160	0.337	0	1
Stock of patents of the $\text{organization}_{o,t-1}$	228,810	2.385	2.407	0	12.100
Number of $\text{workers}_{o,t-1}$	228,810	7.392	2.425	0.693	13.060
Ratio of higher $\text{education}_{f,t-1}$	228,810	0.036	0.090	0	1
Stock of patents of the $\text{region}_{r,t-1}$	279,486	2.083	0.728	0	3.576
Population $\text{density}_{r,t-1}$	293,660	738.665	783.191	0.568	2071.454

Source: Own elaboration

3.4 RESULTS AND DISCUSSION

We perform nine estimations using patents as the dependent variable following our hypothesis. The data cover 1997 to 2018 for $27,347$ inventors (Table 3.4). First, we estimate two models to assess the effect of being a hybrid inventor on patenting using industrial (Model 1) and

Table 3.3 – Frequency Distribution of Inventors

	# number of inventors	% of inventors	Total # of patents
Total	27,347	100	56,778
$\text{Academic}_{i,t-1}$	8,142	29.8	12,103
$\text{Industry}_{i,t-1}$	23,262	85.1	25,420
$\text{Hybrid}_{i,t-1}$	1,542	5.6	682
Gatekeeper_i	4,549	16.7	15,726
$\text{Academic}_{i,t-1} * \text{Gatekeeper}_i$	2,740	10.0	7,244
$\text{Industry}_{i,t-1} * \text{Gatekeeper}_i$	3,531	12.1	6,283
$\text{Hybrid}_{i,t-1} * \text{Gatekeeper}_i$	586	2.1	605

Source: Own elaboration
Notes: This table presents individuals who were Academic or Industry inventors for at least one year throughout our whole sample.

academic inventors (Model 2) as the reference group. Second, we estimate a set of regressions to evaluate how gatekeeper inventors perform better than the average individual (Model 3). Then, we interact this variable with the dummies for academics (Model 4) and industrial inventors (Model 5). Finally, we estimate our final models of how inventors are, at the same time, hybrids and gatekeepers using industrial and academics as references (Models 6 and 7) and including interaction terms with these dummies (Models 8 and 9).

Table 3.4 – Main results. Patents as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\text{Academic}_{i,t-1}$	0.243***			0.069		0.266***		0.126**	
	(0.054)			(0.050)		(0.052)		(0.056)	
$\text{Industry}_{i,t-1}$		-0.243***			-0.112**		-0.266***		-0.126**
		(0.054)			(0.056)		(0.052)		(0.056)
$\text{Hybrid}_{i,t-1}$	-0.028	0.215**				-0.510***	-0.244	-0.414**	-0.288*
	(0.104)	(0.102)				(0.165)	(0.157)	(0.165)	(0.156)
Gatekeeper_i			0.708***	0.583***	0.824***	0.704***	0.704***	0.587***	0.824***
			(0.021)	(0.033)	(0.026)	(0.021)	(0.021)	(0.033)	(0.026)
$\text{Academic}_{i,t-1} * \text{Gatekeeper}_i$				0.247***				0.237***	
				(0.041)				(0.041)	
$\text{Industry}_{i,t-1} * \text{Gatekeeper}_i$					-0.221***				-0.237***
					(0.041)				(0.041)
$\text{Hybrid}_{i,t-1} * \text{Gatekeeper}_i$						0.456**	0.456**	0.320*	0.557***
						(0.182)	(0.182)	(0.182)	(0.182)
$\text{Education}_{i,t-1}$	-0.004	-0.004	0.036***	0.036***	0.037***	0.036***	0.036***	0.037***	0.037***
	(0.009)	(0.009)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
$\text{Technological Occupation}_{i,t-1}$	0.121***	0.121***	0.146***	0.156***	0.156***	0.151***	0.151***	0.157***	0.157***
	(0.038)	(0.038)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
$\text{Closeness}_{i,t-1}$	0.107***	0.107***	0.367***	0.370***	0.371***	0.368***	0.368***	0.370***	0.370***
	(0.031)	(0.031)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
$\text{Stock of patents of organization}_{o,t-1}$	0.105***	0.105***	0.086***	0.080***	0.079***	0.079***	0.079***	0.079***	0.079***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
$\text{Number of workers}_{o,t-1}$	0.042***	0.042***	0.038***	0.032**	0.031**	0.031**	0.031**	0.032**	0.032**
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
$\text{Ratio of higher education}_{o,t-1}$	0.835***	0.835***	0.539***	0.520***	0.503***	0.505***	0.505***	0.504***	0.504***
	(0.154)	(0.154)	(0.142)	(0.142)	(0.143)	(0.143)	(0.143)	(0.143)	(0.143)
$\text{Stock of patents of region}_{r,t-1}$	0.116**	0.116**	0.107**	0.100**	0.101**	0.102**	0.102**	0.100**	0.100**
	(0.053)	(0.053)	(0.048)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)
$\text{Population density}_{r,t-1}$	0.0003	0.0003	0.0001	0.0001	0.0001	0.0001	0.0001	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$\text{Population density}^2_{r,t-1}$	-1.91e-07*	-1.91e-07*	-6.92e-08	-8.95e-08	-8.96e-08	-8.65e-08	-8.65e-08	-9.05e-08	-9.05e-08
	(1.02e-07)	(1.02e-07)	(8.80e-08)	(8.90e-08)	(8.93e-08)	(8.93e-08)	(8.93e-08)	(8.91e-08)	(8.91e-08)
Constant	-1.572***	-1.329***	-3.104***	-3.069***	-2.968***	-3.113***	-2.847***	-3.082***	-2.956***
	(0.214)	(0.214)	(0.176)	(0.181)	(0.182)	(0.182)	(0.182)	(0.182)	(0.182)
N	129883	129883	162326	160718	160718	160718	160718	160718	160718
R^2	0.2199	0.2199	0.1084	0.1080	0.1080	0.1077	0.1077	0.1081	0.1081
Individual FE	Yes	Yes	No	No	No	No	No	No	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Own elaboration
Notes: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

We defined hybrid inventors as individuals with both academic and industry affiliations by interacting the dummies for academic and industrial inventors. Our analysis encompasses two regression models, each using a distinct reference group. In Model 1, we use industrial inventors as the reference group. In this case, the coefficient for the academic dummy variable is positive and statistically significant. However, the interaction term for hybrid inventors does not exhibit statistical significance. This suggests that academics tend to patent more than industrial inventors, but hybrids do not necessarily perform better than both groups.

When we shift our reference to academic inventors (Model 2), we observe a negative coefficient for the industrial dummy, reinforcing that academic inventors outperform their industrial peers. However, in this case, the coefficient for the interaction term for hybrid inventors is positive and significant, meaning that hybrid inventors present a higher level of innovative performance than academic and industrial inventors.

Therefore, from our results from Models 1 and 2, we can partially confirm Hypothesis 1. Hybrid inventors perform at a similar level or surpass academics and industrial inventors in certain circumstances. Our findings align with literature suggesting that the nature of work linkages significantly impacts inventors' performance (Drejer; Østergaard, 2017). This result can be related to easier access to knowledge and capabilities from academic and industrial communities, as stated by the learning by hiring literature (Lee, 2000; Buenstorf; Heinisch, 2020).

In our second set of regressions (Models 3 to 5), we introduce three specifications, including a gatekeeper dummy, while maintaining the same control variables and fixed effects as in our previous estimations. However, these models can not include individual fixed effects since the gatekeeper status remains constant over time. In Model 3, the gatekeeper coefficient is positive and statistically significant. This suggests that gatekeepers perform better than non-gatekeepers, implying that individuals collaborating effectively with inventors from academic and industrial communities in copatenting networks tend to be more productive. This finding confirms Hypothesis 2 and aligns with previous research regarding gatekeeper roles fostering innovative productivity (Lissoni, 2010; Capellari; De Stefano, 2016).

Next, we introduce the dummies for academic (Model 4) and industrial inventors (Model 5) along with their respective interaction terms, allowing us to assess the heterogeneity of our prior findings concerning these distinct inventor groups. In both models, we find that the coefficient for the gatekeeper remains positive and statistically significant, reconfirming Hypothesis 2. Furthermore, we observe statistically significant coefficients for the interaction terms, with a positive sign in Model 4 and a negative sign in Model 5. To assess the total effect for each inventor group, we sum the gatekeeper coefficients, which amount to 0.792 and 0.559 for academic and industrial inventors, respectively.

These results underscore the heterogeneity in the significance of gatekeeping roles within these two distinct realms. While being a gatekeeper holds importance for both academic and industrial inventors, it seems to carry greater relevance for the academic group (Lissoni, 2012).

Our findings suggest that relational ties are instrumental in enhancing inventive performance for both inventor categories, with academics benefiting more. These results align with previous studies highlighting that academics often operate within larger and more interconnected communities. Besides, the institutional setting of universities fosters an open science model leading to the generation of new knowledge and patents (Forti; Franzoni; Sobrero, 2013; Baldini, 2011).

Nevertheless, it is essential to deeply understand how and why differences emerge for industrial and academic inventors and how work and relational ties affect patenting differently. So, in our final regressions (Models 6 to 9), we interact the dummies for gatekeepers and hybrid inventors. Concerning gatekeepers, the effect in all models remains positive and significant for all models, underscoring that these individuals leverage their relational ties to patenting activities. However, the same can not be attested for hybrid inventors that present negative coefficients in all estimations. Finally, the coefficients for the interaction between hybrid inventors and gatekeepers present a positive and statistically significant effect in all four models.

Hence, we reconfirm H2, ensuring that gatekeepers outperform their peers in all cases. However, the same does not occur for hybrids that present a negative coefficient, showing that hybrid inventors without gatekeeper abilities perform worse than others. Additionally, the interaction term between hybrid and gatekeeper is positive. These last two results attest that hybrid inventors with relational ties benefit from resources and knowledge from both working linkages while bridging disconnected inventors and fostering knowledge sharing, confirming H3.

Furthermore, we must understand how they can use this position to generate more patents. Isolated hybrid inventors present negative results in their inventive performance. So, even though these individuals have access to better resources than their counterparts, they do not use them to generate new patents due to the lack of relational ties. In this sense, non-gatekeeper hybrid inventors could suffer more from the negative aspects of multiple working linkages, such as reporting and paperwork that limit their participation in more complex research projects, relegating them to more bureaucratic aspects of their jobs (Thompson, 1965).

Nonetheless, the negative result for isolated hybrids does not indicate that working ties are not relevant for individual inventive productivity since hybrid gatekeepers outperform others even after controlling for academic and industrial gatekeepers (Models 8 and 9). Consequently, while being a gatekeeper holds major importance, we cannot dismiss the relevance of being a hybrid inventor who could tap into knowledge and resources from academic and industrial affiliations.

Based on our results, we can point out that relational ties are more relevant to individual innovation measured by patents than working linkages. In this sense, our results point out that benefits related to typical working ties for hybrids are probably more related to relational ties and social networks rather than exclusively the former experience in the university or industry. Thus, it is essential to consider relational ties when evaluating the effect of hiring specific inventors and their previous experience (Hayter, 2016).

Altogether, our results indicate that individuals who are simultaneously hybrids and gatekeepers combine the advantages of their work and relational ties to patent more (H3). In this sense, these individuals can combine different mechanisms. This could occur for hybrid inventors due to easier access to resources and knowledge from firms and universities. For gatekeepers, the ability to bridge coinventors that share essential knowledge and capabilities that can overcome technological lock-in of ideas that were previously disconnected.

Finally, our controls' coefficients are, in general, in line with previous evidence in the literature. We find evidence that more educated individuals in technological occupations and with higher importance within their patent network (Zwick et al., 2017; Tóth; Lengyel, 2021) patent more. They also benefit from working in larger organizations, with higher absorptive capacity and a more extensive patent stock (Breschi; Lissoni, 2004; Hussinger, 2021). Additionally, they are more productive in regions with more patents (Karlsson; Gråsjö, 2014; Howells, 2002). The only exception is related to agglomeration effects, but it can be explained by the fact that we use several fixed effects, including region.

3.4.1 ROBUSTNESS CHECK

We perform several robustness checks, and the main findings stand for all. First, since our gatekeeper definition is related to the same coinventor networks, our results for gatekeepers could be sensitive to including the closeness variable. So, we reestimate our models without the network variables reaching similar results to the previous one (Table B1). Second, we also estimate a model excluding firm fixed effects since excessive use of fixed effects can lead to a risk of being overfitted, reporting spurious correlations[20]. In this case, our results remain similar, ensuring the quality of our estimations (Table B2). Finally, we estimate our models using Patents and Utility Models as our dependent variable. Utility models often serve as a significant means of disseminating new knowledge, especially in the industrial sector. Using patents and utility models could provide a broader view of the effect on innovation; thus, neglecting their influence could result in an incomplete understanding of innovation. Again, our results remain similar (Table B3).

3.5 FINAL REMARKS AND POLICY IMPLICATIONS

This article aims to evaluate how the ability to connect knowledge from universities and industry can increase inventors' productivity. So, we assess how being a hybrid and gatekeeper inventor can improve individual innovative performance and whether working ties or relational connections play a more relevant role in this context.

This paper contributes to the literature on inventors' productivity by focusing on working linkages and relational ties with universities and firms. Also, we investigate the effects of simultaneous working linkages with universities and industry. Finally, we verify which connections

[20] We also estimate new results without sector and region fixed effects, these results are available upon request.

exert a dominant effect on individual performance. To our knowledge, these topics have not yet been addressed in the literature.

To do so, we estimate a Poisson Pseudo Maximum Likelihood model using patents as our dependent variable. We recover the working linkages from the employment records of 27,347 inventors and the gatekeeper position from the copatent network. We also control for individual characteristics, organization size, patent portfolio and absorptive capacity, and regional agglomeration and patenting. Our panel consists of 56,778 patents filed in Brazil between 1997 and 2018.

Our results indicate that, in some contexts, hybrid inventors perform better. Easier access to knowledge and capabilities from academia and industry could be the mechanism behind this advantage, as reported by the learning-by-hiring literature (Lee, 2000; Buenstorf; Heinisch, 2020). We also found evidence that gatekeeper inventors can foster innovative productivity. Collaborating with individuals from academic and industrial communities may allow these inventors to transcode and diffuse new knowledge that leads to patenting. Moreover, we find that these relational ties benefit more academics.

Finally, our results show that individuals acting as hybrid inventors and gatekeepers simultaneously compound the advantages of their work and relational ties to patent more. This result ensures that well-connected individuals with access to both organizations' resources can improve their productivity by combining knowledge and resources. However, we have evidence that isolated hybrids perform worse, which can indicate that relational ties are more relevant to innovation than working linkages. So, although working links play a role in innovation, our results shed new light on the primary function of networks for inventors.

Our results could set new topics for the research agenda. First, it is essential to analyze this topic using other more qualified innovation proxies such as patent citations and other national contexts. Since we do not have information on graduate students that often bridge academia and industry (Arts; Veugelers, 2020; Colombo; Garcia, 2022), evaluating these inventors in depth is also necessary. At the same time, we delve into other ties both from a theoretical point of view and assess how they interact and their hierarchical relevance in inventors' productivity. Finally, the same focus could be used to evaluate other contexts, such as local-international or regional-national communities. For example, one could verify simultaneous linkages to national and multinational environments.

Regarding policy implications, a better understanding of how these different layers affect innovation can improve innovation policy. Since individuals connected to both communities patent more, our results reinforce the policy stream that fosters university-industry collaboration. However, the fact that gatekeepers are more productive suggests that relational ties are pivotal for increasing the effect of innovation policies. To do so, policymakers should consider inventors' previous experiences and researchers' connections and create mechanisms that enhance the abilities of individuals to connect distant actors.

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A FIRST APPENDIX

Table A1 – Patents and Utility Models Robustness Total Effects. Patents and utility models as dependent variable

Variables	(4) Total Patents	(5) Industrial Patents	(6) University Patents
Industry R&D$_{r,t-1}$	0.276**	0.228***	0.041***
	(0.115)	(0.079)	(0.012)
University R&D$_{r,t-1}$	-0.194**	-0.229***	0.287***
	(0.092)	(0.064)	(0.017)
Population density$_{r,t-1}$	0.019***	0.013***	0.003***
	(0.005)	(0.004)	(0.001)
Population density$^2_{r,t-1}$	-9.14e-06***	-7.09e-06***	-1.23e-06***
	(2.37e-06)	(1.65e-06)	(2.20e-07)
Closeness$_{r,t-1}$	0.032	0.075	0.016
	(0.090)	(0.063)	(0.036)
Betweenness$_{r,t-1}$	4.374***	0.272	2.078***
	(1.190)	(0.751)	(0.330)

Source: Own elaboration

Notes: Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Estimates for the 133 intermediate regions using an inverse distance spatial weight matrix with a 500-kilometer cutoff from 2003 to 2018. We use fractional patents per 100,000 inhabitants of the region in log form as our dependent variable for total, industry, and university patents. We use a three-year moving average specification. coinventor network variables do not include spatially lagged terms. Omitted controls: Employment Hirschman-Herfindahl Index and import participation in GDP. We also include region and patent technological field fixed effects.

Table A2 – Outliers Robustness Total Effects. Patents as dependent variable

Variables	(4) Total Patents	(5) Industrial Patents	(6) University Patents
Industry R&D$_{r,t-1}$	0.313***	0.181**	0.286***
	(0.113)	(0.074)	(0.097)
University R&D$_{r,t-1}$	-0.146*	-0.170***	0.170**
	(0.088)	(0.060)	(0.078)
Population density$_{r,t-1}$	0.019***	0.009***	0.010***
	(0.004)	(0.003)	(0.004)
Population density$^2_{r,t-1}$	-7.34e-06***	-3.67e-06***	-3.11e-06*
	(1.96e-06)	(1.30e-06)	(1.77e-06)
Closeness$_{r,t-1}$	-0.025	0.122**	-0.023
	(0.082)	(0.055)	(0.078)
Betweenness$_{r,t-1}$	3.563***	-0.410	4.561***
	(1.138)	(0.700)	(0.919)

Source: Own elaboration
Notes: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Estimates for the 133 intermediate regions using an inverse distance spatial weight matrix with a 500-kilometer cutoff from 2003 to 2018. We use fractional patents per 100,000 inhabitants of the region in log form as our dependent variable for total, industry, and university patents. We use a three-year moving average specification. coinventor network variables do not include spatially lagged terms. Omitted controls: Employment Hirschman-Herfindahl Index and import participation in GDP. We also include region and patent technological field fixed effects.

Table A3 – All Patents Robustness Total Effects. Patents as dependent variable

Variables	(4) Total Patents	(5) Industrial Patents	(6) University Patents
Industry R&D$_{r,t-1}$	0.223**	0.175***	0.248***
	(0.106)	(0.067)	(0.082)
University R&D$_{r,t-1}$	-0.134	-0.200***	0.166**
	(0.084)	(0.054)	(0.075)
Population density$_{r,t-1}$	0.020***	0.011***	0.013***
	(0.005)	(0.003)	(0.004)
Population density$^2_{r,t-1}$	-8.28e-06***	-4.98e-06***	-3.99e-06**
	(2.18e-06)	(1.38e-06)	(1.97e-06)
Closeness$_{r,t-1}$	0.031	0.119**	-0.0001
	(0.083)	(0.054)	(0.078)
Betweenness$_{r,t-1}$	4.323***	-0.105	4 584***
	(1.111)	(0.638)	(0.804)

Source: Own elaboration
Notes: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Estimates for the 133 intermediate regions using an inverse distance spatial weight matrix with a 500-kilometer cutoff from 2003 to 2018. We use fractional patents per 100,000 inhabitants of the region in log form as our dependent variable for total, industry, and university patents. We use a three-year moving average specification. coinventor network variables do not include spatially lagged terms. Omitted controls: Employment Hirschman-Herfindahl Index and import participation in GDP. We also include region and patent technological field fixed effects.

Table A4 – Heterogeneity Total Effects. Patents as dependent variable

Variables	(4) Total Patents	(5) Industrial Patents	(6) University Patents
Industry R&D$_{r,t-1}$	0.189*	0.146**	0.208**
	(0.111)	(0.066)	(0.092)
University R&D$_{r,t-1}$	-0.306	-0.438***	0.092
	(0.193)	(0.117)	(0.167)
Industry R&D$_{r,t-1}$ * University R&D$_{r,t-1}$	0.105	0.140**	0.054
	(0.106)	(0.063)	(0.090)
Population density$_{r,t-1}$	0.022***	0.012***	0.012***
	(0.005)	(0.003)	(0.004)
Population density$^2_{r,t-1}$	-9.49e-06***	-6.81e-06***	-3.71e-06*
	(2.53e-06)	(1.58e-06)	(2.19e-06)
Closeness$_{r,t-1}$	0.055	0.117**	0.064
	(0.087)	(0.052)	(0.079)
Betweenness$_{r,t-1}$	4.473***	-0.118	5.154***
	(1.127)	(0.625)	(0.828)

Source: Own elaboration

Notes: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Estimates for the 133 intermediate regions using an inverse distance spatial weight matrix with a 500-kilometer cutoff from 2003 to 2018. We use fractional patents per 100,000 inhabitants of the region in log form as our dependent variable for total, industry, and university patents. We use a three-year moving average specification. coinventor network variables do not include spatially lagged terms. Omitted controls: Employment Hirschman-Herfindahl Index and import participation in GDP. We also include region and patent technological field fixed effects.

B SECOND APPENDIX

Table B1 – Excluding Networking Variables Robustness Results. Patents as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\text{Academic}_{i,t-1}$	0.239***			0.0712		0.262***		0.125**	
	(0.0544)			(0.0497)		(0.0519)		(0.0558)	
$\text{Industry}_{i,t-1}$		-0.239***			-0.109**		-0.262***		-0.125**
		(0.0544)			(0.0554)		(0.0519)		(0.0558)
$\text{Hybrid}_{i,t-1}$	-0.0234	0.215**				-0.519***	-0.258	-0.426***	-0.301*
	(0.103)	(0.102)				(0.165)	(0.157)	(0.165)	(0.156)
Gatekeeper_{i}			0.725***	0.603***	0.838***	0.721***	0.721***	0.606***	0.838***
			(0.0205)	(0.0328)	(0.0256)	(0.0207)	(0.0207)	(0.0328)	(0.0256)
$\text{Academic}_{i,t-1} * \text{Gatekeeper}_{i}$				0.243***				0.232***	
				(0.0410)				(0.0414)	
$\text{Industry}_{i,t-1} * \text{Gatekeeper}_{i}$					-0.214***				-0.232***
					(0.0409)				(0.0414)
$\text{Hybrid}_{i,t-1} * \text{Gatekeeper}_{i}$						0.496***	0.496***	0.362**	0.594***
						(0.182)	(0.182)	(0.182)	(0.182)
N	129883	129883	162326	160718	160718	160718	160718	160718	160718
R^2	0.2198	0.2198	0.1063	0.1058	0.1058	0.1056	0.1056	0.1059	0.1059
Individual FE	Yes	Yes	No	No	No	No	No	No	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Own elaboration

Notes: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Other controls are omitted due to space restrictions and are available upon request.

Table B2 – Excluding Firm Fixed Effects Robustness Results. Patents as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\text{Academic}_{i,t-1}$	0.144***			-0.293***		-0.105***		-0.290***	
	(0.0469)			(0.0314)		(0.0277)		(0.0321)	
$\text{Industry}_{i,t-1}$		-0.144***			0.285***		0.105***		0.290***
		(0.0469)			(0.0320)		(0.0277)		(0.0321)
$\text{Hybrid}_{i,t-1}$	0.141	0.286***				-0.319**	-0.423***	-0.184	-0.474***
	(0.0937)	(0.0924)				(0.142)	(0.141)	(0.142)	(0.141)
Gatekeeper_i			0.610***	0.455***	0.823***	0.612***	0.612***	0.455***	0.823***
			(0.0181)	(0.0271)	(0.0253)	(0.0183)	(0.0183)	(0.0271)	(0.0253)
$\text{Academic}_{i,t-1} * \text{Gatekeeper}_i$				0.377***				0.368***	
				(0.0366)				(0.0369)	
$\text{Industry}_{i,t-1} * \text{Gatekeeper}_i$					-0.354***				-0.368***
					(0.0365)				(0.0369)
$\text{Hybrid}_{i,t-1} * \text{Gatekeeper}_i$						0.509***	0.509***	0.291*	0.660***
						(0.164)	(0.164)	(0.166)	(0.165)
N	139600	139600	199921	193863	193863	193863	193863	193863	193863
R^2	0.1999	0.1999	0.0759	0.0749	0.0748	0.0740	0.0740	0.0749	0.0749
Individual FE	Yes	Yes	No	No	No	No	No	No	No
Time FE	No	No	No	No	No	No	No	No	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Own elaboration

Notes: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Other controls are omitted due to space restrictions and are available upon request.

Table B3 – Patents and Utility Models Robustness Results. Patents and utility models as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\text{Academic}_{i,t-1}$	0.243***			0.0685		0.266***		0.126**	
	(0.0544)			(0.0496)		(0.0520)		(0.0559)	
$\text{Hybrid}_{i,t-1}$	-0.0281	0.215**				-0.510***	-0.244	-0.414**	-0.288*
	(0.104)	(0.102)				(0.165)	(0.157)	(0.165)	(0.156)
$\text{Industry}_{i,t-1}$		-0.243***			-0.112**		-0.266***		-0.126**
		(0.0544)			(0.0555)		(0.0520)		(0.0559)
Gatekeeper_i			0.708***	0.583***	0.824***	0.704***	0.704***	0.587***	0.824***
			(0.0205)	(0.0327)	(0.0256)	(0.0206)	(0.0206)	(0.0328)	(0.0256)
$\text{Academic}_{i,t-1} * \text{Gatekeeper}_i$				0.247***				0.237***	
				(0.0410)				(0.0413)	
$\text{Industry}_{i,t-1} * \text{Gatekeeper}_i$					-0.221***				-0.237***
					(0.0409)				(0.0413)
$\text{Hybrid}_{i,t-1} * \text{Gatekeeper}_i$						0.456**	0.456**	0.320*	0.557***
						(0.182)	(0.182)	(0.182)	(0.182)
N	129883	129883	162326	160718	160718	160718	160718	160718	160718
R^2	0.2448	0.2448	0.1198	0.1193	0.1193	0.1190	0.1190	0.1194	0.1194
Individual FE	Yes	Yes	No	No	No	No	No	No	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Own elaboration

Notes: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Other controls are omitted due to space restrictions and are available upon request.