Academic and industrial inventor productivity: a patent micro-data panel analysis on the role of organizations, networks and location

Sarah Ferreira[1], Renato Garcia[1], and Veneziano Araújo[2]

[1]Institute of Economics, University of Campinas, Brazil

[2]Department of Economics, Federal University of São Paulo, Brazil

Abstract

Academic and industrial inventors play a main role for the generation of new knowledge, innovation and technological development. However, they contrast in intensity, collaboration and technological profile and have different responses to incentives. Despite this, in general, the literature do not empirically assess how these inventors' productivity varies. In this sense, we analyze how individual, organizational and locational factors affect their patenting and verify the determinants of productivity of Brazilian academic and industrial inventors. We use a Negative Binomial panel regression for a individual patent counts between 2003 and 2018 with different specifications and fixed effects. Our main results point that being a 'star' inventor, participating in networks, the size of the inventor's organization and the local regional size and patents stock are relevant for more patenting. Regarding the differences between academic and industrial inventors, academic inventors - in general and the 'star' ones - patent more than their industrial peers. Academic inventors are also more benefited by acting as brokers in their networks, the absorptive capacity of their organizations and the regional stock of patents. 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 agenda on this topic.

Keywords: inventor productivity; patents panel; co-inventors networks; firms innovation; microdata.

JEL Code: O31, O33, O34

Introduction

The productivity of inventors is very heterogeneous. The vast majority file only one patent in a lifetime, while the most productive are responsible for a large number. In addition, the inventor's productivity depends significantly on his individual characteristics and the organization for which he works, but is also influenced by his location and his collaboration networks. Therefore, to assess in depth the productivity of inventors, it is necessary to consider as many different factors as their individual characteristics, the local context and their networks collaboration (AKCIGIT et al., 2018; LAWSON; STERZI, 2014; SCHETTINO; STERLACCHINI; VENTURINI, 2013).

Although the paradigmatic inventor is from the industrial scope, academics have increased significantly their patenting in the last years and have a remarkable portion of inventions corresponding to a share of 16 to

31% of patents in France, Spain and Portugal according to Anna Villarroya and Menéndez (2022). Besides that, industrial and university patenting have different profiles in terms of intensity, collaboration and technological profile. Thus, when analyzing the patenting of industrial and academic inventors, it is necessary to consider that they face distinguished economic incentives and appreciate the prestige resulting from this activity in a different way. At the same time, the 'open science' paradigm of the university environment favors openness and collaboration either through networks or in localities, while the industrial world tends towards greater secrecy protecting the intellectual property of firms.

In this context, it is expected that many studies would seek to empirically assess the existence and magnitude of these differences in the inventor's productivity. However, the literature in general ignores these differences, with few exceptions (LAWSON; STERZI, 2014), disregarding whether the inventors are industrial or academics, or analyzes one of these groups separately preventing from evaluating the effect of these dimensions in the productivity. In this sense, the aim of the present study is to evaluate the difference in the productivity of academic and industrial inventors in relation to individual, organizational and region characteristics.

However, few studies manage to deal with the role of all these dimensions at the same time, given the low availability of microdata. The absence of any of these dimensions makes it difficult to understand in depth the role of each of these elements in the inventive activity. Limiting both the understanding of the dynamics of innovation and the correct evaluation and proposal of public policies for innovation. In addition, this paper contributes to the literature by analyzing a developing country. As far as it was possible to verify, there is no other study that analyzes patenting in Brazil at the individual level. With regard to other developing countries, only Alnuaimi, Opsahl, and George (2012) for India and Pinto, Vallone, and Honores (2019) for Chile evaluated the same topic. However, in both cases, they do not control for individual, organization and location characteristics.

Literature Review

Several studies analyze the different factors that drive the inventors' productivity. In general, they point that individual, organizational, regional and the collaboration network characteristics are the main factors to explain it.

Regarding the inventors' individual characteristics, Zwick et al. (2017) find that higher education, working in R&D-intensive occupations and personal facts imply in greater innovative performance. These results are also found by Schettino, Sterlacchini, and Venturini (2013), that point out that the quality of each individual's patents is positively affected by individual characteristics such as age, education and gender. Finally, Alnuaimi, Opsahl, and George (2012) and Ferrucci and Lissoni (2019) found that the inventor's experience measured by his precedent stock of patents is an important indicator of his productivity.

Since the distribution of patenting is right skewed tailed and most patents are produced by a small number of inventors (LOTKA, 1926), some studies assess the differences of high-productive inventors. Zucker and Darby (2001) called these inventors 'star scientists' and found that firms that cooperate with them increase patenting. Cassiman, Veugelers, and Arts (2018) found that star scientists generate more valuable patents. Finally, Crescenzi, Filippetti, and Iammarino (2017) verified that a tie with an academic star implies more co-invented patents.

Another relevant individual attribute is collaboration networks (CRESCENZI; FILIPPETTI; IAMMARINO, 2017). Crescenzi, Nathan, and Rodríguez-Pose (2016) found that external networks of inventors are key feature of innovation teams. Breschi and Lenzi (2015) also found that socially closer interactions are more valuable for broadening the existing knowledge base, as knowledge passes through a lower number of intermediaries and it is, thus, more trusted and less distorted. Tóth and Lengyel (2021) shows that the more inventors with cohesive networks the firm receives the more firms' patents are cited. The new knowledge brought to the firm by connected inventors is easier to combine with existing knowledge.

Regarding the firm, Kim, Lee, and Marschke (2009) point out that inventors from larger firms are more productive. The same result is found by Cassiman, Veugelers, and Arts (2018) using the count of firms' previous patents and Schettino, Sterlacchini, and Venturini (2013) that indicate that inventors from companies with a larger patent portfolio tend to be more productive. The literature also points out that interfirm mobility affects productivity of the inventors. Rahko (2017) finds that hiring inventors with several previous patents and greater technological experience affects the firm's future patenting.

Concerning the location of inventors and firms, Tubiana, Miguelez, and Moreno (2022) found that inventors are more productive in metropolitan regions with a greater stock of patents. Moretti (2021) also found that an inventor who moves to a larger metropolitan region presents a significant gain in patent productivity and an increase in the number of citations. Ferrucci and Lissoni (2019) argued that STEM workers can increase the innovative potential of a given location by reinforcing local human capital through migration of better professionals.

Industrial and Academic inventors: similarities and differences

Being an academic or industrial inventor implies different incentives for patenting. In both cases, patenting implies economic and prestige gains for the inventor. However, Baldini, Grimaldi, and Sobrero (2007) argues that academic can have greater prestige and reputation gains. On the other hand, it could be argued that patenting can divert academics' efforts from scientific publication (MERTON, 1973). However, several studies point to a positive correlation between patenting and scientific publication (AGRAWAL; COCKBURN, 2003; VAN LOOY et al., 2004). Therefore, we expect that academics patent more than industry inventors.

But what are the expected effects on inventor's productivity for academics with regard to each of those dimensions? With regard to star inventors, it appears that in addition to greater productivity and ability to deal with patent application procedures, both industry and academic star inventors tend to patent more seeking to signal their quality to the market or academia (LAWSON; STERZI, 2014; BALDINI; GRIMALDI; SOBRERO, 2007). Therefore, being a star inventor is expected to be relevant for both cases.

Regarding the inventor's networks, it is well known that better connected inventors are more productive. However, there are institutional differences that lead the academy to be more open and willing to work in this way. In fact, university co-patenting networks are associated with a greater joint publication network (FORTI; FRANZONI; SOBRERO, 2013). In this sense, networks are expected to be more relevant to academic inventors.

Organizations that have larger patent stock and more qualified employees should generate positive effects for academic and industrial inventors. However, the mobility effect should be greater in the industry, due to the institutional mechanisms of universities that promote the stability of academics with mechanism such as tenured positions (LISSONI, 2010). Once inventors move, the effects can be positive if coming from better organizations or negative due to loss of connections and local relearning (RAHKO, 2017; DI LORENZO; ALMEIDA, 2017).

Universities have a greater ability to exploit spillovers of local knowledge, in addition to human capital formation and university-industry interaction (KANTOR; WHALLEY, 2014). Firms are more concerned about the secrecy of its inventions, so there is a restriction on the interaction with other organizations for the purpose of protecting its own stock (FURMAN; NAGLER; WATZINGER, 2021). In this way, it is expected that academic inventors benefit more from a larger stock of patents in the region. Migrations, on the other hand, can have effects in both directions since foreign inventors depend on the characteristics of the new region (MORETTI, 2021).

Model

Our empirical model that estimates the individual inventor productivity takes the form below and include independent variables for different factors that drive individual innovation.

$$Y_{i,t} = \beta_0 + \beta_1 \cdot I_{i,t} + \beta_2 \cdot O_{i,t} + \beta_3 \cdot L_{i,t} + \beta_4 \cdot X'_{i,t} + \varepsilon_t$$

Where $Y_{r,t}$ is the count of patents for each individual i in period t. The vectors I, O and L represent the characteristics of the individual, organization and local. The vector X indicates our controls. Since our dependent variable is a count variable we estimate a negative binomial panel regression as Cassiman, Veugelers, and Arts (2018), Rahko (2017) and Ferrucci and Lissoni (2019).

Dependent variable: Patents per inventor

We generate our data from the count of patents applied in Brazil. Patent application data are aggregated in a database by the National Patent Office (INPI - Statistical Database on Intellectual Property – BADEPI). Our main dataset is an inventor panel by year built using two different versions of BADEPI. The first one has details on individuals who patent including their id number but covers a shorter period (2000 until 2011). The other covers a longer period (1998 until 2018) but the inventor are not identified so we can not recover information from other data sources to control for individual characteristics. So, we choose to merge both datasets to include additional characteristics and cover a longer period. After the merge, our dataset covers $17,411$ patents from $8,084$ inventors between 2003 and 2018*.

Akcigit et al. (2018) argue that patent data are ideal for studying innovation. First, patent data includes the applicant, inventors, and patent characteristics. In addition, they allow you to evaluate inventors over time and how they participate in networks. Patents have long been considered the best, though not perfect, output for innovation activity possessing the advantage of being immediately available, measurable and comparable, both over time and across space (ASCANI et al., 2020).

Vector I: Individual

Lotka (1926) found that the distribution of the number of publications across scientists was skewed at the right tail, indicating that a restricted set of 'star' individuals outperformed the majority of their colleagues. To

*Since, the individual and organizational characteristics are obtained from RAIS database, we can only retrieve data after 2003 because there was a change in the identification of individuals on that year.

capture the effect of star inventors on innovation, we use a variable based on Zucker, Darby, and Brewer (1998) as follow: $WP = SCP/Exp$, where WP is weighted productivity, SCP is the stock of co-invented patents in the period and Exp a proxy for the experience of the inventor. We follow the authors and define as star inventors those who are above two standard deviation of the mean which represent 2.9% of the sample.

To assess the individual characteristics of inventors we used a dummy if the individual has high education as a proxy for the human capital (HOISL, 2009; SCHETTINO; STERLACCHINI; VENTURINI, 2013; ZWICK et al., 2017). In order to measure the differences between industry and university we label patents into two groups: those that are applied with university participation, industrial patents. We considered as academic inventors those for whom most patents were university patents.

Finally, to measure the network's linkages, we use Closeness centrality of the inventor in the co-patenting network and Betweenness centrality which accounts for the position of the inventor in the whole network as a broker. Broker inventors bridge otherwise unconnected parts and, thus, can foster knowledge sharing (TÓTH; LENGYEL, 2021). We follow Ter Wal (2013) and generate co-patent networks in a cumulative way assuming that social links persist over time.

Vector O: Organization

To capture the organization characteristics, we calculated the size of the organization by the number of employees (SCHETTINO; STERLACCHINI; VENTURINI, 2013; ZWICK et al., 2017). We counted patents applied from 1997 until the year t as net stock of patents of the organization. This variable absorbs scale effects in terms of organization patenting activity. Firms with more patents may both hold higher quality patents and attract more inventors (ALNUAIMI; OPSAHL; GEORGE, 2012; FERRUCCI; LISSONI, 2019).

Absorptive capacity is proxied by the ratio of employees with high education to measure the ability to recognize, assimilate and exploit external knowledge (HUSSINGER, 2012). We also generated information whether an inventor changed organizations using a dummy variable was built that takes the value 1 for inventors when they change organizations (HOISL, 2009; DI LORENZO; ALMEIDA, 2017).

Vector L: Local

We used employment density in linear and quadratic form to measure agglomeration effects on region (MORETTI, 2021). Net stock of patents of the region is generated by total number of patents in the region from 1997 until the year t. Again, regions with more patents may both hold higher quality patents and attract more inventors (FERRUCCI; LISSONI, 2019). A dummy variable was generated taking the value 1 for inventors that migrate (FERRUCCI; LISSONI, 2019; CAPPELLI et al., 2019).

Furthermore, our regional units r are IBGE (2017) Regic intermediate regions which correspond to immediate needs related to labor inflows, public and private services and the existence of more complex urban functions. These regions size are similar to European NUTS-2 regions.

Vector X: Controls

Finally, we add several controls. For individual characteristics we used age in linear and quadratic form, and dummies for male and white (EJERMO; HUSSINGER, et al., 2022; HOISL, 2009; SCHETTINO; STERLACCHINI; VENTURINI, 2013; ZWICK et al., 2017). Regarding to the organization level, we control for technological occupations and tenure (ZWICK et al., 2017; CASSIMAN; VEUGELERS; ARTS, 2018). Crescenzi, Filippetti, and Iammarino (2017) points to highly heterogeneous across scientific disciplines between academic and industrial inventors, thus we used controls for technological fields of patents[†]. We also add fixed effects for time, region and industry.

Our variables are summarized in tables below (Table 1 and 2). We also present the correlation matrix in our appendix (Table A1).

Table 1: Definition of the Variables

Variables	Description	Source
Patents$_{i,t}$	Patent count of inventor *i* in year *t*	BADEPI
Academic$_{i,t}$	Dummy for academic inventors	BADEPI
Star$_{i,t}$	Dummy for star inventors	BADEPI
High Education$_{i,t}$	Dummy for individuals with higher education	RAIS
Closeness$_{i,t}$	Centrality level of the inventor in the co-patenting network	BADEPI
Betweenness$_{i,t}$	Position of the inventor in the whole network as a broker inventor	BADEPI
Stock of patents$_{f,t-1}$	Patents applied by inventor's firm from 1997 until the year *t*	BADEPI
Employees$_{f,t-1}$	Employees in the inventor's firm in log form	RAIS
Absorptive capacity$_{f,t-1}$	Ratio of employees with high education in the inventor's firm	RAIS
Mobility$_{i,t-1}$	Dummy variable for inventors when they change firms	RAIS
Stock of patents$_{r,t-1}$	Patents applied of the firm from 1997 until the year *t*	BADEPI
Population density$_{r,t-1}$	Population density of the region *r* in linear and quadratic form	IBGE
Migration$_{i,t-1}$	Dummy variable for inventors when they change regions	RAIS

Source: Own elaboration

Table 2: Descriptive statistics

Variables	Obs	Mean	Std. Dev.	Min	Max
Patents$_{i,t}$	129,344	0.135	0.528	0 36	
Academic$_{i,t}$	129,344	0.151	0.358	0	1
Star$_{i,t}$	129,344	0.029	0.168	0	1
High Education$_{i,t}$	127,077	0.650	0.477	0	1
Closeness$_{i,t}$	129,344	0.138	0.309	0	1
Betweenness$_{i,t}$	129,344	0.00001	0.0002	0	0.010
Stock of patents$_{f,t-1}$	77,691	0.128	1.591	0	210.4
Employees$_{f,t-1}$	77,691	6.105	2.398	0.693	13.096
Absorptive capacity$_{f,t-1}$	77,690	0.417	0.317	0	1
Mobility$_{i,t-1}$	129,344	0.085	0.279	0	1
Stock of patents$_{r,t-1}$	123,216	6.444	4.618	-0.143	25.888
Population density$_{r,t-1}$	123,216	592.239	755.482	0.795	2071.454
Migration$_{i,t-1}$	129,344	0.0325	0.177	0	1

Source: Own elaboration

To reassure that there is a difference between academic and industrial inventors, we perform a T-Test

[†]We use as IPC-technology concordance table to convert 35 corresponding fields of technology into Electrical engineering, Instruments, Chemistry, Mechanical engineering and Other Fields(**WIPO2021**).

of our variables (Table 3). The T-Test outcomes stress the separate analysis between academic and industrial inventors means.

Table 3: Mean Comparative T-Test of variables

Variables	Mean	Mean (D=1)	
$\text{Patents}_{i,t-1}$	0.129 (0.002)	0.168 (0.004)	***
$\text{Star}_{i,t-1}$	0.030 (0.001)	0.016 (0.001)	***
$\text{High Education}_{i,t-1}$	0.594 (0.001)	0.957 (0.001)	***
$\text{Closeness}_{i,t-1}$	0.117 (0.001)	0.256 (0.002)	***
$\text{Betweenness}_{i,t-1}$	0.000006 (0.000003)	0.0003 (0.000002)	***
$\text{Stock of patents}_{f,t-1}$	0.102 (0.007)	0.237 (0.007)	***
$\text{Employees}_{f,t-1}$	5.868 (0.010)	7.146 (0.016)	***
$\text{Absorptive capacity}_{f,t-1}$	0.357 (0.001)	0.675 (0.002)	***
$\text{Mobility}_{i,t-1}$	0.088 (0.001)	0.070 (0.002)	***
$\text{Stock of patents}_{r,t-1}$	6.476 (0.014)	6.291 (0.033)	***
$\text{Population density}_{r,t-1}$	602.355 (2.367)	535.977 (5.100)	***
$\text{Migration}_{i,t-1}$	0.033 (0.001)	0.032 (0.001)	

Source: Own elaboration

Results

Table 4 presents the estimations of Negative Binomial regression for three different specifications of the model (Models 1-3). Model (1) includes only individual characteristics. In model (2), we add the organization attributes and, finally, in model (3) we add also the regional characteristics. We include other controls and Fixed Effects for year, industries, region and for the main technological field of inventor's patents.

Table 4: Negative binomial results. Patents as dependent variable

Variables	(1)	(2)	(3)
$\text{Academic}_{i,t}$	0.141*** (0.034)	0.214*** (0.045)	0.215*** (0.045)
$\text{Star}_{i,t}$	1.033*** (0.049)	1.117*** (0.063)	1.121*** (0.063)
$\text{Human Capital}_{i,t}$	0.0007 (0.025)	-0.054 (0.040)	-0.058 (0.040)
$\text{Closeness}_{i,t}$	0.693***	0.660***	0.663***

	(0.029)	(0.039)	(0.039)
$\text{Betweenness}_{i,t}$	469.8***	438.1***	430.1***
	(26.14)	(29.35)	(29.45)
$\text{Stock of patents}_{o,t-1}$		-0.002	-0.002
		(0.014)	(0.014)
$\text{Employees}_{o,t-1}$		0.025***	0.024***
		(0.008)	(0.008)
$\text{Absorptive capacity}_{o,t-1}$		0.052	0.067
		(0.065)	(0.066)
$\text{Mobility}_{i,t-1}$		-0.127***	-0.078
		(0.044)	(0.048)
$\text{Stock of patents}_{r,t-1}$			0.016**
			(0.008)
$\text{Population density}_{r,t-1}$			0.001*
			(0.0003)
$\text{Population density}^2_{r,t-1}$			-3.51e-07**
			(1.66e-07)
$\text{Migration}_{i,t-1}$			-0.186**
			(0.074)
Constant	-1.925***	-1.762***	-1.692***
	(0.311)	(0.483)	(0.485)
ln_r	2.900***	2.534***	2.538***
	(0.049)	(0.059)	(0.059)
ln_s	1.716***	1.266***	1.263***
	(0.051)	(0.063)	(0.063)
Observations	117,945	60,215	60,215
Number of inventors	7,833	7,669	7,669
Tech Field FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Additional controls for age in linear and quadratic form, dummies for man, white and technological occupations and occupational tenure.

Source: Own elaboration

Regarding being individuals characteristics inventor, the estimated coefficient for academic inventors is positive and significant in all models, confirming our expectations that academic inventors patent more than their industrial peers (AGRAWAL; COCKBURN, 2003; VAN LOOY et al., 2004). In line with Lawson and Sterzi (2014), we also found a positive and significant coefficient for 'star' inventor in all models. This result confirm that high ranked inventors are more productive even after controlling for other individual, organizational and local factors. So, this personal characteristic can increase the patenting activity of inventors.

Concerning the inventor's collaboration networks, both closeness and betwenness variables are positive and significant. Which attest the importance of networks as a source of knowledge production because the knowledge of the inventor can be transmitted to other projects through connections and the inventor can benefit from accessing knowledge of indirect partners (TÓTH; LENGYEL, 2021). Closeness is related to the centrality of the inventor in the network so higher closeness means that more connected individuals have a higher inventor productivity. Betweenness is related to the number of two nodes connection that an individual can bridge in the network. So, a higher value means individuals that can be a more valuable brokers in the network of co-inventors patent more. Besides, since both variables are normalized, the coefficient of betwenness have a greater magnitude than closeness meaning that inventors who act as brokers could have a higher impact in patenting activity than others.

We also analyzed organization's characteristics. The size of the firm coefficient is positive and significant, suggesting that it's easier for large organizations engage in patenting due to access to more resources, better infrastructure and the presence of larger R&D offices (BRESCHI; LISSONI, 2004). This finding supports that larger firms can better recognize, assimilate and exploit the knowledge and ideas introduced by inventors (HUSSINGER, 2012).

We found that the regional stock of patents of the region and agglomeration have a positive effect on inventors' productivity. These results show that knowledge have a cumulative nature and interaction between parts of this stock foster the generation of new ideas (KARLSSON; GRÅSJÖ, 2014; HOWELLS, 2002). Besides, region's characteristics influence both firms and universities innovative activities, but especially individual productivity. Individuals with a given set of personal characteristics have distinguish levels of productivity depending on their location (RIGBY; ESSLETZBICHLER, 2002). Additionally, the agglomeration of highly qualified individuals and organizations in a given region can ease this process and increase the inventor's productivity.

Finally, the migration variable presents a negative coefficient pointing that inventors that move between regions reduces productivity. This result could be linked to the fact that since an inventor moves to another region, he implies in new costs to reconstruct his connections and need to implement new strategies to explore the local learning opportunities (EJERMO; KARLSSON, 2006; DI LORENZO; ALMEIDA, 2017).

In general, these results point that the academic inventors are quite different from their industrial peers. Besides, the 'star' inventors are more productive and individual, organizational and local characteristics affect how they patent. To explore in depth these differences and verify if these characteristics play a different role for academics and industrial inventors, we estimate a new specification of our Negative Binomial panel regression interacting the academic dummy variable with all these factors.

Industrial and Academic inventors: results

We present the result of this estimation in Table 5. In this case, our base group is the industrial inventors and column (a) present the general result for this group. Column (b) shows the coefficients estimated for the interaction term between each variable and the academic dummy. So, these coefficients present the difference between the academic and industrial inventor for each factor.

Table 5: Negative binomial results. Patents as dependent variable

Variables	(3)	(4) (a)	(4) (b)
$\text{Academic}_{i,t}$	0.215***		
	(0.045)		
$\text{Star}_{i,t}$	1.121***	1.092***	0.341*
	(0.063)	(0.067)	(0.185)
$\text{Human Capital}_{i,t}$	-0.058	-0.007	-0.625***
	(0.040)	(0.041)	(0.145)
$\text{Closeness}_{i,t}$	0.663***	0.661***	0.038
	(0.039)	(0.046)	(0.082)
$\text{Betweenness}_{i,t}$	430.1***	303.0***	265.1***
	(29.45)	(40.87)	(60.16)
$\text{Stock of patents}_{o,t-1}$	-0.002	-0.001	-0.022
	(0.014)	(0.014)	(0.050)
$\text{Employees}_{o,t-1}$	0.024***	0.023***	0.012
	(0.008)	(0.008)	(0.016)
$\text{Absorptive capacity}_{o,t-1}$	0.067	-0.100	1.086***
	(0.066)	(0.070)	(0.170)
$\text{Mobility}_{i,t-1}$	-0.078	-0.065	-0.055
	(0.048)	(0.052)	(0.133)
$\text{Stock of patents}_{r,t-1}$	0.016**	0.017**	0.027***
	(0.008)	(0.008)	(0.009)
$\text{Population density}_{r,t-1}$	0.001*	0.001	-0.0002
	(0.0003)	(0.0004)	(0.0003)
$\text{Population density}^2_{r,t-1}$	-3.51e-07**	-3.18e-07*	1.06e-08
	(1.66e-07)	(1.71e-07)	(1.44e-07)
$\text{Migration}_{i,t-1}$	-0.186**	-0.135*	-0.200
	(0.074)	(0.081)	(0.198)
Constant	-1.692***	-1.653***	
	(0.485)	(0.484)	
ln_r	2.538***	2.566***	
	(0.059)	(0.060)	
ln_s	1.263***	1.280***	
	(0.063)	(0.064)	
Observations	60,215	60,215	
Number of inventors	7,669	7,669	

Tech Field FE	Yes	Yes
Sector FE	Yes	Yes
Region FE	Yes	Yes
Year FE	Yes	Yes
Controls	Yes	Yes

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Additional controls for age in linear and quadratic form, dummies for man, white and technological occupations and occupational tenure.

Source: Own elaboration

The estimation results for the industrial inventor (column a) remains quite the same what is expected (Model 3) since this group is the more numerous one and attest the previous general estimations. We used an interaction term, the interpretation of the results for an academic inventor is the sum of the coefficient of a given variable itself and the respective interaction term. In other words, the results in column (b) shows only the additional effect for the academic inventors' group. Now, we can turn our focus to the difference between academics and industrial inventors.

Being a 'star' inventor have a greater effect on inventor's productivity of academics. This can be related to career gains of academic inventors mainly in reputation and prestige (BALDINI; GRIMALDI; SOBRERO, 2007). This pattern can be more intense in Brazil since a patent is treat for career promotion and tenure track as a qualified scientific publication on most universities.

We also find a positive difference for betwenness in academic inventors, meaning that academics that act as brokers have an increase in their productivity when compared with their industrial peers. This result could be mainly due to the incentives in academic to 'openness' of scientific efforts (FORTI; FRANZONI; SOBRERO, 2013).

The absorptive capacity of universities has a positive and significant coefficient pointing that academics benefit more from a qualified staff in their surroundings. This result can be related to the fact that the academics gain more than their industrial peers from the access to more resources, better infrastructure and larger R&D offices (BRESCHI; LISSONI, 2004).

Regarding the regional factors, we find a positive difference for region's stock of patents for academic inventors. This result is in line with Kantor and Whalley (2014), since they found that universities have a higher capability to exploit local knowledge spillovers. Besides, universities have institutional mechanisms that promote open science can improve the for local accumulated knowledge (MERTON, 1973).

An unexpected final result is that the human capital variable present a negative interaction term signal, showing that academic with college degree patent less than their industrial peers. This result could be driven by the few inventors in the academic staff that does not have a college degree and support lab experiences and are reported as an inventor in the patent file. Despite they are not highly educated, their patenting activity can be higher than the average leading to this negative coefficient.

Together, this analysis of the different effect of some characteristic for academic inventors points that 'star' academic inventors patent more than an industrial 'star'. Also, the networks seem to be more important for the university's innovation, since the betweenness have an additional positive effect. Academic inventors also have an increased productivity when they are located in organizations with a larger absorptive capacity and in regions with a greater local stock of patents. These results together reinforce the necessity to analyze separately academic and industrial inventors.

Robustness Check

We also perform a few robustness checks to ensure the quality of our estimations. Our results remain similar for all specifications. First, since patenting is a expensive activity, one could argue that small firms often do not patent their inventions. To ensure that the small firms does not affect our main results, we performed estimations only for individuals in firms with more than five employees and results remain very similar (Model 5 in Table A2). Regarding the regions, we also perform regressions using the regional employment density instead of population density (Model 6 in Table A2). Again, the results are similar.

Preliminary Conclusions

Academic and industrial inventors have distinguished incentives and gains in patenting, since they have different profiles in terms of intensity, collaboration and technological fields. However, the literature only analyzes both groups isolated and does not try to evaluate these differences on individual inventor's productivity. This fact prevents the correct evaluation of the effects of individual, organizational and location factors on inventor's productivity.

In this sense, this study aims to fill this gap by assessing if academic inventors can be distinguished by industrial inventors and how the contribution of individual, organizational and locational characteristics for patenting differ between academics and industrial inventors. We estimate a negative binomial panel regression for Brazilian inventors for 2003 to 2018 using patents records from the national patent office.

We find that academic inventors patent more than their industrial peers. Concerning their individual characteristics, we found that 'star' inventors have a higher productivity and connected individuals patent more, regardless of they are central in the network or acting as bridges to other inventors. We also find a positive effect for larger organizations and for larger regions with a greater stock of patents. We find a negative result for inventors that migrate, due to loss of connection and relearning.

Finally, regarding the differences between these characteristics for inventor's productivity, we find that academic 'star' scientists have a positive difference from their industrial peers. Besides, academic inventors that act as brokers at their network tend to patent more. We also find a difference for academic inventors regarding the absorptive capacity of their organizations and the local stock of patents.

These results attest the importance of separating these groups at analyzing inventor's productivity. The absence of this makes it difficult to understand in depth the role of each of these elements in the inventive activity, limiting both the understanding of the dynamics of innovation and the correct evaluation and proposal of public policies for innovation.

It's important to note that our results point the differences in patenting for academics. The different roles that some characteristics play for academics are already related in the literature. However, a future research agenda could try to explore better the mechanisms that underlie these effects.

References

AGRAWAL, A.; COCKBURN, I. The anchor tenant hypothesis: Exploring the role of large, local, R&D-intensive firms in regional innovation systems. **International Journal of Industrial Organization**, v. 21, n. 9, p. 1227–1253, 2003.

AKCIGIT, U.; CAICEDO, S.; MIGUELEZ, E.; STANTCHEVA, S.; STERZI, V. Dancing with the Stars: Innovation Through Interactions. **NBER Working Paper Series**, Mar. 2018. Publication Title: NBER Working Paper Series Volume: 5 Issue: 4 ISSN: 23973366.

ALNUAIMI, T.; OPSAHL, T.; GEORGE, G. Innovating in the periphery: The impact of local and foreign inventor mobility on the value of Indian patents. **Research Policy**, v. 41, n. 9, p. 1534–1543, Nov. 2012. Publisher: Elsevier B.V.

ANNA VILLARROYA, L. S.; MENÉNDEZ, T. S. P. **Research and innovation in Spain and Portugal**. Palma, Spain, 2022.

ASCANI, A.; BETTARELLI, L.; RESMINI, L.; BALLAND, P.-A. Global networks, local specialisation and regional patterns of innovation. **Research Policy**, v. 49, n. 8, p. 104031, Oct. 2020. Publisher: Elsevier.

BALDINI, N.; GRIMALDI, R.; SOBRERO, M. To patent or not to patent? A survey of Italian inventors on motivations, incentives, and obstacles to university patenting. **Scientometrics**, v. 70, n. 2, p. 333–354, 2007.

BRESCHI, S.; LENZI, C. The Role of External Linkages and Gatekeepers for the Renewal and Expansion of US Cities' Knowledge Base, 1990–2004. **Regional Studies**, v. 49, n. 5, p. 782–797, 4 May 2015.

BRESCHI, S.; LISSONI, F. Knowledge Networks from Patent Data. In: MOED, H. F.; GLÄNZEL, W.; SCHMOCH, U. (Eds.). **Handbook of Quantitative Science and Technology Research**. Dordrecht: Springer Netherlands, 2004. p. 613–643.

CAPPELLI, R.; CZARNITZKI, D.; DOHERR, T.; MONTOBBIO, F. Inventor mobility and productivity in Italian regions. **Regional Studies**, v. 53, n. 1, p. 43–54, 2019.

CASSIMAN, B.; VEUGELERS, R.; ARTS, S. Mind the gap: Capturing value from basic research through combining mobile inventors and partnerships. **Research Policy**, v. 47, n. 9, p. 1811–1824, Nov. 2018. Publisher: Elsevier.

CRESCENZI, R.; FILIPPETTI, A.; IAMMARINO, S. Academic inventors: collaboration and proximity with industry. **Journal of Technology Transfer**, v. 42, n. 4, p. 730–762, 2017. Publisher: Springer US.

CRESCENZI, R.; NATHAN, M.; RODRÍGUEZ-POSE, A. Do inventors talk to strangers? on proximity and collaborative knowledge creation. **Research Policy**, v. 45, n. 1, p. 177–194, 2016. Publisher: Elsevier B.V.

DI LORENZO, F.; ALMEIDA, P. The role of relative performance in inter-firm mobility of inventors. **Research Policy**, v. 46, n. 6, p. 1162–1174, 2017. Publisher: Elsevier.

EJERMO, O.; HUSSINGER, K.; KALASH, B.; SCHUBERT, T. Innovation in Malmö after the Öresund Bridge. **Journal of Regional Science**, v. 62, n. 1, p. 5–20, 7 Jan. 2022.

EJERMO, O.; KARLSSON, C. Interregional inventor networks as studied by patent coinventorships. **Research Policy**, v. 35, n. 3, p. 412–430, Apr. 2006.

FERRUCCI, E.; LISSONI, F. Foreign inventors in Europe and the United States: Diversity and Patent Quality. **Research Policy**, v. 48, n. 9, p. 103774, Nov. 2019. Publisher: Elsevier.

FORTI, E.; FRANZONI, C.; SOBRERO, M. Bridges or isolates? Investigating the social networks of academic inventors. **Research Policy**, v. 42, n. 8, p. 1378–1388, 2013. Publisher: Elsevier B.V.

FURMAN, J. L.; NAGLER, M.; WATZINGER, M. Disclosure and Subsequent Innovation: Evidence from the Patent Depository Library Program. **American Economic Journal: Economic Policy**, v. 13, n. 4, p. 239–270, 2021.

HOISL, K. Does mobility increase the productivity of inventors? **The Journal of Technology Transfer**, v. 34, n. 2, p. 212–225, 28 Apr. 2009.

HOWELLS, J. R. L. Tacit Knowledge, Innovation and Economic Geography. **Urban Studies**, v. 39, n. 5, p. 871–884, May 2002.

HUSSINGER, K. Absorptive capacity and post-acquisition inventor productivity. **Journal of Technology Transfer**, v. 37, n. 4, p. 490–507, 2012.

IBGE. **Divisão regional do Brasil em regiões geográficas imediatas e regiões geográficas intermediárias.** Ed. by IBGE. Rio de Janeiro: IBGE, 2017. 82 pp.

KANTOR, S.; WHALLEY, A. Knowledge Spillovers from research universities: Evidence from endowment value shocks. **Review of Economics and Statistics**, v. 96, n. 1, p. 171–188, 2014.

KARLSSON, C.; GRÅSJÖ, U. Knowledge Flows, Knowledge Externalities, and Regional Economic Development. In: FISCHER, M. M.; NIJKAMP, P. (Eds.). **Handbook of Regional Science**. Berlin, Heidelberg: Springer Berlin Heidelberg, 2014. p. 413–437.

KIM, J.; LEE, S. J.; MARSCHKE, G. Inventor productivity and firm size: Evidence from panel data on inventors. **Pacific Economic Review**, v. 14, n. 4, p. 516–531, Oct. 2009.

LAWSON, C.; STERZI, V. The role of early-career factors in the formation of serial academic inventors. **Science and Public Policy**, v. 41, n. 4, p. 464–479, 1 July 2014.

LISSONI, F. Academic inventors as brokers. **Research Policy**, v. 39, n. 7, p. 843–857, 2010. Publisher: Elsevier B.V.

LOTKA, A. J. The frequency distribution of scientific productivity. **Journal of the Washington Academy of Sciences**, v. 16, n. 12, p. 317–323, 1926.

MERTON, R. K. **The Sociology of Science: Theoretical and Empirical Investigations**. London: University of Chicago Press, 1973.

MORETTI, E. The Effect of High-Tech Clusters on the Productivity of Top Inventors. **American Economic Review**, v. 111, n. 10, p. 3328–3375, 1 Oct. 2021.

PINTO, P. E.; VALLONE, A.; HONORES, G. The structure of collaboration networks: Findings from three decades of co-invention patents in Chile. **Journal of Informetrics**, v. 13, n. 4, p. 100984, Nov. 2019. Publisher: Elsevier Ltd.

RAHKO, J. Knowledge spillovers through inventor mobility: the effect on firm-level patenting. **The Journal of Technology Transfer**, v. 42, n. 3, p. 585–614, 30 June 2017. Publisher: Springer US.

RIGBY, D. L.; ESSLETZBICHLER, J. Agglomeration economies and productivity differences in US cities. **Journal of Economic Geography**, v. 2, n. 4, p. 407–432, 1 Oct. 2002.

SCHETTINO, F.; STERLACCHINI, A.; VENTURINI, F. Inventive productivity and patent quality: Evidence from Italian inventors. **Journal of Policy Modeling**, v. 35, n. 6, p. 1043–1056, Nov. 2013. Publisher: The Society for Policy Modeling.

TER WAL, A. L. Cluster Emergence and Network Evolution: A Longitudinal Analysis of the Inventor Network in Sophia-Antipolis. **Regional Studies**, v. 47, n. 5, p. 651–668, 2013.

TÓTH, G.; LENGYEL, B. Inter-firm inventor mobility and the role of co-inventor networks in producing high-impact innovation. **The Journal of Technology Transfer**, v. 46, n. 1, p. 117–137, 12 Feb. 2021. Publisher: Springer US ISBN: 0123456789.

TUBIANA, M.; MIGUELEZ, E.; MORENO, R. In knowledge we trust: Learning-by-interacting and the productivity of inventors. **Research Policy**, v. 51, n. 1, p. 104388, Jan. 2022. Publisher: Elsevier B.V.

VAN LOOY, B.; RANGA, M.; CALLAERT, J.; DEBACKERE, K.; ZIMMERMANN, E. Combining entrepreneurial and scientific performance in academia: towards a compounded and reciprocal Matthew-effect? **Research Policy**, v. 33, n. 3, p. 425–441, Apr. 2004.

ZUCKER, B. L. G.; DARBY, M. R.; BREWER, M. B. Intellectual Human Capital and the Birth of U.S. Biotechnology Enterprises. **American Economic Review**, v. 88, n. 1, p. 290–306, 1998.

ZUCKER, L. G.; DARBY, M. R. Capturing technological opportunity Via Japan's Star Scientists: Evidence from Japanese firms' biotech patents and products. **Journal of Technology Transfer**, v. 26, n. 1, p. 37–58, 2001.

ZWICK, T.; FROSCH, K.; HOISL, K.; HARHOFF, D. The power of individual-level drivers of inventive performance. **Research Policy**, v. 46, n. 1, p. 121–137, Feb. 2017. Publisher: Elsevier B.V.

Appendix

Table A1: Correlation Matrix

	Variables	$P_{i,t-1}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	$Academic_{i,t}$	0.028											
(2)	$Star_{i,t}$	0.216	0.078										
(3)	High $Education_{i,t}$	0.029	0.270	0.060									
(4)	$Closeness_{i,t}$	0.114	0.172	0.070	0.152								
(5)	$Betweenness_{i,t}$	0.106	0.079	0.184	0.047	-0.014							
(6)	Stock of $patents_{f,t-1}$	0.0002	0.033	0.007	0.027	0.013	0.009						
(7)	$Employees_{f,t-1}$	0.044	0.208	0.082	0.247	0.075	0.055	-0.042					
(8)	Absorptive $capacity_{f,t-1}$	0.008	0.391	0.009	0.483	0.148	0.064	0.045	0.279				
(9)	$Mobility_{i,t-1}$	-0.013	-0.045	0.0013=	-0.056	-0.029	-0.019	-0.020	-0.109	-0.067			
(10)	Stock of $patents_{r,t-1}$	0.009	-0.007	0.115	0.104	0.080	0.086	0.036	0.056	0.046	-0.039		
(11)	Population $density_{r,t-1}$	-0.026	-0.026	-0.060	0.047	-0.0001	-0.005	-0.007	0.031	0.142	0.004	0.151	
(12)	$Migration_{i,t-1}$	-0.007	-0.013	0.003	-0.003	-0.008	-0.010	-0.005	-0.054	-0.015	0.468	-0.040	-0.016

Source: Own elaboration

P: Patents

Table A2: Robustness check. Patents as dependent variable

Variables	(5)	(6)
$\text{Academic}_{i,t}$	0.211***	0.214***
	(0.0453)	(0.0450)
$\text{Star}_{i,t}$	1.133***	1.122***
	(0.0632)	(0.0628)
$\text{Human Capital}_{i,t}$	-0.0560	-0.0589
	(0.0411)	(0.0403)
$\text{Closeness}_{i,t}$	0.670***	0.664***
	(0.0392)	(0.0388)
$\text{Betweenness}_{i,t}$	428.1***	428.0***
	(29.45)	(29.35)
$\text{Stock of patents}_{o,t-1}$	0.00107	-0.00183
	(0.0152)	(0.0137)
$\text{Employees}_{o,t-1}$	0.0224***	0.0244***
	(0.00829)	(0.00786)
$\text{Absorptive capacity}_{o,t-1}$	0.0367	0.0630
	(0.0675)	(0.0656)
$\text{Mobility}_{i,t-1}$	-0.0890*	-0.0758
	(0.0492)	(0.0479)
$\text{Stock of patents}_{r,t-1}$	0.0159*	0.0152*
	(0.00814)	(0.00801)
$\text{Population density}_{r,t-1}$	0.000667*	
	(0.000345)	
$\text{Population density}^2_{r,t-1}$	-3.88e-07**	
	(1.68e-07)	
$\text{Employment density}_{r,t-1}$		0.00161***
		(0.000554)
$\text{Employment density}^2_{r,t-1}$		-3.04e-06***
		(7.27e-07)
$\text{Migration}_{i,t-1}$	-0.190**	-0.187**
	(0.0758)	(0.0741)
Constant	-1.735***	-1.732***
	(0.487)	(0.485)
ln_r	2.530***	2.541***
	(0.0593)	(0.0586)
ln_s	1.268***	1.265***
	(0.0639)	(0.0631)

Observations	57,829	60,215
Number of inventors	7,593	7,669
Tech Field FE	Yes	Yes
Sector FE	Yes	Yes
Region FE	Yes	Yes
Year FE	Yes	Yes
Controls	Yes	Yes

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Additional controls for age in linear and quadratic form, dummies for man, white and technological occupations and occupational tenure.

Source: Own elaboration