The Geography of Green Innovators in the United States (extended abstract)

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Abstract

In the last decades, the geography of innovation activity became much more concentrated. By focusing on the US metropolitan statistical area of residence of the inventors of patents filed to the United States Patents and Trademark Office between 1990 and 2016, we show that this is increasingly true also for "green" innovation, i.e. patents covering mitigation or adaptation to climate change. We find a sharp increase in concentration across areas after the beginning of the 2000s, with areas that are generally more innovative also producing more green patents. Focusing on the relationship between green innovation and urban density, we find evidence of a positive significant relationship only after 2002. To shed some light on this puzzling outcome, we further qualified the concept of density to urban human capital density, finding the expected significant relationship between green innovation and density before and after 2002, and we aim at possibly rationalizing these findings.

Keywords: agglomeration, climate change, innovation, spatial distribution, patents.

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1 Introduction

The spatial distribution of innovative activity is clearly uneven, with a tendency for innovation to cluster in urban areas. Starting from Jacobs (1969), a sizeable theoretical literature (see, among others, Glaeser et al., 1992, Black and Henderson, 1999, Glaeser, 1999) has recognized that cities, characterized by their high concentrations of individuals, firms, and institutions, are powerful engines of innovation and economic growth. In parallel, starting from the seminal paper by Ciccone and Hall (1996), a vast number of empirical studies have reported the existence of a positive relationship between population density, a fundamental characteristic of urban environments, and the intensity of innovation, often measured by patenting activity. The explanation for this behavior rests mainly on the role of knowledge spillovers and the circulation of ideas: dense urban environments act as fertile breeding grounds for the rapid dissemination of knowledge and ideas.

In the present paper, we study the differences in the locational patterns of "green" patenting activity compared to other types of patenting across US metropolitan urban areas between 1990 to 2016. In particular, we do so by placing a strong attention on how density is measured. While population and employment density are rather immediate concepts, other forms of qualification of density may be more complex to be calculated but may demonstrate to be more appropriate from a conceptual point of view. In our case, given the nature of the phenomenon under study, we follow a process of progressive qualification of the density variable employed in the empirical analysis, guided by the theoretical considerations and empirical evidence at hand.

In particular, after starting with a traditional measure of population density, the first qualification of density we provide stems from the observation that, given the way in which the spatial units of analysis, namely the Metropolitan Statistical Areas, are constructed, a simple calculation of density as the number of individuals per unit geographic area may not accurately reflect the level of density actually faced by economic agents. In particular, the problem arises from the fact that metro areas are built as aggregations of counties, and especially in some parts of the United States, the more peripheral counties include substantial portions of rural territory. To overcome this problem, we first derive an estimate of the urban component of the counties, both in terms of area and population, and through this estimate, we "clean up" the notion of population density.

Subsequently, we enter more directly into the nature of the density relevant to the phenomenon we are studying. There is in fact a significant body of literature that emphasizes the role of human capital in shaping the agglomeration economies which are relevant to the innovation process. We refer here to the role played by human capital both in knowledge spillover processes and in defining the quality of the labor supply within an urban labor market. Consequently, after deriving a measure of the number of individuals with at least two years of college education in each metro area, we analyze how a measure of urban density of human capital modifies the relationship between density and innovative activity, with a specific focus on green patenting activity.

In the next sections, we present our analysis and our preliminary results, as well as the lines along which our ongoing research in proceeding.

2 Data

We measure innovation with the flow number of patents (an exclusionary right conferred for a set period to the patent holder, in exchange for sharing the details of the invention) eventually granted by the United States Patents and Trademarks Office (USPTO). We associate a patent to a year using the application date, which is the year when the provisional application is considered complete by the USPTO.[1] Since patent application data should be considered 95% complete for applications filed 8 years prior (Aghion et al., 2019), we limit our analysis to patent filed before 2017; for other data limitations explained below, we start our analysis from patents filed in 1990. As common in the literature, we restrict our attention to utility patents (thus excluding design patents and plant patents), which cover the creation of a new or improved product, process or machine; these represent approximately 90% of all patents granted by USPTO.

We focus on inventors residing in the conterminous United States (i.e. the 48 adjoining states and the District of Columbia). We assign patents to areas according to the location in which the inventor of the innovation resides (as in e.g. Castaldi and Los, 2017, Aghion et al., 2019, Berkes and Gaetani, 2021, Moretti, 2021), which is extracted from patent text and used to determine latitude and longitude. We use the residential addresses of the inventors and not the one of the assignee (usually, the company that first owned the patent), because we are mainly interested in the location of processes that lead to inventions, whereas the assignee address often reflects the address of the corporate headquarters and not the R&D facility (Moretti, 2021). When a patent is coauthored by more than one inventor, we split it equally among them, as in e.g. Aghion et al. (2019), Berkes and Gaetani (2021), and Moretti (2021). Henceforth, we thus attribute a fraction m/n of a patent to an area a, where n is the total number of inventors in that patent and m is the number of inventors of that patent who reside in area a.

To define a patent as "green", we use the Cooperative Patent Classifications (CPC), which has been introduced in 2013 by the USPTO and the European Patent Office. Unlike existing patent classifications such as the International Patent Classifications, the CPC can be indexed with a focus on emerging technologies (Veefkind et al., 2012). These new

[1]We follow the patent literature in focusing on application year rather than the award year. As noted by Lerner and Seru (2022), the motivation is that, whereas firms will generally tend to file for patents as soon as the discoveries are made in order to protect their intellectual property, the time at which the patent is granted depends on many external factors, like the technological area or the state of the patent office.

Table 1: The Y02/Y04S Scheme

CPC Code	Technological Domain
Y02A	Technologies for adaptation to climate change
Y02B	Climate change mitigation technologies related to buildings, e.g. housing, house appliances or related end-user applications
Y02C	Capture, storage, sequestration or disposal of GHG
Y02D	Climate change mitigation technologies in information and communication technologies, i.e. information and communication technologies aiming at the reduction of their own energy use
Y02E	Reduction of GHG emissions, related to energy generation, transmission or distribution
Y02P	Climate change mitigation technologies in the production or processing of goods
Y02T	Climate change mitigation technologies related to transportation
Y02W	Climate change mitigation technologies related to wastewater treatment or waste management
Y04S	Systems integrating technologies related to power network operation, communication or information technologies for improving the electrical power generation, transmission, distribution, management or usage, i.e. smart grids

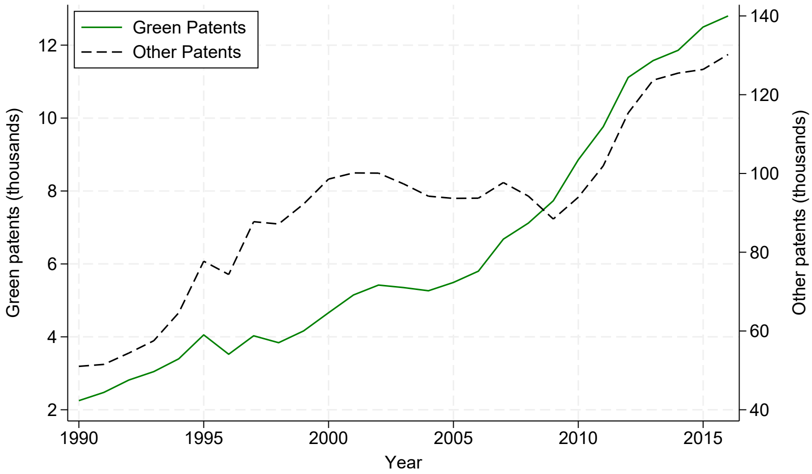
Source: `https://www.uspto.gov/web/patents/classification/cpc/html/cpc-Y.html`

classifications have been backtracked into the existing databases. We exploit this system by classifying a patent as green if it belongs to at least one subclass in the Y02/Y04S scheme, like e.g. Corrocher et al. (2021). Within the CPC, the Y02 class covers *"technologies which control, reduce, or prevent anthropogenic emissions of greenhouse gases (GHG), in the framework of the Kyoto Protocol and the Paris Agreement, and technologies which allow the adaptation to the adverse effects of climate change"*, whereas the Y04S covers *"systems integrating technologies related to power network operation, communication, or information technologies for improving the electrical power generation, transmission, distribution, management, or usage"*. Table 1 identifies the technological classes under investigation.

In total, there are 2,750,623 utility patents filed by inventors residing in the conterminous US between 1990 and 2016, of which 178,653 (approximately 6.5%) belong to at least one green subclass. It is well known that the number of patents granted by the USPTO annually has greatly increased since the 1990s. Figure 1 shows that the number of green patents granted has also been growing, with an impressive acceleration from 2006 (in line with the findings by Corrocher et al., 2021).

In terms of areas, we focus on metropolitan statistical areas (MSAs), i.e. regions *"consisting of a large urban core together with surrounding communities that have a high degree of economic and social integration with the urban core"* (Ruggles et al., 2020). We consider MSAs for various reasons. First, MSAs represent economic spatial units and so are

Figure 1: Total Patents



Notes. Number of utility patents filed to USPTO in any given year between 1990 and 2016 by innovators residing in the conterminous US. Own elaborations using data from USPTO.

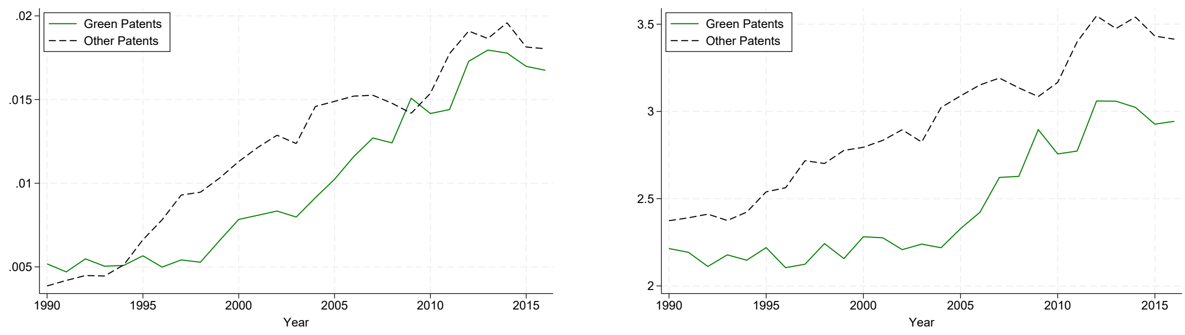
considered more appropriate to study economic dynamics than states, regions, or even counties (e.g. Drennan, 2005). Second, innovation is mainly an urban phenomenon (Bettencourt et al., 2007); for example, the vast majority of patents in our dataset come from inventors residing in a metropolitan area (approximately 85% for utility patents and 83% for green patents). Third, there is large heterogeneity across MSAs in terms of capacity to innovate. We assign an inventor location to a MSA using the 2013 Cartographic Boundary Files provided by the United States Census Bureau.[2]

3 Concentration and Agglomeration

There is a great deal of evidence that research and development activities tend to be more concentrated than manufacturing activities (e.g. Buzard et al., 2017) and that patenting activities in the US have become more geographically concentrated since the end of the last century (e.g. Castaldi and Los, 2017, Andrews and Whalley, 2021, Forman and Goldfarb, 2021, Magrini and Spiganti, 2024). In this section, we first measure the spatial concentration in green patenting activities and then examine the relationship between green patenting and urban density across MSAs, comparing these patterns with those for other (i.e. non-green) patents.

[2] Source: `https://www.census.gov/geographies/mapping-files/time-series/geo/cartographic-boundary.html`. The definition used for the identification of MSAs has evolved over time, with significant changes made especially around census years: results are qualitatively identical independently of the boundary files used.

Figure 2: Patents Concentration



(a) Dartboard

(b) Herfindahl-Hirschman

Notes. The first (second) panel shows the yearly dartboard (Herfindahl-Hirschman) innovation intensity concentration index across metropolitan statistical areas in the United States between 1990 and 2016. Own elaborations using data from USPTO, Manson et al. (2020), and US Census.

3.1 Concentration

Following Andrews and Whalley (2021), we first measure concentration using Ellison and Glaeser's (1997) dartboard approach. This consists of calculating an index of the spatial concentration of innovation intensity by comparing the observed spatial distribution of innovators to what it would have been if it had been proportional to (urban) population distribution. In particular, for each year t and all areas $a \in A$, the dartboard innovation intensity concentration index is

$$Concentration_t = \frac{\sum_{a=1}^{A} (SharePat_{at} - SharePop_{at})^2}{1 - \sum_{a=1}^{A} SharePop_{at}^2}, \tag{1}$$

where $SharePat_{at}$ and $SharePop_{at}$ are, respectively, the shares of patents granted and of urban population living in area a in year t. The scale of this index is such that a value of zero can be interpreted as indicating a complete lack of agglomerative forces, whereas a value of one would indicate that all patenting occurs in one area.

The evolution of this index is reported in Figure 2a, where an increase in concentration across areas is evident, starting in the mid 1990s for non-green patents and at the beginning of the 2000s for green ones. Figure 2b confirms these findings using the Herfindahl-Hirschman index, which is calculated by taking each area's share of total patents in a year, squaring them, and summing the result; this index equals 10,000 if all patents come from one area and approaches zero if each area is responsible for a low share of patents. As underlined by e.g. Andrews and Whalley (2021), the increase in concentration goes hand-in-hand with increasing assortative sorting of skills across cities and the emergence of superstar cities.

A second feature that clearly emerges from the evolution of the Herfindahl-Hirschman index is the sudden and sizeable change in the slope of the series related to green patents at the beginning of the 2000s, which seems to suggest the presence of a structural break in the relationship between green and brown patents. To further explore this aspect, we apply a Bai and Perron (1998) test of structural breaks to the monthly series of the Herfindal-Hirschman concentration index of green and brown patenting activity from January 1990 to December 2016. Before carrying out the test, however, we handle an evident outlier in the index for green patents by applying a 6-month average (excluding current observation), and then concentrate on the trend component of the series obtained by applying an Hodrick-Prescott filter with a smoothing parameter as suggested by Ravn and Uhlig (2002). As shown in Table 2, the test (Bai and Perron, 1998) detects a statistically significant break in March 2002; consequently, hereafter we split our samples into two parts: 1990-2001 and 2002-2016.

Table 2: Test for Structural Breaks at Unknown Breakdates

	test statistic	1% critical value	5% critical value	10% critical value
supW(tau)	1,306.71	7.68	5.74	4.91
Estimated break point	2002m3			

Notes: the Bai and Perron (1998) test is carried out using the Stata package **xtbreak**

3.2 Urban Density and Innovation

Cities, characterized by their high concentrations of individuals, firms, and institutions, have often been recognized as the engines of innovation and economic growth. This observation has spurred extensive research into the relationship between population density and the intensity of innovation.

High population density, by its very nature, fosters several distinct types of agglomeration economies. Dense urban environments act as fertile breeding grounds for the rapid dissemination of knowledge and ideas. This occurs through both formal and informal channels. Formally, universities, research institutions, and specialized training centers provide structured platforms for knowledge creation and transfer. Informally, the constant interaction between individuals in diverse fields, whether through professional networks, social gatherings, or chance encounters, facilitates the cross-fertilization of ideas and the serendipitous sparking of innovation. Several empirical studies thus suggest that larger cities exhibit increasing returns to scale in innovation activity, a phenomenon largely attributable to the amplified knowledge spillovers that occur within these densely populated areas. Carlino et al. (2007) focus on employment density and find that doubling its level determines a 20 percent increase in patent intensity. Similarly, Bettencourt et al. (2007) provide evidence supporting the presence of a superlinear relationship between metropolitan size and patenting rates.

Dense urban areas attract a diverse and highly specialized labor pool, creating a "thick" labor market. This concentration of skilled workers, researchers, and entrepreneurs provides firms with unparalleled access to the specific human capital they require. The presence of a large and diverse labor pool allows for more efficient matching between inventors and firms, optimizing the allocation of talent and facilitating the complex processes of technology development and commercialization. Moretti (2021) analyses the productivity-enhancing effects of high-tech clusters on top inventors and reports the presence of significant benefits accruing to inventors from being embedded within localized, specialized labor markets, where they can readily collaborate with peers, access specialized resources, and benefit from a supportive ecosystem.

While agglomeration forces generally exert a positive influence on innovation, the unrelenting increase in population density can, beyond a certain point, lead to significant congestion diseconomies. These negative effects can counteract the benefits of agglomeration and ultimately stifle innovative activity. High population density invariably leads to increased competition for limited resources, particularly land and housing. This drives up the costs of both residential and commercial real estate, making it increasingly challenging for startups and smaller, resource-constrained firms to compete with established, larger corporations. The high cost of living can also deter skilled workers from relocating to or remaining in extremely dense areas, eroding the specialized labor pool that is so crucial for innovation. Overcrowding places immense strain on existing infrastructure, including transportation networks, utilities (water, electricity, waste management), and public services. This can result in traffic congestion, power outages, water shortages, and other disruptions that negatively impact productivity and the overall efficiency of research and development activities. Congestion often leads to a decline in the overall quality of life. Increased noise levels, air pollution, limited access to green spaces, and longer commute times can contribute to higher stress levels and a reduced sense of well-being. These factors can make it significantly harder to attract and retain the top-tier talent that is essential for driving innovation. The simultaneous presence of agglomeration economies and congestion diseconomies strongly suggests that the relationship between population density and patenting activity is inherently non-linear. The work of Berkes and Gaetani (2021) on the geography of "unconventional innovation" provides valuable insights into this non-linear dynamic. Their research indicates that while conventional innovation (incremental improvements to existing technologies) tends to be highly concentrated in dense urban cores, unconventional innovation (more radical and disruptive breakthroughs) exhibits a more dispersed spatial pattern. This finding lends support to the argument that optimal conditions for innovation may not be found at the absolute highest densities.

We now have a look at the relationship between urban density and innovative activity across the US. Before doing that, however, we must address a fundamental issue:

the choice of the scale of the analysis. The overview of the forces that, via population density, can exert an influence on innovation activity clearly suggests that, conceptually, the *urban area* constitutes the most appropriate spatial unit for this type of analysis. In the US context, a possible choice would then be the Metropolitan Statistical Area. Quite simply, the MSA comprises a core with a relatively high population density and adjacent communities linked to the core by intense commuting flows. On the positive side, as MSAs include both employment and the residents who hold the jobs, they are in economic terms as self-contained as spatial subdivisions of national economies are likely to be thus containing within themselves most of the agglomeration economies and diseconomies described above. However, metropolitan areas comprise complete counties, and counties on the outer fringes often have the majority of their land areas and significant portions of their populations classified as rural. As emphasized by Duranton and Puga (2020), MSAs tend to understate the density experienced by most economic actors, particularly where the match between urban and county boundaries is systematically looser as in the western part of the Unites States. Seeking to avoid this bias, researchers have exploited the availability of data at a finer spatial resolution. Berkes and Gaetani (2021), for instance, conduct their analysis at the County Sub-Division (CSD) level, which allows them to separate low- and high-density areas within larger units. However, because in western and southern parts of the United States County Sub-Division boundaries tend to align with County boundaries, this approach makes it difficult to address the bias problem previously discussed. Hence, we follow a different route.

In particular, to address the issue and concentrate on urban population density, we resort to census data, originally at census block level and then to county level (for coterminous US), about the percentage of population and land that is defined urban.[3] It should be emphasized that urban is sometimes confused with metropolitan, but they are different concepts. The metropolitan concept is more related to whether the population live in an area where they are either within or have access to an urban center, for example because they can commute to work there (this is the primary criteria to being included in a metro area), or they have access local TV and radio stations, subscribe to local newspapers, et cetera. Urban (as opposed to rural) does not focus on the distance from the urban center; instead, it has to do with the density of the population in the immediate area around.

The data set includes 4 observations (years 1990, 2000, 2012, 2022) and from these it is possible extrapolate other years for our analysis. With the percentage of urban density at county level, we derived the percentage of the urban density at MSA level that, in turn, gives us what we call the urban population density.

[3]The database is Master Area Block-Level Equivalency (MABLE) to create the correlation lists, where "block" refers to census blocks. The MABLE databases are almost entirely based on the Census Bureau's TIGER databases. Each version of MABLE is based on its own set of census blocks (1990, 2000, 2010, 2020), source: `https://mcdc.missouri.edu/`

Now we look at the relationship between urban population density and innovative activity across MSAs. To do this, we first employ binned scatterplots (Cattaneo et al., 2024), a tool which provides a graphical representation of the conditional, nonparametric relationship between two variables. For large samples, binned scatterplots condense the information from a traditional scatterplot by partitioning the x-axis into bins, and calculating the mean of y within each bin. The resulting plot thus shows the nonparametric relationship between the independent variable (in bins) and the mean of dependent variable.

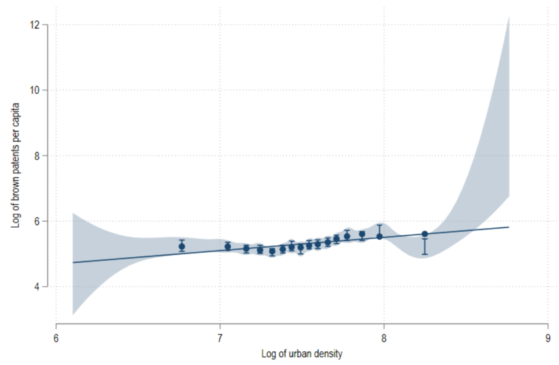
Figure 3 reports the binned scatterplots for green and brown patents sub-dividing the analysis in the two periods separated by the structural break detected in Section 3.1. The main features that emerge can be summarized as follows. In both sub-periods, the relationship between the log of urban density and the log of brown patents (Figure 3, panes (a) and (b)) is globally increasing, although not necessarily in a linear fashion: it seems more strongly positive in the left portion of the distribution, while easing off for MSAs with a higher density. This result is in line with Berkes and Gaetani (2021) who report a inverted U-shaped relationship between population density and patents per capita across CSDs between 2000 and 2010. A similar behavior is found in the later period for green patents. As shown in Figure 3, panel (d), also the relationship between urban density and per capita green patents, whilst globally positive, lessens in the right-most portion of the distribution.

In contrast, a different behavior characterizes green patenting activity during the first period of analysis. Here, net of a limited degree of variation, the relationship between green patents per capita and urban density is essentially flat.

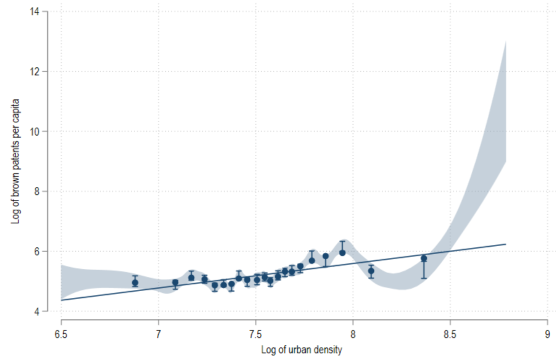
To further examine these features, we run fixed-effects, linear regressions on the same data. In particular, we regress the log of patents per capita against the log of urban density for both green and brown innovative activity and over both periods thus producing estimates of the elasticity of patenting with respect to urban population density. Table 3 shows that the elasticity of brown patenting is always statistically significant, increasing from a value of 0.41 in the first sub-period, to a value of 0.82 in the second; in contrast, the elasticity of green patenting is statistically significant only in the 2001-2016 period, whilst being not-significant in the earlier one.

To sum up, we have found that patenting activities have increasingly became more concentrated over time. In addition, we have found that the relationship between brown patenting and urban population density is, in general, positive, although not necessarily linear, during the entire period, while green patenting shows a positive relationship with urban density only over the 2001-2016 sub-period.

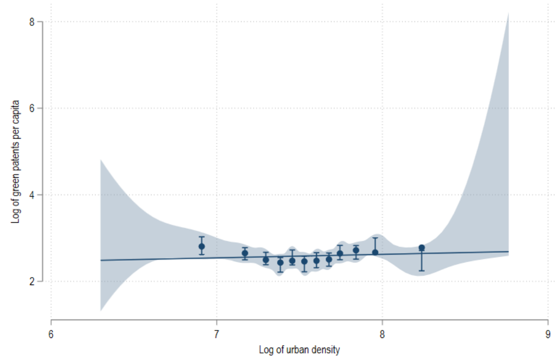
Figure 3: Urban Population Density and Patenting Per Capita



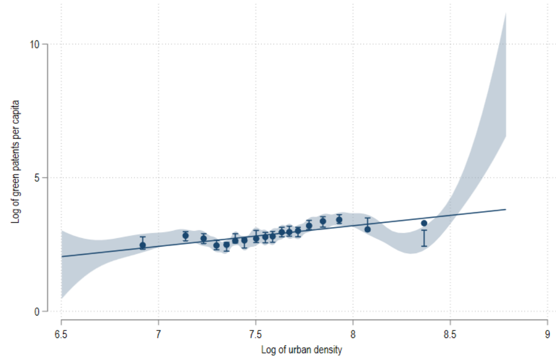
(a) 1990-2001, Brown Patents



(b) 2002-2016, Brown Patents



(c) 1990-2001, Green Patents



(d) 2002-2016, Green Patents

Notes. The bin-scatter plot is obtained applying the methodology described Cattaneo et al. (2024) through the Stata package **Binsreg**. The dependent variable is the log number of patents per inventor per year, and the independent variable is the log density of urban population. Binscatter estimates are based on log population weights and control for year fixed effects. Pointwise intervals and global bands denote 95 percent nominal confidence level using a robust variance estimator. The number of bins is chosen following the IMSE-optimal direct plugh-in rule.

4 Geographical Patterns

In the previous section, we have found that brown patenting activities have increasingly became more concentrated in the period 1990-2016 while the degree of concentration in green patenting has remained rather stable in the first sub-period, whilst substantially increasing in the second. It is not clear however whether these activities have concentrated across the same areas. This is the focus of this Section.

Figure 4 shows the evolution of the number of total and green innovators across MSAs and over time; to make the comparisons meaningful, the number of patents is scaled by the area's urban population (as in e.g. Aghion et al., 2019, Castaldi and Los, 2017).

Through these maps, we have a further qualification of the results established in Section 3. Each maps reports, through the grey dots, the location of the MSAs in the sample, together with the level of green or brown patenting activity for those MSAs with a

Table 3: Fixed-effect Regressions - Urban Population Density

	(1)	(2)	(3)	(4)
	log patents green		log patents brown	
	1990-2001	2002-2016	1990-2001	2002-2016
urban density	0.0812	0.773***	0.406***	0.817***
	(0.0654)	(0.0716)	(0.0495)	(0.0600)
constant	1.975***	-2.978***	2.254***	-0.940**
	(0.494)	(0.542)	(0.369)	(0.451)
N	3199	4432	4171	5228

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: log of (green or browns patents) on log of urban population density over the subperiods 1990-2001 and 2002-1996. Models control for year and state fixed effects. Robust standard errors are used. Weighting is done with log of urban population. The measure of innovation is winsorized at the 1% level.

level of activity that exceeds the sample average through the colored cicles. Looking at the spatial distribution of the circles we can note a high degree of stability: brown patents tend to concentrate within the same MSAs over the entire period. In particular, the areas that end up showing the highest concentration of patenting activity of this type are Boulder, CO; Burlington-South Burlington, VT; Corvallis, OR; Midland, MI; Rochester, MN; and Sunnyvale-Santa Clara, CA. In contrast, we once more note a different behavior of green patenting activity over the two sub-periods: the spatial distribution of brown patenting is more evenly spread across the MSAs during the first sub-period and tends to exhibit the same spatial characteristics as brown activity in the most recent period.

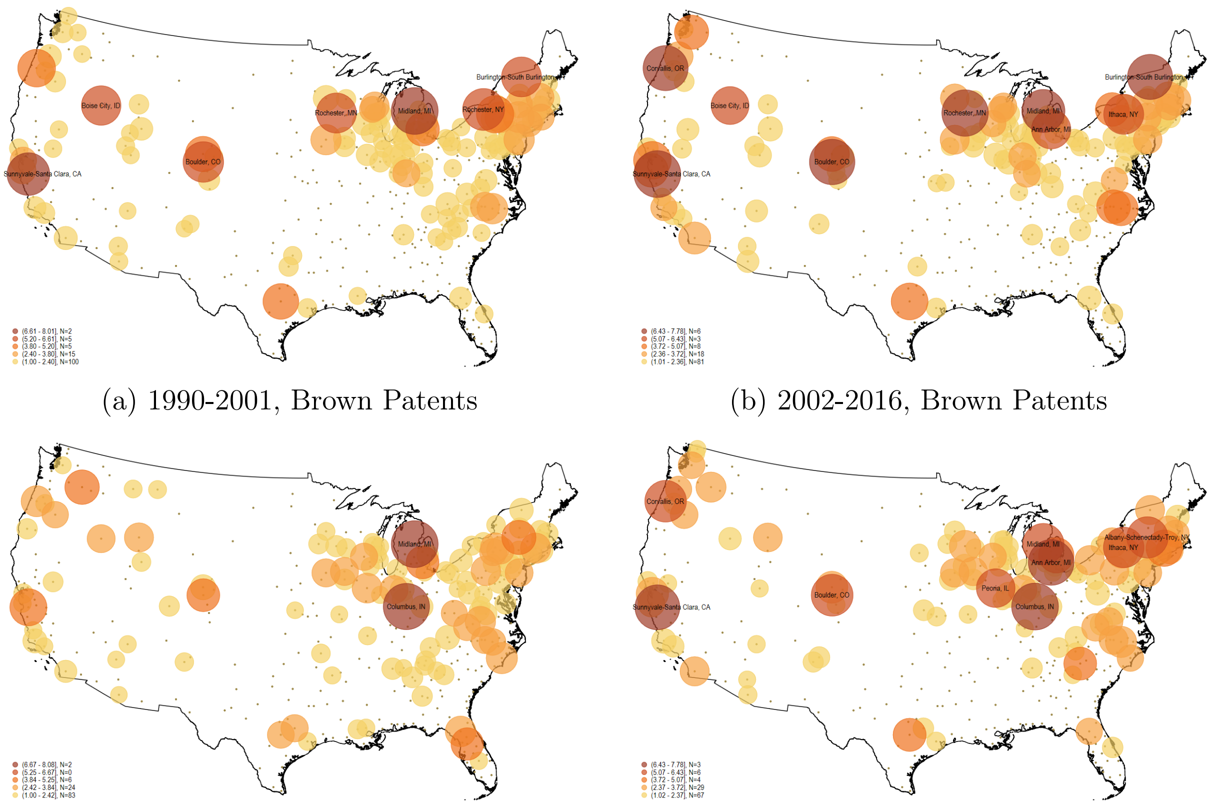
5 Green Patenting and the Nature of Density

As stressed by Duranton and Puga (2020), population or employment density is easy to calculate but, on the other hand, may not appropriately reflect the density actually faced by relevant economic agents. In other words, other types of density may matter for the phenomenon under study and alternative characteristics of population should be considered.

In Section 3.2, we noted that the agglomeration forces that might exert a positive influence on innovation activity involve learning and knowledge spillovers. The extent and intensity of these phenomena, in turn, may be influenced by the size and quality of the human capital stock that is present within the urban area, a point similar to Abel et al. (2012) suggestion regarding the role of the density of human capital in urban productivity.

Consequently, while in the previous analyses we concentrated on urban population density, we now further qualify the concept of density by considering a form of urban human capital density. To do this, we divide the number of people in each MSA with at

Figure 4: Map of patenting activity



(a) 1990-2001, Brown Patents (b) 2002-2016, Brown Patents

(c) 1990-2001, Green Patents (d) 2002-2016, Green Patents

Notes. Own elaborations. Each dot represents an MSA in the sample. The circles are proportional to the extent of patenting activity; circles, grouped into quintiles, are depicted only for MSAs with patenting activity above the sample average.

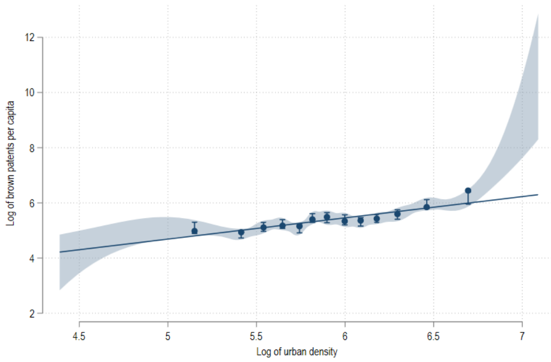
least 2 years of college by the extent of the urban area, a rather conventional measure of human capital (although focusing exclusively on educational attainment might not be able to capture the full array of knowledge and skills within a metropolitan area).

Figure 5 shows the binned scatterplots obtained, for green and brown patents, when density takes the form of human capital density. The effect of the change in independent variable is rather evident: all four plots display a clear, positive relationship between density and innovative activity. In other words, both the tendency for patenting activity to ease off at higher levels of density, and the anomaly in the slope of the relationship for green patents during the first sub-period are not present anymore.

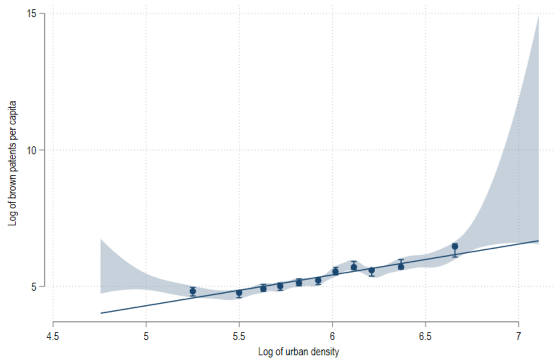
The latter aspect is confirmed by the regression results reported in Table 4. The elasticity of green patents per capita with respect to urban human capital density is now significant also in the first of the two sub-periods, and has a size that is comparable to the one estimated for green patents. In addition, also the elasticities estimated in the second sub-period are similar for green and brown patents, reaching a value slightly above 1.

These results, still rather preliminary, indicate that human capital may play a particularly significant role in shaping the relationship between density and innovative activity.

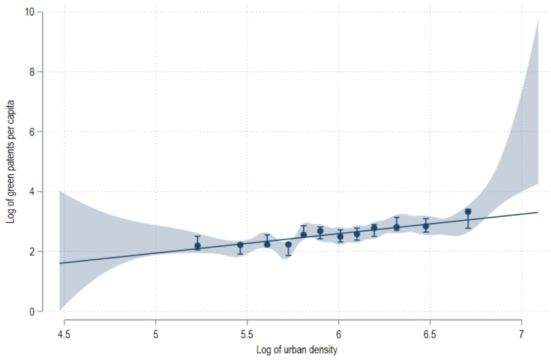
Figure 5: Urban Human Capital Density and Patenting Per Capita



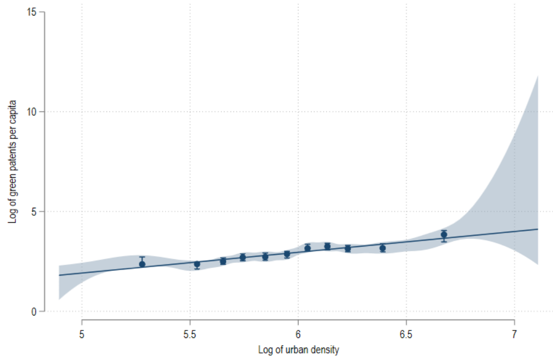
(a) 1990-2001, Brown Patents



(b) 2002-2016, Brown Patents



(c) 1990-2001, Green Patents



(d) 2002-2016, Green Patents

Notes. The bin-scatter plot is obtained applying the methodology described Cattaneo et al. (2024) through the Stata package **Binsreg**. The dependent variable is the log number of patents per inventor per year, and the independent variable is the log density of urban human capital. Binscatter estimates are based on log population weights and control for year fixed effects. Pointwise intervals and global bands denote 95 percent nominal confidence level using a robust variance estimator. The number of bins is chosen following the IMSE-optimal direct plug-in rule.

This opens up the possibility of multiple perspectives along which we will seek to further deepen our analysis.

Table 4: Fixed-effect Regressions - Urban Human Capital Density

	(1)	(2)	(3)	(4)
	log patents green		log patents brown	
	1990-2001	2002-2016	1990-2001	2002-2016
urban density	0.649***	1.041***	0.770***	1.128***
	(0.075)	(0.077)	(0.052)	(0.064)
constant	-1.303***	-3.287***	0.837***	-1.348**
	(0.442)	(0.458)	(0.307)	(0.378)
N	1905	3001	2320	3361

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: log of (green or browns patents) on log of urban human capital density over the sub-periods 1990-2001 and 2002-1996. Models control for year and state fixed effects. Robust standard errors are used. Weighting is done with log of urban population. The measure of innovation is winsorized at the 1% level.

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