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Smart innovative cities:

The impact of Smart City policies on urban innovation

Abstract

Smart City policies have attracted relevant attention and funding over the last few years. While the time seems now ripe to conclude that such policies have a positive impact on urban economic growth, the picture is much less clear when looking at the microfoundations of this effect.

In this paper we look at the urban innovation impact of Smart City policies. In fact, typical Smart City projects imply the involvement not only of major multinational corporations, along with local public authorities, but also of local companies, typically with the aim to translate general technological solutions to the local needs.

A new data set collected for these analyses comprises data on Smart City features for 309 European metropolitan areas, Smart City policy intensity, and urban innovation outputs. The latter are proxied by calculating total patent applications to the European Patent Office between 2008 and 2013. Patent counts also include technologically narrower classes, namely high-tech, ICT, and specific Smart City technologies patent applications.

Propensity Score Matching estimates suggest that cities engaging in Smart City policies above the EU average also tend to patent more intensively. This effect is stronger for high-tech patents, while decreases for more narrowly defined technological classes. This last result suggests possible technological spillovers from technologies directly involved in Smart City policies.

Keywords: Smart City; Program Evaluation; Propensity Score Matching

JEL classification codes: R11, R12, H43

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1. Introduction

Smart City policies have attracted relevant attention and funding over the last few years. While the time seems now ripe to conclude that such policies have a positive impact on urban economic growth, the picture is not as clear when looking at the microfoundations of this effect. In fact, while statistical evidence does suggest the existence of a positive association between the implementation of Smart City policies and urban economic performance (Caragliu and Del Bo, 2018a), how this exactly comes about is much less clear.

One possible channel for Smart City policies to exert a positive impact on economic performance and growth is through fostering urban innovation. In fact, Smart City projects are often the result of a strategic interaction between major multinational corporations heavily investing in these technologies, and municipal and regional authorities seeking to enhance local performance by means of adapting such technologies to the local need. While the latter seek to maximize public value creation (Anthopoulos et al., 2016), cities also resort to private investors both as additional means of financing as well as a way to enact public investment strategies (Galati, 2017).

The literature on Smart Cities stresses the need for local context conditions for fully reaping the benefits of large investments in high-tech solutions (Caragliu and Del Bo, 2011). It therefore comes as no surprise if technologies that are conceived for a vast audience need to be translated, with the involvement of local actors, to the specific context where they are deployed.

In GSMA (2013), several examples of local-global partnerships have been documented. For instance, over the last few years the municipality of San Francisco has started a pilot project called "SFpark" to collect, with mobile sensors, information on parking space availability throughout the city to be distributed to drivers by means of a dedicated app. Moreover, the app also prices available parking spots on the basis of present demand and supply conditions. While sensors used for identifying parking availability have been provided by Fybr, a Saint Louis-based company with international clients (https://fybr.com; at the time the project began, *StreetSmart Technologies*), three local public agencies, viz. the City of San Francisco, San Francisco Municipal Transportation Agency (SFMTA) and the San Francisco County Transportation Authority (SFCTA), have been involved in the deployment of the sensors and in monitoring the project's performance (UPADE, 2014).

Another example also discussed in GSMA (2013) is the municipality of Busan's (South Korea) partnership with Cisco and KT to promote an App Development Centre to co-create smart city services by means of start-ups. A cloud-based mobile app development platform has helped establishing over the first year since inception 13 start-ups, which yielded a grand total of 70 new apps, with total revenues equal to 2.2 million USD and revenues from online sales equal to 42,000 USD.

Other celebrated examples of effective public-private partnerships for delivering innovative Smart City technologies are also discussed in the literature on European case studies. For instance, Amsterdam's *Climate Street* initiative has the aim to transform a traditional retail street, Utrechtsestraat, into a sustainable shopping area by optimizing the street's stores energy and logistics management, along with the related public services. Smart meters constantly monitor the demand and supply of energy, and grids also constantly measure how full public trashcans are, so that waste collection only takes place when needed. These combined actions have allowed the city of Amsterdam reduce annual CO^2 emissions from 3,400 tons in 2010 to 1,276 tons in 2012 GSMA (2013).

These examples provide a rich background against which our empirical approach can be usefully tested. Urban innovation, therefore, seems at first glance to be a potentially relevant channel of Smart City policy impact, and this paper sheds light on its extent. A new data set collected for these analyses comprises data on Smart City features for 309 European metropolitan areas, Smart City policy intensity, and urban innovation outputs. The latter are proxied by calculating total patent applications to the European Patent Office on the basis of the OECD RegPat data base. Patent counts also include technologically narrower classes, namely high-tech, ICT, and specific Smart City technologies patent applications.[3]

Estimates are built on Propensity Score Matching (henceforth, PSM), in order to undercover causation links. Results suggest that cities engaging in Smart City policies above the EU average also tend to patent more intensively. This effect is stronger for high-tech patents, while it decreases for more narrowly defined technological classes.

In order to understand the impact of Smart City policies on urban innovation, we move as follows. In Section 2 we critically summarize two main strands of literature within which our empirical work is framed. In Section 2.1 we briefly discuss the burgeoning literature on cities as innovation hubs. In Section 2.2, instead, we deal with the much less prominent, but growing, literature on Smart City policies. In Section 3 we describe the identification strategy adopted for testing the main assumption of the paper. Data and details on the Propensity Score procedure are discussed in Section 4, while Section 5 presents the main empirical findings of the paper. Finally, Section 6 concludes by drawing the main policy lessons, as well as by highlighting future developments in this promising line of research.

2. Literature review

In this section we critically summarize the two main strands of literature to which our empirical findings are anchored. In Section 2.1 we review some highlights of the urban economics literature on agglomeration economies, which stresses a set of urban productivity- enhancing externalities. In Section 2.2, instead, we discuss the (to date rather thin) literature on Smart City policies, in particular in terms of their expected impact.

2.1 Innovation in cities

A crucial issue underlying the literature positioning of the analyses discussed in this paper is the role played by urban areas as innovation cradles. The very existence of cities has been justified in terms of the role they play in facilitating the production, diffusion, and accumulation of knowledge (Duranton and Puga, 2004). Easier face-to-face contacts allow consumers and firms to lower transaction costs in transmitting, decoding, and exploiting new knowledge. However, it is important to dig deeper into these microfoundations to better link the rather generic literature on Smart Cities and the impact we expect from the adoption of Smart City policies on urban innovation performance.

Theoretically, the key concept that links Smart Cities with innovation is the notion of agglomeration economies. Because of a denser and more concentrated structure of production and consumption, urban areas lower production and consumption costs, thus representing potentially attractive locations for consumers and producers. Such externalities are a convenient way to justify the very existence of cities, that otherwise also cause non-negligible environmental and social costs.

Classical economists (Smith, 1776; Marshall, 1920) have stressed how these externalities can represent an additional competitive advantage for production. Following the classification proposed in Hoover (1936), Marshallian scale economies can be decomposed in pure scale economies (internal to the firm and the

[3] Section 5.2 (“Robustness checks”) also exploits a broader definition of IPC classes aiming at capturing Smart-City related fields, in particular encompassing IPC 1 digit classes F (“Mechanical engineering; Lighting; Heating; Weapons; Blasting”), G (“Physics”), and H (“Electricity”).

industry); localization economies (accruing outside the firm's perimeter, but well within a given industry's boundaries); and pure urbanization economies, i.e. those due to the co-location of diverse industries that learn from one another exactly because they are closely located.

Within this framework, many of the sources of agglomeration economies can be related to the first and second type of externalities. Hoover's classification identifies three main sources of production-related localization economies, viz. the joint exploitation of fixed social capital (transport and communication infrastructure, public utilities); indivisibilities in the supply of goods and services; and the synergy due to the existence of an industrial and managerial culture. Within the Smart City paradigm, all these factors can be enhanced by enacting efficient Smart City policies.

However, the world depicted in classical economics has changed. Manufacturing activities have been relocating away from major urban areas for decades now (Donogue, 2014), at least in advanced economies. Traditional traded goods become increasingly standardized, and can hence be produced more conveniently in more peripheral locations, with lower rents. However, cities still remain on the rise: how can this trend be reconciled with the Marshallian framework? Two possible candidates can be identified in (i.) The nature of cities as large markets (i.e., the increasing importance of cities as consumption centers: Glaeser et al., 2001), and (ii.) The nature of cities as knowledge hubs, which is supported by overwhelming empirical evidence (Rosenthal and Strange, 2004; Moretti, 2004; Camagni et al., 2016; Caragliu et al., 2016).

In both cases, Smart City policies can act as facilitators for these effects. Smart City projects at least partially translate into more business opportunities for local companies joining public procurement. This is expected to thicken local markets thus contributing to the city's performance. Moreover, because Smart City policies do tend to make cities more efficient (Caragliu and Del Bo, 2018a and 2018b), innovation processes are also expected to be fostered, mainly through a general improvement of local knowledge production functions, as well as through the positive fallout from the generation of local solutions for international Smart City projects.

2.2 Smart City policies

What is a "Smart City policy"? How does it differ from other, more traditional urban policies? The aim of this Section is to provide a working definition of Smart City policies, based on existing literature, by highlighting their main characteristics, links to the definition of Smart City, implementation and funding strategies and peculiarities which allow to distinguish them from other urban policy initiatives.

Within the EU, several policy projects revolving around the Smart City concept have been initiated, also thanks to community-wide initiatives and funding opportunities, which are often made easier by creating specific platforms such as the European Commission's "European Innovation Partnership on Smart Cities and Communities (EIP-SCC)".[4] A recent report (Collins et al., 2017) provides a synthesis of the characteristics of 114 EU Smart City projects between 2005 and 2016. The median project lasts 4 years and costs around mil. € 9.935, with a contribution by the EU for the same median project of mil. € 5.039. Countries implementing the highest number of individual initiatives are Spain, UK, Germany and Italy. In terms of the projects' targeted areas, environmental and energy projects dominate between 2005 and 2007 and after 2010, with more ICT related initiatives between 2008 and 2010. These trends are related, on the

[4] http://ec.europa.eu/eip/smartcities/index_en.htm.
SCC is the innovation platform providing a marketplace and possible public–private partnership developments for both priorities and policies. We would like to thank an anonymous reviewer for highlighting this role for SCC initiatives.

one hand, to the policy goals set at the EU level, where smartness in terms of energy sustainability is one of the Horizon 2020 targets (EP, 2012); on the other, to the evolution of the definition itself of Smart Cities. In fact, initial analyses revolved around the concept of "*sustainable cities*" (Ahvenniemi et al., 2017), with specific attention to environmental issues and on ICT as the main driver of smartness (Caragliu and Del Bo, 2017).

Angelidou (2017) examines the Smart City plans of 15 world-wide major cities and shows how the focus is mainly on ICT as a factor that can improve urban systems and ultimately foster urban innovation. A critical review of the implemented project, however, highlights a lack of bottom-up approaches and stakeholder involvement and a general disregard of local conditions, in clear contrast with the (theoretical) tenets of Smart City policies and practices.

In order to gain further insight on the characteristics of actual implemented Smart City policies, a recent document by the national association of Italian municipalities (ANCI, 2016) describes the characteristics of Italian Smart City projects implemented in recent years. Of the 1300 projects as of 2015, councilors are in charge of the project in 61% of the cases, while in 3 (large) municipalities out to 10 the responsibility rests with the mayor, suggesting the importance attributed to these initiatives by the local public authorities. Furthermore, 29% of cities involved have established an ad hoc "Smart City" office, reinforcing the prominence of this specific urban policy orientation. In terms of thematic orientation, 20% of projects are concentrated in the mobility sector, while the remaining projects are more or less equally distributed over the remaining topics considered by the report (environment, energy, economy, people, living, government, planning). However, a common feature is represented by a focus on participative processes, an integrated approach to urban planning across municipal offices and a focus on ICT, although not always seen explicitly as policy tools.

These nation-specific findings can be framed in a more conceptual literature examining Smart City policies from a planning and policy evaluation perspective. Nam and Pardo (2011), for example, analyze Smart City policies within the broader group of urban development policies and stress the importance of policy integration, an explicit and focused branding strategy and a demand-driven perspective. Angelidou (2014) suggests the importance of building on a city's existing strengths focusing on a limited number of interventions, coordinating the policy definition and implementation within different municipal departments, and involving the various stakeholders.

On the basis of these two strands of literature, the following research question calls for specific empirical verification:

RQ. What is the impact of Smart City policies on urban innovation?

Such question hides non-negligible identification issues. Reverse causality may be due to the fact that innovative cities also tend to engage more in Smart City policies. In the next section, therefore, specific attention is devoted to how such issues are tackled in our analyses.

3. Identification strategy

In this section, the way to assess the direction of causality in the empirical model of the paper is discussed and statistically tested. In fact, along with the usual means to empirically verify whether the chosen Propensity Score methodology is a sound way to rule out reverse causality, it is important to understand the microfoundations of the expected impact.

In this sense, we summarize some relevant features of the landscape of Smart City policy impact which has been recently clarifying and cristallizing around a few stylized facts:

1. Some Smart Cities focus on hard infrastructure, such as the deployment of optic fiber networks or other types of fast internet connection, the installation of sensors in the built environment, the exploitation of open data and Internet-of-Things, henceforth IoT (Stratigea et al., 2015), while others seem to hinge more on soft infrastructure such as human and social capital, or the quality of governance (Ahvenniemi et al., 2017);
2. The interplay between policy interventions on hard and soft infrastructure seems to characterize the very concept of Smart City; in fact, infrastructure without the local characteristics enhancing its efficient exploitation implies serious risks of policy failure (Caragliu et al., 2011);
3. Quantitative evidence of a direct impact of urban smartness seems to be scant. Some (e.g. Caragliu and Del Bo, 2016) find a positive association between urban smartness and the probability to invest in smart policies, while in Caragliu and Del Bo (2018) the latter are found to improve urban economic performance.

Within this framework, insufficient attention has been paid to the possible intermediate channels that explain the positive impact of adopting Smart City policies on urban performance. In fact, most previous works leave the transmission mechanism between policies and growth in a black box, simply assuming that policies with a Smart flavor will automatically enhance urban economic performance.

It can be argued that urban administrations investing in Smart City policies trigger chain reactions that ultimately do lead to faster growth, but how this comes about should be empirically verified on the basis of sound microfoundations. In particular, to date insufficient attention has been paid to the possible innovative fallout of the local adoption of Smart City policies. The core investment in these cases is in fact in the acquisition and deployment of Smart City technologies – e.g., sensors for monitoring the built environment, integrated platforms, management software - which, while typically engineered in some core multinational companies located far away, need to be translated and adapted to the local needs. This is expected to potentially engender several positive feedbacks among local ICT firms, thereby stimulating local innovation which represents one of the most direct impacts of adopting such policies. In this paper we tackle this last impact by means of Propensity Score Matching (henceforth, PSM).

PSM assumes that the units of observation, in the present paper identified as EU cities, are subject to an exogenous shock that, all else being equal, stimulates a differential change in an outcome variable of interest. Given the literature previously discussed, this paper deal in particular with the effect of Smart City policies on innovation rates in cities engaged in such policies.[5]

Therefore, in this case, treatment is defined as the intensity of engagement in Smart City policies. While a sound definition of such policies would entail a much deeper discussion of how the definitions of Smart Cities available in the literature are empirically translated into policy objectives, it is here convenient to refer to Angelidou (2014) and Caragliu and Del Bo (2016) to briefly recap the main features of Smart City policies:

- Policies are based on existing strengths and typically focus on a subset of core areas of intervention;
- Coordination takes place between different policy departments;
- Stakeholders are involved in the design and implementation of the policies;
- Investment in ICTs is typically matched by physical and institutional changes;

[5] While the strict exogeneity of this instrument can also be verified from a statistical point of view, it is important to stress that Smart City policies are not directly meant at fostering urban innovation, but rather at stimulating a better management of the city.

- The scale of interventions is usually relatively small, so that small-scale integrated projects are more likely to succeed.

While advanced technologies are generically the object of such interventions, a few technological classes typically draw the attention of companies and policymakers. Among those, a major, although not exclusive, role is played by technologies related to the IoT (Deakin, 2013), mostly because of the crucial importance of sensors used in the built environment to monitor urban performance in some crucial dimensions (traffic flows, air and water pollution, waste management, etc.). The notion of IoT was first discussed in a presentation given by Kevin Ashton to P&G in 1999,[6] and literally took off at the end of the 1990s with the pervasive diffusion of sensors connected by means of networks that allow inter-operability, remote controlling, and sensing. A recent classification of IPC classes[7] presented in IPO (2014) allows to more precisely pinpoint and describe the type of technological classes identified within this paradigm. (Table 1).

IPC code	Description of technological class
H04L029/08	Communication control; Communication processing characterised by a protocol; Transmission control procedure, e.g. data link level control procedure
H04L012/28	Data switching networks characterised by path configuration, e.g. LAN (Local Area Networks) or WAN (Wide Area Networks)
H04L029/06	Communication control; Communication processing characterised by a protocol
G06F015/16	Digital computers in general; Data processing equipment in general; Combinations of two or more digital computers each having at least an arithmetic unit, a programme unit and a register, e.g. for a simultaneous processing of several programmes
G05B019/418	Programme-control systems -> electric -> Total factory control, i.e. centrally controlling a plurality of machines, e.g. direct or distributed numerical control (DNC), flexible manufacturing systems (FMS), integrated manufacturing systems (IMS), computer integrated manufacturing (CIM)
H04W084/18	Network topologies -> Self-organising networks, e.g. ad hoc networks or sensor networks
H04W004/00	Services or facilities specially adapted for wireless communication networks
G08C017/02	Arrangements for transmitting signals characterised by the use of a wireless electrical link -> using a radio link
H04W072/04	Local resource management, e.g. selection or allocation of wireless resources or wireless traffic scheduling -> Wireless resource allocation
H04B007/26	Radio transmission systems, i.e. using radiation field for communication between two or more posts, at least one of which is mobile

Table 1. Smart City IPC codes and description of technological classes

Source: IPO (2014)

[6] Ashton (1999).
[7] "*The International Patent Classification (IPC), established by the Strasbourg Agreement 1971, provides for a hierarchical system of language independent symbols for the classification of patents and utility models according to the different areas of technology to which they pertain*" (WIPO, 2017).

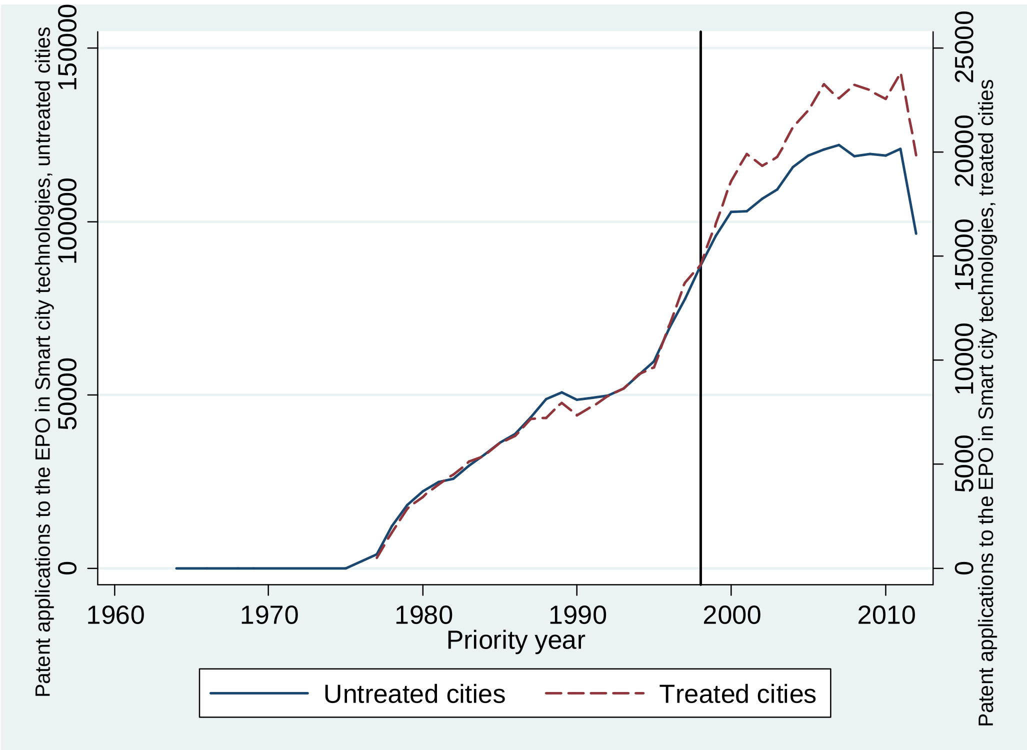
Given the relatively recent development of these technologies, it is reasonable to assume that patenting activities in the IPC classes defined above should have taken off around the second half of the 1990s. A valid treatment in our case would thus be associated to a differential impact of innovations in these classes for cities engaging at different levels in Smart City policies. If cities enacting Smart City policies behave significantly differently from those that do not, thereby presenting more patent applications in the relevant classes, then this represents an ideal identification strategy for an empirical setting aimed at assessing whether such policies cause higher innovation in cities.

We first provide statistical evidence that this may indeed be the case. We reach this goal by exploiting the RegPat data base (Maraut et al., 2008), which bears information on all patent applications filed to the European Patent Office since 1976. Patents are classified according to their main (i.e., prevailing) technological class. They can be matched to their inventor and/or assignee (both associated to their georeferentiation in terms of Territorial Level 3 regions, corresponding to the EU's NUTS3 level). Also, each patent bears information about its priority year (viz. the year when the patent was first filed; other dates depend on administrative procedures and may thus bias the correct interpretation of technological change). Combining all this information for all patents filed in the technological classes shown in Table 1 for cities engaging in Smart City Policies (henceforth, SCPs) and for those that do not, we can first statistically verify that the number of patent applications filed by cities active in SCPs is significantly higher than in less engaged cities. A classical t-test for mean differences suggests that cities engaged in SCPs tend to file 13.6 patent applications to the EPO in the technological classes synthesized in Table 1, against a mean of 4.2 for cities less active on the SCPs front, on the whole analyzed time period (viz. between 1976 and 2016). The difference is statistically significant at all conventional levels, thus suggesting a rather strong difference.

Next, we can exploit the same information to graphically represent the time evolution of the patenting activity in SC-related technological classes for cities engaged, or non-engaged, in SCPs. Policies in this sense act as a treatment proper: in the absence of other confounding factors, we can use SCPs engagement as a shock allowing to identify possible causality directions in any impact. Figure 1 shows that, while a positive trend in patenting activity for SC-related technological classes characterizes both treated and untreated cities, the former show a remarkable increase at the end of the 1990s, when Smart City policies have been first enacted (Komninos and Mora, 2018).[8] This evidence strengthens the case for using SC policies as a treatment in assessing the impact of such policies on urban innovation. The Propensity Score Matching procedure used to perform this impact analysis is described in the next section.

[8] Details on the data set assembled for performing both this descriptive analysis as well as econometric estimates are presented in Section 4.1 below.

Figure 1. Patent applications to the EPO in Smart City technologies for cities engaging or non-engaging in Smart City policies



Source: Authors' elaboration on EPO data

Lastly, on the basis of this identification strategy, an estimable reduced form model for translating the research question discussed in Section 2 can now be formalized (Eq. 1):

$$inn_{i,t} = X_{i,t} + Z_{i,t} + \varepsilon_{i,t} \quad (1.)$$

where *inn* stands for urban innovation., *i* indexes cities and *t* indexes time. In Eq. (1.), X is a matrix of controls, including a proxy (population density) for agglomeration economies, that are typically a major driver of urban innovation (Section 2.1), and two locational dummies, equal to one when the city is located in Central and Eastern European countries and is a Country capital, respectively. The former captures the convergence process that took place over the accession period to the EU; the latter aims at measuring the higher probability to enact SC policies in cities where control centers and high-rank administrative and economic functions are typically located. Matriz Z includes instead the full breakdown of the six Smart City axes identified in the Caragliu et al. (2011) definition, namely human and social capital, transport and ICT infrastructure, e-government and natural resources. Lastly, $\varepsilon_{i,t}$ is the usual *i.i.d.* disturbance.

4. Data and Propensity Score procedure

4.1 Data

Our empirical strategy requires different urban level data. In this paper data are measured at the metropolitan area level, following the EUROSTAT classification (EUROSTAT, 2017a). Specifically, we need information on Smart city policies implemented by the municipalities; a measure of urban Smartness; a set of city-level characteristics not summarized by the Smart City indicator and, finally, information on patenting activity. In what follows we provide a description of the strategies to obtain the different information needed for the empirical analyses.

Smart city policies are measured following the approach proposed in Caragliu and Del Bo (2016), to which the interested reader is directed for a more in depth description of the methodology. Intensity of smart urban policies is gauged by summarizing the information gathered from four data sources:

1. A list of cities engaged in smart city policies provided in European Parliament (2014). Cities within this list are considered successful in implementing smart urban policies in the sense of presenting an alignment between their objectives and those encompassed by the EU2020 strategy. We thus used this information to create a dummy variable, equal to 1 if cities are included in this study and 0 otherwise;
2. Members of the Eurocities network.[9] The Eurocities network dates back to 1986 and was created by a small group of European cities wishing to create a formal relationship of non-capital cities. The members have now grown to 103 and are active in forums, working groups and projects with the major focus on smart city projects, seen as conducive to the EU goal of smart and sustainable growth.[10] Based on this network, an indicator variable was created, taking on value 1 if cities belong to this network and 0 otherwise;
3. Cities actively involved in Framework Programme 7 (henceforth, FP7) smart city initiatives. Information on urban involvement and funding from FP7 projects was gathered from the factsheets on Smart City Projects[11] and the European Commission's SCC web page.[12] An indicator variable was creating merging information on both already-funded projects and commitments, in order to have the most comprehensive possible picture of a city's involvement of smart urban projects. This indicator assigns value 1 if a city is engaged in a FP7 project (both already funded and as a commitment) and 0 otherwise. However, since cities can be part of more than one EU-funded project or commitment, we considered a count measure of participation. Variables were then standardized on a 0-1 scale, with 1 indicating participation in various activities and 0 assigned to cities that are not participating in any activity;
4. Cities cooperating with a private actor providing ICT solutions for Smart City projects. Since policy initiatives on smart city issues often rely on solutions provided by private businesses, the involvement of private players, alongside public actors, in the

[9] http://www.eurocities.eu/

[10] http://www.eurocities.eu/eurocities/activities/working_groups/Smart-Cities&tpl=home.

[11] http://ec.europa.eu/digital-agenda/en/node/72869.

[12] http://ec.europa.eu/eip/smartcities/index_en.htm.

development of smart city policies is considered. While several private firms are involved in these activities, IBM is the only one which maintains an official website listing the partnership with individual cities, and for this reason is the basis for the indicator variable “private” which takes on value 1 if the municipality has partnered with IBM to develop smart city policies and 0 otherwise.[13]

The indicator thus obtained is used as a treatment discriminant as suggested in Section 3. In particular, the overall count of the four dummy/standardized variables just discussed is ranked in decreasing order of intensity, and cities are defined as treated if this last indicator is above the sample median. In other words, we define cities as treated when their Smart City Policy intensity is above the EU median policy engagement.

Urban smartness is measured by operationalizing the definition of Caragliu et al. (2011) and following the methodology proposed in Caragliu and Del Bo (2015). Proxies for the six axes of the definition (human capital; social capital; transport infrastructure; ICTs; natural resources; e-government) are collected. Table 2 summarizes the variables used and their sources in detail. Smart City indicators are constructed for a sample of 309 EU cities with data between 2008 and 2012. Specifically, for each axis of the definition, four individual indicators have been used and then reduced through PCA techniques. To increase data availability, mean values for the Urban Audit data for the period 2008-2012 have been considered. Missing data has been dealt with linear interpolation and mean values of previous years or similar cities.

[13] Additional list of cities engaged in quasi-Smart City initiatives are next exploited in Section 5.2 (Robustness checks). The interests reader is referred to this subsection for further details on this data source.

Urban smartness axis	Raw data
1. Human capital	Proportion of population aged 15-64 qualified at tertiary level (ISCED 5-6) living in Urban Audit cities - %
	Students in tertiary education (ISCED 5-6) living in Urban Audit cities - number of students per ,1000 inhabitants
	Proportion of employment in financial intermediation business activities
	Proportion of employment public administration health education
	Number of companies with headquarters in the city quoted on the national stock market
2. Social capital	Car thefts per 1,000 pop.
	Burglaries per 1,000 pop.
	Crimes per 1,000 pop.
	Number of elected city representatives
3. Transport infrastructure	Length of public transport network per inhabitant
	Share of restricted bus lanes from public transport network
	Number of buses (or bus equivalents) operating in the public transport per 1,000 pop
	Number of stops of public transport per 1,000 pop.
4. ICT infrastructure	Percentage of families with internet access at home
	Number of local units producing ICT products
	Number of local units producing ICT-related services
	Number of local units producing web content
5. Natural resources	Proportion of solid waste arising within the boundary processed by recycling
	Proportion of the area in green space
	Green space (in m2) to which the public has access, per capita
	Annual average concentration of PM_{10}
	Annual average concentration of NO_2
6. E-government	% of internet users who interacted via internet with the public authorities in the last 12 months (Country data)
	% of internet users who sent filled forms to public authorities in the last 12 months (Country data)
	Number of administrative forms available for download from official web site
	Number of administrative forms which can be submitted electronically

Table 2. Indicators for the 6 axes of the Smart City definition
Source: Caragliu and Del Bo (2015)

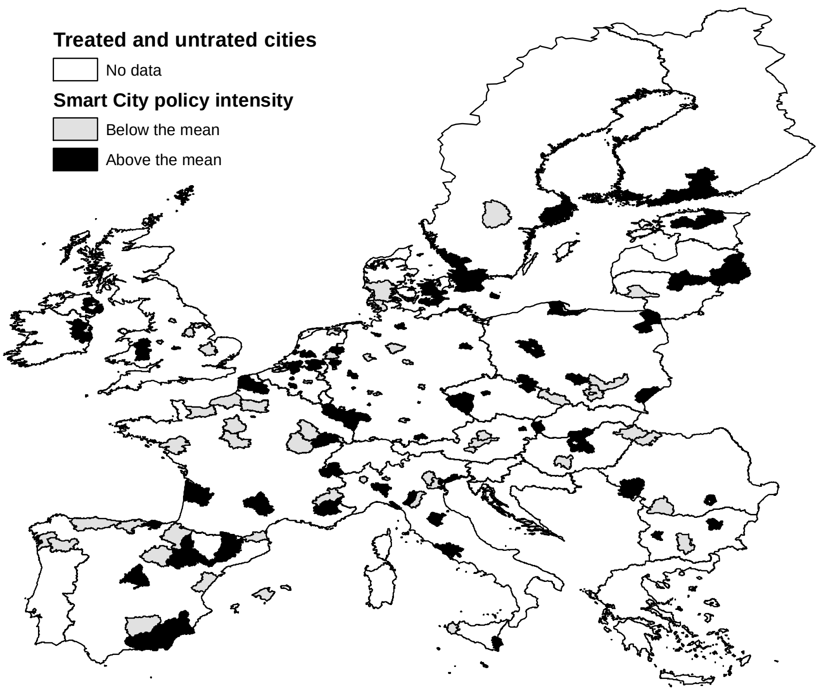
Lastly, urban innovation is measured by counting patent applications to the European Patent Office in various classes. The RegPat data base (Maraut et al., 2008) classifies information on all patent applications filed to the European Patent Office since 1976 on the basis of their inventor, applying institution, and IPC technological classes. By counting the number of patents filed by inventors located in each NUTS3 region over the observed time frame in each classification of technological classes relevant for measuring SC technologies, we obtain a picture of the intensity of the outcome of innovative activity. In particular, we use four patent counts, with a general-to-particular approach: total patents, high-tech patents (including all IPC classes listed in EUROSTAT, 2016), ICT patents (EUROSTAT, 2017b), and Smart City patents (following the classification shown in Table 1).[14]

[14] Other IPC classes are exploited in Section 5.2 as ways to further assess the robustness of our findings. Such definitions are described in more detail in the robustness checks subsection.

4.2 Propensity Score procedure

The indicator built on the basis of the intensity of Smart City policies is classified in two classes, viz. cities above and below the mean of Smart City policy intensity. The two types of cities identified on the basis of the sample of cities for which data have been collected is shown in Figure 2, with black areas representing cities with a Smart City policy intensity above the EU mean, and light grey shapes indicating cities with a Smart City policy intensity below the EU mean.

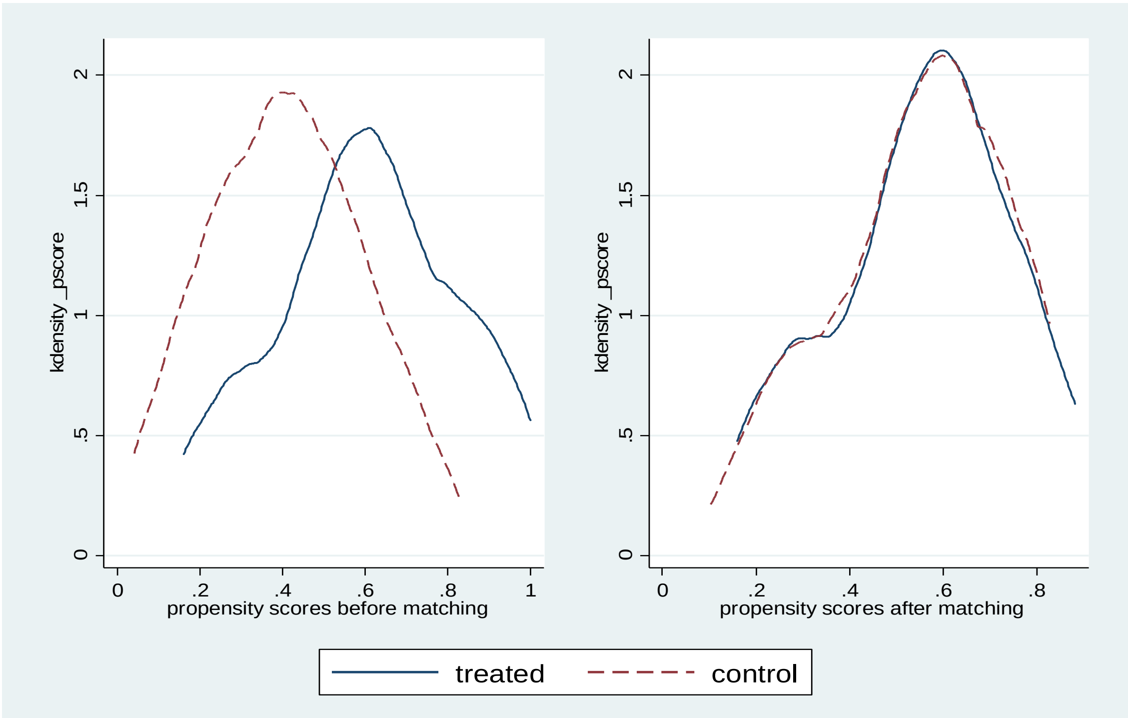
Figure 2. Treated and untreated cities



Source: Authors' elaboration

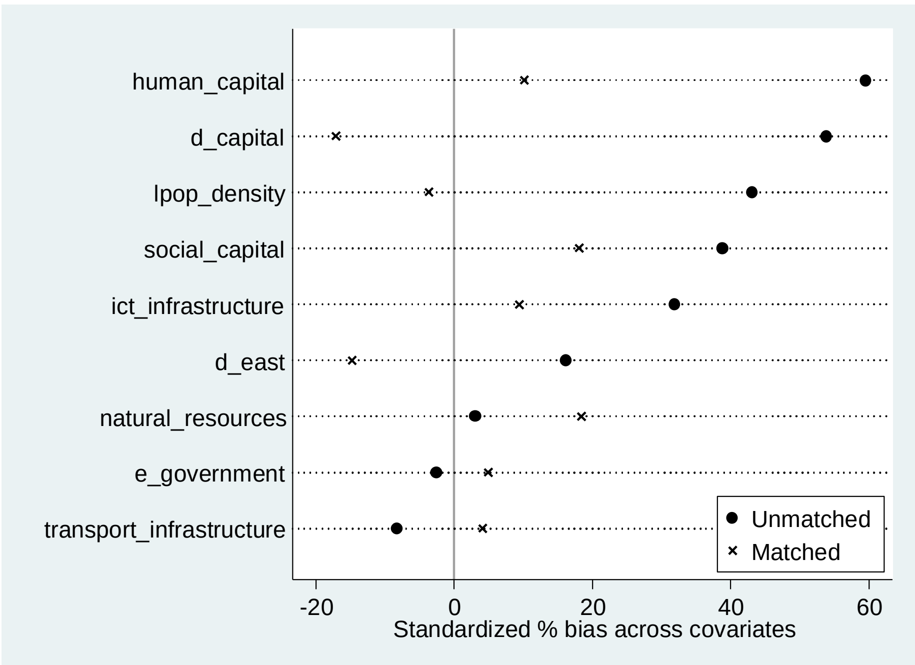
Matching of the treated and untreated cities is performed on the basis of the Kernel procedure. Kernel matching typically yields lower variance, although it may possibly lead to including observations that are bad matches (Caliendo and Kopeinig, 2008). Results of the pre-and post-matching procedure balancing of the sample suggest a remarkable overlapping of the treated and untreated cities' density functions (Figure 3). However, it must be noted that some positive bias characterizes the distribution of the cities within the treated and untreated samples, in particular for what concerns intangible growth assets (most notably human and social capital, and population density; Figure 4 plots the relative extent of the variable-specific bias).

Figure 3. Balancing before and after the matching procedure



Source: Authors' elaboration

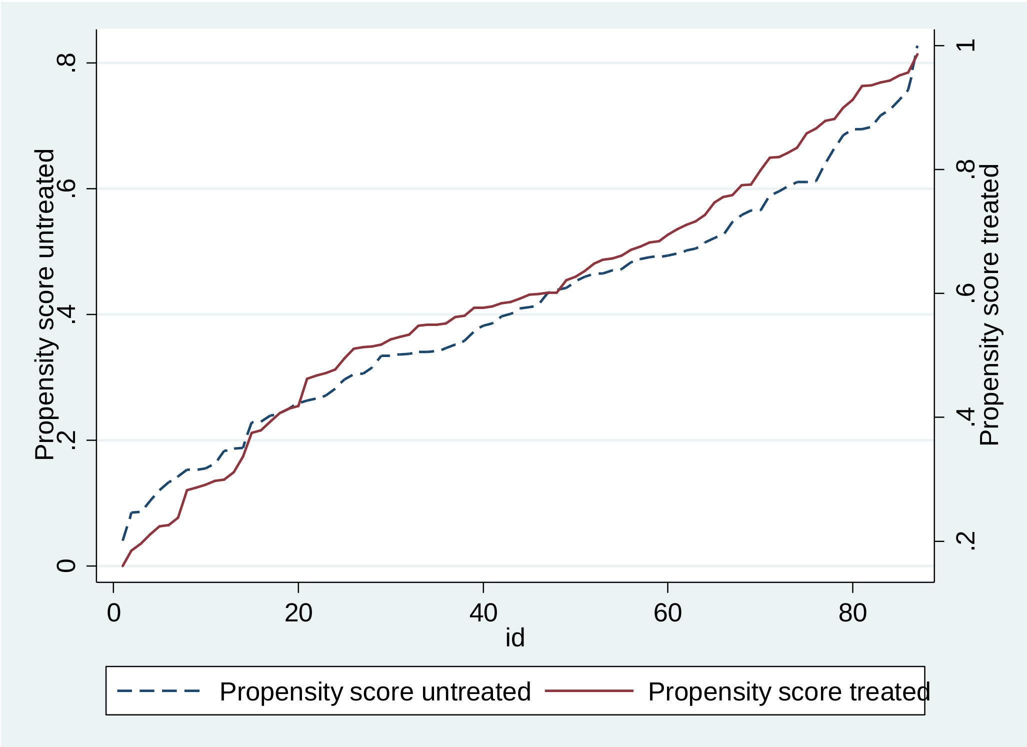
Figure 4. Standardized percentage bias across covariates



Source: Authors' elaboration

Lastly, the quality of the matching procedure can also be evidenced by ranking treated and untreated units (in this case, cities with a SC policy intensity above or below the mean EU value) according to their propensity score (Dehejia and Wahba, 2002). Figure 5 shows untreated cities with a dashed line and treated cities with a continuous line; the two lines largely overlap.

Figure 5. Treated and untreated cities in increasing order of propensity score



Source: Authors' elaboration

In conclusion, the matching procedure seems to be reliable and to offer a good means by which to assess the causal link between engagement in SC policies and urban innovation.

5. Do Smart City policies make cities more innovative? Results of Propensity Score Matching estimates

5.1 Baseline estimates

This section discusses the results of empirically testing the relation between Smart City policies and urban innovation. The impact of SC policies on innovation can be manifold; consequently, we verify such impact on four different patent counts indicators, discussed in Section 3.

Results are presented as follows. Table 3 shows Probit estimates of the determinants of adopting smart city policies (Eq. 1). This represents the first stage of the PSM procedure. Table 4 shows instead the outcome of the PSM procedure proper. We estimate the impact of SC policies on urban innovation by looking at the average treatment effects on the treated for different urban innovation measures, viz. average treatment effects on the treated for different urban innovation measures (total patents, high-tech patents, ICT patents, and Smart City patents).

Results shown in Table 3 provide a few hints on the real determinants of SC policy adoption within the black box of urban smartness. In Caragliu and Del Bo (2016), an aggregate indicator of urban smartness is found to be positively associated with the probability to invest in SC policies. Table 3 hints at a positive role of intangible features (human and social capital) in increasing the likelihood that cities engage in Smart City policies. The infrastructure and e-government/natural resources components provide instead a more blurred picture. Taken together, these two results suggest that context conditions within each urban area still crucially matter in driving cities towards engaging in challenging policy programs.

Dep. variable: probability to enact Smart City policies				
Model	(1.)	(2.)	(3.)	(4.)
Constant term	-0.65	-053	-0.65	-0.55
	(0.62)	(0.63)	(0.62)	(0.61)
Population density	0.09	0.07	0.09	0.06
	(0.12)	(0.12)	(0.12)	(0.11)
Dummy capital	0.66*	0.67*	0.66*	0.82**
	(0.38)	(0.38)	(0.38)	(0.40)
Dummy Eastern countries	0.78**	0.77**	0.78**	0.74**
	(0.35)	(0.35)	(0.35)	(0.35)
Human capital	0.39***	0.39***	0.39***	0.36***
	(0.13)	(0.13)	(0.13)	(0.13)
Social capital	0.19*	0.19**	0.19*	0.19*
	(0.10)	(0.10)	(0.10)	(0.10)
Transport infrastructure	-0.13	-0.13	-0.13	-0.13
	(0.10)	(0.10)	(0.10)	(0.10)
ICT infrastructure	0.17*	0.16*	0.17*	0.11
	(0.09)	(0.09)	(0.09)	(0.07)
e-government	0.01	-0.01	0.01	0.01
	(0.10)	(0.10)	(0.10)	(0.10)
Natural resources	0.01	0.02	0.01	0.05
	(0.10)	(0.09)	(0.10)	(0.09)
Number of obs.	173	173	173	176
LR $\chi^2(8)$	41.28***	40.20***	41.28***	38.95***
Pseudo R^2	0.17	0.17	0.17	0.16

Table 3. Probit regressions: determinants of adopting smart city policies
*Notes: *= significant at 90% level; **= significant at 95% level; ***= significant at 99% level.*

As for control variables, while the impact of urban density, as a proxy for agglomeration economies, is found to be insignificantly associated with the probability to adopt SC policies, a positive and significant coefficient is estimated for both locational dummies (cities located in Central and Eastern European countries, and capital cities), confirming the role of the convergence process taking place within the EU and the importance for cities of being central policy centers.

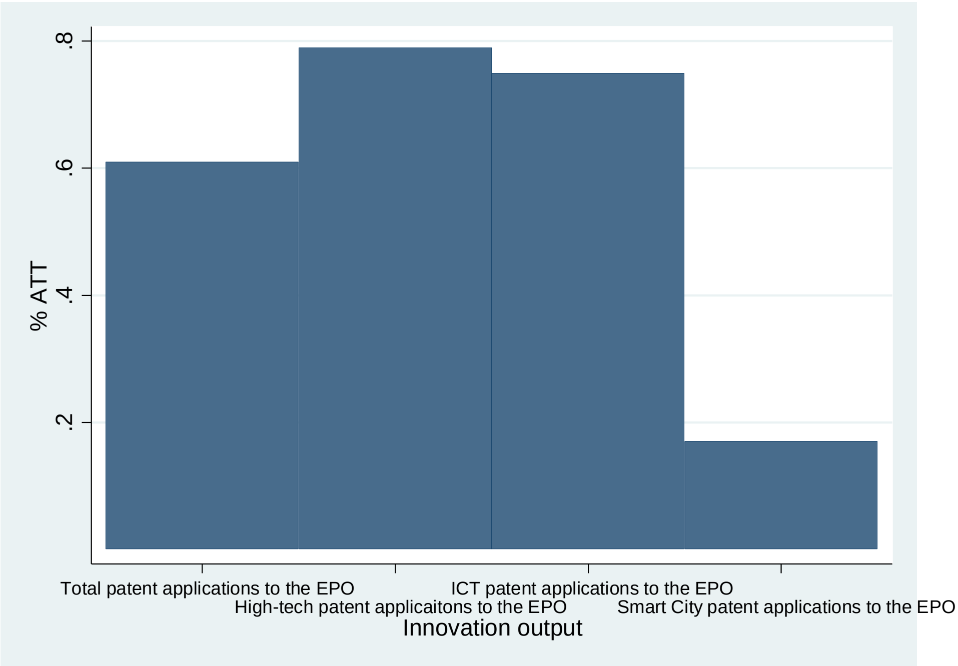
Table 4 shows instead average treatment effects on treated units (ATT); in other words, controlling for the determinants of propensity scores, ATT shows the mean value of total patent, high-tech patent, ICT patent, and Smart City patent applications to the EPO over the 2008-2013 period. Results suggest that across different measures of innovation outputs, cities that do enact Smart City policies tend to deliver a significantly higher innovation output. Mean differences are statistically significant at least at the 90 per cent level for all innovation output measures. Clearly, as the definition of the technological class we measure narrows down, average patent applications per urban area decrease in number, the minimum being reached at the Smart City level, i.e. within the narrowly defined IoT class including IPC classes listed in Table 1. Interestingly, while mean differences are rather substantial for both treated and untreated units across different innovation output measures, with a higher difference for unmatched units, the contrary happens for more narrowly defined Smart City technologies. In this last case the difference in the impact estimated for matched and unmatched cities is higher for the latter, thus further hinting at an effective choice of the matching strategy.

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Total patent applications to the EPO	Unmatched	219.89	77.97	141.92	41.47	3.42
	ATT	180.16	70.11	110.05	39.30	2.8
High-tech patent applications to the EPO	Unmatched	48.70	9.72	38.98	10.79	3.61
	ATT	40.70	8.71	31.99	8.89	3.6
ICT patent applications to the EPO	Unmatched	66.41	16.43	49.98	14.63	3.42
	ATT	56.69	14.31	42.38	12.92	3.28
Smart City patent applications to the EPO	Unmatched	5.47	4.56	0.91	0.38	2.41
	ATT	5.37	4.45	0.92	0.49	1.88

Table 4. Average treatment effects on the treated for different urban innovation measures

The intensity of the impact varies across different measures. Figure 6 shows the percentage mean difference between treated and control cities for the four innovation output measures. In Figure 6, percentage impacts are calculated as the ratio of the difference of mean patent applications between treated and control cities and the number of patent applications in treated units.

Figure 6. Percentage Average Treatment on the Treated cities effect



Source: Authors' elaboration

Figure 6 suggests that the maximum impact is found when measuring innovation output through high-tech patent applications, while the measured impacts decreases as we narrow down the scope to more detailed technological classifications (i.e. ICTs and Smart City applications proper). While being purely suggestive, this result may hint at possible technological spillovers across technological fields, which implies that investing in Smart City policies may trigger innovative processes well beyond the relatively limited scope of the technologies directly involved in those policies.

In fact, Figure 6 suggests that the differential impact of adopting Smart City policies is larger when measured at an intermediate level of technological detail. Some of the patent applications stimulated by adopting SC policies may not be limited to the very IPC classes that are more directly related to such policies (i.e. those listed in Table 1), but rather indirectly induced by the need to translate general technologies into the local needs – for instance, by conceiving innovative electrical equipment that cooperates with the sensors installed by a major multinational corporation and as such does not fall into the narrowly defined SC technological field.

5.2 Robustness checks

In this section we provide a number of robustness checks to verify the resilience of our empirical choices to several alternative specifications.

The first robustness check involves the selection of cities engaged in Smart City policies. While we are aware of the relatively narrow scope of selecting IBM as the only private corporation included in our data set, we still found it impossible to retrieve analogously large data bases for other major players in this segment of the market. However, we did run a number of robustness checks on the public side. The original Smart City policy indicator has been broadened to encompass three additional vectors with cities members respectively of the Lightouse, ERRIN, and ICLEI networks.[15]

Lighthouse cities are classified as cities joining at least one of the projects funded by the Smart Cities and Communities lighthouse projects. The aim of these projects is to bring together "*cities, industry and citizens to demonstrate solutions and business models that can be scaled up and replicated, and that lead to measurable benefits in energy and resource efficiency, new markets and new jobs*" (EC, 2018, p. 2).

ERRIN is instead a Brussels-based platform comprising more than 120 regional stakeholders organization, largely represented by their Brussels offices. ERRIN is meant to enhance "*knowledge exchange between its members, focusing on joint actions and project partnerships to strengthen regional research and innovation capacities. Through these actions ERRIN seeks to contribute to the implementation of the Europe 2020 Strategy, the Innovation Union flagship initiative and Smart Specialisation strategies" (ERRIN, 2018).*

Lastly, ICLEI is a global network of city comprising more than 1,500 members, whose main focus lies in the sustainable development of urban areas. "*ICLEI provides technical consulting, training and information services to build capacity, share knowledge and support local government in the implementation of sustainable development at the local level. Our basic premise is that locally designed and driven initiatives can provide an effective and cost-efficient way to achieve local, national and global sustainability objectives*" (ICLEI, 2018).

These three networks thus provide a more comprehensive framework to assess the multifaceted nature of Smart City policies. Lighthouse cities are a specific type of city engaged in EU-funded SCC projects; ERRIN is expected to cover the diplomatic relations between EU cities and European institutions; and, finally, ICLEI is best suited to capture sustainability issues.

Results of these first round of robustness checks are presented in Table 5 below. When compared to the baseline estimates discussed in Section 5.1, results clearly show minor differences, with a qualitatively identical result in terms of impact of Smart City policies on urban innovation.

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Total patent applications to the EPO	Unmatched	219.52	81.65	137.87	41.53	3.32
	ATT	187.52	83.08	104.44	43.43	2.40
High-tech patent applications to the EPO	Unmatched	46.86	12.51	34.35	10.87	3.16
	ATT	40.53	14.91	25.62	9.80	2.61
ICT patent applications to the EPO	Unmatched	64.19	19.85	44.34	14.73	3.01
	ATT	56.18	21.42	34.77	14.13	2.46
Smart City patent applications to the EPO	Unmatched	5.40	4.65	0.75	0.38	1.98
	ATT	5.49	5.18	0.31	0.63	0.50

Table 5. Average treatment effects on the treated for different urban innovation measures

Note: Smart City Policy Intensity now comprises three additional city networks w.r.t. Table 4.

Another potential issue with our findings is related to the relatively narrow definition of Smart City technologies provided in Table 1. In fact, the Smart City paradigm extends beyond the IoT and some may argue it also cuts across other broader fields such as energy. While this aspect is partially taken into account in Section 5.1 by narrowing the scope of the impact analyses from assessing the increase in generic patent applications due to adopting Smart Policies through High-tech and ICTs, which are already

[15] We would like to thank an anonymous reviewer for drawing our attention on these three city networks.

relatively broad paradigms, cutting across several IPC classes, Table 6 provides a further robustness check as follows. We calculated a gross count of patent applications in IPC 1 digit classes F ("*Mechanical engineering; Lighting; Heating; Weapons; Blasting*"), G ("*Physics*"), and H ("*Electricity*").

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Patent applications to the EPO in IPC 1-digit classes F, G, and H.	Unmatched	6.53	5.92	0.61	0.23	2.60
	ATT	6.57	5.45	1.12	0.37	3.00

Table 6. Average treatment effects on the treated for different urban innovation measures

Note: F class: Mechanical engineering; Lighting; Heating; Weapons; Blasting. G class: Physics. H class: Electricity

Results show a remarkable consistency of the previous empirical framework, which strengthens the case made by our estimates. As expected, the estimated net impact is somewhat larger in absolute terms given the broader definition of technological classes adopted for this exercise. In relative terms, instead, the impact of engaging in SC policies seems comparable when adopting either definition of what makes for a SC technology. Baseline estimates suggest a 20% increase in patent applications to the EPO in the IoT classes summarized in Table 1, which is very close to the relative impact of SC policy adoption estimated on the basis of the broader classification of SC technologies shown in Table 6. [16]

6. Conclusions

Are Smart City policies the new direction for urban initiatives? Are they conducive to sustainability, livability and economic growth? While these questions are still unanswered (and will probably be so for quite a while), in this paper we have added to our understanding of the mechanisms through which Smart City policies foster urban economic performance by investigating their impact through urban innovation. Our empirical findings, based on PSM, allow us to conclude that SC policies do have a non-negligible positive impact on urban innovation measured through patenting activity, especially in high-tech classes. Results are robust to a number of consistency checks, both in terms of the way Smart City policies are identified, as well as the way Smart City-related technologies are measured (i.e., which IPC classes are used to calculate Smart City technology intensity).

Results also suggest that SC policies indeed stimulate innovation that increases a city's stock of knowledge, one of the main recognized drivers of economic growth. Our findings are based on the analysis of 309 EU cities and exploit the differences in the intensity of SC policy adoption. Cities that engage in SC policy above the EU average tend to innovate more. The propensity to innovate is measured by the number of patents filed in four alternative technology class definitions (total patent applications, high tech patent applications, ICT patent applications and SC patent application). A relevant commitment to SC policy initiatives is in particular positively associated to higher overall innovation rates, as well as innovation rates in high tech, ICT, and SC patents. The use of a PSM procedure also allows to safely infer that reverse causality is not an issue and that this positive association can be interpreted in a causal sense.

Moreover, the fact that investing in SC policies does not translate simply to the narrowly defined class of SC patents but seems to impact high tech patents the most suggests that there might be a spillover effect

[16] This back of the envelop calculation is obtained by looking at the figures in the last rows of Tables 4 and 6, and dividing the difference between treated and untreated cities in the ATT by the patent application in the untreated cities. For IoT technologies (Table 4), this implies 0.92/4.45=20.67%; for the broader definition of SC technologies (Table 6), this ratio is equal to 1.12/5.45=20.55%.

in place. While SC policies tend to be focused on a narrow set of projects and areas of intervention, mostly related to ICT applications, the positive effect on innovative activity trickles down to other more broadly defined technological classes.

These results can be seen as a first step in clarifying the channels through which investing in policy initiatives based on the SC model can have a positive impact on urban level performance, defined in terms of economic growth, quality of life, sustainability and overall well-being. More research is needed to understand the overall effect of SC policies and how this translates into long-term objectives, along with a more precise definition of what SC policies actually are.

This last issue is also related to the need for reaching a consensus over a working definition of the SC model, which is an important step for defining the scope and evaluating the effects of SC policies. Our analysis is based on a model that considers the SC concept as an urban production function, where economic performance is the result of the interplay between urban inputs organized around six axes (human and social capital, transport and ICT infrastructure, e-government and natural resources). Based on this common conceptual model, SC policies can have a common blueprint which has to then be declined based on local economic, social, institutional and territorial characteristics.

While the fortune of the SC concept is apparent, as can be inferred by the sheer number of projects and initiatives in several cities around the world, the implications of this policy model have attracted several criticisms. Critics of this concept have expressed concerns related to privacy issues that can arise as a consequence of the collection of Big Data from SC infrastructures; the risk of a hegemony of a limited number of private ICT multinationals in defining the trajectory of urban policies worldwide; exclusion of the fragile and less technological members of the urban society thus increasing social and economic inequality; to a leveling of the differences of policy models and goals leading to a single and fundamentally top down approach to urban policy issues. More nuanced views of these challenges are discussed in Schaffers (2018), who proposes to focus the present and close future developments of the Smart City concept towards the need to set up policies bridging technological change and bottom-up governance of such evolution.

While most of these points are relevant and well taken, we believe that the risks associated with a universal model proposed and promoted by the private sector can be balanced by involving local actors (in order to translate the general one-size-fits-all template to the local conditions) at different levels. The decision to implement SC policy initiatives and their policy goals should be firmly kept in the hands of local public authorities, based on the involvement of stakeholders, including citizens and local businesses, in partnership with ICT companies providing technical solutions. SC policies should have a bottom-up, demand-driven component and should be closely monitored by municipalities and local governments, and many more efforts in evaluating the impacts of these programs should be undertaken. Further research is finally needed to understand how to aid local governments in designing urban policies that can reap the benefits of the SC model while at the same time avoiding its pitfalls.

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