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Public procurement, local labor markets and green technological change. Evidence from US Commuting Zones

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Abstract The present paper investigates whether and through which channels green public procurement (GPP) and the skills composition stimulate local environmental innovation capacity. We use detailed data sources on green patents and procurement expenditure at the level of US Commuting Zones for the period 2001-2011. We also check for the moderating effects of local labor market composition in the relation between GPP and green innovation capacity. Lastly, we exploit the richness of patent information to test for differential effects of GPP on different classes of green technologies (GTs). The main finding is that GPP is an important driver for the local generation of GTs. High availability of abstract skills in the local workforce also drives the generation of GTs and magnifies the positive effect of GPP. When separated by type of GTs, we find evidence of a more pronounced effect of GPP on the local generation of mitigation, relative to adaptation, technologies.

Keywords Green public procurement · Green technology · Innovation policy · Human capital

1 Introduction

While all the avenues of the debate about climate change seemingly lead to innovation, the nature of the problem, of the possible solutions and the roadmap towards implementation remain highly contested. The academic and policy circles place great expectations in the prospect that technology, both old and new, can assist in striking that balance between running business operations within the limits of environmental sustainability while staying in the game for innovation and high competitiveness (Porter and van der

Linde, 1995).[1] There is wide consensus on the importance of other forces that, alongside technology, can accelerate the transition to sustainable growth. For one, policy can create propitious conditions across the board, not just for technological innovation but, also, for promoting broader social engagement on the benefits of a low-carbon economy. It goes without saying that none of the above would be feasible absent a body of know-how that enables the necessary adjustments in the attendant technological, organizational and institutional domains. Last but not least, climate change is a global phenomenon with marked local manifestations, so that both policy and human capital carry spatial connotations that cannot be neglected. The present paper enters this debate with a view to explore empirically the extent to which policy and human capital enable or thwart local green innovation capacity in the local economies of the United States (US).

The three dimensions of interest for our study are connected in complex ways. To begin with, innovation in green technologies (GTs) suffers from a double externality problem (Rennings, 2000). On the one hand, non-appropriability and non-exclusivity of technological knowledge give way to the kind of externalities that are common to any innovation, and that lead to under-investment in the private sector. On the other hand, because of their potentially pervasive influence, GTs that effectively contribute to containing or preventing the negative effects of climate change bring about global benefits in the form of environmental protection that represents a positive externality for society, therein including non-innovating firms (Jaffe et al, 2002). This double externality exacerbates the traditional uncertainty that surrounds the development of new technologies and provides a rationale for the second dimension of interest, namely public policy interventions that create positive preconditions for investments in GTs (del Río González, 2009; Mowery et al, 2010). The portfolio of available mechanisms is wide and encompasses setting emission standards, stimulating the demand for green technologies (pull effect) or restoring incentives for private investments in innovation (push effect) (Johnstone et al, 2012). Last but not least, the scale of changes involved in these diverse but interconnected dimensions call upon specialized know-how. Human capital is a key asset to facilitate the development of new technology but the transition towards low-carbon economies calls upon capabilities beyond the strictly technical sphere, for example operation management skills to manage the reconfiguration of industrial processes as well as legal and administrative skills to comply with regulatory standards (Vona et al, 2018).

In the view proposed here the interplay between policy, technology and human capital offers a compelling framework to account for the space-bound co-existence of technology push and demand pull forces (Requate, 2005; Horbach, 2008; Ghisetti and Quatraro, 2013; Costantini et al, 2015). The paper draws on and contributes to this research by investigating whether and to what extent Green Public Procurement (GPP) of environmentally sustain-

[1] See Barbieri et al (2016) for an extensive survey.

able products and services, as well as the skills composition of local labor markets, enhance the introduction of new GTs in 722 US Commuting Zones (CZs) over the period 2000-2011. Our proxy for environmental innovation at local level is the annual number of new green patents granted to CZ residents. The main findings of our analysis are four. First, GPP exerts a positive impact on the generation of GTs in US CZs. Second, availability of human capital, in particular of high-level abstract skills, is a significant predictor of green knowledge production. Third, these two dimensions, procurement and human capital, exhibit a high degree of interdependence in the form of positive and significant mutual reinforcing effect. Fourth, we observe differences between types of green technology when we disentangle mitigation from adaptation oriented GTs.

Our findings add to prior literature in several respects. To begin with, in spite of an intense debate about the importance of demand-side policy instruments, there is a gap on the role of public procurement at the regional level (Gerritse and Rodriguez-Pose, 2018). Further, while existing research has focused on the impact of public procurement on innovation in general (Nelson, 1982; Geroski, 1990; Ruttan, 2006), only a few studies concentrate on the domain of innovation for environmental sustainability. In particular, Ghisetti (2017) provides a firm-level analysis of the relationship between innovative public procurement and investments in green technologies, by looking at firms' adoption of eco-innovation. Conversely, our study provides a step forward in that it is based on data on GPP, and not generic innovative public procurement. Moreover, we investigate the effects on the generation of green technologies, by stressing that the creation of new markets engendered by demand-side green policy instruments represent an economic incentive for green technology suppliers to commit resources to green R&D. Second, the inclusion of occupational structure as a proxy of the skill endowment of the local workforce brings to the fore explicitly the dynamics of know-how and learning that can either enable or thwart the development of a new technological trajectory. While recent exploratory studies propose novel approaches to account for the analysis of environmental skills and green jobs at the level of occupations (Consoli et al, 2016; Vona et al, 2018) and of US geographical areas (Vona et al, 2019), no study has so far explored the role of local human capital endowment for green technological change. Further, our focus on the determinants of eco-innovation in the US enriches existing empirical evidence that is mainly centered on European countries. On the whole, our empirical analysis connects the spatial dimension of eco-innovation and the literature on the determinants of eco-innovation which remains an appealing, yet arguably underdeveloped, space of future research (Ghisetti and Quatraro, 2017; Montresor and Quatraro, 2017; Barbieri and Consoli, 2019).

The rest of the paper is structured as follows. Section 2 articulates the theoretical framework and develops the working hypotheses. In Section 3 we outline the research design. Section 4 presents the results of the econometric analysis. In Section 5 we provide a critical discussion of our findings and derive concluding remarks.

2 Theory and hypotheses development

Knowledge generation and diffusion stem out of local interactions that confer innovation a space-bound nature. According to an established tenet, geographical and cognitive proximity are necessary, but not sufficient, to reduce coordination and transaction costs among otherwise dispersed individuals, and to eventually spur learning, knowledge creation and innovation (Breschi and Lissoni, 2001; Boschma, 2005; Quatraro and Usai, 2017). The spatial dimension of innovation is especially relevant to analyse cross-regional heterogeneity in the composition of economic activities and in the attendant competences and innovation capabilities (Quatraro, 2009; Storper and Scott, 2009).

Empirical studies based on the knowledge production function (KPF) approach of Griliches (1984) and Jaffe (1986) insist that the variance in the quality of regional innovation systems and of intensity of investments in R&D activities explains a substantial portion of the difference of cross-regional innovation performance (Acs et al, 2002; Fritsch, 2002; Paci et al, 2014; Miguelez and Moreno, 2017). A strand in evolutionary economic geography adds to this that regional idiosyncratic factors affect not only the rate of local innovation activities but also their direction, thus accounting for the effects of path-dependency on regional technological branching (Colombelli et al, 2014; Montresor and Quatraro, 2017; Barbieri and Consoli, 2019).

Following on the above, we argue that the spatial features underlying the generation and diffusion of green technology have been somewhat underplayed. The only exceptions are studies based on the KPF approach that emphasize the role of R&D activities and of the regulatory framework in influencing the rate of green technological change (Ghisetti and Quatraro, 2013; Costantini et al, 2015). Spatial patterns of GTs production have been analyzed from an evolutionary perspective only in the fuel cell industry in EU regions with a view to capture the role of technological relatedness (Tanner, 2014 and 2015). We propose to fill this gap by articulating the analysis of eco-innovation in the KPF framework with a view to gain greater understanding of the spatial characteristics of green innovation.

Eco-innovations carry a number of features that set them apart from other types of innovation (Rennings, 2000). Indeed, besides the classical sources of externalities that affect any kind of knowledge, green knowledge also has positive effects on firm-level, and hence local-level, environmental performance. The associated market failure and the difficulty to internalize the external effects are likely to lead to suboptimal investments in the generation of GTs. Policy intervention is therefore crucial to ensure optimal investment levels. Accordingly, the positive impact between environmental regulation and innovation is the core of Porter's hypothesis about environment and competitiveness (Porter and van der Linde, 1995).

Several types of environmental policy instruments can be observed, which can be classified either as supply-side or demand side-measures. The former basically aim at fostering the development of technological capabilities in green domains through R&D supporting schemes (Costantini et al, 2015).

Demand-side policies instead range from setting of technological standards to regulating prices or establishing pollution thresholds so as to induce firms to renew their production processes. These measures create an incentive for firms to improve their environmental performances by means of the technological upgrading of their production processes. Such an inducement effect stems from the comparison between the costs that firms would incur keeping polluting and the costs associated to the technological upgrading of their production processes to meet the more stringent environmental regulation (Johnstone et al, 2012; Beise and Rennings, 2005; Ghisetti and Quatraro, 2013; Ambec et al, 2013; Horbach et al, 2013; Borghesi et al, 2015).[2] According to this inducement mechanism, the more stringent is the regulatory framework, the higher are the incentive for firms to adopt organizational and technological innovations to comply with it. Overall, the increase in downstream firms' demand for green technologies is expected to open up opportunities for the emergence of new markets for GTs or the extension of existing ones, creating the economic incentives for upstream green technology suppliers to commit resources in green R&D activities (Nemet, 2009; Hoppmann et al, 2013; Costantini et al, 2015).

In this context, much less explored is a demand-side tool that exploits a traditional fiscal policy lever, i.e. public procurement. This has been mostly studied in the economics of innovation literature wherein government R&D spending has been found to have a positive effect at the collective level because it generates public knowledge that generates spill-overs to the actors of the innovation system. Moreover, positive effects are related to the triggering of private firms R&D spending (Lichtenberg, 1987, 1988; Wallsten, 2000).

The impact of innovative public procurement on the generation of green technologies has been largely underplayed. To the best of our knowledge only Ghisetti (2017) has hitherto explored this issue. Innovative public procurement can be useful for innovation in general, and for green innovation in particular. At the general level, the positive effects is related to the impact on location choices of firms, the launch of highly risky and uncertain R&D projects avoiding market failures and the improvement of public infrastructures and services (Edler and Georghiou, 2007). Ghisetti (2017) stresses that innovative public procurement can also foster green innovation by activating

[2]These dynamics can be considered a specific application of the general price-inducement theory that is well-established in economics of innovation (Antonelli, 1998; Lichtenberg, 1986).

demand-pull mechanisms that create new market niches, and favouring in turn the diffusion of these technologies. [3]

These considerations bring the institutional context at the core of the analysis of the drivers of GTs (Hitaj, 2013; Nesta et al, 2014). Building on the tenet that public procurement is place-specific and that it exhibits variance both between and within regions over time (Heald and Short, 2002; Morgenroth, 2010), we propose a framework to gain a better understanding of the spatial determinants of eco-innovation (Cole et al, 2013).

Since institutions are place-specific, empirical studies at the micro, meso and at the macro-level consider the regional or national regulatory framework as a key discriminant to explain differences in the ability to generate eco-innovations across firms, regions and countries (Barbieri et al., 2016). GPP is touted as a key lever to stimulate the local development of new technologies that can facilitate meeting environmental sustainability targets. This is because the pathway to successfully developing green technology entails dealing with substantial uncertainty (Mowery et al, 2010). Under this perspective, place-specific GPP is regarded as a direct form of public intervention to stimulate the demand for GTs by the government (Parikka-Alhola, 2008).

In particular, the mechanisms through which GPP is expected to foster green technology in local areas are those described in the literature on eco-innovation (Rennings, 2000) whereby public policies can counter the double externality problem by creating propitious conditions for eco-innovation via two channels: the first is indirectly stimulating the derived demand of green technologies on the part of polluting firms that are prepared to comply with stricter and stricter environmental regulation. The other channel is direct supporting of demand via procurement contracts (Johnstone et al, 2012). In both cases the final outcome is the creation of new market niches or the extension of existing markets for green technologies (Nemet, 2009; Hoppmann et al, 2013). Accordingly, our first hypothesis is:

H1: *Territorial differences in GPP are associated with green technological change differentials across regions.*

The full appreciation of the mechanisms underlying knowledge production is crucial to gain a comprehensive view on the spatial dynamics of GTs generation. Knowledge recombination has long been understood as a key driver of new competences that are eventually embodied in new technology (Weitzman, 1996 and 1998; Fleming and Sorenson, 2001). Proximity in the cognitive domain facilitates the recombination of know-how, and highly coherent knowledge bases increase significantly the chances of successful innovation (Quatraro, 2010; Krafft et al., 2014).

Recent contributions have elaborated upon the recombinant approach to stress that green technologies are often the outcome of search patterns carried out across diversified and loosely related areas of the technology land-

[3] Unfortunately the author's data do not allow to disentangle the effects of green public procurement

scape (Zeppini and van den Bergh, 2011; Zeppini, 2015). These theories are consistent with established view on eco-innovations as highly sophisticated and complex technologies (del Río González, 2009; Del Río et al, 2011; del Río et al, 2016; Barbieri et al, 2018). Following this line of reasoning, recent empirical studies have investigated the extent to which the generation of eco-innovation is associated with the hybridization of green and dirty technologies (Dechezlepetre et al., 2004; Colombelli and Quatraro, 2017). Other studies have instead elaborated on the complexity of green technologies to show that the ability to deal with boundary-spanning search activities are crucial to successful innovation efforts in this domain (Orsatti et al, 2017; Quatraro and Scandura, 2019). Overall, this growing body of literature points to the systemic and complex nature of green technologies, which are deemed as the outcome of a new technological paradigm stemming from exploration across technological boundaries and the implementation of unprecedented knowledge recombination.

According to an established tenet, skilled individuals can more quickly adapt their activities to the changing incentives that follow the emergence of new technologies (Nelson and Phelps, 1966) and, in the case at hand, the transition to low carbon economies calls upon a broad competence base that goes beyond the merely technical domain (Vona et al, 2018). As noticed by Del Río et al (2011): "Some clean technologies are complex and sophisticated, requiring skillful human resources which the firm may not have" (ibidem: p. 1172). However, geographical areas are likely to differ in terms of both the endowment of human capital as well as in the capacity to adapt their occupational structure to the new opportunities (Vona et al, 2019).[4] This entails that agglomeration economies due to geographic concentration of economic activities may account for significant differences in the capacity to generate green technology across space. On these grounds, we propose the second hypothesis:

H2: *The prevalence of exploration-oriented skills in local contexts is associated with higher levels of green technological change.*

Last but not least, human capital endowment and GPP are ideal candidates to explain the green innovation capacity of local economies. This holds true also for their interaction. Due to the double externality problem of eco-innovation, the endowment of exploration-oriented skills at the local level can hardly display its full potential in terms of GTs enablers because of the reluctance of economic agents to bear the uncertainty associated with externalities and low appropriability conditions. At the same time, high levels of GPP are likely to be more effective in the stimulation of the production of

[4]Notice that we infer from this literature that differences between green and non-green jobs and skills are not as straightforward so as to allow setting rigid boundaries between these two only apparently separated domains (Consoli et al, 2016). Rather, pursuing environmental sustainability entails the recombination of both green and non-green capabilities (Vona et al, 2019). Accordingly, the issue of interest here is how green jobs and skills diffuse in the existing workforce and in the attending human capital infrastructure. We are indebted to the editor and an anonymous referee for pushing us to reflect more carefully on this issue.

environmentally sound technologies in areas that are characterized by local availability of exploration-oriented skills. Accordingly, we expect the two dimensions to show a high degree of interdependence and mutual enforcing effect on green innovation capacity. These considerations lead us to spell out our third hypothesis.

H3: *The prevalence of exploration-oriented skills and high levels of GPP in local context are mutually enforcing in affecting the rate of green technological change.*

The remainder of the paper will elaborate an empirical analysis to test the hypotheses laid out in this section.

3 Research design

This section details the key data sources, the variable construction and the proposed empirical strategy. As anticipated earlier, all the key dimensions of interest for the present study, eco-innovation, public procurement and human capital, are space-bound. For the purpose of their analysis we focus on US Commuting Zones. These spatial units were first developed by Tolbert and Sizer (1996) using county-level commuting data from the 1990 Census data to create 741 clusters of counties that are characterized by strong and weak commuting.[5] Compared to other territorial units, CZs carry the advantage of covering the entirety of the US territory while at the same time being constructed in such a way that meaningful mobility patterns are accounted for.[6]

3.1 Data and variables

We exploit three main sources of data at the level of CZs to measure: *i)* the local green innovation capacity proxied by patenting activity; *ii)* the level of local green procurement expenditures and *iii)* the local composition of human capital proxied by the occupational structure of the attendant local labor market.

Patent data–We measure green innovation capacity as propensity to introduce eco-innovations using data on US-invented patents with priority year between 1970 and 2012 (Source: PATSTAT, version 2016a).

Patents are assigned to the environment-related domain using the ENV-TECH classification (OECD, 2015) based on the International Patent Classification (IPC) and the Collaborative Patent Classification (CPC). Therein, eight environmental areas are featured: (a) environmental management, (b) water related adaptation technologies, (c) climate change mitigation technologies

[5]Of them, we only consider the 722 CZs that cover the entire mainland United States (both metropolitan and rural areas).

[6]See Dorn (2009) for further details on empirical analysis at the US CZ level.

related to energy generation, transmission or distribution, (d) capture, storage, sequestration or disposal of greenhouse gases, (e) climate change mitigation technologies related to transportation, (f) climate change mitigation technologies related to buildings, (g) climate change mitigation technologies related to wastewater treatment or waste management, and (h) climate change mitigation technologies in the production or processing of goods.

Since the ENV-TECH classification uses both IPC and CPC codes[7] we first convert IPC codes into CPC codes using the concordance tables of EPO and USPTO.[8] Subsequently, we use information contained in patent documents to extract CPC codes and assign patents to ENV-TECH categories. For what concerns the geographical dimension, we assign a patent to a US territory by means of information contained in inventors' addresses. This is an original methodology for geo-localizing US green patents to the level of counties. The 2016a version of PATSTAT does not provide an address for every inventor. To minimize the number of missing addresses, we follow two parallel strategies. First, we rely on the IFRIS version of PATSTAT. IFRIS recovers missing addresses combining several external patent sources (REGPAT, INPI, etc). Second, we propagate the inventor's address into the relative patent family: for each patent family and missing address, we check if there is an inventor with a similar name (applying the Levenshtein distance) and with a non-missing address. If it is the case, we fill the missing address with the one related to the most similar inventor recovered. Combining both sources, we reduce the missing rate to around 10%.

The next step consists in assigning precise geographical coordinates to each address and, thus, to each patent. First, we extract the postal code included in the inventor's address, when available, to identify US cities according to the GeoNames postal code table.[9] Indeed, GeoNames provides a regular expression to find postal codes according to their official format for each country. We apply it to identify postal codes in inventor's addresses. Second, addresses that could not be assigned to a specific postal code were parsed through an iterative algorithm that would identify the name of the city within the address field. Once extracted, this information was matched with names of US city above 5,000 inhabitants in GeoNames.[10] Third, we exploit the Google Geocoding API resource to assign geographical coordinates to all the remaining addresses. This procedure allowed us to assign geographical coordinates to around 90% of unique US inventors' addresses. These coordinates were subsequently matched with the 1990 US CZs map to assign inventors to CZs.

[7] Almost all the IPC codes are present in the CPC classification but not the other way around.

[8] `http://www.cooperativepatentclassification.org/cpcConcordances.html`

[9] `https://www.geonames.org/postal-codes/`

[10] We set a threshold on the city population to limit noise in the results. We checked manually results to remove false positives.

The local level of green innovation activity is measured through the fractionalized[11] number of US-invented patents with at least one CPC class which relates to the green domain. To retrieve the earliest patent priority year for each protected invention we rely on information contained in INPADOC patent families data.[12]

Furthermore, by exploiting the ENV-TECH classification, we differentiate GTs between two macro-technology groups: *i)* green adaptation technologies (ENV-TECH areas (a) and (b)); and *ii)* green mitigation technologies (ENV-TECH areas from (c) to (h)).

Procurement data–Second, we collect data on environmental-related procurement expenditures by exploiting public information provided by the USAspending.gov resource.[13] Procurement information are available from 2000 onward.

The Federal Funding Accountability and Transparency Act of 2006 (FFATA) was signed into law on September 26, 2006. The legislation required that federal contract, grant, loan, and other financial assistance awards of more than $25,000 be displayed on a searchable, publicly accessible website, USAspending.gov, to give the American public access to information on how their tax dollars are being spent. As a matter of discretion, USAspending.gov also displays certain federal contracts of more than $3,000. The initial site went live in 2007. Federal agencies are required to report the name of the entity receiving the award, the amount of the award, the recipient's location, the place of performance location, as well as other information.

In particular, using data on all registered federal contracts we extract information about the location of funding provision (5-digits Zipcode)[14] where the contract is executed and the amount of resources dedicated (in 2010 USD). The Product and Service Codes Manual (PSC, August 2015 Edition) is the guide to identify procured 'green' contracts and to distinguish between product-, and service-related.[15] Indeed, the PSC Manual provides codes to

[11]Patent p is assigned to CZ c according to the fraction of inventors resident in CZ c over the total number of inventors filing the patent p.

[12]Patent families essentially originate from a company or an inventor applying for the protection of the same invention at different patent offices. This results in a series of equivalent filings with, possibly, different years of registration. Simple patent families are quite restrictive sets of equivalents, all sharing the same priority (an original filing at one or another patent once, before extension elsewhere). For a complete discussion about patent families, see Martínez (2011).

[13]`https://www.usaspending.gov`

[14]5-digits Zipcodes allow us to assign precise levels of expenditures to counties and, consequently, to CZs.

[15]Statutory requirements and Executive Order 13514 direct the Office of Management and Budget (OMB) Office of Federal Procurement Policy (OFPP) to report on procurement of products and services with environmental attributes including recycled content, biobased, and energy efficient. Data collected in the Federal Procurement Data System include these three environmental attributes plus an 'environmentally preferable' attribute. This last attribute means products or services that have a lesser or reduced effect on human health and the environment when compared with competing products or services that serve the same purpose.

describe products, services, and R&D purchased by the federal government for each contract action reported in the Federal Procurement Data System (FPDS). Since a contract may include multiple products/services, with and without environmental attributes, the PSC data element code has been selected based on the predominant product or service that is being purchased.

Occupational-task data–To capture the role of human capital in local labor markets, we rely on the task-based framework originally proposed by Autor et al (2003) and recently extended to the analysis at geographical level by Autor and Dorn (2013). This approach differs from the traditional operationalization of human capital because it focuses on the relative importance of occupations rather than on educational-based proxies such as i.e. the average number of years of education in the workforce or the share of individuals with postgraduate degrees. In this view, labor is the institutional mechanism that allows the application of individual know-how, and the changing structure of occupation reflects the growth or decline in the relative importance of the attending human capital endowment (Consoli and Rentocchini, 2015; Vona and Consoli, 2015).

In this framework work activities are grouped in three broad categories defined on the basis of the match between the main work tasks and the skills needed to perform them. First, routine tasks that entail executing codified instructions with minimal discretion on the part of the worker. Routine tasks are characteristic of middle-skilled jobs that entail repetitive cognitive (i.e. clerks) or manual (i.e. blue-collar) duties. The second main category of work task include activities that require creativity, problem-solving, intuition and social perceptiveness. These abstract tasks are characteristic of professional, managerial, technical and creative occupations that require high levels of formal education. Since analytic and interpersonal capabilities are so important, technology accrue productivity benefits to these workers by facilitating the transmission, organization, and processing of information. On the other side of the skill spectrum are manual tasks, which demand visual and language recognition, personal interaction and physical dexterity. Occupations that use intensively these tasks are typically low-skill service jobs such as food preparation, catering, driving and cleaning.

Following prior empirical studies (Autor et al, 2003, 2006; Dorn, 2009; Autor and Dorn, 2013) we merge job task requirements from the fourth edition of the US Department of Labor’s Dictionary of Occupational Titles (DOT) (US Department of Labor 1977) to their corresponding Census occupation classifications to measure routine, abstract, and manual task content by occupation.[16] We combine these measures to create summary indicators of task-intensity by occupation (routine RTI, abstract ATI and manual MTI), calculated as

$$ATI_k = ln(T^A_{k,1980}) - ln(T^R_{k,1980}) - ln(T^M_{k,1980}) \tag{1}$$

[16]The DOT permits an occupation to comprise multiple tasks at different levels of intensity.

$$RTI_k = ln(T^R_{k,1980}) - ln(T^A_{k,1980}) - ln(T^M_{k,1980}) \tag{2}$$

$$MTI_k = ln(T^M_{k,1980}) - ln(T^A_{k,1980}) - ln(T^R_{k,1980}) \tag{3}$$

where, T^R_k, T^A_k and T^M_k are, respectively, the routine, abstract, and manual task inputs in each occupation k in 1980.[17] For each kind of task, this measure rises in its importance in each occupation and declines in the importance of the other two tasks.

Next, to operationalize these measures constructs at the geographic level, we take two additional steps. We first use the task intensity index to identify the set of occupations that are in the top employment-weighted third of task-intensity in 1980. We refer to these as either abstract-, routine- or manual-intensive occupations. We next calculate for each CZ j task employment share measures (RSH_{jt}, ASH_{jt} and MSH_{jt}) equal to:

$$ASH_{jt} = \left(\sum_{k=1}^{K} L_{jkt} \cdot \mathbb{1} \left[ATI_k > ATI^{P66} \right] \right) \left(\sum_{k=1}^{K} L_{jkt} \right)^{-1} \tag{4}$$

$$RSH_{jt} = \left(\sum_{k=1}^{K} L_{jkt} \cdot \mathbb{1} \left[RTI_k > RTI^{P66} \right] \right) \left(\sum_{k=1}^{K} L_{jkt} \right)^{-1} \tag{5}$$

$$MSH_{jt} = \left(\sum_{k=1}^{K} L_{jkt} \cdot \mathbb{1} \left[MTI_k > MTI^{P66} \right] \right) \left(\sum_{k=1}^{K} L_{jkt} \right)^{-1} \tag{6}$$

where L_{jkt} is the employment in occupation k in CZ j at time t, and $\mathbb{1}[\cdot]$ is the indicator function, which takes the value of one if the occupation is task intensive by our definition.

Finally, according to the shares calculated from (4) to (6), we assign a set of dummies equal to 1 if the CZ j is in the top third of national task share at time t:

$$AI_{jt} = \mathbb{1} \left[ASH_{jt} > ASH^{P66}_t \right] \tag{7}$$

$$RI_{jt} = \mathbb{1} \left[RSH_{jt} > RSH^{P66}_t \right] \tag{8}$$

$$MI_{jt} = \mathbb{1} \left[MSH_{jt} > MSH^{P66}_t \right] \tag{9}$$

This characterization of local labor markets allows us to investigate whether diverse occupational task compositions moderate the effect of green public procurement on the generation of GTs.

Table 1 reports the main descriptive statistics of the variables used in the analysis. Figures 1, 2 and 3 offer a visual summary of the the geographical distribution of key dimensions across CZs. Therein area boundaries are outlined in grey, the interior of each CZ is shaded according to the quintile rank in the distribution of the relevant dimension – color coding is darker for higher quintiles and progressively lighter for lower quintiles. For all the

[17] Tasks are measured on a zero to ten scale.

figures, quintiles are weighted by population density. The quintile distribution of the average annual number of new GT patents filed during the period 2000-2011 in Figure 1 (panel c) shows that green inventive activity is more concentrated along coastal areas (especially California and the north east) as well as in lakeside CZs of the north and in Texas. The figure also indicates that there is no significant difference in the distribution of patenting of the component sub-categories, namely green mitigation technologies (panel a) and green adaptation technologies (panel b). Figure 2 plots the geographic quintile distribution of the average amount of GPP expenditures (2010 USD) at the level of CZs for the period 2000-2011. Precisely, panel c) refers to the total level of expenditures, panel a) to GPP for products, panel b) to GPP for services, respectively. This reveals some overlap between the distribution of GPP and that of green inventive activities of the previous figure. Finally, Figure 3 shows the geographic quintile distribution of task-intensive occupations at the level of CZs in 2005. Precisely, panel a) refers to abstract-intensive occupations, panel b) to routine-intensive occupations, panel c) to manual-intensive occupations, respectively. The noticeable feature is that, relative to the other categories, routine intensive occupations are more concentrated in CZs in the center and the east of the US. This resonates with the prominence of the attendant jobs in areas with high density (i.e. clerical occupations) and with higher levels of industrial activity (i.e. blue collar jobs).

On the whole the maps show that for all the measures there is a large variance across CZs, as well as a marked evidence of spatial concentration. The maps also show interesting converging patterns in the spatial distribution of GPP, GTs and abstract-skills intensity. This evidence suggests that an economic geography approach is very suitable to analyze how policy levers and skills-intensity affect the local production of GTs over time.

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3.2 Empirical strategy

Using the full sample of 722 CZs observed from 2001 to 2011, we fit models of the following form to investigate the relationship between green public procurement and the local level of green technological activity:

$$Y_{j,t} = \beta_0 + \beta_1 GPP_{j,t-1} + \boldsymbol{X'_{j,t}}\beta_2 + \epsilon_{j,t} \tag{10}$$

where $Y_{j,t}$ is the (log transformed) fractionalized number of green patents filed by inventors resident in CZ j at time t; $GPP_{j,t-1}$ is the (log transformed) level of expenditures for green public procurement performed in CZ j at time $t-1$ (2010 USD); additionally, the vector $\boldsymbol{X'_{j,t}}$ contains (in most specifications) a rich set of controls for CZ labor force and demographic composition that might independently affect innovation outcomes. Precisely, we add the population level and the number of firms to control for the CZ economic size. Importantly, the latter is of crucial importance since it is very likely to affect both the local level of GPP and the generation of GTs. Moreover, we include the share of R&D employment to control for the local innovation capacity, and the population density as further control for CZ size. Finally, we also include year dummies to control for all yearly shocks common to all CZs, such as business cycles, and Census macro-areas dummies (or, alternatively, CZ fixed effects for robustness reasons). Standard errors are clustered at the State level to account for spatial correlations across CZs.

To test for moderating effects of local heterogeneity in terms of CZ occupational task compositions on green innovation activities, we estimate three models, augmenting (10) as follows:

$$Y_{j,t} = \beta_0 + \beta_1 GPP_{j,t-1} + \beta_2 RI_{j,t-1} + \beta_3 GPP_{j,t-1} \times RI_{j,t-1} + \boldsymbol{X'_{j,t}}\beta_4 + \epsilon_{j,t} \quad (11)$$

$$Y_{j,t} = \beta_0 + \beta_1 GPP_{j,t-1} + \beta_2 AI_{j,t-1} + \beta_3 GPP_{j,t-1} \times AI_{j,t-1} + \boldsymbol{X'_{j,t}}\beta_4 + \epsilon_{j,t} \quad (12)$$

$$Y_{j,t} = \beta_0 + \beta_1 GPP_{j,t-1} + \beta_2 MI_{j,t-1} + \beta_3 GPP_{j,t-1} \times MI_{j,t-1} + \boldsymbol{X'_{j,t}}\beta_4 + \epsilon_{j,t} \quad (13)$$

where dummy variables $RI_{j,t-1}$, $AI_{j,t-1}$ and $MI_{j,t-1}$ are calculated according to equations from (7) to (9).[18]

Exploiting the ENV-TECH classification, we can also differentiate between diverse types of green technologies. In the final step of the analysis we thus substitute our dependent variable accordingly, re-estimating equations from (10) to (13). Precisely, we aggregate technologies in two groups: mitigation and adaptation GTs.[19]

4 Results

Section 2 puts forward the key hypotheses of the present study. The first is that GPP exerts a positive impact on the local dynamics of GT generation against the backdrop of the double externality problem and the regulatory push/pull effect. Moreover, the second hypothesis is that the configuration of the skill bundle in local labor markets also affect the process by which green inventions are brought about, because of the spanning of the recombinant innovation process over a large number of heterogeneous technological components.

Table 2 presents the results of the baseline estimates of the relationship between expenditures in GPP and local environmental innovation capacity.

[18] Due to occupational data availability, the period considered for this second step of the analysis reduces (2006-2011). For robustness, we therefore re-estimate Equation 10 (baseline) also for this reduced sample. Results (reported in Table 3, Column I) are consistent with the ones obtained for the full period 2001-2011 (Table 2, Column III).

[19] As described in Section 3.1, mitigation technologies aggregate ENV-TECH technologies from (c) to (h). Adaptation technologies are instead the ones related to groups (a) and (b).

Columns I, II and III report the estimates for the effect of the overall level of GPP. In the first two columns we include CZ fixed effects while in the latter we include Census macro-area dummies instead of CZ fixed effects. Columns IV and V focus on product-related and service-related GPP, respectively. The dependent variable is the (log transformed) fractionalized number of local environmental patents.

Column I contains the results when controlling only for CZ fixed effects and year dummies. The GPP coefficient is positive and significant. Although we include CZ fixed effects, this result can hide some effects of unobserved variables that one may want to mitigate. Therefore, in Column II we provide estimates when the full set of controls at the CZ level, discussed in Section 3.2, are included (i.e. population density, employment level, number of firms and the share of R&D employment). The coefficient of GPP remains positive and significant if slightly lower. As for the control variables, we find a significant and positive coefficient for the number of firms, while the employment level shows a negative and significant coefficient.[20]

Column III estimates equation (10) obtained by substituting US Census macro-areas fixed effects for CZ fixed-effects. The overall results suggest that the effect of GPP is robust across different model specifications. In particular, we can quantify the positive and significant impact of GPP on local green innovation activities: a 1% increase in GPP leads to some 0.043% increase in the number of new green patents.

Columns IV and V in Table 2 replicate column III but focusing on the effects of, respectively, GPP for products and GPP for services on the local generation of GTs. For both types of public procurement expenditures we find significant and positive coefficients that show similar magnitude.

The overall picture emerging from this first set of estimates provides empirical support to Hypothesis 1, namely that GPP is expected to have a positive association with the generation of GTs in US Commuting Zones. We can now turn to the investigation of the role of the local skill compositions drawing upon the measures proposed in Section 3.1. Our aim is to test for the direct effect of the local skills configuration on the local generation of GTs, as well as how they moderate the relationship between GPP and local green innovation capacity.

Table 3 takes as a benchmark Column III proposed in Table 2. As explained in Section 3.1, we built dummy variables equal to 1 if a CZ is in the top 33% of task-intensive occupations shares: abstract (AI), routine (RI) and manual (MI). We include these dummy variables in the estimations, as well as their interaction with (total) GPP. When including local skill composition into the empirical framework, the sample reduces due to data availability

[20]The coefficient for the employment level turns to be not significant in the rest of the analysis, where we include local occupational-task indicators (i.e. Tables 3 to 8). The significant and negative coefficient found in our baseline estimates might be due to the fact that employment growth is likely to be mainly driven by manual-intensive occupations (Autor and Dorn, 2013), while we expect abstract-intensive occupations to be relatively more relevant for the local generation of GTs.

(now the period considered is 2006-2011). Before adding occupational-task indicators to the analysis, we first re-estimate the same model proposed in Table 2 Column III, but on the reduced sample. Column I reports the related results, showing that the GPP coefficient is still significant and positive. Precisely it reduces from 0.043 to 0.027. We then start including local occupational-task indicators and their interactions with GPP into our estimates. Columns II and III focus on the abstract-intensive indicator (AI). Both the coefficient of the direct and moderating effects are positive and significant. Columns IV and V deal with routine-intensive indicators (RI). The coefficient of the direct effect as well as the coefficient for the interaction with GPP are not significant. Columns VI and VII report the estimations of the effect of the manual-intensive indicator (MI). The direct effect is negative and significant in column VI, while it becomes not significant when the interaction with GPP is included (Column VII). However, in this latter case, the moderating effect is negative and significant.

Overall, the inclusion of the local skills composition in the empirical framework seems to reduce the magnitude of the GPP coefficient. According to the estimates in table 3, a 1% increase in GPP yields an increase in GTs ranging from 0.014% to 0.042%, which is slightly lower than the 0.043% increase found in Table 2. AI is the only skill category yielding a positive correlation with GTs at the local level. According to the results reported in Column III, in the areas in the top 33% of abstract-task intensive occupations (AI=1), the overall impact of 1% increase in GPP consists of some 0.03% increase in the local generation of GTs.[21]

Tables 4 and 5 complement the analysis proposed in Table 3 by investigating whether there are differences in the effect of GPP expenditures for, respectively, products and services on GTs. Results show a direct association for both types of expenditures, with similar intensity. This set of results is in line with the initial estimates proposed in Table 2. Moreover, both the direct and the moderating effect of AI hold for both GPP for products and GPP for services.

Figure 4 plots the average marginal effects calculated on the basis of the results from Tables 3, 4 and 5. The bottom parts of the three panels plot average marginal effects of respectively, total, product- and service-related GPP when the CZ is in the top third share of task-intensive occupations (abstract, routine and manual, alternatively). Top areas plot the reverse case (average marginal effects when the CZ is not in the top third share of task-intensive occupations).

> > > INSERT FIGURE 4 ABOUT HERE < < <

[21]To provide more robust evidence, we also consider further lags of the variable GPP. Results are fully consistent to the ones commented here when lagging GPP two and three years, respectively, and are reported in Appendix A-1. Moreover, to control also for possible technology and policy geographical spillovers, we estimate models as the one reported in Tables 2 and 3, augmenting the vector of controls with the inclusion of two further variables, named the number of GTs and the level of GPP in the neighboring CZs. Again, results are fully consistent with the main findings reported in Tables 2 and 3, and are reported in Appendix A-2.

Focusing on areas in the top third of the skill endowment (bottom area of the figure), we find that the local knowledge base proxied by means of occupations brings about heterogeneity in the results. In particular, the coefficient for abstract occupations is always significant and exhibits similar association between GPP types. Recall that abstract occupations are intensive in activities that require problem-solving, intuition, persuasion, and creativity. These characteristics are over-represented in professional, managerial, technical and creative occupations in areas as diverse as law, medicine, science, engineering, design, and management. Workers who are most adept in these tasks typically have high levels of education and analytic capability. The coefficient for routine occupations is only slightly significant for green-service procurement. These jobs encompass many middle-skilled cognitive (i.e., bookkeeping, clerical work) or manual (i.e., repetitive physical operations in production jobs) activities. Even though the growth of routine jobs has been in decline for some time (Autor et al, 2003; Autor and Dorn, 2013), routine occupations still make up the bulk of employment in the United States. In the case under analysis, we ascribe the positive correlation with routine occupations to the persistent important role of clerical and administrative workers in services. Lastly, the endowment of manual skills is never significant (and always negative). This is not surprising considering that low-skill manual intensive jobs are mainly concentrated in areas such as assistance and hospitality, and thus we expect them to be only marginally related to the relation between innovation and public procurement.

4.1 A comparison between GTs for adaptation and mitigation

As a further step of the analysis, we exploit the OECD ENV-TECH classification to test for the differential effects of GPP on the two main groups of green technologies: mitigation and adaptation, respectively. Tables 6, 7 and 8 present estimates for the effect of, respectively, total, product- and service-related GPP on the generation of the two main groups of GTs, separately. Figures 5 and 6 summarize the average marginal effects of total GPP and its components (i.e. GPP for products and GPP for services) on the local generation of GTs for, respectively, mitigation and adaptation groups.

Panel (a) in Table 6 focuses on green mitigation technologies, while Panel (b) focuses on green adaptation technologies. In both cases we replicate the same framework proposed in Table 3. Results reported in Columns I show that GPP is strongly associated with the local generation of mitigation-related GTs, while it has a non significant association with adaptation GTs. The coefficient of total GPP for the case of mitigation GTs is higher than the one estimated when considering all GTs (i.e. Column I in Table 3).

Then, we investigate more in depth the moderating effect of local labor market composition in the relation between total GPP and green innovation across macro-families of green technology. In short, mitigation strategies, and the attendant technologies, seek to tackle the causes of climate change such as accumulation of greenhouse gases in the atmosphere. Mitigation is understood as having a global character as opposed to adaptation strategies which, instead, aim at reducing the local impact of climate change. Mitigation is a priority in a broad range of domains such as energy, transportation, manufacturing and waste management. Conversely, adaptation strategies target primarily water and health sectors. Results largely confirm what found in the main analysis. The positive association between GPP and GTs is enhanced in areas where there is high concentration of abstract-intensive occupations. This reinforcing mechanism is particularly relevant for mitigation GTs. Once again, a high endowment of managerial, scientific and interpersonal (viz. abstract) skills yields an innovation premium for GPP.

Finally, we provide the results for the two groups of GTs when splitting GPP into its components, named GPP for products (Table 7) and GPP for services (Table 8). Focusing on the model that refers to Equation 10 (Column I), in both cases we find a positive and significant association between GPP and local green innovation activity for the sub-group of mitigation technologies (panel (a)), with similar intensity. With respect to adaptation technologies (panel (b)) , we do not find a significant coefficient of GPP for services, while the coefficient of GPP for products is slightly significant and positive, showing a lower magnitude than in the case of mitigation GTs. In the rest of the columns (from II to VII) we report the results when incorporating local skills composition variables into the model. We follow the same strategy described when discussing results reported in Tables 4 and 5. In short, the effect of GPP for both products and services on the local generation of mitigation-related GTs is enhanced in abstract-occupation intensive areas. As for adaptation-related technologies, we find this positive reinforcing mechanism significant only when considering GPP for services. Overall, results for GT sub-groups provide a robust evidence of what reported in Tables 2, 3, 4 and 5, both in terms of significance and magnitude, confirming the main findings already discussed.

> > > INSERT FIGURES 5 AND 6 ABOUT HERE < < <

5 Conclusions

Green technologies are a means to successfully decoupling economic growth and environmental degradation. Their adoption allows firms to improve both their economic and environmental performances. In view of the social desirability of the diffusion of this type of technologies, creating economic incentives for private investments in innovation remains a key issue in the policy agenda. Due to the double externality problem, sub-optimal allocation of resources in these activities is highly likely unless public intervention puts in place policies that restore incentives to invest in green technologies. In this paper we have analyzed the impact of a somewhat neglected type of public intervention, green public procurement, on the generation of GTs. The present paper marks an important difference with most of the extant literature in that we consider a direct demand-side policy lever (i.e. government expenditure) instead of indirect demand-pull effects engendered by the implementation of stringent environmental regulatory frameworks.

Our analysis of the link between GPP and skill composition of local labor markets on the one hand, and the generation of GTs on the other hand, has been conducted at the territorial level of US commuting zones. We put forward the hypothesis that the local accumulation of competences represents a key enabling condition for the generation of new technologies in general. GTs show some specificity in this respect, in that they appear to emerge as an outcome of the hybridization of a variety of technologies that often are loosely related with one another. The configuration of the local bundle of skills is therefore much important in affecting local differences in the capacity to sustain green inventive activities. The prevalence of abstract skills is crucial in this respect, in that it is related to cognitive abilities to combine ideas and inputs from different fields in new and previously untried ways.

The findings of this empirical study provide support to our hypotheses, showing that GPP is a positive predictor on the generation of GTs in US Commuting Zones. The government expenditure lever can therefore prove to be efficient in the promotion of technology-driven sustainability transitions.

The configuration of the local labor market plays also a role in the dynamics of GTs generation. In particular, the prevalence of abstract skills is positively associated to the generation of GTs. Moreover, this specific set of skills moderates the effect of GPP on GTs, by magnifying its coefficient. Finally, our analysis brings to the fore the differential impact of GPP and local skills bundle configuration on mitigation vis-à-vis adaptation oriented green technologies, with the former showing a more pronounced positive response.

Our results bear important implications for policy. Dealing with climate change will require timely interventions to minimize the risks of further environmental damage while at the same time making the most of the opportunities provided by the reconfiguration of intertwined legislative, production, distribution and consumption systems. Transition assistance at all levels will be important for regions that are home to high emission industries, and thus candidates for disruption, as well as for regions that can leverage natural or built assets to seize opportunities for growth. Our analysis highlights two areas of intervention.

The first concerns the role of public expenditure in boosting technology-driven sustainable development. Most of the extant literature has focused on technology push or demand pull deployment policies. We do not deny the relevance of these policy instruments. However, we show that besides these options, policymakers can affect the rate and the direction of green inventive activities by demanding for specific green services or products. While these are expected to satisfy specific needs of public administrations, the GTs that are produced are expected to be relevant for a wider set of economic activities, bearing important spillovers for prospective adopters. On the other hand, the transition to green growth entails much more than just new technologies, in that much of the innovation that is required is organizational and institutional. These innovations represent a break from established practice and entail considerable uncertainty about how to make the new practice work effectively. Therefore, supporting the creation and adaptation of human capital is the second domain of policy intervention. Active labor market policies are essential to both favor the rapid re-absorption of displaced workers and to counter, or prevent altogether, skill gaps. A smooth adaptation of the labor markets to these pressures calls upon dedicated efforts are needed to identify the direct (i.e. market demand) and indirect (i.e. through regulations) effects of dealing with climate change on existing occupational profiles and on the skills mix that is needed for new green activities. Beyond merely quantitative impact, public authorities should support business firms in facilitating the creation of decent jobs as they undergo transformations and adaptations of local labor markets to greener demands. In a dynamic perspective, nimble, adaptable and focused education and training systems are the key to prepare the ground for an egalitarian transition to a low-carbon economy. Because climate change is a global phenomenon with strong territorial specificity, local labor market institutions will be at the forefront of the dual task of accommodating national or supranational regulations while seeking to promote incentives to stimulate sustainable business activities.

Tables

Tables

Table 1: Descriptive statistics

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
GT*	N. of green patents	7,942	4.266	14.892	0	218.661
mitig GT*	N. of green mitigation patents	7,942	2.858	10.934	0	190.378
adapt GT*	N. of green adaptation patents	7,942	1.408	4.576	0	68.585
tot GPP**	Total GPP	7,942	14.716	108.481	0	4,219.370
prod GPP**	GPP for products	7,942	4.034	55.727	0	3,675.805
serv GPP**	GPP for services	7,942	9.410	77.682	0	2,425.968
RI***	Routine-intensive areas (dummy)	3,855	.336	.472	0	1
AI***	Abstract-intensive areas (dummy)	3,855	.332	.471	0	1
MI***	Manual-intensive areas (dummy)	3,855	.329	.470	0	1
pop density***	Population density	7,942	149.493	770.308	.255	19643.86
employment***	Level of employment	7,942	156,266.7	452,654	138.5	6,787,960
N. of firms***	Number of establishments	7,942	10,167.78	28,528.9	23	434,368
R&D empl share***	Share of R&D employment	7,942	.001	.002	0	.055

Note: All the variables are calculated at the CZ level. The time-span of our baseline analysis is 2001-2011. Since information on CZ occupational structures are available from 2005 onward, for task-endowment variables the sample reduces to 3,855 observations. * Source: PATSTAT; ** USAspending.gov; *** Source: US Census.

Table 2: Effect of GPP on GT patents (2001-2011)

	(I)	(II)	(III)	(IV)	(V)
tot GPP	0.038***	0.026***	0.039***		
	(0.008)	(0.007)	(0.008)		
prod GPP				0.047***	
				(0.008)	
serv GPP					0.041***
					(0.010)
pop density		0.002	0.000**	0.000**	0.000**
		(0.001)	(0.000)	(0.000)	(0.000)
employment		-0.230***	-0.199**	-0.216***	-0.206**
		(0.079)	(0.081)	(0.081)	(0.082)
N. of firms		0.653***	0.684***	0.712***	0.694***
		(0.138)	(0.098)	(0.096)	(0.099)
R&D empl share		3.893	6.613	6.669	6.570
		(4.309)	(4.912)	(5.094)	(4.878)
CZ dummies	YES	YES	NO	NO	NO
Macro-area dummies	NO	NO	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES
R^2	0.135	0.362	0.630	0.627	0.629
N	7942	7942	7942	7942	7942

Dep. Var.: Number of GT patents (log). GPP, prod GPP and serv GPP lagged 1-year. Robust standard errors, in parentheses, clustered at the level of State. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3: Effect of total GPP and task composition on GT patents (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
tot GPP	0.025***	0.026***	0.004	0.025***	0.026***	0.025***	0.038***
	(0.008)	(0.008)	(0.013)	(0.008)	(0.008)	(0.008)	(0.008)
AI		0.064***	0.036**				
		(0.016)	(0.017)				
AI*GPP			0.049***				
			(0.015)				
RI				-0.006	-0.004		
				(0.012)	(0.012)		
RI*GPP					-0.004		
					(0.017)		
MI						-0.047***	-0.027**
						(0.014)	(0.012)
MI*GPP							-0.058***
							(0.015)
pop density	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
employment	-0.065	-0.061	-0.052	-0.065	-0.065	-0.065	-0.058
	(0.086)	(0.087)	(0.087)	(0.086)	(0.086)	(0.086)	(0.087)
N. of firms	0.568***	0.557***	0.539***	0.568***	0.567***	0.563***	0.550***
	(0.103)	(0.102)	(0.101)	(0.102)	(0.102)	(0.102)	(0.102)
R&D empl share	10.319*	11.006*	10.977*	10.305*	10.335*	10.880*	11.178*
	(5.975)	(6.088)	(6.206)	(5.996)	(5.996)	(6.020)	(6.172)
Macro-area dummies	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES
R^2	0.643	0.650	0.659	0.643	0.644	0.646	0.652
N	3855	3855	3855	3855	3855	3855	3855

Dep. Var.: Number of GT patents (log). GPP, AI, RI and MI lagged 1-year. Robust standard errors, in parentheses, clustered at the level of State. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 4: Effect of GPP for products and task composition on GTs (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
prod GPP	0.027**	0.028***	-0.002	0.028**	0.028**	0.028**	0.034***
	(0.011)	(0.011)	(0.017)	(0.011)	(0.012)	(0.011)	(0.011)
AI		0.063***	0.056***				
		(0.016)	(0.017)				
AI*GPP			0.050***				
			(0.018)				
RI				-0.006	-0.006		
				(0.012)	(0.012)		
RI*GPP					0.000		
					(0.025)		
MI						-0.047***	-0.042***
						(0.014)	(0.014)
MI*GPP							-0.081**
							(0.032)
pop density	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
employment	-0.067	-0.063	-0.061	-0.067	-0.067	-0.067	-0.068
	(0.086)	(0.087)	(0.087)	(0.086)	(0.086)	(0.086)	(0.086)
N. of firms	0.577***	0.566***	0.562***	0.576***	0.576***	0.572***	0.571***
	(0.101)	(0.101)	(0.100)	(0.101)	(0.101)	(0.100)	(0.101)
R&D empl share	10.390*	11.109*	11.064*	10.394*	10.392*	10.964*	11.245*
	(6.010)	(6.126)	(6.118)	(6.032)	(6.026)	(6.057)	(6.127)
Macro-area dummies	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES
R^2	0.641	0.649	0.652	0.642	0.642	0.645	0.646
N	3855	3855	3855	3855	3855	3855	3855

Dep. Var.: Number of GT patents (log). GPP, AI, RI and MI lagged 1-year. Robust standard errors, in parentheses, clustered at the level of State. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 5: Effect of GPP for services and task composition on GTs (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
serv GPP	0.029***	0.030***	0.010	0.029***	0.028***	0.029***	0.040***
	(0.010)	(0.010)	(0.015)	(0.010)	(0.010)	(0.010)	(0.010)
AI		0.064***	0.044***				
		(0.016)	(0.017)				
AI*GPP			0.045***				
			(0.016)				
RI				-0.006	-0.007		
				(0.011)	(0.012)		
RI*GPP					0.002		
					(0.016)		
MI						-0.047***	-0.033**
						(0.014)	(0.013)
MI*GPP							-0.048***
							(0.016)
pop density	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
employment	-0.065	-0.060	-0.052	-0.064	-0.064	-0.064	-0.058
	(0.087)	(0.088)	(0.088)	(0.087)	(0.087)	(0.086)	(0.087)
N. of firms	0.567***	0.556***	0.541***	0.567***	0.567***	0.562***	0.552***
	(0.103)	(0.103)	(0.103)	(0.103)	(0.102)	(0.102)	(0.103)
R&D empl share	10.173*	10.885*	10.927*	10.162*	10.169*	10.750*	10.956*
	(5.928)	(6.047)	(6.179)	(5.949)	(5.942)	(5.976)	(6.108)
Macro-area dummies	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES
R^2	0.643	0.650	0.657	0.643	0.643	0.646	0.651
N	3855	3855	3855	3855	3855	3855	3855

Dep. Var.: Number of GT patents (log). GPP, AI, RI and MI lagged 1-year. Robust standard errors, in parentheses, clustered at the level of State. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 6: Effect of total GPP and task composition on GT patents, by type (2006-2011)

	Panel (a): Mitigation GTs						
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
tot GPP	0.033***	0.034***	0.009	0.033***	0.034***	0.033***	0.044***
	(0.007)	(0.007)	(0.011)	(0.007)	(0.007)	(0.007)	(0.008)
AI		0.065***	0.034**				
		(0.015)	(0.017)				
AI*GPP			0.057***				
			(0.014)				
RI				-0.010	-0.008		
				(0.011)	(0.013)		
RI*GPP					-0.003		
					(0.017)		
MI						-0.038***	-0.021*
						(0.013)	(0.011)
MI*GPP							-0.046***
							(0.014)
Controls	YES	YES	YES	YES	YES	YES	YES
Macro-area dummies	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES
R^2	0.613	0.622	0.635	0.613	0.614	0.616	0.622
N	3855	3855	3855	3855	3855	3855	3855

	Panel (b): Adaptation GTs						
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
tot GPP	0.012	0.013	-0.003	0.012	0.016*	0.012	0.024**
	(0.008)	(0.008)	(0.010)	(0.008)	(0.008)	(0.008)	(0.009)
AI		0.039***	0.019*				
		(0.012)	(0.010)				
AI*GPP			0.037**				
			(0.015)				
RI				-0.004	0.004		
				(0.011)	(0.010)		
RI*GPP					-0.014		
					(0.012)		
MI						-0.036***	-0.018*
						(0.012)	(0.010)
MI*GPP							-0.050***
							(0.013)
Controls	YES	YES	YES	YES	YES	YES	YES
Macro-area dummies	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES
R^2	0.568	0.574	0.585	0.568	0.569	0.570	0.579
N	3855	3855	3855	3855	3855	3855	3855

Dep. Var.: Number of GT mitigation (Panel (a)) and adaptation (Panel (b)) patents (log). GPP, AI, RI and MI lagged 1-year. *Controls* includes *pop density*, *employment*, *N. of firms* and *R&D empl*. Robust standard errors, in parentheses, clustered at the level of State. $^{*}\ p < .1$, $^{**}\ p < .05$, $^{***}\ p < .01$

Table 7: Effect of GPP for products and task composition on GT patents, by type (2006-2011)

	Panel (a): Mitigation GTs						
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
prod GPP	0.033***	0.034***	-0.007	0.033***	0.036***	0.034***	0.039***
	(0.011)	(0.011)	(0.019)	(0.011)	(0.010)	(0.011)	(0.012)
AI		0.065***	0.056***				
		(0.015)	(0.015)				
AI*GPP			0.067***				
			(0.022)				
RI				-0.009	-0.007		
				(0.011)	(0.010)		
RI*GPP					-0.015		
					(0.026)		
MI						-0.038***	-0.033***
						(0.013)	(0.012)
MI*GPP							-0.067***
							(0.026)
Controls	YES	YES	YES	YES	YES	YES	YES
Macro-area dummies	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES
R^2	0.609	0.618	0.624	0.610	0.610	0.612	0.614
N	3855	3855	3855	3855	3855	3855	3855

	Panel (b): Adaptation GTs						
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
prod GPP	0.026*	0.027*	0.011	0.026*	0.028	0.026*	0.032*
	(0.016)	(0.016)	(0.016)	(0.016)	(0.018)	(0.016)	(0.017)
AI		0.039***	0.036***				
		(0.012)	(0.012)				
AI*GPP			0.027				
			(0.018)				
RI				-0.004	-0.003		
				(0.011)	(0.011)		
RI*GPP					-0.006		
					(0.027)		
MI						-0.036***	-0.032***
						(0.011)	(0.011)
MI*GPP							-0.064**
							(0.031)
Controls	YES	YES	YES	YES	YES	YES	YES
Macro-area dummies	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES
R^2	0.571	0.578	0.581	0.572	0.572	0.574	0.576
N	3855	3855	3855	3855	3855	3855	3855

Dep. Var.: Number of GT mitigation (Panel (a)) and adaptation (Panel (b)) patents (log). GPP, AI, RI and MI lagged 1-year. *Controls* includes *pop density*, *employment*, *N. of firms* and *R&D empl*. Robust standard errors, in parentheses, clustered at the level of State. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 8: Effect of GPP for services and task composition on GT patents, by type (2006-2011)

	Panel (a): Mitigation GTs						
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
serv GPP	0.036***	0.037***	0.015	0.036***	0.034***	0.036***	0.045***
	(0.010)	(0.010)	(0.013)	(0.010)	(0.010)	(0.010)	(0.010)
AI		0.066***	0.045***				
		(0.015)	(0.017)				
AI*GPP			0.049***				
			(0.015)				
RI				-0.010	-0.014		
				(0.011)	(0.013)		
RI*GPP					0.008		
					(0.015)		
MI						-0.038***	-0.026**
						(0.012)	(0.012)
MI*GPP							-0.039***
							(0.015)
Controls	YES	YES	YES	YES	YES	YES	YES
Macro-area dummies	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES
R^2	0.612	0.621	0.631	0.613	0.612	0.615	0.619
N	3855	3855	3855	3855	3855	3855	3855
	Panel (b): Adaptation GTs						
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
serv GPP	0.014	0.015*	-0.003	0.014	0.018**	0.014	0.024**
	(0.009)	(0.009)	(0.013)	(0.009)	(0.009)	(0.009)	(0.010)
AI		0.040***	0.021**				
		(0.012)	(0.010)				
AI*GPP			0.042**				
			(0.017)				
RI				-0.004	0.003		
				(0.010)	(0.010)		
RI*GPP					-0.016		
					(0.013)		
MI						-0.036***	-0.022**
						(0.012)	(0.010)
MI*GPP							-0.043***
							(0.012)
Controls	YES	YES	YES	YES	YES	YES	YES
Macro-area dummies	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES
R^2	0.568	0.574	0.585	0.568	0.569	0.570	0.577
N	3855	3855	3855	3855	3855	3855	3855

Dep. Var.: Number of GT mitigation (Panel (a)) and adaptation (Panel (b)) patents (log). GPP, AI, RI and MI lagged 1-year. *Controls* includes *pop density*, *employment*, *N. of firms* and *R&D empl*. Robust standard errors, in parentheses, clustered at the level of State. * $p < .1$, ** $p < .05$, *** $p < .01$

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Appendix

A-1 Robustness checks: GPP lags

TABLE A-1: EFFECT OF GPP (LAGGED 2-YEARS) ON GT PATENTS (2002-2011)

	(I)	(II)	(III)	(IV)	(V)
tot GPP	0.038***	0.026***	0.041***		
	(0.008)	(0.008)	(0.008)		
prod GPP				0.049***	
				(0.011)	
serv GPP					0.044***
					(0.010)
pop density		0.002	0.000**	0.000**	0.000**
		(0.001)	(0.000)	(0.000)	(0.000)
employment		-0.239***	-0.198**	-0.216**	-0.204**
		(0.088)	(0.088)	(0.088)	(0.089)
N. of firms		0.706***	0.687***	0.716***	0.696***
		(0.155)	(0.105)	(0.104)	(0.106)
R&D empl share		4.669	7.565*	7.350	7.415*
		-3.695	-4.411	-4.483	-4.368
CZ dummies	YES	YES	NO	NO	NO
Macro-area dummies	NO	NO	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES
R^2	0.135	0.400	0.632	0.629	0.631
N	7220	7220	7220	7220	7220

Dep. Var.: Number of GT patents (log). GPP, prod GPP and serv GPP lagged 2-years. Robust standard errors, in parentheses, clustered at the level of State. * $p < .1$, ** $p < .05$, *** $p < .01$

Table A-2: Effect of total GPP (lagged 2-years) and task composition on GT patents (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
tot GPP	0.018**	0.019**	-0.001	0.018**	0.023**	0.018**	0.034***
	(0.008)	(0.008)	(0.011)	(0.008)	(0.010)	(0.008)	(0.010)
AI		0.065***	0.042***				
		(0.016)	(0.016)				
AI*GPP			0.047***				
			(0.013)				
RI				-0.007	0.004		
				(0.012)	(0.012)		
RI*GPP					-0.020		
					(0.018)		
MI						-0.049***	-0.028**
						(0.014)	(0.012)
MI*GPP							-0.065***
							(0.012)
pop density	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
employment	-0.066	-0.061	-0.051	-0.065	-0.063	-0.065	-0.061
	(0.087)	(0.088)	(0.087)	(0.087)	(0.087)	(0.087)	(0.087)
N. of firms	0.573***	0.561***	0.542***	0.572***	0.569***	0.567***	0.558***
	(0.104)	(0.103)	(0.102)	(0.103)	(0.103)	(0.103)	(0.102)
R&D empl share	10.557*	11.228*	11.288*	10.542*	10.593*	11.121*	11.427*
	(6.039)	(6.145)	(6.257)	(6.060)	(6.050)	(6.080)	(6.275)
Macro-area dummies	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES
R^2	0.641	0.649	0.657	0.642	0.643	0.645	0.652
N	3855	3855	3855	3855	3855	3855	3855

Dep. Var.: Number of GT patents (log). GPP, AI, RI and MI lagged 2-years. Robust standard errors, in parentheses, clustered at the level of State. * $p < .1$, ** $p < .05$, *** $p < .01$

Table A-3: Effect of GPP (lagged 3-years) on GT patents (2003-2011)

	(I)	(II)	(III)	(IV)	(V)
tot GPP	0.046***	0.036***	0.051***		
	(0.008)	(0.009)	(0.009)		
prod GPP				0.063***	
				(0.012)	
serv GPP					0.050***
					(0.009)
pop density		0.001	0.000**	0.000**	0.000**
		(0.001)	(0.000)	(0.000)	(0.000)
employment		-0.237***	-0.182**	-0.199**	-0.194**
		(0.086)	(0.088)	(0.087)	(0.089)
N. of firms		0.639***	0.671***	0.699***	0.688***
		(0.165)	(0.105)	(0.103)	(0.107)
R&D empl share		5.383	8.437*	8.235	8.235
		(4.340)	(5.052)	(5.135)	(5.047)
CZ dummies	YES	YES	NO	NO	NO
Macro-area dummies	NO	NO	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES
R^2	0.168	0.390	0.636	0.633	0.634
N	6498	6498	6498	6498	6498

Dep. Var.: Number of GT patents (log). GPP, prod GPP and serv GPP lagged 3-years. Robust standard errors, in parentheses, clustered at the level of State. * $p < .1$, ** $p < .05$, *** $p < .01$

Table A-4: Effect of total GPP (lagged 3-years) and task composition on GT patents (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
tot GPP	0.039***	0.039***	0.014	0.039***	0.050***	0.039***	0.052***
	(0.011)	(0.011)	(0.015)	(0.011)	(0.013)	(0.011)	(0.013)
AI		0.063***	0.038**				
		(0.016)	(0.017)				
AI*GPP			0.056***				
			(0.019)				
RI				-0.009	0.007		
				(0.011)	(0.011)		
RI*GPP					-0.034*		
					(0.018)		
MI						-0.048***	-0.033**
						(0.014)	(0.013)
MI*GPP							-0.060***
							(0.022)
pop density	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
employment	-0.064	-0.060	-0.052	-0.064	-0.061	-0.064	-0.063
	(0.087)	(0.088)	(0.088)	(0.087)	(0.088)	(0.087)	(0.087)
N. of firms	0.562***	0.551***	0.533***	0.560***	0.554***	0.556***	0.551***
	(0.105)	(0.105)	(0.104)	(0.105)	(0.106)	(0.104)	(0.104)
R&D empl share	10.513*	11.136*	11.265*	10.480*	10.518*	11.063*	11.515*
	(5.932)	(6.028)	(6.122)	(5.958)	(5.930)	(5.968)	(6.199)
Macro-area dummies	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES
R^2	0.647	0.654	0.664	0.648	0.650	0.651	0.656
N	3855	3855	3855	3855	3855	3855	3855

Dep. Var.: Number of GT patents (log). GPP, AI, RI and MI lagged 3-years. Robust standard errors, in parentheses, clustered at the level of State. * $p < .1$, ** $p < .05$, *** $p < .01$

A-2 Robustness checks: spillover effects

Table A-5: Effect of GPP on GT generation, baseline – spillover controls

	(I)	(II)	(III)	(IV)	(V)
tot GPP	0.038***	0.025***	0.039***		
	(0.008)	(0.007)	(0.008)		
prod GPP				0.047***	
				(0.008)	
serv GPP					0.040***
					(0.009)
pop density		0.002	0.000**	0.000**	0.000**
		(0.001)	(0.000)	(0.000)	(0.000)
employment		-0.225***	-0.197**	-0.213***	-0.203**
		(0.078)	(0.081)	(0.080)	(0.082)
N. of firms		0.644***	0.676***	0.702***	0.684***
		(0.136)	(0.097)	(0.095)	(0.098)
R&D empl share		4.003	6.850	6.930	6.828
		(0.005)	(0.005)	(0.005)	(0.005)
GT spill		0.010	0.014	0.013	0.014
		(0.009)	(0.009)	(0.009)	(0.009)
GPP spill		0.002	0.003	0.005	0.004
		(0.005)	(0.005)	(0.005)	(0.005)
CZ dummies	YES	YES	NO	NO	NO
Macro-area dummies	NO	NO	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES
R^2	0.135	0.366	0.631	0.628	0.630
N	7942	7942	7942	7942	7942

Dep. Var.: Number of GT patents (log). GPP, prod GPP, serv GPP, GPP spill and GT spill lagged 1-year. Robust standard errors, in parentheses, clustered at the level of State. * $p < .1$, ** $p < .05$, *** $p < .01$

Table A-6: Effect of total GPP and task composition on GTs (2006-2011) – spillover controls

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
tot GPP	0.025***	0.026***	0.005	0.025***	0.027***	0.025***	0.039***
	(0.008)	(0.008)	(0.013)	(0.008)	(0.008)	(0.008)	(0.008)
AI		0.064***	0.037**				
		(0.016)	(0.017)				
AI*GPP			0.049***				
			(0.015)				
RI				-0.007	-0.004		
				(0.012)	(0.012)		
RI*GPP					-0.005		
					(0.017)		
MI						-0.048***	-0.027**
						(0.014)	(0.012)
MI*GPP							-0.058***
							(0.014)
pop density	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
employment	-0.074	-0.070	-0.061	-0.073	-0.073	-0.074	-0.067
	(0.086)	(0.087)	(0.087)	(0.086)	(0.086)	(0.086)	(0.087)
N. of firms	0.571***	0.561***	0.542***	0.571***	0.570***	0.567***	0.554***
	(0.103)	(0.103)	(0.102)	(0.103)	(0.102)	(0.102)	(0.103)
R&D empl share	10.212*	10.968*	10.951*	10.204*	10.239*	10.792*	11.128*
	(6.102)	(6.233)	(6.362)	(6.125)	(6.126)	(6.155)	(6.324)
GT spill	0.017	0.018	0.018	0.017	0.017	0.018	0.018
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
GPP spill	-0.005	-0.004	-0.004	-0.005	-0.005	-0.005	-0.005
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Macro-area dummies	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES
R^2	0.643	0.651	0.660	0.644	0.644	0.647	0.653
N	3855	3855	3855	3855	3855	3855	3855

Dep. Var.: Number of GT patents (log). GPP, AI, RI, MI, GPP spill and GT spill lagged 1-year. Robust standard errors, in parentheses, clustered at the level of State. * $p < .1$, ** $p < .05$, *** $p < .01$