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PUBLIC PROCUREMENT, LOCAL LABOR MARKETS AND GREEN TECHNOLOGICAL CHANGE: EVIDENCE FROM US COMMUTING ZONES

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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) stimulates local environmental innovation capacity. To this end, we use detailed data sources on green patents and procurement expenditure at the level of US Commuting Zones for the period 2000-2011. We also check for the moderating effects of local labor market composition in the relation between green public procurement and green innovation capacity. Lastly, we exploit the richness of patent information to test for differential effects of green public procurement on different classes of green technologies. The main finding is that GPP is an important driver in explaining the growth of local green-tech stock. The positive effect of GPP is mainly driven by expenditures for procured green services and is magnified by the local presence of high shares of abstract-intensive occupations. When separately considering diverse kinds of green technologies, we do find evidence of a more pronounced effect of GPP on the growth of local knowledge stocks of mitigation 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 exists 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, which entails that the dynamics of both policy and of the knowledge base carry strong spatial dimensions 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 environmen-

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

tal 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 requires 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 coexistence 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 sustainable products and services enhances 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 stock of 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, the configuration of the local bundle of skills has a significant impact on green knowledge production. In particular, the positive effect of abstract skills intensity is persistent across all estimates. Third, these two dimensions show a high degree of interdependence, as the positive and significant coefficient for the interaction between the variables suggests the existence of a mutual reinforcing effects. Fourth, we find interesting patterns when disentangling the effects of product-related vis-à-vis service related GPP, as well as when we disentangle mitigation vis-à-vis 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 as a driver of green innovation. 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 environmental sustainability and innovation (Ghisetti, 2017). 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 both 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., 2017), no study has so far explored the role of local human capital endowment on green technological change. Further, our focus on the determinants of eco-innovation in the US enriches existing empirical studies 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).

The rest of the paper is structured as follows. Section 2 articulates the theoretical framework and develops the 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).

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). To begin with, besides the classical sources of externalities that affect any kind of knowledge, green knowledge has positive effects on firm-level, and hence local-level, environmental performance. These effects can be internalized by private agents only after policy has restored the appropriate incentive for private investments. To be sure, there are several variants of environmental policy such as setting technological standards, regulating prices or establishing pollution thresholds that induce firms to renew their production processes. As a result of these inducement effects new market for GTs emerge due to higher R&D efforts (Johnstone et al., 2012; Nemet, 2009; Hoppmann et al., 2013; Costantini et al., 2015). These considerations bring the institutional context to the core of the analysis of the drivers of GTs (Hitaj, 2013; Nesta et al., 2014). 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). Only few scholars have so far considered the role of supply side policies aimed at fostering the development of technological capabilities in green domains through R&D supporting schemes (Costantini et al., 2015). More than this, to the best of our knowledge only Ghisetti (2017) has hitherto explored the role of innovative green public procurement.

Building on the notion 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 that filling such a gap would allow to gain a better understanding of the spatial determinants of eco-innovation (Cole et al., 2013). GPP is touted as a key lever to stimulate the development of new technology 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, GPP is regarded as a direct form of public intervention to stimulate the demand for GTs by the government (Parikka-Alhola, 2008). These arguments lead us to propose the first hypothesis:

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 to be 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 indeed highly coherent knowledge bases increase significantly the chances of successful innovation (Quatraro, 2010; Krafft et al., 2014). This is relevant to eco-innovations in that their emergence is associated with the hybridization of green and dirty technologies (Zeppini and van der Bergh, 2011; Dechezlepetre et al., 2004; Colombelli and Quatraro, 2017). 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). 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., 2017). 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 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.[2] Compared to other territorial units, CZs carry the advantage of covering the

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

entirety of the US territory while at the same time being constructed in such a way that meaningful mobility patterns are accounted for.[3]

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 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[4] we first convert IPC codes into CPC codes using the concordance tables of EPO and USPTO.[5] Subsequently, we use information contained in patent documents to extract CPC codes and assign patents to ENV-TECH categories. For what

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

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

[5]http://www.cooperativepatentclassification.org/cpcConcordances.html

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 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 found. Combining both sources, we diminish the missing rate to 10%.

The next step consists in assigning precise geographical coordinates to each address and, thus, to each patent. To do this we, first, extract the postal code included in the inventor's address, when available, to identify US cities according to the GeoNames postal code table. For each country, GeoNames indeed provides a regular expression to find postal codes according to their official format. 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 5000 inhabitants in GeoNames.[6] Third, we exploit the Google's Geocoding API resource to assign geographical coordinates to all the remaining addresses. This procedure allowed us to assign geographical coordinates to 90% of unique US inventors' addresses. These coordinates were subsequently matched with the 1990 US CZs map to assign each inventor to a CZ.

The local level of green innovation activity is measured through the fractionalized[7] stock of US-invented patents with at least one CPC class which relates

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

[7]Patent p is assigned to CZ c according to the fraction of inventors resident in CZ c over

to a green technology. The stock of green patents is corrected for INPADOC patent families[8] and weighted by forward (family) citations received[9]. Weighting by forward citations allows us to account for the intrinsic technological value of the local protected inventions.

The green patent stock per CZ j at time t is thus calculated as:

$$Stock_{j,t} = N.Pat_{j,t} + \left[(1-\delta) \times Stock_{j,t-1}\right], \tag{1}$$

where δ is the decay rate.[10]

Furthermore, by exploiting the ENV-TECH classification, we differentiate the GT-stock 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.[11] Procurement information are available from 2000 onwards.

The Federal Funding Accountability and Transparency Act of 2006 (FFATA) was signed into law on September 26, 2006. The legislation required that federal

the total number of inventors filing the patent p.

[8]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 that patent examiners and attorneys can cite indifferently. 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 the opportunity of correcting citations for patent families, see Martínez (2011).

[9]In order to make citations comparable across years and ENV-TECH technologies, we calculate a weighted number of citations, dividing the raw number of citations by the average number of citations in the same year t and the same technology j, and then by the average number of citations in the same year t, following the method proposed by Hall et al. (2001): $N.cit.weighted = \frac{\frac{N.cit}{AvgN.cit_{t,j}}}{AvgN.cit_t}$

[10]We calculate patent stocks with the permanent inventory method, applying a 15% annual rate of obsolescence.

[11]https://www.usaspending.gov

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)[12] 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.[13] Indeed, the PSC Manual provides codes to 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

[12] 5-digits Zipcodes allow us to assign precise levels of expenditures to counties and, consequently, to CZs.

[13] 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.

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.[14] We combine these measures to create summary indicators of task-intensity by

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

occupation (routine RTI, abstract ATI and manual MTI), calculated as

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

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

$$MTI_k = ln(T^M_{k,1980}) - ln(T^A_{k,1980}) - ln(T^R_{k,1980}), \tag{4}$$

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.[15] 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 a task employment share measure (RSH_{jt}, ASH_{jt} and MSH_{jt}) equal to:

$$ASH_{jt} = \left(\sum_{k=1}^{K} L_{jkt} \cdot \mathbb{1}\left[ATI_k > ATI^{P66}\right]\right)\left(\sum_{k=1}^{K} L_{jkt}\right)^{-1}, \tag{5}$$

$$RSH_{jt} = \left(\sum_{k=1}^{K} L_{jkt} \cdot \mathbb{1}\left[RTI_k > RTI^{P66}\right]\right)\left(\sum_{k=1}^{K} L_{jkt}\right)^{-1}, \tag{6}$$

$$MSH_{jt} = \left(\sum_{k=1}^{K} L_{jkt} \cdot \mathbb{1}\left[MTI_k > MTI^{P66}\right]\right)\left(\sum_{k=1}^{K} L_{jkt}\right)^{-1}, \tag{7}$$

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 form (5) to (7), 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:

$$AI_{jt} = \mathbb{1}\left[ASH_{jt} > ASH^{P66}_t\right], \tag{8}$$

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

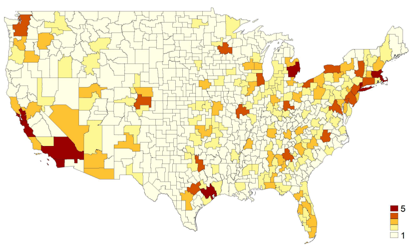
$$RI_{jt} = \mathbb{1}\left[RSH_{jt} > RSH_t^{P66}\right], \tag{9}$$

$$MI_{jt} = \mathbb{1}\left[MSH_{jt} > MSH_t^{P66}\right]. \tag{10}$$

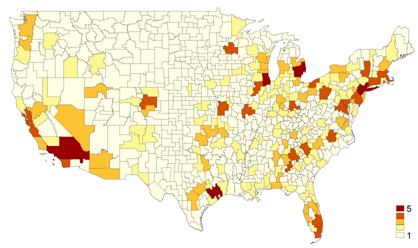
This characterization of local labor markets allows us to investigate whether diverse occupational task compositions moderate the effect of green public procurement on the generation of GTs.

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 - colour coding is darker for higher quintiles and progressively lighter for lower quintiles. The distribution of GT patent stock in Figure 1 (panel a) shows that inventive activity is more concentrated along coastal areas (especially California, Florida and the north east) as well as in lakeside CZs of the north and of Texas. The figure also indicates that there is no significant difference in the distribution of patenting of the component subcategories, namely green mitigation technologies (panel b) and green adaptation technologies (panel c). 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 a) refers to the total level of expenditures, panel b) to GPP for products, panel c) to GPP for services, respectively. This pattern reveals some degree of overlap between the distribution of GPP and that of 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).

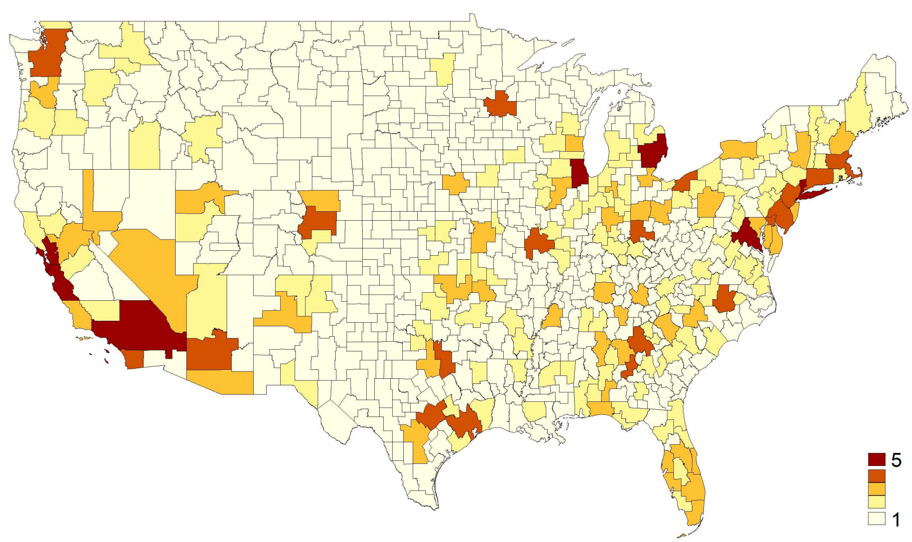
On the whole the maps show that for all the measures there is a large variance across CZs, as well as a marked evidence of spatial concentration. The maps also show interesting converging patterns in the spatial distribution of GPP, GTs and abstract-skills intensity. This evidence suggests that an economic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



(a) GT-mitigation patents

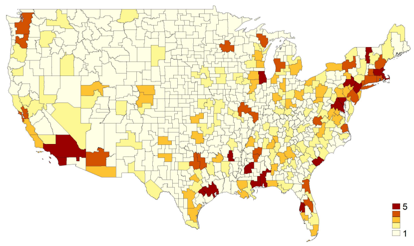


(b) GT-adaptation patents

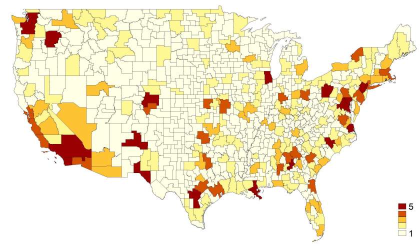


(c) Total GT patents

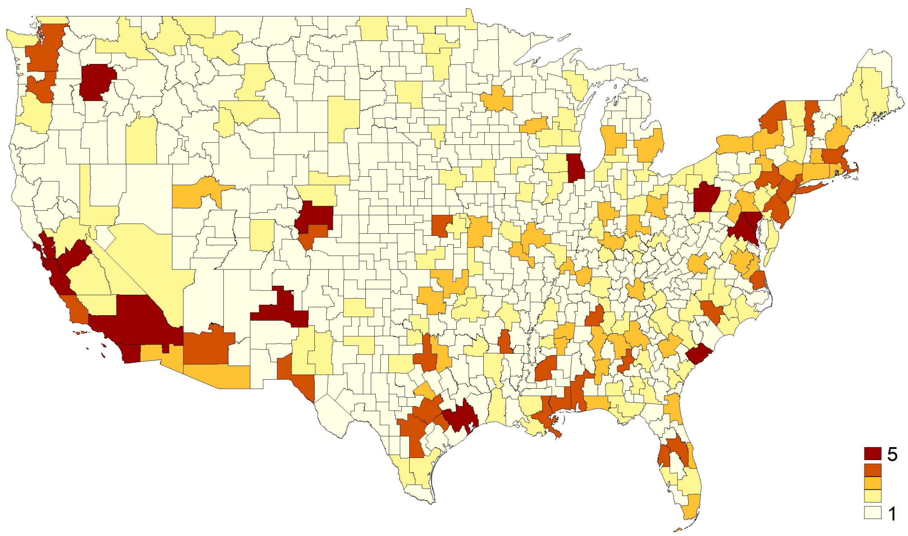
Figure 1: Geographic distribution of GT patent stock, 2011 (quintiles)



(a) Product GPP

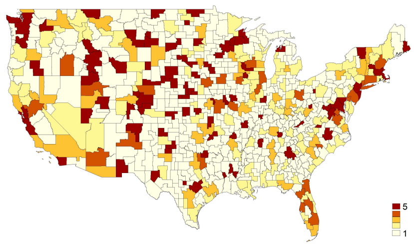


(b) Service GPP

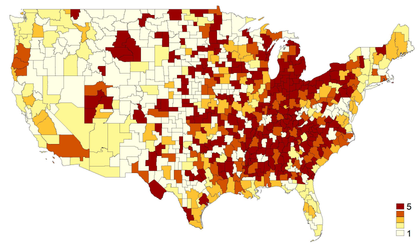


(c) Total GPP

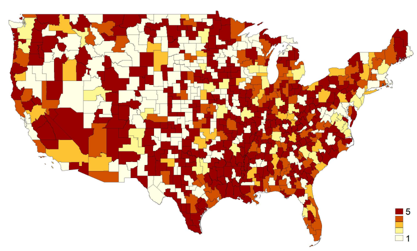
Figure 2: Geographic distribution of GPP average expenditures, 2000-2011 (quintiles)



(a) Abstract



(b) Routine



(c) Manual

Figure 3: Geographic distribution of task-intensive occupations, 2005 (quintiles)

3.2 Empirical strategy

Using the full sample of 722 CZs observed from 2000 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:

$$Y_{j,t} = \beta_0 + \beta_1 GPP_{j,t-1} + \boldsymbol{X'_{j,t}}\beta_2 + \epsilon_{j,t}, \tag{11}$$

where $Y_{j,t}$ is the (log transformed) fractionalized stock of green patent families (weighted by forward citations) at time t filed by inventors resident in CZ j; $GPP_{j,t-1}$ 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 CZs' labor force and demographic composition that might independently affect innovation outcomes. 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 (11) as follows:

$$Y_{j,t} = \beta_0 + \beta_1 GPP_{j,t-1} + \beta_2 RI_{j,t-1} + \beta_3 GPP_{j,t-1} \times RI_{j,t-1} + \boldsymbol{X'_{j,t}}\beta_4 + \epsilon_{j,t}. \tag{12}$$

$$Y_{j,t} = \beta_0 + \beta_1 GPP_{j,t-1} + \beta_2 AI_{j,t-1} + \beta_3 GPP_{j,t-1} \times AI_{j,t-1} + \boldsymbol{X'_{j,t}}\beta_4 + \epsilon_{j,t}. \tag{13}$$

$$\begin{aligned} Y_{j,t} \quad = \quad & \beta_0 + \beta_1 GPP_{j,t-1} + \beta_2 MI_{j,t-1} + \beta_3 GPP_{j,t-1} \times MI_{j,t-1} + \\ & + \boldsymbol{X'_{j,t}}\beta_4 + \epsilon_{j,t}. \end{aligned} \tag{14}$$

where dummy variables $RI_{j,t-1}$, $AI_{j,t-1}$ and $MI_{j,t-1}$ are calculated according to equations from (8) to (10).[16]

[16] Due to occupational data availability, the period considered for this second step of the analysis reduces (2005-2011).

Exploiting the ENV-TECH classification, we are also able to differentiate between diverse types of green technologies. In the final step of the analysis we thus change our dependent variable accordingly, re-estimating equations from (11) to (14). Precisely, we aggregate technologies in two precise groups: mitigation and adaptation GTs.[17]

4 Results

Section 2 puts forward the key hypotheses driving our study, according to which we expect that GPP exerts a positive impact on the local dynamics of GT generation, because of the double externality problem and the regulatory push/pull effect. Moreover, we expect 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.

Tables 2, 3 and 4 present the results of the baseline estimates of the relationship between expenditures in GPP and the local environmental innovation capacity. Table 2 shows the estimates for the effect of the overall levels of GPP. Tables 3 and 4 focus instead on product-related and service-related GPP, respectively. Our dependent variable is the log transformed level of fractionalized stock of local environmental patents, weighted by forward citations corrected for patent equivalents (INPADOC patent families).

Columns from I to V of Table 2 provide the results of CZ fixed-effect estimations of equation (11), by gradually saturating the empirical model with the controls described in Section 3.1. GPP in column one shows a positive and significant coefficient. Although we use CZ fixed effects, this result can hide some effects of unobserved variables that one may want to mitigate. The coefficient of GPP remains positive and significant, if slightly lower, after controlling for

[17] Mitigation technologies aggregate ENV-TECH technologies from (c) to (h). Adaptation technologies are the ones related to groups (a) and (b).

the population density of the area (Column II). The estimates in Column III includes also employment share, the coefficient of which is negative and significant . The other coefficients are in line with previous estimations. In Columns IV and V we control, respectively, for the number of firms in the area and the share of R&D employment. Both coefficient are positive and significant. Still, the coefficient of GPP preserves the sign and statistical significance.

Column VI estimates equation (11) obtained by substituting fixed effects for the nine US Census macro-areas 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 0.077% increase in the stock of green patents in the local areas.

Tables 3 and 4 replicate the same strategy as the one proposed in Table 2 but focusing on the effects of, respectively, GPP for products and GPP for services on the total stock of green technological knowledge at the local level. We find a significant and positive effect of both types of public procurement expenditures. Importantly, we do observe that expenditures for procured green services show higher effectiveness in boosting the overall level of local green innovation activity than expenditures for procured green products. If one looks at Column VI of both tables, it comes that a 1% increase in GPP for products yields a 0.053% increase in the local stock of GTs, while the same variation in GPP for services yields a 0.087% increase in the local stock of GTs.

The overall picture emerging from this first set of estimates provides empirical support to our Hypothesis 1, according to which GPP is expected to positively affect the local accumulation of GT stock. We can now turn to investigation of the effects of the local occupational task compositions on GTs stock, 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 stock of GTs, as well as how they moderate the relationship between GPP and local green innovation capacity.

Table 5 takes as a benchmark Column VI proposed in Tables 2 to 4. 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 (ASH), routine (RSH) and manual (MSH). We include these dummy variables in the estimations, as well as their interaction with (total) GPP. Column I and II focus on RSH. Both the coefficient of the direct and moderating effects do not appear to significantly affect local GTs generation. Columns III and IV deal with AHS. The coefficient of the direct effect is positive and significant in column III, but it loses significance in column IV, when the interaction with GPP is introduced. The moderating effect shows a positive and significant coefficient. Columns V and VI report the estimations of the effect of RHS. The direct effect does not appear to be significant in any of the estimations, while the moderating effect is negative. The prevalence of routine skills appears to reduce the impact of GPP on local accumulation of GTs.

Overall, the inclusion of the local skills composition in the empirical framework seems to reduce the magnitude of the direct effect of GPP. According to the estimates in table 5, a 1% increase in GPP yields an increase in GTs ranging from 0.021% to 0.048%, which is far lower than the 0.077% increase found in Table 2. ASH is the only skill category yielding a positive impact on GTs at the local level. If one sums the coefficient of GPP and the one of the interaction of ASH with GPP, the overall effect of GPP appears to be much closer to the evidence reported in Table 2. Focusing on Column IV, in the areas in the top 33% of abstract-task intensive occupations (ASH=1), the overall impact of 1% increase in GPP consists of some 0.063% increase in local GTs stock.

Tables 6 and 7 complement the analysis proposed in Table 5 by investigating whether there are differences in the effect of GPP expenditures for, respectively, products and services on total GT stock. Results show that the direct impact found before exists for both types of expenditures. However, it is strongly driven by GPP expenditures for services, confirming the initial estimates proposed in Tables 2, 3 and 4. Moreover, the moderating effect of ASH holds for what concern GPP for services, while when one focuses on GPP for products, only the direct effect of ASH shows a positive and significant coefficient.

Figure 4 plots average marginal effects calculated on the basis of the results from Tables 5, 6 and 7. 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).

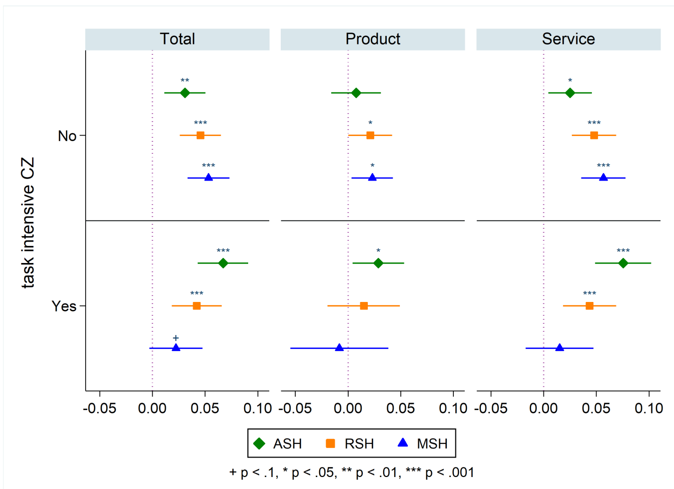


Figure 4: Average marginal effects of GPP on total GT stock with 95% CIs

Focusing on areas in the top third of the skill endowment, 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, with a stronger effect of expenditure on services as compared to product. 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. This resonates with the high level of knowledge intensity of service activities that entail personal interaction, social perceptiveness and adaptability and which, in our model, augment the innovation outcome of public procurement. The coefficient for routine occupations is only significant for green-service procurement. These jobs encompass many middle-skilled cognitive (i.e., bookkeeping, clerical work) or manual activities (i.e., repetitive physical operations in production jobs). 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 effect of routine occupations to the persistent important role of clerical and administrative workers in services. Lastly, the endowment of manual skills is only mildly significant in the general category of public procurement but not in the sub-components. 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 technological stock: adaptation and mitigation, respectively. Columns I, II and III of Table 8 present estimates for the effect of, respectively, total, product- and service-related GPP on the stock of green mitigation technologies. Columns IV, V and VI report the similar estimates concerning the determinants of green adaptation technologies. Results demonstrate that the overall level of GPP positively affects both kinds of green technological stock (Columns I and IV). The magnitude is higher for mitigation technologies. When splitting GPP between product- and service-related, we do find a significant positive effect of both, with service-related GPP expenditures showing higher effectiveness within both groups of green technologies. The highest effect is found for service-related GPP on mitigation GT stock (results from Column III suggest that a 1% increase in service-related GPP leads to a 0.096% increase in the stock of green mitigation patents).

Next, we investigate more in depth the moderating effect of local labor market composition in the relation between green public procurement and green innovation capacity across macro-families of green technology. In particular, we analyze separately the effects on GT stock in mitigation (Tables 9, 10 and 11) and in adaptation technologies (Tables 12, 13 and 14). 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.

We find that the average marginal effects for mitigation technologies are the same as those observed in the general case above. This applies to both the significance and the magnitude of the coefficients. Once again, a high endowment of managerial, scientific and interpersonal (viz. abstract) skills yields an innovation premium (Figure 5) for public procurement in both green products and green services. Routine intensive occupations have a significant moderating effect only for green service expenditures. Conversely, among adaptation technologies, the coefficients of both routine and abstract occupations are significant only for service-related GPP (Figure 6). We ascribe this to the preponderance of intangible nature of coordinating, planning and implementing adaptation strategies at local level.

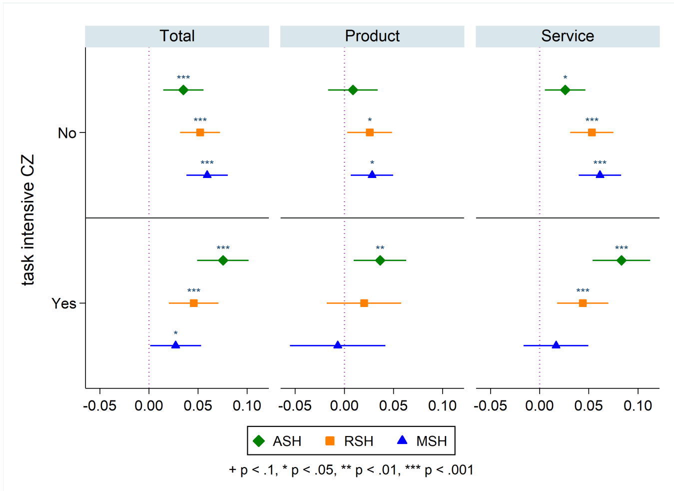


Figure 5: Average marginal effects of GPP on GT-mitigation stock with 95% CIs

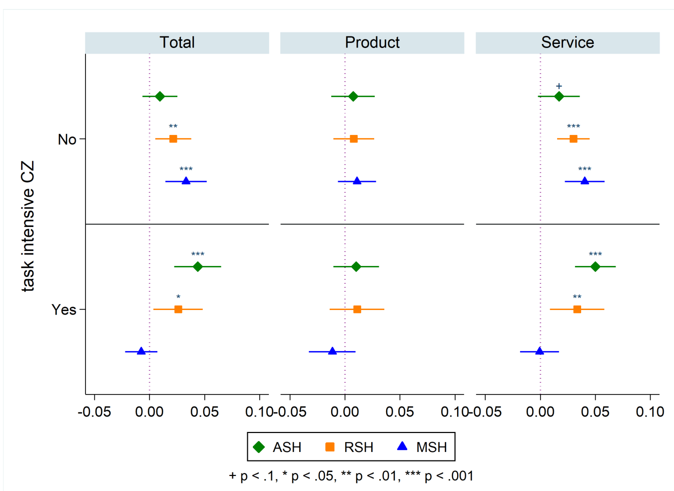


Figure 6: Average marginal effects of GPP on GT-adaptation stock with 95% CIs

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 the generation of GTs 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.

Our results provide empirical support to our hypotheses, showing that GPP exerts a positive impact on the generation of GTs. In particular, we have found that a 1% increase in GPP engenders some 0.077% increase in the local stock of GTs. The government expenditure lever can therefore prove to be efficient in the promotion of technology-driven sustainability transitions. Moreover, we have found that GPP for services yield a stronger impact than GPP for products. This suggests the existence of bandwagon effects upwards in the value chain, for which the demand for green services stimulate the generation of the technologies that make them possible.

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. According to our estimates, the overall impact of GPP in areas in which abstract skills are prevalent is almost twice the impact of GPP in areas in which this prevalence is not observed. Finally, our analysis allowed to investigating the differential impact of GPP and local skills bundle configuration on mitigation vis-à-vis adaptation oriented green technologies.

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.

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Tables

Table 1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
total GT stock	7,937	20.325	87.865	0	2092.176
mitigation GT stock	7,937	16.932	77.027	0	1989.022
adaptation GT stock	7,937	3.393	12.845	0	318.381
total GPP	7,937	14.681	108.543	-203.139	4219.37
product GPP	7,937	4.025	55.748	-44.238	3675.805
service GPP	7,937	9.377	77.731	-158.900	2425.968
RSH	4,476	.336	.472	0	1
ASH	4,476	.333	.471	0	1
MSH	4,476	.330	.470	0	1
pop density	7,937	149.478	770.542	.255	19643.86
employment	7,937	156279.6	452789	138.5	6787960
# of establishments	7,937	10168.18	28537.29	23	434368
R&D employment share	7,937	.001	.002	0	.055

Note: The time-span of our analysis is 2000-2011. Because information on CZ occupational structures are available from 2005 onwards, the sample is reduced to 4,476 observations (from 7,937).

Table 2: Effect of total green procurement on GT stock (2001-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
tot GPP	0.082***	0.068***	0.067***	0.064***	0.063***	0.077***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
pop density		0.003**	0.004***	0.003***	0.003***	-0.000
		(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
empl share			-0.000***	-0.000***	-0.000***	-0.000*
			(0.000)	(0.000)	(0.000)	(0.000)
N. of firms				0.000*	0.000*	0.000***
				(0.000)	(0.000)	(0.000)
R&D empl					6.686*	8.584**
					(3.824)	(4.260)
r2_w	0.383	0.399	0.403	0.404	0.405	0.386
r2_o	0.147	0.127	0.073	0.084	0.085	0.501
r2_b	0.551	0.125	0.071	0.082	0.082	0.508
N	7937	7937	7937	7937	7937	7937

Dep. Var.: Stock of fractionalized patent families weighted by forward citations (log). GPP lagged 1-year. Standard errors clustered at the level of State. Models I to V, estimated in fixed effect, include a constant and year dummies. Model VI includes also geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3: Effect of GPP for products on GT stock (2001-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
prod GPP	0.073***	0.050***	0.049***	0.041***	0.041***	0.053***
	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)
pop density		0.004**	0.004***	0.004***	0.004***	-0.000
		(0.002)	(0.001)	(0.001)	(0.001)	(0.000)
empl share			-0.000***	-0.000***	-0.000***	-0.000**
			(0.000)	(0.000)	(0.000)	(0.000)
N. of firms				0.000**	0.000**	0.000***
				(0.000)	(0.000)	(0.000)
R&D empl					6.972*	8.609**
					(3.888)	(4.378)
r2_w	0.365	0.385	0.389	0.391	0.392	0.371
r2_o	0.067	0.118	0.069	0.082	0.083	0.472
r2_b	0.432	0.118	0.068	0.080	0.081	0.478
N	7937	7937	7937	7937	7937	7937

Dep. Var.: Stock of fractionalized patent families weighted by forward citations (log). GPP lagged 1-year. Standard errors clustered at the level of State. Models I to V, estimated in fixed effect, include a constant and year dummies. Model VI includes also geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Table 4: Effect of GPP for services on GT stock (2001-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
serv GPP	0.093***	0.078***	0.077***	0.073***	0.073***	0.087***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
pop density		0.003**	0.004***	0.003***	0.003***	-0.000
		(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
empl share			-0.000***	-0.000***	-0.000***	-0.000**
			(0.000)	(0.000)	(0.000)	(0.000)
N. of firms				0.000**	0.000**	0.000***
				(0.000)	(0.000)	(0.000)
R&D empl					6.716*	8.510**
					(3.772)	(4.168)
r2_w	0.384	0.400	0.404	0.406	0.406	0.388
r2_o	0.138	0.126	0.074	0.086	0.086	0.498
r2_b	0.495	0.125	0.072	0.083	0.084	0.505
N	7937	7937	7937	7937	7937	7937

Dep. Var.: Stock of fractionalized patent families weighted by forward citations (log). GPP lagged 1-year. Standard errors clustered at the level of State. Models I to V, estimated in fixed effect, include a constant and year dummies. Model VI includes also geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Table 5: Effect of total GPP and task composition on GT stock (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
tot GPP	0.039***	0.039***	0.039***	0.021**	0.040***	0.048***
	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)
RSH	0.003	0.004				
	(0.013)	(0.012)				
GPP*RSH		-0.000				
		(0.011)				
ASH			0.041***	0.017		
			(0.014)	(0.015)		
GPP*ASH				0.042***		
				(0.010)		
MSH					-0.013	0.001
					(0.010)	(0.010)
GPP*MSH						-0.037***
						(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)
empl share	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of firms	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D empl	6.101	6.100	6.533	6.378	6.455	6.561
	(6.303)	(6.298)	(6.272)	(6.264)	(6.348)	(6.418)
r2_w	0.328	0.328	0.328	0.331	0.327	0.329
r2_o	0.458	0.458	0.464	0.469	0.461	0.464
r2_b	0.467	0.467	0.473	0.478	0.471	0.473
N	3851	3851	3851	3851	3851	3851

Dep. Var.: Stock of fractionalized patent families weighted by forward citations (log). GPP, RSH, ASH and MSH lagged 1-year. Standard errors clustered at the level of State. All models include a constant, year and geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Table 6: Effect of GPP for products and task composition on GT stock (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
prod GPP	0.020*	0.021**	0.020**	0.008	0.021**	0.023**
	(0.010)	(0.011)	(0.010)	(0.012)	(0.010)	(0.010)
RSH	0.005	0.006				
	(0.013)	(0.013)				
GPP*RSH		-0.006				
		(0.018)				
ASH			0.038***	0.036**		
			(0.014)	(0.014)		
GPP*ASH				0.021		
				(0.014)		
MSH					-0.012	-0.009
					(0.010)	(0.010)
GPP*MSH						-0.031
						(0.023)
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)
empl share	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of firms	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D empl	5.782	5.845	6.243	6.257	6.164	6.248
	(6.243)	(6.248)	(6.220)	(6.233)	(6.302)	(6.320)
r2_w	0.327	0.327	0.327	0.327	0.326	0.326
r2_o	0.440	0.440	0.446	0.447	0.444	0.444
r2_b	0.449	0.449	0.455	0.455	0.453	0.453
N	3851	3851	3851	3851	3851	3851

Dep. Var.: Stock of fractionalized patent families weighted by forward citations (log). GPP, RSH, ASH and MSH lagged 1-year. Standard errors clustered at the level of State. All models include a constant, year and geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Table 7: Effect of GPP for services and task composition on GT stock (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
serv GPP	0.047***	0.048***	0.048***	0.025**	0.048***	0.057***
	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)
RSH	0.003	0.005				
	(0.013)	(0.012)				
GPP*RSH		-0.004				
		(0.012)				
ASH			0.041***	0.018		
			(0.014)	(0.015)		
GPP*ASH				0.050***		
				(0.012)		
MSH					-0.013	0.001
					(0.010)	(0.011)
GPP*MSH						-0.042***
						(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)
empl share	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of firms	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D empl	5.875	5.881	6.324	6.167	6.245	6.292
	(6.254)	(6.249)	(6.230)	(6.224)	(6.301)	(6.383)
r2_w	0.331	0.331	0.331	0.334	0.330	0.331
r2_o	0.458	0.459	0.465	0.470	0.462	0.464
r2_b	0.468	0.468	0.474	0.479	0.472	0.474
N	3851	3851	3851	3851	3851	3851

Dep. Var.: Stock of fractionalized patent families weighted by forward citations (log). GPP, RSH, ASH and MSH lagged 1-year. Standard errors clustered at the level of State. All models include a constant, year and geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Table 8: Effect of GPP on GT stock: mitigation and adaptation (2001-2011)

	Mitigation GT			Adaptation GT		
	(I)	(II)	(III)	(IV)	(V)	(VI)
total GPP	0.086***			0.043***		
	(0.011)			(0.008)		
prod GPP		0.061***			0.036***	
		(0.014)			(0.010)	
serv GPP			0.096***			0.049***
			(0.011)			(0.009)
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)
empl share	-0.000**	-0.000***	-0.000**	-0.000*	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of firms	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D empl	7.089	7.115	7.016	4.603	4.640	4.558
	(4.438)	(4.379)	(4.367)	(4.983)	(5.283)	(4.917)
r2_w	0.381	0.364	0.382	0.245	0.236	0.247
r2_o	0.510	0.479	0.507	0.558	0.539	0.556
r2_b	0.519	0.486	0.516	0.576	0.555	0.573
N	7937	7937	7937	7937	7937	7937

Dep. Var.: Stock of fractionalized patent families (mitigation and adaptation) weighted by fwd. cits. GPP variables lagged 1-year. Standard errors clustered at the level of State. All models include a constant, year and geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Table 9: Effect of total GPP and task composition on GT-mitigation stock (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
tot GPP	0.043***	0.044***	0.044***	0.023***	0.045***	0.053***
	(0.009)	(0.010)	(0.009)	(0.008)	(0.009)	(0.010)
RSH	0.001	0.003				
	(0.013)	(0.013)				
GPP*RSH		-0.003				
		(0.011)				
ASH			0.044***	0.016		
			(0.016)	(0.017)		
GPP*ASH				0.049***		
				(0.011)		
MSH					-0.010	0.005
					(0.011)	(0.011)
GPP*MSH						-0.040***
						(0.013)
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)
empl share	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of firms	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D empl	5.863	5.870	6.360	6.177	6.206	6.320
	(6.416)	(6.413)	(6.391)	(6.384)	(6.451)	(6.528)
r2_w	0.319	0.319	0.319	0.322	0.318	0.320
r2_o	0.463	0.463	0.469	0.476	0.466	0.469
r2_b	0.473	0.473	0.479	0.485	0.476	0.479
N	3851	3851	3851	3851	3851	3851

Dep. Var.: Stock of fractionalized patent families (mitigation and adaptation) weighted by fwd. cits. GPP, RSH, ASH and MSH lagged 1-year. Standard errors clustered at the level of State. All models include a constant, year and geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Table 10: Effect of GPP for products and task composition on GT-mitigation stock (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
prod GPP	0.024**	0.026**	0.025**	0.009	0.026**	0.028**
	(0.011)	(0.012)	(0.011)	(0.013)	(0.011)	(0.011)
RSH	0.003	0.004				
	(0.013)	(0.013)				
GPP*RSH		-0.006				
		(0.020)				
ASH			0.041***	0.037**		
			(0.016)	(0.016)		
GPP*ASH				0.027*		
				(0.016)		
MSH					-0.008	-0.005
					(0.011)	(0.011)
GPP*MSH						-0.035
						(0.024)
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)
empl share	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of firms	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D empl	5.514	5.581	6.046	6.055	5.890	5.983
	(6.337)	(6.345)	(6.320)	(6.336)	(6.388)	(6.411)
r2_w	0.318	0.318	0.317	0.318	0.317	0.317
r2_o	0.443	0.443	0.450	0.450	0.446	0.446
r2_b	0.452	0.452	0.458	0.459	0.455	0.456
N	3851	3851	3851	3851	3851	3851

Dep. Var.: Stock of fractionalized patent families (mitigation and adaptation) weighted by fwd. cits. GPP, RSH, ASH and MSH lagged 1-year. Standard errors clustered at the level of State. All models include a constant, year and geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Table 11: Effect of GPP for services and task composition on GT-mitigation stock (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
serv GPP	0.051***	0.053***	0.052***	0.026**	0.052***	0.061***
	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)
RSH	0.001	0.005				
	(0.013)	(0.013)				
GPP*RSH		-0.009				
		(0.013)				
ASH			0.044***	0.018		
			(0.016)	(0.017)		
GPP*ASH				0.057***		
				(0.013)		
MSH					-0.009	0.005
					(0.011)	(0.011)
GPP*MSH						-0.045***
						(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)
empl share	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of firms	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D empl	5.621	5.639	6.140	5.960	5.987	6.036
	(6.375)	(6.369)	(6.357)	(6.353)	(6.413)	(6.502)
r2_w	0.321	0.321	0.321	0.325	0.320	0.322
r2_o	0.463	0.463	0.470	0.476	0.466	0.469
r2_b	0.473	0.473	0.479	0.486	0.476	0.479
N	3851	3851	3851	3851	3851	3851

Dep. Var.: Stock of fractionalized patent families (mitigation and adaptation) weighted by fwd. cits. GPP, RSH, ASH and MSH lagged 1-year. Standard errors clustered at the level of State. All models include a constant, year and geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Table 12: Effect of total GPP and task composition on GT-adaptation stock (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
tot GPP	0.021***	0.020***	0.022***	0.012	0.022***	0.030***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)
RSH	0.003	0.002				
	(0.007)	(0.007)				
GPP*RSH		0.003				
		(0.011)				
ASH			0.020**	0.007		
			(0.009)	(0.008)		
GPP*ASH				0.023**		
				(0.010)		
MSH					-0.019***	-0.006
					(0.006)	(0.007)
GPP*MSH						-0.036***
						(0.008)
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)
empl share	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of firms	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D empl	2.601	2.590	2.815	2.737	2.902	3.013
	(4.737)	(4.732)	(4.707)	(4.720)	(4.760)	(4.856)
r2_w	0.188	0.188	0.187	0.188	0.187	0.190
r2_o	0.511	0.511	0.515	0.520	0.516	0.520
r2_b	0.525	0.525	0.530	0.535	0.530	0.535
N	3851	3851	3851	3851	3851	3851

Dep. Var.: Stock of fractionalized patent families (mitigation and adaptation) weighted by fwd. cits. GPP, RSH, ASH and MSH lagged 1-year. Standard errors clustered at the level of State. All models include a constant, year and geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Table 13: Effect of GPP for products and task composition on GT-adaptation stock (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
prod GPP	0.009	0.008	0.009	0.007	0.009	0.011
	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)
RSH	0.004	0.004				
	(0.007)	(0.007)				
GPP*RSH		0.003				
		(0.014)				
ASH			0.018**	0.018**		
			(0.009)	(0.009)		
GPP*ASH				0.003		
				(0.012)		
MSH					-0.018***	-0.017***
					(0.006)	(0.006)
GPP*MSH						-0.022*
						(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)
empl share	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of firms	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D empl	2.474	2.488	2.708	2.713	2.799	2.867
	(4.790)	(4.783)	(4.771)	(4.774)	(4.826)	(4.844)
r2_w	0.189	0.189	0.188	0.187	0.188	0.188
r2_o	0.497	0.498	0.502	0.502	0.502	0.503
r2_b	0.511	0.511	0.516	0.516	0.516	0.517
N	3851	3851	3851	3851	3851	3851

Dep. Var.: Stock of fractionalized patent families (mitigation and adaptation) weighted by fwd. cits. GPP, RSH, ASH and MSH lagged 1-year. Standard errors clustered at the level of State. All models include a constant, year and geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Table 14: Effect of GPP for services and task composition on GT-adaptation stock (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
serv GPP	0.031***	0.030***	0.032***	0.017*	0.032***	0.040***
	(0.008)	(0.008)	(0.008)	(0.010)	(0.008)	(0.009)
RSH	0.003	0.001				
	(0.007)	(0.007)				
GPP*RSH		0.003				
		(0.010)				
ASH			0.020**	0.005		
			(0.009)	(0.008)		
GPP*ASH				0.033***		
				(0.010)		
MSH					-0.018***	-0.006
					(0.006)	(0.007)
GPP*MSH						-0.041***
						(0.009)
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)
empl share	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of firms	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D empl	2.453	2.444	2.677	2.585	2.762	2.815
	(4.653)	(4.649)	(4.625)	(4.649)	(4.677)	(4.785)
r2_w	0.192	0.192	0.191	0.194	0.191	0.194
r2_o	0.514	0.514	0.519	0.525	0.519	0.523
r2_b	0.529	0.528	0.533	0.540	0.534	0.538
N	3851	3851	3851	3851	3851	3851

Dep. Var.: Stock of fractionalized patent families (mitigation and adaptation) weighted by fwd. cits. GPP, RSH, ASH and MSH lagged 1-year. Standard errors clustered at the level of State. All models include a constant, year and geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$