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 (CZs) 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 public demand; Local innovation dynamics; Innovation policies; Local occupational-task composition.

Very preliminary draft (please do not circulate)

1 Introduction

The aim of this paper is to assess the impact of public procurement on local green innovation capacity. Public procurement is the acquisition of goods and services by government or public sector organizations. The specialised literature makes a distinction between the purchase of ready-made products for which no R&D is required and about which there is readily available information on price, quantity and performance ('normal' public procurement) and the circumstance in which a public agency places an order for a product or a service that does not yet exist ('public technology' procurement). The latter scenario entails that the procured goods or services be developed within a reasonable period of time through efforts that may or may not involve *ad hoc* R&D (Edquist et al. 2000). The basic rationale for public procurement is that triggering demand beyond a minimum volume reduces uncertainty about the scale of production, thus enabling firms to invest in otherwise insecure ventures. Depending on the nature of the technological investments, procurement can also ignite dynamic increasing returns and network externalities (Katz & Shapiro 1985).

Prior literature classifies the multiple pathways through which public procurement stimulates innovation. Therein, further distinctions are made with regards to the type of end users (Edler & Georghiou 2007, Hommen & Rolfstam 2009), the degree of competitiveness in the market of suppliers (Edquist et al. 2000), the type of innovation and the degree of maturity of technology (Edler et al. 2006, Hommen & Rolfstam 2009). Such a renewed interest in public demand as a lever for innovation has acquired momentum in innovation studies but, also, within policy circles (EC, 2011). This is due to the peculiar nature of public procurement as policy tool for innovation that aims at addressing a social challenge by targeting functions rather than products (Edquist & Zabala-Iturriagagoitia 2012, Edquist et al. 2015). We propose that these nuances make environmental innovation a suitable empirical domain for the study of public procurement.

Scholars agree that green technologies confront the so-called double externality problem due to the juxtaposition of environmental externalities on top of the traditional knowledge externalities. As the seminal paper by Nelson (1959) first poised, private returns to green R&D are too low to guarantee the optimal allocation of the necessary resources. The inability to rely solely on market forces has inspired much research aimed at elaborating viable policy responses to stimulate technical change. A critical review of the literature suggests that within the receptacle of known policy tools much of the emphasis is on supply-oriented effects while the demand-side has been arguably neglected. The potential of public procurement to ignite demand for environmental goods and, further down the line, for environmental innovation offers a chance to fill this gap.

The debate on the effects of procurement on general innovation is predominantly informed by anecdotal findings on successful ventures at the high end of technology. This raises concerns regarding how representative these examples may be, and about what lessons can be learned to inform green policy. The limited generalizability of the existing evidence is a gap which the present paper seeks to fill by means of a large-scale study. The main shortcomings of the current debate provide us with a compass for identifying relevant research questions for the green innovation realm.

First, the academic and policy discourses neglect the space-bound nature of general procurement (and, by extension, of green-related public procurement). This implies that scarce attention is devoted to analysing the benefits and the challenges associated with implementing policy at local level. Peculiarities of local institutional and socioeconomic contexts have also been understudied in the literature on the drivers of green innovation (del Río González 2009). To this end, we propose a large-scale empirical study of US Commuting Zones. This spatial construct carries the benefits of covering the entirety of the US national territory while, at the same time, offering enough detail of the underlying socio-economic structure that is suitable to the analysis of whether and to what extent public procurement enables local green innovation capacity.

Second, prior literature sings the praises of public procurement by means of a selective focus on successful cases, with little or no attention to the circumstances that end in failure. Contemplating such cases however promises to enrich our understanding of where uncertainty persists, where traditional market forces fall short and where, ultimately, green policy is most needed. Our point of departure is that public procurement serves specific public needs and that innovation should be encouraged, where possible, but also that it is unrealistic that public procurement should have as a primary goal the promotion of innovation. Accordingly, and connected to the first point above, we envisage our empirical analysis to identify the geographical areas in which public procurement has successfully spurred green innovation capacity, and to make sense of the main attendant local features. We are also interested, however, in areas that experienced no such improvements, and of the potential barriers therein.

Third, the current debate downplays both the varied nature of the range of goods and services procured by the public sector as well as the diverse nature of innovation. Accordingly, we propose to adapt existing typologies of public procurement (Uyarra & Flanagan 2010) to the case of heterogeneous environmental technologies. In particular, our data-set allows a distinction between standardized products that serve a generic market (efficient procurement); specific products that cater demand niches employing known production methods (adapted procurement); new technical solutions to meet a generic need (technological procurement); and adapted technical solutions (experimental procurement). Similarly, by exploiting the richness of information contained in patent data, we are also able to assess the effect of this heterogeneous bundle of procurement tools on diverse types of green innovation, according to their main domain of reference and their level of maturity. The main challenge in this exercise is to understand the trade-offs involved in each category, and the drivers of moving from one segment to another.

To study the relationship between public (green) procurement and environmental innovation dynamics at the local level, we rely on detailed information on both green innovative effort and procurement expenditures at the level of US Commuting Zones (CZs) for the period from 2000 to 2011. Furthermore, we characterize CZs in terms of their local knowledge base by exploiting occupational, task and skill information derived from US Census micro-data. This exercise allows us to test for heterogeneous effects of green public procurement on green innovation activities according to diverse occupational-task compositions of local labor markets. As a complement to our analysis, we enter more deeply the content of both patent and procurement data. Precisely, we exploit the richness of patent information to differentiate between several diverse kinds of green technologies and test for heterogeneity in channels through which procurement fosters green innovation. On the other side, we open the procurement box by differentiating between procurement for green products and procurement for green services.

2 Public procurement and environmental innovation

The extant literature on the determinants of eco-innovations[1] has much focused on the notion of induced innovation. The inducement hypothesis in the domain of environmental economics points to the moderating role played by regulation on the generation of green technologies (Johnstone et al. 2012).

Stringent policy is conceived as an additional cost, increasing firms' production costs by changing relative factor prices. This dynamics stimulates firms to commit resources to introduce innovations aimed at reducing this increased cost, *e.g.* emissions-reducing technologies. Regulation plays an important role, due to the 'double externality' problem (Rennings 2000). Market failures lead indeed to sub-optimal allocation of resources to the generation of green technological knowledge, calling for public intervention to bring efforts to optimal levels. This mechanism is known in the literature as 'regulatory push/pull' effect, and it has been documented by several empirical studies drawing either on survey data (e.g. Frondel et al. 2008, Horbach et al. 2012*b*, Renning & Rammer 2011; for a review see del Río González 2009) or on the information contained in patent documents (e.g. Lanjouw & Mody (1996), Brunnermeier & Cohen (2003), Jaffe & Palmer (1997), Popp (2006), Johnstone et al. (2010)).

Both technology-push and demand-pull deployment policies have proven to be useful instruments to trigger the generation of green technologies (Costantini et al. 2015, Horbach et al. 2012*a*, Requate 2005). The main effect of demand-pull

[1] There are various definitions of eco-innovation.Kemp (2010: p. 398) notes that "The absence of a common definition led the European Commission to fund two projects on measuring eco-innovation: Measuring Eco-Innovation (MEI) and Eco-Drive. The eco-innovation definition of the Eco-Drive is «a change in economic activities that improves both the economic performance and the environmental performance». The definition of MEI is «the production, assimilation or exploitation of a product, production process, service or management or business method that is novel to the organisation (developing or adopting it) and which results, throughout its life cycle, in a reduction of environmental risk, pollution and other negative impacts of resources use (including energy use) compared to relevant alternatives»".

deployment policies consists of the creation of new markets for green technologies. The size of markets for GTs is also affected by policy-driven demand, so that prospects for growth of inventing firms are boosted by policy-induced market growth (Nemet 2009, Hoppmann et al. 2013). Thus, while deployment policies may represent a cost for firms, they provide firms inventing green technologies with market opportunities, and hence prospects for sales' growth.

From the viewpoint of macroeconomic policy levers, an important demand side instrument is represented by public procurement. While the impact of public procurement on general innovation has received constant, even if not extensive attention by the extant literature (Nelson 1982; Geroski, 1990; Ruttan 2006), the relationship between public procurement[2] and the generation of green technologies has not received full appreciation yet.

Public procurement has been indicated as a key channel favouring the introduction of technologies allowing for meeting targets of environmental sustainability, because of the strong radical, and hence uncertain, nature of this kind of technologies (Mowery et al. 2010). From the international policy perspective, procurement is increasingly seen as a way to improve sustainability. The United Nations 2030 Agenda for Sustainable Development explicitly refers to the need for countries to promote sustainable procurement as one of the Sustainable Development Goals (UN, 2015). The European Commission's Green Public Procurement initiative (EC, 2008) sets a non-binding green public procurement target to favour improvements in the environmental, energy and social performance of products and services and to stimulate their development. However, few studies provide empirical evidence about this relationship.

Simcoe & Toffel (2014) test the spillover effect of public procurement for

[2]It must be stressed that public procurement for green inventions is a form of innovative public procurement that is distinct from green public procurement (Ghisetti 2017). The former indeed refers to methods, products and services that have not yet been developed and, therefore, involves significant commitment of resources in research and development activities. The latter refers to governments' purchase of products and services already existing in the market.

green adoption on green adoption in the private sector. Precisely, they investigate whether the construction of public buildings complying with green standards stimulates the adoption of green building standards also in the private sector. To test for this effect, they rely on data about several Californian municipalities from 2001 to 2008. Their results reveal that private adoption has been higher in municipalities where public adoption was present, in comparison to matched non-adopting control municipalities. They argue that three main mechanisms related to public demand are likely to stimulate private demand. First, public procurement might raise "awareness" on the green standard. Second, it might encourage the development of "complementary input markets". Third, it might ameliorate the "coordination failure" between developers and suppliers.

Ghisetti (2017) analyses the role of innovative public procurement in driving the adoption and diffusion of sustainable manufacturing technologies. Her results, based on cross-section firm-level data in the 28 Member States of the European Union, Switzerland and the USA, outline the positive effect of innovative public procurement on the uptake of environmental innovations.

As stressed in the introduction, several fundamental avenues of research are still unexplored, leaving the understanding of the relationship between public procurement and green innovation dynamics too ambiguous to inform green policy. First, the space-bound nature of both procurement and innovative (green) activities must be cautiously considered when approaching this field of enquiry. Second, diverse local knowledge- and skills-configurations may magnify or cancel the effect of public procurement on eco-innovation. Third, heterogeneity in both procurement configurations and innovation processes is likely to reveal strong divergence in terms of net policy effectiveness.

The present paper tries to partially fill these gaps by exploiting information about green public procurement, green innovation activities and local occupational-task compositions at the level of US Commuting Zones from 2000 to 2011.

3 Data and methods

Following the literature on US local labor market dynamics, we focus our analysis at the level of Commuting Zones (CZs). Both public procurement and innovation dynamics are indeed likely to be strongly attached to local features of employment and skills endowments. The spatial level of analysis should thus be cautiously selected when innovation and procurement dynamics are under scrutiny. CZs seem to be really suitable in this sense. The concept of CZs was firstly developed by Tolbert and Sizer (1996) who used county-level commuting data from the 1990 Census data to create 741 clusters of counties that are characterized by strong commuting ties within CZs, and weak commuting ties across CZs. Since the contribution by Dorn (2009), this geographic construction for defining regional economies in the US has been widely accepted as the best tool for studying local labor market dynamics. Even if we do not directly focus on labor market dynamics, local occupational-task compositions play a crucial role in our analysis. This justifies our choice.

We exploit three main sources of data at the level of CZs to measure: *i)* the green innovative local effort, proxied by patenting activity; *ii)* the level of local green procurement expenditures and *iii)* the local composition of occupational tasks and skills.

Patent data To measure the local level of green technological activity, we collect data on US-invented patents. The raw source of this part of the data comes from PATSTAT 2016a. Patents collected are patents with priority year between 1970 and 2012.

Patents are considered as environment-related according to the ENV-TECH classification (OECD, 2015). The ENV-TECH classification, based on the International Patent Classification (IPC) and the Collaborative Patent Classification (CPC), features eight environmental areas: (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 exploits both IPC and CPC codes[3] we first convert the IPC codes into CPC codes according to the concordance table proposed by EPO and USPTO.[4] Then, we exploit information contained in patent documents and extract CPC codes classifying patented technologies. Finally, we assign patents to ENV-TECH technologies accordingly.

To define a patent as US-invented, we exploit information contained in inventors' addresses, proposing an original methodology for geo-localizing and assigning green patents to US counties.

Even if the information contained in PATSTAT is every year more complete, the 2016a version still 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 completion of data being done, the next step consists in individuating precise geographical coordinates to be assigned to each address and, thus, to each patent. First, we extract the postal code included in the inventor's address, when present, to identify US cities according to the GeoNames postal code table.

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

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

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, for all the addresses not possible to assign to a precise postal code, we build an iterative algorithm to directly identify the name of the city within the address field. Once extracted, we match the retrieved city names with the names of US city above 5000 inhabitants provided by GeoNames.[5] Third, we exploit the Google's Geocoding API resource to assign geographical coordinates to all the remaining addresses.

Finally, we are able to assign geographical coordinates to the 90% of unique US inventors' addresses. We then project these coordinates on the 1990 US CZs map to assign each inventor to a CZ.

The local level of green innovation activity is measured through the fractionalized[6] stock of US-invented patents with at least one CPC class which relates to a green technology. The stock of green patents is corrected for INPADOC patent families[7] and weighted by forward (family) citations received[8]. Weighting by forward citations allows us to account for the intrinsic technological value of the local protected inventions.

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

[6]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.

[7]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 Martinez (2010).

[8]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): $N.cit.weighted = \frac{\frac{N.cit}{AvgN.cit_{t,j}}}{AvgN.cit_t}$

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

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

where δ is the decay rate.[9]

Procurement data Second, we collect data on environmental-related procurement expenditures by exploiting public information provided by the USAspending.gov resource.[10] Procurement information are available from 2000 on.

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.

Precisely, we exploit data on all registered federal contracts. From each funded contract we extract information about the place of performance location (5-digits Zipcode)[11] where the contract is executed and the amount of resources dedicated (in 2010 USD). According to the Product and Service Codes Manual (PSC, August 2015 Edition), we are able to individuate procured 'green' contracts and to distinguish them between product-, and service-related.[12] Indeed, the PSC Manual provides codes to describe products, services, and R&D

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

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

[11] 5-digits Zipcodes allow us to assign precise levels of expenditures to counties and, consequently, to CZs.

[12] 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

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 ALM (2003) and recently extended to the analysis at geographical level by Autor & Dorn (2013). This line of empirical research represents a significant break from the traditional approach to human capital. Rather than relying on indicators such as i.e. the average number of years of education in the workforce or the share of individuals with postgraduate degrees, the human capital endowment is proxied by the relative importance of particular types of occupations that are identified on the basis of their main work activities and of the attending skills that are needed to perform the essential tasks of that job.

In this framework work activities are grouped in three broad categories. 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

products and services with environmental attributes including recycled content, biobased, and energy efficient. Data collected in 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.

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 along these tracks (i.e., ALM, 2003; Autor, Katz, and Kearney, 2006; Dorn, 2009; and Autor & 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.[13] We combine these measures to create summary indicators of task-intensity by occupation (routine RTI, abstract ATI and manual MTI), calculated as

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

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

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

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.[14] 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:

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

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

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

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

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

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:

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

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

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

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.

3.1 Descriptive Analysis

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:

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

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

$X'_{j,t}$ 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:

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

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

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

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).[15]

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.[16]

4 Results

Tables 1, 2 and 3 present initial estimates of the relationship between expenditures in GPP and the local environmental innovation capacity. Precisely, Table

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

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

1 presents estimates for the effect of the overall level of GPP. Tables 2 and 3 focus 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 1 estimate equation (11) in CZ fixed effects, adding one by one the controls described above. Column VI estimates equation (11) replacing CZ fixed effects with dummies fixed effects for the nine US Census macro-areas. We rely on this last specification for commenting the results. Estimates show a positive and significant effect of green public procurement on local green innovation activities: a 1% increase in green public procurement leads to a 0.077% increase in the stock of green patents.

Tables 2 and 3 replicate the same strategy as the one proposed in Table 1 but focusing on the effects of, respectively, GPP for products and GPP for services on the total stock of green technological knowledge. 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.

As a further step of this first part of the analysis, we exploit the ENV-TECH classification to test for the differential effect of GPP on the two main groups of green technological stock: adaptation and mitigation, respectively. Columns I, II and III of Table 4 present estimates for the effect of, respectively, total, product- and service-related GPP on green mitigation technological stock. Columns IV, V and VI do the same for 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).

The overall picture emerging from this first part of the empirical analysis demonstrates that GPP positively affects the accumulation of GT stock. Importantly, public procurement for green services has higher effectiveness on the overall level of green technological stock and on both macro-groups of GTs, namely adaptation and mitigation.

In the second part of the empirical analysis we introduce measures proposed in Section 3 for defining local occupational task compositions. Our aim is to test for the moderating effect of local labor market composition in the relation between green public procurement and green innovation capacity.

Table 5 replicates Column VI proposed in Table 1, adding one by one dummies depending on whether a CZ is in the top 30% of task intensity shares of occupations and their interactions with total GPP. Dummies are built according to equations (8), (9) and (10). Precisely, Column II estimates equation (12), Column IV equation (13) and Column VI equation (14) when the dependent variable is the total GT stock. Comparing estimations from Columns II, IV and VI, results reveal that the marginal effect of total GPP on GT stock is higher for CZs characterized by higher shares of abstract intensive occupations.

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 premium 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 1, 2 and 3. 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).

Focusing on areas in the top third, 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 in expenditure on services relative 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 analytical capability. This resonates with the high level of knowledge intensity of service activities which 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 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 routine jobs has been in decline for some time (see i.e., ALM, 2003; Acemoglu and Autor, 2011), 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 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.

Before concluding, 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 analyse separately the effects on GT stock in mitigation (Tables 8, 9 and 10) and in adaptation technologies (Tables 11, 12 and 13). 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 products and services. Routine intensive occupations have a significant moderating effect only for service expenditure. Conversely, among adaptation technologies, the coefficients of both routine and abstract occupations are significant only for service-related GPP (Fig. 6). We ascribe this to the preponderance of intangible nature of coordinating, planning and implementing adaptation strategies at local level.

5 Conclusion

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Tables

Table 1: 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)
employment 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)
share of R&D employment					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 2: Effect of GPP for products on GT stock (2001-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
product 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)
employment 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)
share of R&D employment					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	7933	7933	7933	7933	7933	7933

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 services on GT stock (2001-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
service 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)
employment 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)
share of R&D employment					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 4: 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)		
product GPP		0.061***			0.036***	
		(0.014)			(0.010)	
service 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)
employment 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)
share of R&D employment	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	7933	7937	7937	7933	7937

Dep. Var.: Stock of fractionalized patent families (mitigation and adaptation) weighted by forward citations (log).

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 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)
employment 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)
share of R&D employment	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)
product 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)
employment 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)
share of R&D employment	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	3849	3849	3849	3849	3849	3849

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)
service 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)
employment 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)
share of R&D employment	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 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)
employment 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)
share of R&D employment	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 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 9: Effect of GPP for products and task composition on GT-mitigation stock (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
product 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)
employment 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)
share of R&D employment	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	3849	3849	3849	3849	3849	3849

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

	(I)	(II)	(III)	(IV)	(V)	(VI)
service 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)
employment 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)
share of R&D employment	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 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 11: 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)
employment 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)
share of R&D employment	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 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 12: Effect of GPP for products and task composition on GT-adaptation stock (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
product 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)
employment 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)
share of R&D employment	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	3849	3849	3849	3849	3849	3849

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

	(I)	(II)	(III)	(IV)	(V)	(VI)
service 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)
employment 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)
share of R&D employment	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 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).

* $p < .1$, ** $p < .05$, *** $p < .01$

Figures

Figure 1:

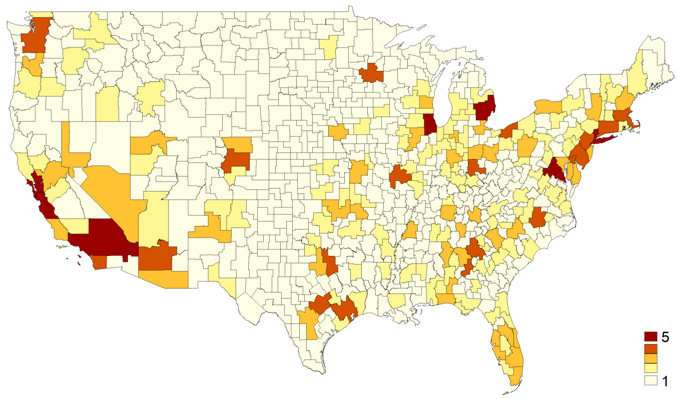

Figure 2:

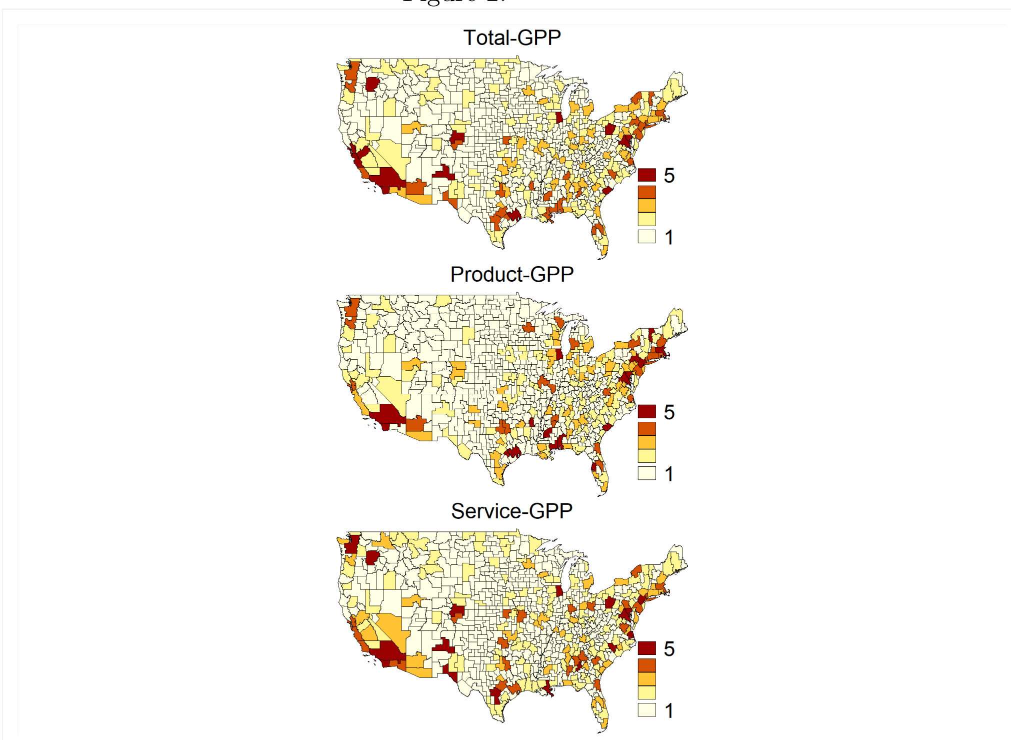

Figure 3:

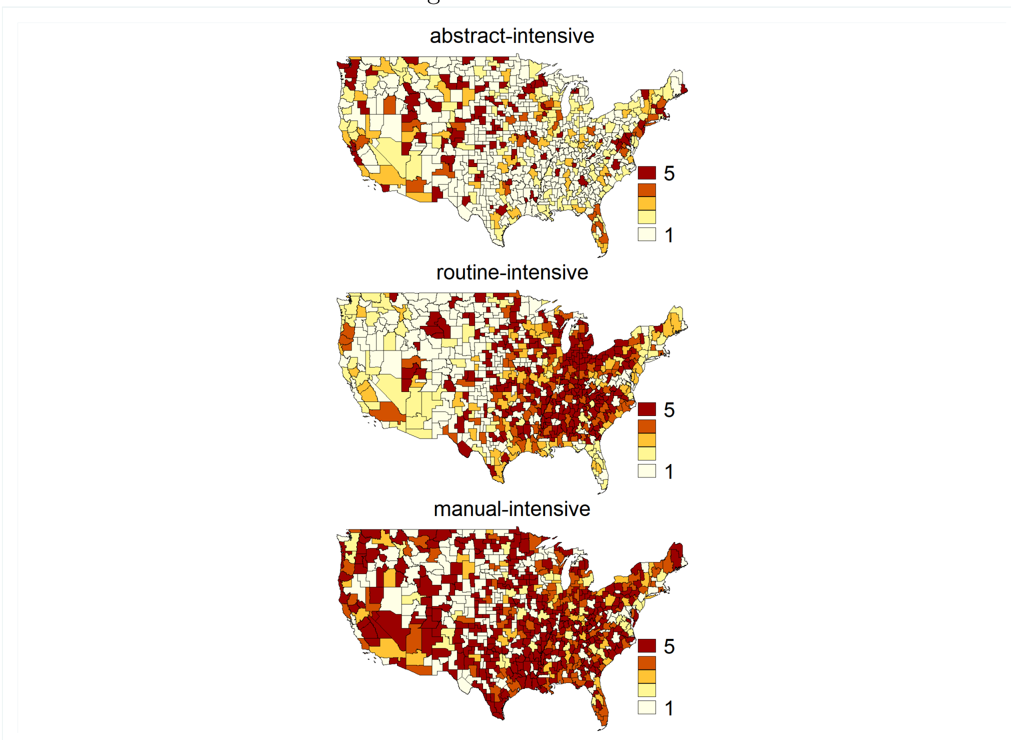

Figure 4: A.M.E. of GPP on total GT stock with 95% CIs

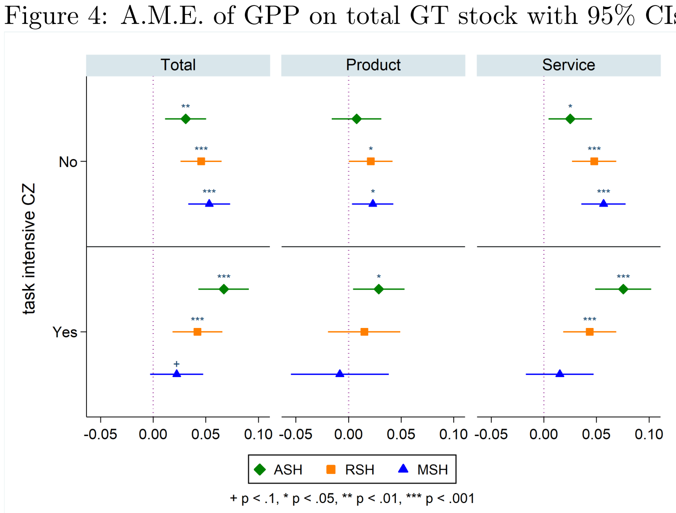

Figure 5: A.M.E. of GPP on GT-mitigation stock with 95% CIs

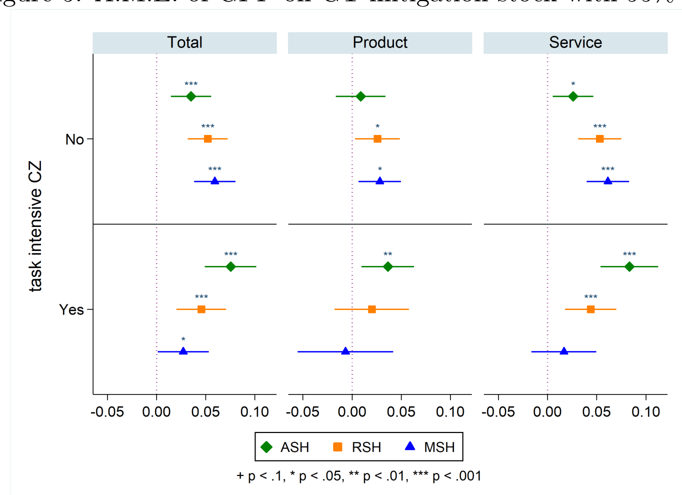

Figure 6: A.M.E. of GPP on GT-adaptation stock with 95% CIs