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LOCAL LABOUR TASKS AND PATENTING IN US COMMUTING ZONES

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Abstract

In this paper we adopt a task approach to measure the local pool of capabilities which can more effectively spur innovation. By focusing on the core activities that workers undertake in their jobs, we build an abstract task intensity measure of occupations to proxy the ability in analysing and solving complex problems, as well as in coordinating and integrating people with different knowledge endowments, that should be especially relevant for the process of invention and innovation. We thus estimate the relationship between the local abstract intensity and the inventive performance, proxied by granted patents, of US Commuting Zones during the period 2000-2015. The evidence provided, robust to a wide array of sensitivity checks, points to the extent of workers' engagement in abstract tasks across Commuting Zones as a crucial determinant of the local inventive activity.

JEL Class.: R10, R12, O31, O33.
Keywords: human capital, labour tasks, local abstract intensity, patents, US Commuting Zones

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1 Introduction

The economic literature recognises invention and innovation as the core engines of growth, with human capital as the main input (Lucas Jr, 1988; Romer, 1990; Grossman and Helpman, 1993; Verspagen, 2006). These processes mainly involve the deployment of cognitive skills to produce advances in scientific and technological knowledge, as well as of organisational capabilities to combine and transform such knowledge into new ideas and working artifacts (Pavitt, 2003; Deming, 2017). The output of these activities increasingly results from the combination of the capabilities of different entities: it may originate from buyer-supplier relations, or from cooperative agreements between firms specialised in separate steps of production, and even between firms and public entities (Pavitt, 2003; Jones, 2009; Bercovitz and Feldman, 2011; Deming, 2017). As these entities are often located in the same place, the role of geography emerges as an important ingredient of the overall innovation process, implying that aggregate location-level studies are better suited, than firm-level ones, to capture these types of interactions (Porter and Sölvell, 2003; Jaffe *et al.*, 1993). Moreover, since innovation-related capabilities are produced and deployed on the job, a stream of literature has focused on what people do at workplace, rather than on their educational attainment or industry affiliation, to measure the knowledge base of regions. Different studies have thus inspected the role of locations' effective endowments in terms of specific occupations, such as high skilled, STEM, and creative jobs (Thompson and Thompson, 1985; Florida, 2004; Feser, 2003; Boschma and Fritsch, 2009; Beaudry *et al.*, 2010; The National Science Board, 2015).

In this work, we move a step further by adopting a task-based approach and investigating the role of the local abstract task intensity on the patenting activity in the US Commuting Zones (CZs) over the 2000-2015 time span. Compared to the human capital framework, this approach depicts a job as the result of the combination of different work activities - tasks - with the aim of better capturing the extent of substitution between labour and technology/trade (Autor *et al.*, 2003; Acemoglu and Autor, 2011).

We claim that moving from workers' education levels or occupational title (e.g. STEM/non-STEM) to their actual work activities on the job is an effective analytical switch also for explaining the heterogeneous inventive performances of places. As moving from industries to occupations allows for a better isolation of the effects of human capital, so moving from occupations to their task content should help to shed light on which particular feature of occupations actually drives the creation of new and valuable knowledge at the local level. In this respect, with our economic geography perspective, we contribute to advance the recent firm level literature showing that firms with higher shares of employees engaged in abstract, rather than routine or manual, work activities are more productive and innovative (Fonseca *et al.*, 2018, 2019). Indeed, to uncover whether a significant nexus between abstract tasks and innovation exists, an empirical analysis needs to be conducted at a relevant location level where both phenomena can be better observed and measured.

The abstract task intensity, with its composition of non-routine cognitive - technical/analytical and managerial/interactive - activities required in a job (Autor *et al.*, 2003; Acemoglu and Autor, 2011), represents a measure of the ability in analysing and solving complex problems, as well as in coordinating and integrating people, knowledge, and learning, which should be crucial especially under the uncertainty that typically characterises the innovation process. On the one hand, since these activities involve different entities often co-located in space (Jaffe *et al.*, 1993), a firm level approach *per se* would not be sufficient to capture how much the local composition in terms of tasks actually affects the inventive activities. On the other hand, as the introduction of a new product by a firm is not necessarily the outcome of an inventive activity, an aggregate regional level perspective is again more appropriate, likewise the use of the local patenting activity as a proxy of innovation to capture the actual ability to engender new valuable knowledge.

Anticipating our findings, our proposed measure of local abstract task intensity is a strong predictor of local patenting and this evidence is robust to a wide array of sensitivity checks. Hence, a task approach significantly improves the explanatory capacity of models based on the usual measures of regional human capital employed in the empirical literature. In particular, the local level of abstract task intensity better captures the endowment of capabilities that more effectively spur inventing activities.

The work is organised as follows: Section 2, discusses the theoretical background and places our contribution into the literature; Section 3 describes the data, the main variables construction, and some preliminary evidence; Section 4 and Section 5 report the empirical model and the results, respectively; Section 6 concludes.

2 Theoretical background

2.1 Innovation, geography and measures of the local pool of capabilities

Porter and Sölvell (2003) identify three essential features of the process of innovation that bridge it to geography. As a first point, they stress both the highly technical and economic uncertain nature of innovation and the risk containment nature of geography: the possibility of interaction in informal networks and in formal cooperation agreements would reduce the uncertainty by favouring a more rapid and effective trial-and-error problem-solving phase. Second, the process of innovation increasingly emerges outside the firm. Hence, the innovation process is highly interactive, and its output is often the product of the combination and deployment of the capabilities of different entities. Third, the process of innovation is rooted in informal exchange of tacit knowledge, and face-to-face contacts have been found to improve the efficacy of such an exchange.

From an evolutionary perspective of technological change, tacit knowledge is widely recognised as a central component of the learning economy and a key to value creation through the generation of original ideas and discoveries (Nelson and Winter, 1985). Although the general level of education and skills of the workforce is an essential precondition to ensure the ability of workers and firms to absorb both tacit and codified knowledge and engage in learning processes (Cohen and Levinthal, 1990), most of the tacit knowledge produced within firms arises in "doing" and "interacting" (Lundvall, 1988; Howells, 2000). Indeed, in order to be transferred, tacit knowledge requires social interaction and collaboration of individual workers within a shared social, organisational, and cultural context. Since social and cultural interactions are particularly enhanced by geographical proximity, for an effective transmission of tacit knowledge the regional/local dimension exerts a paramount importance (Maskell and Malmberg, 1999; Gertler, 2003; Boschma, 2005). It follows that aggregate location-level studies are better suited to capture these types of interactions, and production locations are focal for learning and knowledge creation (Florida, 1995).

In search of the role of specialised knowledge in the local inventive activity, many empirical studies have focused on the local industry composition, especially highlighting the role played by the presence of economic clusters (Glaeser *et al.*, 1992) and knowledge intensive industries (Barkley and Henry, 2005; Jara-Figueroa *et al.*, 2018). Given the centrality of the knowledge base of regions, however, an influential body of research has pointed at the paramount importance of dissecting the knowledge content of the local pools of labour (Thompson and Thompson, 1985). The call is for an increasing attention by policy makers to develop strategies which target specific occupations as bundles of potentially useful knowledge and skills, rather than just identifying a relevant industrial mix to promote (Feser, 2003; Markusen, 2004; Boschma and Fritsch, 2009). A parallel field of study has thus emerged in which human capital in the form of educated and skilled labour is perceived as the most important factor explaining the rate of inventive activities across territories, even after controlling for R&D inputs or other regional characteristics. Especially, Florida (2004) emphasises that regional development relies not on particular industries, but rather on creative individuals and occupations -i.e. the share of population employed in creative and innovative jobs such as sciences, engineering, education, culture, arts and entertainment - which are not industry specific and are the primary source of knowledge spillovers within and across re-

gions (Zucker *et al.*, 1998; Almeida and Kogut, 1999; Stolarick and Florida, 2006). Florida (2004) defines creative core occupations as those whose economic function is to create new ideas, new technology and/or new creative content; creative professional occupations as those involving complex problem solving, a great deal of independent judgment and high levels of education; and bohemian occupations as those engaged in artistic and cultural activities, who also may have an (indirect) impact on the local inventive capacity by further inspiring creative ideas, even if not directly involved in the innovation process and patenting. According to this theory, what mainly affects the innovative capacity of regions is the "people climate" rather than the "business climate". This implies that places with a good "people climate" tend to retain and attract creative talents, who, in turn, favour inventions and innovations. Hence, the local economic performance is an effect, and not a determinant, of the local agglomeration of inventive capabilities.
Boschma and Fritsch (2009) operationalise Florida's idea and show that creative people are attracted to more open and tolerant places as well as to areas with more job opportunities, though the evidence on the impact of the share of creative workers on regional growth is mixed. In particular, for German regions, they find that the positive effect of employees with high educational levels on patenting activity remained stronger than that of creative core and creative professional occupations, which suggests the need of better understanding and measuring the main sources of inventive processes and regional development. In another direction, for instance, a special attention has been recently paid to the local endowment of Science, Technology, Engineering and Math (STEM) jobs or technology-related occupations (i.e. the so called "techies"), considered as key factors of regional economic growth and competitiveness. Especially (though not exclusively) in the US, the evidence is in favour of this "STEM workforce" as an extensive and critical input to innovation (Peri *et al.*, 2015; Grinis, 2019; Deming and Noray, 2018; Harrigan *et al.*, 2021).

In order to explore the nexus between the local pool of capabilities and innovation, we move a step ahead of the existing literature by considering a task approach. This latter is expected to better capture some specific features of the local occupational base that can be essential to spur inventive activities. The task approach, by decomposing occupations into bundles of different work activities, has been originally proposed to better explain the labour market consequences of technology and trade (Autor *et al.*, 2003; Autor and Dorn, 2013; Fernández-Macías and Bisello, 2022).[1]

[1] In fact, what determines the degree of jobs' substitutability depends on the work method which, in turn, stems from the amount of routine that they entail together with the specific type of technological tools that are used (see Autor *et al.*, 2006; Autor and Handel, 2013 and, especially, Fernández-Macías and Hurley, 2017). Hence, technological change/trade could be especially detrimental for some specific occupations within an industry and for some specific workers within an occupation (Autor and Dorn, 2013; Autor *et al.*, 2015). Autor (2022), however, cautions about the complex relation between technological change and labour tasks, as the latter are not static and the former not only and not necessarily implies substitution of existing work activities, but may also involve a thorough transformation and reinstatement of job tasks. Also, the diffusion and evolution of Artificial

In this paper we claim that shifting the emphasis from occupations to their task content represents an opportunity to more accurately capture the effective human capital contribution to the inventive performances by firms and regions. Drawing on this, we contend that the standard and most widely used indicators for human capital based on education - e.g. the share of workers who attained at least a university degree - may not be adequate to properly detect the local endowment of inventive capabilities. Clearly, advanced education represents an essential condition for a region's absorptive capacity that facilitates the flow of knowledge, ideas, and learning. Nevertheless, we argue that the use of measures based on the educational level of the workforce would provide only partial information in this respect, as they would not capture neither workers' accumulated experience nor individual creativity (Florida, 2004). Moreover, they fail to consider that the way human capital resources are organised on the job matters to enable innovation, which implies that organisational capabilities are also essential (Fonseca *et al.*, 2019; Capriati and Divella, 2020).[2] Furthermore, possible implications in case of mismatch between educational qualifications and job positions must be considered. Indeed, the presence of over-education may lead to partly reallocate high-educated workers into less qualified occupations and more routinized tasks (Beaudry *et al.*, 2010; Brunetti *et al.*, 2020). In such cases, the information provided by the sole level of education could be incorrect. On the other hand, the focus on specific categories of qualified workers and their occupations could be equally misleading. Indeed, an effective workers' engagement in critical thinking and complex problem solving, which are at the core of invention, should be better observed at the level of specific tasks, that is, by focusing directly on the core activities that workers undertake in their jobs, instead of being generically inferred through their professional occupations. Moving from workers' education levels (or generic skill requirements) to their actual work activities on the job, then, can represent an effective analytical switch for explaining the achievement of heterogeneous performances by regions. In this respect, our work is the first contribution to focus on the relationship between the local task content and inventiveness.

2.2 The process of innovation and the importance of abstract tasks

With this work we aim at showing that the actual amount of abstract tasks deployed in the work activity of people in a specific area is strongly associated to the local performance in patenting.

In the literature, abstract tasks are theorized as non-routine cognitive work activities where technical/analytical and managerial/interactive capabilities are applied in varying and creative ways to solve problems and coordinate people, knowledge,

Intelligence (AI) engenders uncertainty about which tasks will be substitutable in the future.

[2] Within the resource-based view of the firm (Penrose, 2009), firms can also differ with respect to the capacity to coordinate, reconfigure and dynamically sustain the creativity endowment (Teece, 2007). Therefore, superior performance crucially depends on the capacity to manage and convert the knowledge embodied in workers into inventions and innovations.

and learning (Autor *et al.*, 2003; Acemoglu and Autor, 2011). Science/engineering, managerial and medical jobs are just few examples of professional occupations that can be considered as more intensive in abstract tasks (Fonseca *et al.*, 2019). In the empirical part of our work, the abstract task measure is retrieved from the work by Autor and Dorn (2013) and derives from a combination of two variables, namely: "GEDMath", measuring mathematical and formal reasoning; and "direction control and planning", which stands for managerial and interactive tasks. Together, these variables represent a specific subset of cognitive activities, i.e. the non-routine ones, which are very different in nature from other, routine and manual, tasks.
Tasks involving mathematical and formal reasoning should especially capture individuals' ability to think logically and analytically and, thus, their intuition and problem solving skills. Indeed, the solutions to mathematical problems are not always straightforward, and often require critical thinking and a deep understanding of the underlying concepts. Additionally, formal reasoning tasks, such as those found in logic and computer science, involve understanding abstract concepts and applying them in new and unique ways. All this contrasts with repetitive tasks, which involve performing the same actions over and over again with little variation.
Managerial and interactive activities are also essential functions that need to be performed in order to ensure a good organisation of people and work activities towards value creation. These tasks are also difficult to be considered repetitive as they necessarily involve a high degree of flexibility and adaptability. In fact, managerial tasks involve making decisions, leading and managing teams and people with different knowledge bases, all of which require a range of skills such as strategic thinking, communication and negotiation. Likewise, interactive tasks often involve working with different people and adapting to changing circumstances.[3]
Hence, by working on abstract tasks, individuals and teams should be required to use their own initiative and imagination to come up with new ideas and solutions that can drive innovation in a variety of fields. We thus claim that our proposed indicator of abstract task intensity can help capturing, beyond what can be measured by educational attainments or indirectly inferred by professional occupations, the local pool of capabilities that can be considered as fundamental in the process of innovation where the outcome is a brand-new product or, as in our case, a patented invention. Being the process of innovation characterised by a great amount of uncertainty, requiring the ability to critically analyse and solve complex problems, particularly by coordinating and integrating different pieces of knowledge and knowledge sources under fast-changing scenarios, the importance of the just mentioned abstract tasks is evident.
Pavitt (2003) corroborates this view by regarding the overall process of innova-

[3]The recent development of Artificial Intelligence increasingly changes the boundaries between routine and non-routine cognitive tasks (Autor, 2022). Nevertheless, several abstract tasks, especially those directed to the inventive activity, highly involve creativity, flexibility/adaptability and the need to interpret and apply context-specific information. These features make these tasks actually difficult to be replaced by AI systems (see Cirillo *et al.*, 2021, 2022).

tion as characterised by three overlapping sub-processes: i) cognitive, involving the production of scientific and technological knowledge; ii) organisational, which refers to the transformation of knowledge into working artifacts; iii) economic, concerning the response to and creation of market demand. Increased specialisation in the production of goods and knowledge has increased the complexity of goods, their knowledge base and the organisational routines for their development and commercial exploitation. Sub-processes i) and iii) are contingent and can be considered strictly dependent on the educational and work experience background acquired by inventors/innovators in the specific field in which the innovation is created. Sub-process ii), instead, is more transversal and requires a great amount of the general-purpose ability in coordinating and integrating specialised knowledge and learning in condition of uncertainty. In this direction, more recently, Deming (2017) has modeled social/interactive skills as fundamental in reducing coordination costs in team work to improve performance in production, showing that math-intensive and social/interactive skills are complements in the labour market.[4]

Although firm level evidence has shown that firms with a higher share of workers performing abstract tasks are the most productive, experience a market share increase over time and have a higher propensity to introduce new products (Fonseca *et al.*, 2018, 2019), [5] we believe that the role of economic geography needs to be taken into account.

First, the inventive performance of regions is not simply the sum of that of the companies located in them, but it is also remarkably affected by the network of interactions and knowledge exchanges that occur between both firms and people. These interactions mainly consist of exchanges of tacit rather than codified knowledge and, in most cases, do not involve formal cooperation agreements. Thus, the aggregate (regional) level of analysis allows to account for the role of knowledge spillovers that would be not captured with a firm-level analysis.

Second, a product innovation at firm level is not necessarily the outcome of an internal inventive activity as firms may introduce products that are new to them but not to the market. Therefore, an aggregate level of analysis is essential in assessing the local innovative performance and patenting is particularly useful as it measures new created knowledge that is not still existing anywhere else.

Finally, the simple aggregation of firm level data would leave out the innovation, knowledge production and coordination activity occurring in the public sector and

[4]Indeed, inventive activities have been increasingly carried out by teams of individuals belonging to different organisations due to the increasing need to rely on knowledge diversity and absorb external knowledge (Jones, 2009; Bercovitz and Feldman, 2011). However, along with enhancing the creativity potential, the increasing diversity of teams engenders organization and coordination costs (Aggarwal *et al.*, 2020). Rothwell (1977) coined the term "business innovators" to identify key individuals within the management structure who are not necessarily part of the inventive teams, but perform the task of coordinating the overall process of invention and innovation.

[5]Specifically, the authors have postulated, and partially confirmed with their evidence, that, while the degree of abstractism has a linear positive relationship with the propensity to innovate, the relationship between abstractism and share of sales from new products follows an inverted u-shaped relationship.

that is relevant for patenting activities (Aghion *et al.*, 2008).

3 Data and variables

To measure the task composition of the US CZs, we source data from the US 2000 census 5% and American Community Survey (ACS) 2005-2010 samples available from IPUMS USA (Ruggles *et al.*, 2018). These samples include homogeneous information on the 2000 Public Use Microdata Areas (PUMAs) that allows to aggregate individual level information on occupation typology and another bunch of individual characteristics (e.g. education and industry) at the CZ level on the basis of the work by Autor and Dorn (2013). The Autor and Dorn's definition of abstract, routine, and manual tasks combines into three dimensions the five tasks identified by Autor *et al.* (2003) and is exclusively based on work activities contained in the DOT 1977. As already mentioned, the abstract tasks measure is the average of two DOT variables as the core content of non-routine cognitive tasks: "GEDMath", capturing mathematical and formal reasoning requirements; and "direction control and planning", as a proxy of managerial and interactive tasks. Moreover, the manual tasks measure corresponds to the DOT variable detecting occupations' demand for "eye-hand-foot coordination". The routine tasks measure is a simple average of two DOT variables: "set limits, tolerances, and standards", which measures an occupation's demand for routine cognitive tasks; and "finger dexterity", which captures occupations' use of routine motor tasks.[6]

Measuring the Abstract Intensity of Occupations of the CZs - To measure the abstract intensity of each CZ we match individuals' occupational codes from IPUMS with the abstract, routine, and manual tasks measures at the occupational level available from Autor and Dorn (2013). We thus harmonise the occupational codes from IPUMS for the different years by means of the occ1990dd classification created by Autor and Dorn (2013) which groups individuals into 330 different 3-digit occupational codes. Then, we define the $abstract\ intensity$ of an occupation o as:

$$Abstract\_Intensity_o = \frac{Abstract\_Tasks_o}{Abstract\_Tasks_o + Routine\_Tasks_o + Manual\_Tasks_o}$$

For each occupation o, $Abstract\_Intensity_o$ measures the ratio of abstract to the total of abstract, routine, and manual task scores. The intensity, indeed, identifies the relative importance of abstract tasks in the total bundle of tasks defining the content of an occupation. Then, from IPUMS we retrieve the importance of

[6]The three task measures can be retrieved from David Dorn's web page. In Section O.2 of the Appendix we compare the abstract task measure with other measures of cognitive and interactive tasks available from the existing literature.

each occupation in each US CZ in terms of the share of workers s performing an occupation o in a CZ i and in a specific year t, and we compute a CZ level measure of $abstract\ intensity$ of the local labour force as:

$$Abstract\_Intensity_{it} = \sum_{o=1}^{O} s_{iot} * Abstract\_Intensity_o \ for \ i = 1, ..., CZ; t = 2000, 2005, 2010 \tag{1}$$

This measure is the weighted average of abstract task intensity of jobs in the CZ where weights s_{iot} are the share of each occupation o in the total CZ i's employment at time t. This intensity, then, is not the simple share of abstract workers like in Fonseca *et al.* (2019) and, in this respect, also differs from previous measures based on the share of particular types of occupations. Our abstract intensity measure takes into account the fact that any two occupations that can be similarly classified as highly skilled may substantially differ in terms of their task composition as well as any two CZs having a similar share of abstract workers may well differ in the distribution of abstract intensities across occupations and, hence, in their overall abstract intensity. Figure 2 shows and contrasts the spatial distribution of our proposed measure of abstract intensity at the CZ level, for the first and last year in which we have managed to compute that, namely in 2000 and 2010. The two maps in the Figure are constructed by dividing the CZs by quintiles of the measure of abstract intensity, with darker shades representing areas characterized by higher levels of local abstract intensity. As can be noticed, over time, abstract intensity has become more spatially concentrated in the Eastern part of the country, mainly due to a reduction experienced by North-Western CZs.

Measuring the Innovation Activity of the CZs - We rely on the number of patents granted to resident inventors as a measure of the CZs' innovation activity. We are aware that patents are affected by inherent limitations. Patents represent just an intermediate output of the innovation process and, for this reason they may greatly differ in their economic impact; moreover, the propensity to patent varies significantly between industries and firms of different sizes (Griliches, 1990). Despite these shortcomings, a specific characteristic of patents, relevant for our study, is that they are good proxies of inventions concerned with the provision of new goods and services. In this direction, eminent literature has corroborated their reliability as a measure of local innovation (Acs *et al.*, 2002). Hence, patents are widely adopted by prominent studies in economic geography as measure of new and commercially exploitable pieces of knowledge (Porter, 2003; Crescenzi *et al.*, 2007; Hunt and Gauthier-Loiselle, 2010; Balland *et al.*, 2015; Balland and Rigby, 2017; Castaldi *et al.*, 2015; Rodríguez-Pose and Wilkie, 2019).
For the purpose of our study, then, we consider the number of patents granted between 2000 and 2015. In the US, patent data at the county level are provided by the United States Patent and Trademark Office (USPTO). The geographical

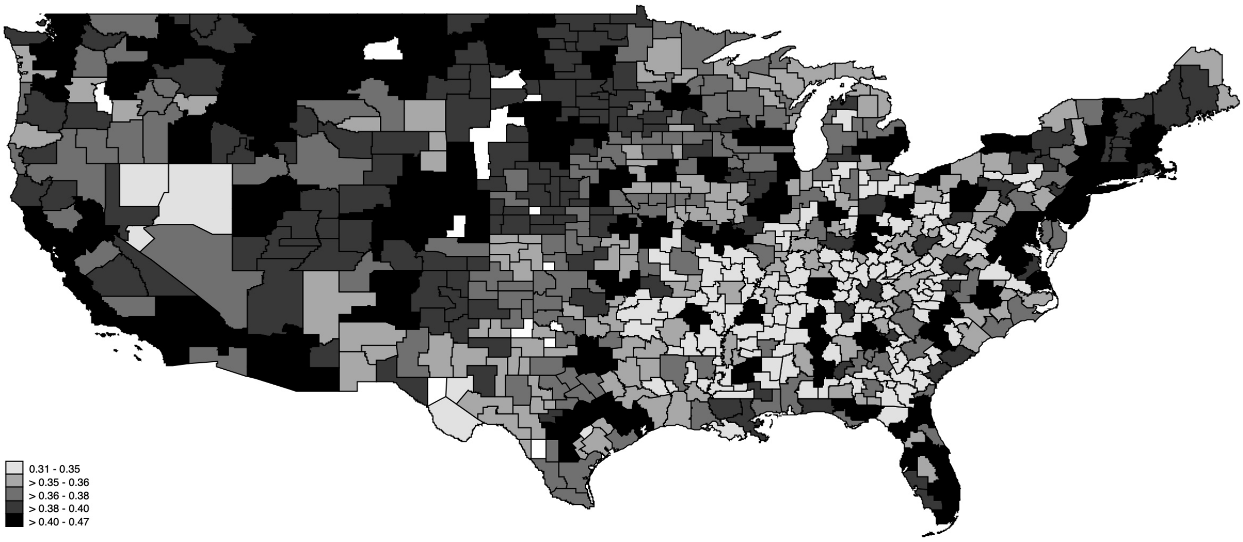
attribution to different cities and counties is based on the residence of the first-named inventor on the patent document at the time of grant (see USTPO, 2000). So, in the US, patent statistics at county level are not based on patent applications (as in Europe), but on patent grants. As our units of analysis are the US CZs, we aggregate the county level information at the CZ level.

The CZs identify local labour markets in the US, therefore patents attributed to them provide a good approximation of regional inventive activities. Indeed, the geographical aggregation alleviates the bias due to possible differences between the county of residence of inventors and that of their employment, i.e. where their inventive activities do actually take place. In the end, we manage to compute the number of patents granted for 721 CZs over 741. The 20 missing CZs correspond to counties for which no patent has ever been recorded over the entire 2000-2015 period and which thus do not appear in the USPTO record of patents by county.

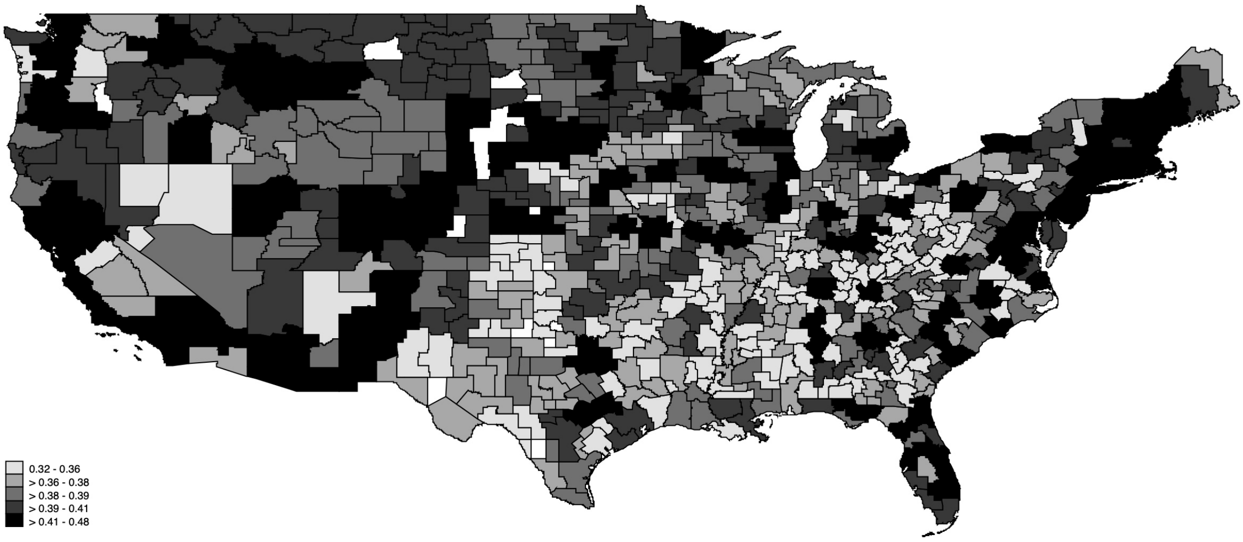
Hence, looking at the number of granted patents at the CZs level in 2000 and 2010, darker shades in the two maps of Figure 3 stand for areas reporting higher presence of inventors. As can be seen, there seems to be some heterogeneity across US main regions: there is evidence of innovation persistence in Western CZs, while, moving from the Central to the Eastern part of the country, a process of innovation diffusion seems at work since new CZs have been able to enter among the top inventing places in the US (see also Andrews and Whalley (2021))[7]. All in all, the spatial pattern of our measures of abstract intensity and patenting at local level, as depicted by Figures 2 and 3, appears to be somehow related: indeed, both measures tend to move and cluster in the same CZs.

[7]This pattern is confirmed if patents are normalised over population (see Figure O.4 in the Appendix).

Figure 2: Abstract Intensity across US CZs in 2000 and 2010



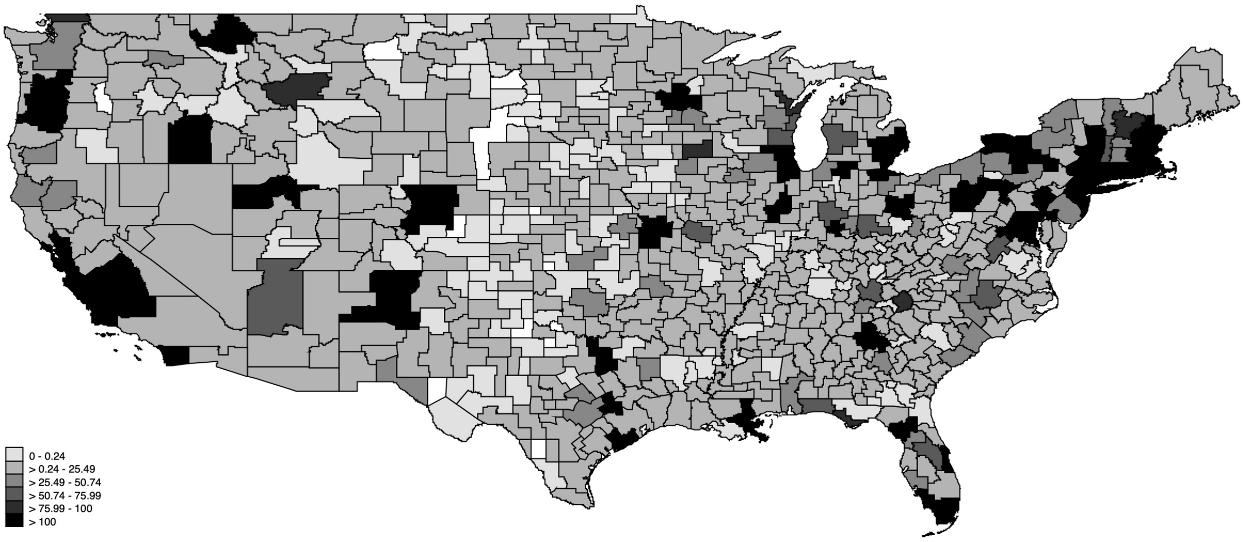
(a) Abstract intensity 2000



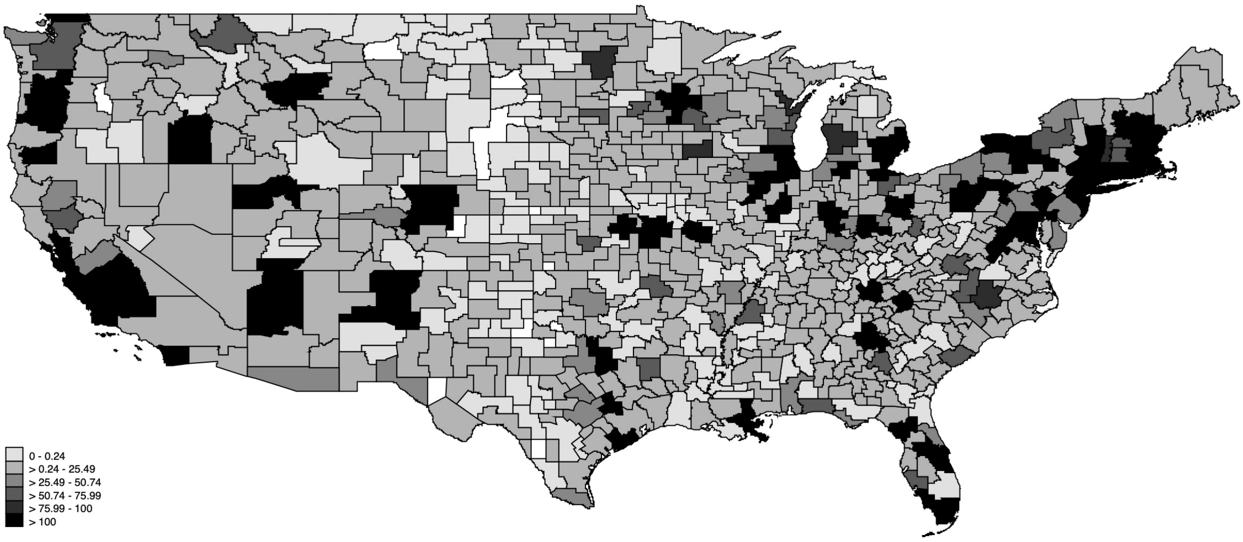
(b) Abstract intensity 2010

Source: IPUMS, Autor and Dorn (2013). Own calculations. For a better readability, we have excluded Alaska and Hawaii from the maps.

Figure 3: Patents Count across US CZs in 2000 and 2010



(a) Patents 2000



(b) Patents 2010

Source: IPUMS, Autor and Dorn (2013). Own calculations. For a better readability, we have excluded Alaska and Hawaii from the maps.

4 Empirical model

To evaluate the relation between the local task composition and patenting in the US CZs we estimate a negative binomial regression model to account for the count and over-dispersed nature of the dependent variable. The baseline specification is as follows:

$$E(Patents_{i\ t_0+\tau/t_0+\tau+2}) = exp[\beta + \gamma * Abstract\_Intensity_{i\ t_0} + \delta' X_{i\ t_0}]\epsilon_{it} \quad (2)$$

where $Patents_{i\ t_0+\tau/t_0+\tau+2}$ is the total number of patents granted to CZ i over the three-year time span $t_0 + \tau/t_0 + \tau + 2$ while $Abstract\_Intensity_{i\ t_0}$ is our main variable of interest that measures the weighted average of the abstract intensity across all occupations and workers in the CZ at the initial period t_0 (see equation 1). Concerning this point, it needs to be stressed that the choice of the past values at which considering the relevant local characteristics depends on the time lag occurring between patent applications and the patent grants that we actually observe. Figure O.5 in the Appendix shows that during most of our sample period the average pendency is around 35 months, hence, we set $\tau = 3$, choosing a conservative three-year time span for local labour task composition to affect the number of granted patents. We, then, consider three different waves of observations: $t_0 = 2000$ with patents aggregated over the 2003-2005 period; $t_0 = 2005$ with patents aggregated over the 2008-2010 period; $t_0 = 2010$ with patents aggregated over the 2013-2015 period. We alternatively treat such three waves as single or pooled cross-sections in the estimations. It is also worth highlighting that we aggregate the number of patents over three years in order to reduce the number of $0s$ in our main outcome variable. As shown in Table O.1 in the Appendix, the three-year aggregation reduces by one half the share of $0s$ in the sample. In the robustness checks, however, we show that our results are not affected by a different span of aggregation.

The vector $X_{i\ t_0}$ includes a set of controls that account for further heterogenous initial conditions and potential confounding factors, other than abstract intensity, which are identified according to the existing literature on innovation determinants. These account for the CZs' size measured by means of the log of population, $Pop_{i\ t_0}$, retrieved from the US Census Bureau, Population Division. Then, from IPUMS, we compute the CZs' per capita wage income, $Wage\_Income_{i\ t_0}$, the share of employment in high-tech industries, $Empl\_sh_{i\ t_0}^{HighTech}$ [8] and the share of college graduates in the labour force, $Graduate\_sh_{i\ t_0}$[9]. Unfortunately, we have no information on the CZ level R&D expenditure; nonetheless, from the

[8] We apply the definition of high-tech industries suggested by the Bureau of Labor Statistics presented in Wolf and Terrell (2016) and based on the share of STEM occupations. Hence, industries are defined as "high-tech" if they have a share of STEM workers that is two and a half times the national average (industries in which at least 14.5 percent of jobs is in STEM occupations).

[9] The share of graduates is measured as the share of individuals having completed 5 or more years of college.

National Science Foundation (NSF), we draw the federal state level business and public expenditure in R&D over GDP, namely $R\&D\_GDP\_sh_{s\ t_0}^{StateIndustrial}$ and $R\&D\_GDP\_sh_{s\ t_0}^{StatePublic}$. The inclusion of the State level R&D expenditures accounts for heterogeneous state-level innovation systems and policies which importantly affect the inventive capacity at the local level (Wilson, 2009; Chang, 2018). Table O.2 in the Appendix shows descriptive statistics for the left- and right-hand side variables of model 2 and Table O.3-O.4 show correlations and VIF test among the latter.
Before turning to the presentation of the results, it is worth discussing the potential role of reverse causality in our empirical framework. On the basis of Florida (2004), the existing evidence shows that the presence of job opportunities is equally important as the presence of an open and tolerant climate in attracting specific types of workers to a location (Boschma and Fritsch, 2009). Hence, as job opportunities are highly dependent on regions' economic performance, it cannot be excluded that reverse causality between patenting and the task composition of CZs may be at work. However, in the robustness checks and in the Appendix (Section O.2) we provide evidence supporting the direction of the nexus going from task composition to patenting.

5 Results

Table 1 presents the baseline results from the estimation of model 2 in Columns [1]-[4]. In all estimates, we cluster standard errors at State level to account for potential correlation across the CZs within the same States[10].

The results show that the coefficient of our variable of main interest is always highly significant and positive, therefore confirming a relevant role of abstract intensity in the local pool of occupations with respect to local patenting.
Turning to controls, both their sign and significance are as expected. Indeed, CZ's size (population) and per capita wage income, as well as the share of employees in high-tech industries and the share of graduates in the local labour force are all positively associated to patent counts. In particular, the results on the share of employment in high-tech industries, as well as those regarding the significant role of state business R&D expenditures are in line with Acs *et al.* (2002), while the emerged positive role of the share of graduates in the labour force is in line with Crescenzi *et al.* (2007). The association between patents and average wage income at the local level is not always significant, but its positive sign seems to be in line with the evidence provided by Porter (2003).[11]

[10] It should be also noticed that a certain number of CZs fall across multiple States. In that case, we attribute them to the State where most of the population is located. Removing the cluster, however, does not alter the significance of our baseline findings.

[11] The last coefficient refers to the estimates of the log-transformed over-dispersion parameter, $ln(\alpha)$, which turns out highly significant. As can be seen in the bottom part of the Table, the implied α is reported together with the likelihood ratio test for the null hypothesis that $\alpha = 0$. According to the associated Chi-squared statistics with one degree of freedom and the corresponding p-value, the

Table 1: Abstract intensity and patent count in US CZs

	[1] 2000	[2] 2005	[3] 2010	[4] Pooled
$Abstract\_Intensity_{t_0}$	12.582***	12.387**	12.956***	13.181***
	[4.025]	[5.791]	[4.811]	[4.111]
$Wage\_Income_{t_0}$	0.35	1.155**	0.618	0.65
	[0.515]	[0.530]	[0.495]	[0.463]
Pop_{t_0}	0.754***	0.793***	0.831***	0.799***
	[0.067]	[0.064]	[0.054]	[0.057]
$Empl\_sh_{t_0}^{High-Tech}$	14.306***	9.967**	7.384**	10.415***
	[3.886]	[4.021]	[3.050]	[3.468]
$Graduate\_sh_{t_0}$	16.307**	12.642**	18.480***	15.530***
	[6.443]	[6.041]	[6.147]	[5.585]
$R\&D\_GDPsh_{t_0}^{State-Business}$	27.278**	27.410**	34.223***	29.123***
	[10.808]	[11.598]	[7.642]	[9.060]
$R\&D\_GDPsh_{t_0}^{State-Public}$	-0.029	-0.067	-0.144**	-0.082
	[0.091]	[0.081]	[0.059]	[0.068]
$ln(\alpha)$	0.571***	0.714***	0.692***	0.663***
	[0.072]	[0.071]	[0.059]	[0.059]
Observations	721	721	721	2,163
PseudoR2	0.152	0.149	0.148	0.15
α	1.771	2.041	1.997	1.940
Chi2	916.1	905.1	657.1	1141
P-value	0	0	0	0

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets clustered at the level of Federal State. Time dummies included in the specification of Column [4].

Concerning the magnitude of the effect, the coefficient estimates of the pooled model of Column [4] and the descriptive statistics of Table O.2 in the Appendix imply that, *ceteris paribus*, a one standard deviation increase in the abstract intensity at the local level is associated with an increase in the number of patents of 0.395. To better grasp the relevance of the contribution of local abstract intensity to patenting, Figure O.6 in the Appendix shows the average count prediction of patents by different levels of abstract intensity computed at the means of the remaining covariates. Moving from the minimum to the maximum of observed abstract intensity in our sample implies a great variation in the number of patents, though the estimates of the marginal effect are much less precise for the highest levels of our abstract intensity measure.

5.1 Robustness checks

To assess the strength of our baseline findings, we run a wide array of robustness checks. We focus on the pooled model of Column [4] of Table 1 and for the sake of brevity we omit to show baseline controls that, nonetheless, are included in all the specifications unless differently specified.[12]

Omitted variables and confounding factors - To better assess the robustness of our findings, in Table 2 we report the results obtained by splitting the industry control (i.e. the share of employment in high-tech manufacturing and service industries) inserted in our baseline specification in two separate indicators for high-tech manufacturing and service industries (Column [1]). Then, by resorting to the OECD industry classification based on R&D intensity, we also replicate our baseline estimation by alternatively employing the share of high R&D intensive (manufacturing and service) industries (Column [2]) and, again, the share of R&D intensive manufacturing and service industries separately considered (Column [3]). Hence, exploiting a finer detail of the classification, we also add the share of medium R&D intensive manufacturing industries [13] and that of low R&D intensive manufacturing and services ones (Column [4]). As can be seen, our indicator of abstract intensity turns out to be robust to the inclusion of any control

hypothesis is strongly rejected, so that we can conclude that alpha is non-zero and that the negative binomial model is more appropriate than the Poisson model.

[12]Beyond the main sensitivity analyses shown in the remainder of this Section, we have run the following further robustness checks: we i) alternatively include State- and CZ-level controls; ii) disaggregate and separately include the single components of our abstract intensity measure; iii) consider the number of patents over local population as alternative dependent variable; iv) reintroduce CZs with always 0 patent records; v) exclude self-employment from the IPUMS original sample; vi)include the interaction terms between time dummies and US main region dummies - Northeast, Midwest, South and West - or, alternatively, CZ population quintile to account for any potential specific trend of patenting activity not driven by the local abstract intensity; vii) add auto-regressive spatial terms to our baseline specification; viii) allow for alternative time lags between local initial conditions and patent grants. In all cases the evidence obtained is consistent with the baseline one. This set of results is presented in Section O.2, Table O.5, in the Appendix.

[13]Please, note that no service industry is classified as medium R&D intensive.

for the industrial structure and, as far as the latter is concerned, the share of high-tech/high R&D intensive manufacturing industries emerges as the most important driver of patenting across CZs.
As we claim that abstract intensity has a crucial role in new knowledge creation, we need to ensure that we are not omitting other features of the local labour force which could represent competing determinants of local patenting activity. To this aim, in Table 3 we alternatively account for the CZs' level share of STEM, technical, professional, non-manual and abstract workers (Columns [1]-[10]).[14] In all cases our abstract intensity measure is highly significant and, in particular, captures the role of the share of non-manual workers which loses its significance when our preferred measure is included. Also, the abstract intensity indicator, based on scores, performs better than the share of abstract workers (workers whose job's abstract intensity is above the median).[15] In Column [11]-[12] we proceed by including the share of core, professional and bohemian creative workers so as measured by Boschma and Fritsch (2009).[16] Interestingly enough, we find that the shares of creative professionals and bohemians are significantly and positively related to the patenting performance of CZs. However, when our abstract intensity indicator is included, the coefficients' size and significance of the three shares all decline. This suggests that, indeed, the local task intensity is capturing a large part of the extent of creativity deployed on the job by the local labour force. Furthermore, in Table 4 we compare the performance of our measure to the performance of other local task composition indicators. We show that our indicator outperforms other local task measures available from the literature and based on the cognitive and interactive abilities and on the STEM skills and knowledge competencies required by an occupation.[17] This evidence and the baseline one are confirmed when abstract, manual

[14]STEM workers are classified on the basis of their employment in STEM occupations so as defined by O*NET ($https://www.onetonline.org/find/stem?t = 0$). Professionals are all workers performing a professional activity pertaining to the major group 2 of the ISCO88 occupational classification. Technical Workers are the subset of STEM workers pertaining to ISCO88 major group 3. Non manual workers are all workers in ISCO88 major groups 7-9 that are not involved in strictly low skilled manual activities.

[15]We also experienced with the share of workers whose job's abstract intensity is in the top 33% and top quartile of the abstract intensity distribution across occupations and results are unchanged.

[16]To this purpose we match the occ1990dd classification at our disposal with the ISCO88 one and closely apply their definition of the three groups. More specifically, $CoreCreative\_sh_{t0}$ measures the share of workers employed in ISCO88 occupations: 211-214, 221, 222, 231-235, 243, 244, 247; $ProfessionalCreative\_sh_{t0}$ measures the share of workers employed in ISCO88 occupations: 111-131, 223, 241, 242, 311-324, 341-343, 345, 346; $Bohemian\_sh_{t_0}$ measures the share of workers employed in ISCO88 occupations: 245, 3131, 347, 521.

[17]Cognitive tasks are measured as in Yamaguchi (2018) using the following set of abilities available from O*NET 2000: *Fluency of Ideas, Originality, Problem Sensitivity, Deductive Reasoning, Inductive Reasoning, Information Ordering, Category Flexibility, Mathematical Reasoning, Category Flexibility, Number Facility, Memorization, Speech Recognition and Clarity*; interactive tasks are measured as in Peri and Sparber (2009) with the following set of abilities available from O*NET 2000: *Written Comprehension, Oral Expression, Written Expression*; STEM skills and knowledge competencies are measured as in Lo Turco and Maggioni (2022) from the O*NET job skill and knowledge base descriptors that are directly related to STEM: knowledge items concern *Physics,*

and routine tasks are computed from the O*NET database according to the definitions by Acemoglu and Autor (2011). The evidence conveyed in these two Tables is further corroborated in Tables O.6 and O.7 in the Appendix when region-year fixed effects are added to the specifications. Worthy of note is the significant role of cognitive and STEM tasks that emerges when purging from heterogeneity in the regional patenting time evolution, which may be affected by different technological trajectories of regional clusters of innovation. Nonetheless, our main finding remains unaffected [18].

Innovation dynamics and potential reverse causality - In Table 5 we test our baseline evidence by using a dynamic panel GMM system estimation (Blundell and Bond, 1998). Hence, we include the log of 1 plus the number of granted patents among the right-hand side variables and, to avoid serial correlation, we use annual observations on granted patents by CZs. As shown in Column titles, we consider from a one to a three-year time lag between the left and the right-hand side variables in Columns [1]-[3] and, in Column [4], we repeat the estimate of Column [1] with the exclusion of year 2000, therefore leaving an annual panel with yearly consecutive observations. The standard tests are reported at the bottom of the Table and are in line with expectations. The coefficient estimates corroborate our baseline finding on the importance of abstract intensity for local patenting. In the last Column, we also repeat the estimate of Column [1] by adding a one-period ahead value of abstract intensity, thus conducting a kind of exogeneity test like the one proposed by Wooldridge (2010), though in a static panel data framework, to account for potential feedback effects from the outcome variable on covariates. The non-significance of the lead term excludes a problem of reverse causation between patent activities and abstract intensity and, hence, the presence of cumulative two-way linkages between the two variables. To further inspect the identification of the effect running from the task composition to the patenting activity, in Column [6] we perform a placebo test by randomly assigning local levels of abstract intensity to CZs. The results point to a non-significant coefficient for our variable of interest, which further corroborates our baseline findings. Finally, in Table 6 we present an empirical exercise where we regress the change in the CZ's abstract intensity between t and $t+1$ on the level of patents in $t-1$ (Columns [1] and [2]), and the change in the CZ's patents between t and $t+1$ on the level of abstract intensity in $t-1$ (Columns [3] and [4]). The Table reveals that, across US CZs, past patenting activity does not predict the future evolution of the local abstract intensity, while the past CZ's occupational composition in terms of abstract tasks does predict the evolution of patenting activity.

Engineering and Technology, Computer Electronics and Mathematics, skill items concern *Science*, *Mathematics* and *Critical Thinking*.

[18] In Table O.8 in the Appendix we also report the results obtained by comparing levels of abstract tasks to other task (i.e. cognitive and interactive) levels, which are also consistent with our main evidence.

Table 2: Abstract intensity and patent count in US CZs - Industry composition

	[1]	[2]	[3]	[4]
$Abstract\_Intensity_{t_0}$	12.931***	17.918***	17.632***	15.901***
	[4.011]	[4.486]	[4.728]	[4.661]
$Empl\_sh^{High-Tech}_{Man\ t_0}$	10.242***			
	[3.500]			
$Empl\_sh^{High-Tech}_{Serv\ t_0}$	12.404			
	[7.745]			
$Empl\_sh^{High-Tech\ OECD}_{t_0}$		5.306***		
		[1.580]		
$Empl\_sh^{High-Tech\ OECD}_{Man\ t_0}$			5.179***	6.044***
			[1.651]	[1.932]
$Empl\_sh^{High-Tech\ OECD}_{Serv\ t_0}$			9.991	11.533
			[7.384]	[8.260]
$Empl\_sh^{Medium-Tech\ OECD}_{Man\ t_0}$				-1.572
				[2.534]
$Empl\_sh^{Low-Tech\ OECD}_{Man\ t_0}$				1.466
				[1.586]
$Empl\_sh^{Low-Tech\ OECD}_{Serv\ t_0}$				1.288
				[1.443]
$ln(\alpha)$	0.663***	0.667***	0.667***	0.662***
	[0.059]	[0.059]	[0.059]	[0.058]
Observations	2,163	2,163	2,163	2,163
PseudoR2	0.15	0.15	0.15	0.15
α	1.94	1.948	1.948	1.938
Chi2	1154	1217	1217	1410
P-value	0	0	0	0

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets clustered at the level of Federal State. Baseline controls are included in each specification.

Table 3: Abstract intensity and patent count in US CZs - occupational composition

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
$Abstract\_Intensity_{t_0}$		16.539***		11.794**		13.219***		12.988***		13.630***		12.409***
		[5.095]		[4.847]		[4.073]		[4.040]		[4.189]		[4.244]
$Abstract\_sh_{t_0}$	0.875	-3.357										
	[2.081]	[2.461]										
$CoreCreative\_sh_{t0}$			4.481	0.556								
			[3.299]	[3.429]								
$ProfessionalCreative\_sh_{t0}$			3.611**	-0.228								
			[1.798]	[2.275]								
$Bohemian\_sh_{t_0}$			15.396*	13.579*								
			[8.096]	[8.054]								
$STEM\_sh_{t_0}$					-0.646	0.076						
					[0.921]	[0.928]						
$Techies\_sh_{t_0}$							-1.168	-0.515				
							[1.068]	[1.051]				
$Professional\_sh_{t_0}$									0.08	-0.391		
									[0.593]	[0.552]		
$Non\ Manual\_sh_{t_0}$											1.635**	0.726
											[0.766]	[0.708]
Observations	2,163	2,163	2,163	2,163	2,163	2,163	2,163	2,163	2,163	2,163	2,163	2,163
PseudoR2	0.148	0.151	0.15	0.151	0.148	0.15	0.148	0.15	0.148	0.15	0.148	0.15
α	1.973	1.932	1.942	1.934	1.972	1.94	1.97	1.94	1.972	1.94	1.965	1.939
Chi2	1250	1162	1388	1517	1246	1154	1235	1157	1227	1140	1222	1164
P-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets clustered at level of Federal State. Time dummies and baseline controls included in all specifications. $Abstract\_sh_{t_0}$ measures the share of workers employed in occupations whose abstract intensity is above the median; $CoreCreative\_sh_{t0}$, $ProfessionalCreative\_sh_{t0}$ and $Bohemian\_sh_{t_0}$ respectively measure the share of workers employed in core, professional and bohemian occupations according to the definition by (Boschma and Fritsch, 2009); $STEM\_sh_{t_0}$, $Techies\_sh_{t_0}$, $Professional\_sh_{t_0}$ and $Non\ Manual\_sh_{t_0}$ measure the share of workers employed in STEM, technical, professional and non manual occupations.

Table 4: Abstract intensity and patent count in US CZs - task composition

	[1]	[2]	[3]	[4]	[5]	[6]
					Abstract Intensity from O*NET Scores	
$Abstract\_Intensity_{t_0}$				19.920***		
				[5.264]		
$Abstract\_Intensity_{t_0}^{O*NET}$					9.445**	36.538***
					[4.437]	[8.690]
$Cognitive_{t_0}$	54.839			52.94		90.869
	[35.624]			[82.593]		[79.912]
$Interactive_{t_0}$		16.201		-71.361**		-165.540***
		[17.427]		[35.997]		[47.281]
$STEM_{t_0}$			46.34	23.974		40.35
			[44.849]	[49.925]		[50.495]
Observations	2,163	2,163	2,163	2,163	2,163	2,163
PseudoR2	0.148	0.148	0.148	0.151	0.149	0.151
α	1.966	1.971	1.968	1.923	1.96	1.927
Chi2	1269	1345	1327	1330	1279	1287
P-value	0.00	0.00	0.00	0.00	0.00	0.00

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets clustered at level of Federal State. Time dummies and baseline controls included in all specifications. $Cognitive_{t_0}$, $Interactive_{t_0}$ and $STEM_{t_0}$ respectively measure the CZ's level of cognitive, interactive and STEM tasks computed according to equation 1 when the abstract intensity is alternatively substituted by the remaining two task measures.

Table 5: Abstract intensity and patent count in US CZs - dynamic panel estimates and Placebo test

	[1]	[2]	[3]	[4]	[5]	[6]
			Dynamic panel			Placebo
	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 1$	$\tau = 1$	
				Excl. 2000	Lead Abstr.Int.	
$Abstract\_Intensity_{t0}$	5.499***	3.806***	4.581***	5.092***	13.988**	2.409
	[1.091]	[1.071]	[1.137]	[1.053]	[5.924]	[2.249]
$Wage\_Income_{pc\ t0}$	0.495***	0.696***	0.643***	0.628***	1.524**	1.076**
	[0.179]	[0.177]	[0.184]	[0.173]	[0.654]	[0.472]
Pop_{t0}	0.361***	0.352***	0.371***	0.365***	0.322***	0.771***
	[0.030]	[0.027]	[0.028]	[0.030]	[0.039]	[0.057]
$Empl\_sh_{t0}^{High-Tech}$	3.368***	2.927**	3.267***	3.069***	3.792***	11.355***
	[1.215]	[1.189]	[1.260]	[1.151]	[1.324]	[3.751]
$Graduate\_sh_{t0}$	6.565***	7.412***	8.461***	5.995***	12.538***	25.525***
	[1.737]	[1.697]	[1.747]	[1.662]	[3.967]	[4.212]
$R\&D\_GDPsh_{t0}^{State-Business}$	17.310***	16.729***	18.158***	17.377***	14.859***	29.181***
	[3.478]	[3.405]	[3.540]	[3.542]	[3.673]	[9.790]
$R\&D\_GDPsh_{t0}^{State-Public}$	0.000	0.018	0.013	0.005	0.043	-0.081
	[0.036]	[0.035]	[0.037]	[0.035]	[0.073]	[0.073]
$Log(1 + patents_{t0})$	0.065*	0.093***	0.047	0.065*	0.085	
	[0.038]	[0.035]	[0.033]	[0.038]	[0.056]	
$Abstract\_Intensity_{t+\tau+1}$					-26.306	
					[17.442]	
Observations	5,047	5,047	5,047	4,326	4,326	2,163
Number of CZs	721	721	721	721	721	
Hansen	13.980	8.969	5.636	13.980	9.530	
Degrees of Freedom	10	10	10	10	6	
P-Value	0.174	0.535	0.845	0.174	0.146	
AR(1)	-14.020	-14.040	-13.590	-14.000	-3.384	
P-Value	0.000	0.000	0.000	0.000	0.001	
AR(2)	1.859	-1.993	1.106	1.844	1.536	
P-Value	0.063	0.046	0.269	0.065	0.124	
PseudoR2						0.148
α						1.968
Chi2						1195
P-value						0.000

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets. Time dummies included in all specifications. First and second lags of the variables in levels and differences used as instruments for auto-regressive term in all specifications.

Table 6: Predictors of the evolution of the local task composition and patenting

	[1]	[2]	[3]	[4]
	Δ $Abstract\_Intensity_{t/t+1}$		Δ $Patents_{t/t+1}$	
$Patents_{t-1}$	0.000	0.000		
	[0.000]	[0.000]		
$Abstract\_Intensity_{t-1}$			589.212***	308.558**
			[84.860]	[136.573]
Observations	1,442	1,442	1,442	1,442
R-squared	0.008	0.022	0.033	0.056
Controls	No	Yes	No	Yes
Time Dummies	Yes	Yes	Yes	Yes

* p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in brackets clustered at level of Federal State. Time dummies included in all specifications.

6 Discussion and conclusions

In this paper, we contribute to the existing literature by adopting a task approach to measure the local pool of abstract capabilities and detect their relation with patenting at the level of US Commuting Zones during the period 2000-2015. We consider a measure of the analytical and coordination - abstract - work activities required in a job that can be crucial for the process of innovation. We find that CZs' abstract intensity is a strong predictor of local patenting. This evidence survives a wide array of robustness checks and implies that the extent to which workers are engaged in abstract activities on their job is a further relevant factor that can contribute to boost local inventive capabilities and innovation.

The main policy implications of our work point to the need of increasing the incidence of abstract job tasks on local economies with a view to promoting technological innovations and, then, economic growth. For this purpose, a mix of policies is needed: policies aimed at strengthening the high-tech manufacturing base of local economies by sustaining R&D and inventive activities are crucial; however they should be coupled with measures fostering not only education, but also training programs and the creation and enlargement of knowledge networks at local level. Such a policy mix could induce more firms to change their work organisation and structure in favour of abstract tasks. Educational and training programmes, then, should be focussed on both analytical and coordination abilities. The former can be achieved mainly through higher education curricula, while the latter can be enhanced by complementary training programs, especially directed to the development of specific soft skills (such as leadership, flexibility, and decision making). These skills are important both for improving the capability of coordinating people and work activities within firms and for enhancing interactions with external actors within local knowledge networks.

A few limitations remain in our study. First, job tasks are measured at the occupational level, which does not allow us to examine the extent to which the content of work varies across markets, even within the same occupations. Regarding this, the future availability of data or more granular approaches to task measurement, i.e. not fixed at the occupational level, would help to improve our analysis in this direction. Also, access to matched employer-employee databases joint with information on the firm-to-firm input-output networks would represent a way to enrich the analysis of the mechanisms at play. Second, the results provided might be specific to the context examined and thus there is the need of validating this evidence on other economies for which similar data are available. Finally, although we show some evidence corroborating the interpretation of our findings in terms of an effect running from the local abstract intensity to patenting activity, the present study lacks an empirical strategy to identify a causation. We, then, identify in these limitations the future avenues for research.

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O.1 Descriptive Statistics

Table O.1: Share of 0s in patents count across US CZs

3-Year Aggregations	Yearly
2003-2005	**2003**
0.19	0.41
2008-2010	**2008**
0.26	0.39
2013-2015	**2005**
0.23	0.42

Table O.2: Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max	Observations
$Patents_{i\ t_0+\tau/t_0+\tau+2}$	78.00	539.43	0.00	15665	2163
$Abstract\_Intensity_{it_0}$	0.35	0.03	0.29	0.45	2163
$Wage\_Income_{it_0}$	9.52	0.22	8.89	10.41	2163
Pop_{it_0}	11.64	1.59	7.47	16.70	2163
$Empl\_sh_{it_0}^{High-Tech}$	0.06	0.02	0.02	0.22	2163
$Graduate\_sh_{it_0}$	0.06	0.02	0.02	0.19	2163
$R\&D\_GDPsh_{st_0}^{State-Business}$	0.01	0.01	0.00	0.05	2163
$R\&D\_GDPsh_{st_0}^{State-Public}$	3.45	1.08	1.19	9.85	2163

Table O.3: Correlations

obs=2163	$Abstract\_Intensity_{t_0}$	$Wage\_Income_{t_0}$	Pop_{t_0}	$R\&D\_GDPsh_{t_0}^{State-Business}$	$R\&D\_GDPsh_{t_0}^{State-Public}$	$Empl\_sh_{t_0}^{High-Tech}$	$Graduate\_sh_{t_0}$
$Abstract\_Intensity_{t_0}$	1						
$Wage\_Income_{t_0}$	0.63	1					
Pop_{t_0}	0.27	0.46	1				
$R\&D\_GDPsh_{t_0}^{State-Business}$	0.12	0.16	0.20	1			
$R\&D\_GDPsh_{t_0}^{State-Public}$	0.19	0.19	-0.06	0.03	1		
$Empl\_sh_{t_0}^{High-Tech}$	0.33	0.43	0.26	0.06	0.00	1	
$Graduate\_sh_{t_0}$	0.75	0.70	0.47	0.21	0.23	0.30	1

Table O.4: VIF among right hands side variables

Variable	VIF	1/VIF
$Abstract\_Intensity_{t_0}$	2.75	0.36
$Wage\_Income_{t_0}$	3.44	0.29
Pop_{t_0}	1.53	0.66
$Empl\_sh_{t_0}^{High-Tech}$	1.32	0.76
$Graduate\_sh_{t_0}$	3.32	0.30
$R\&D\_GDPsh_{t_0}^{State-Business}$	1.07	0.93
$R\&D\_GDPsh_{t_0}^{State-Public}$	1.21	0.82
Mean VIF	2.06	

O.2 Further Robustness Checks

In Table O.5 we run a wide array of robustness checks. We focus on the pooled model of Column [4] of Table 1 in the Text and for the sake of brevity we omit to show baseline controls that, nonetheless, are included in all specification unless differently specified.

First, in Column [1] of panel A we show that, when only the abstract intensity measure is included in the model, its coefficient remains highly significant and large in magnitude, while the inclusion of the State level R&D variables, which are meant to capture the importance of the national innovation systems, in Column [2] does not alter its significance and size. On the contrary, in Column [3] the inclusion of controls at the CZ level absorbs most of the size of the coefficient of the variable of interest, although not substantially affecting its significance. Columns [4]-[7] also shows estimates of the baseline specification when we disaggregate and separately include the single components of our abstract intensity measure. The results reveal that only the abstract nature of tasks performed in the CZ is positively and significantly associated to local patenting. In Column [8] we slightly modify the definition of our dependent variable by dividing the number of patents over local population. The normalisation does not alter the insights from our baseline results, therefore confirming the relevance of the CZs' initial level of abstract intensity for local patenting in subsequent years. Finally, Column [9] reveals that reintroducing the CZs that have 0 patent records all along the 2000-2015 period does not change the insights from our baseline findings.

Turning to results in Panel B, to capture the extent of task performed by employees we first exclude self-employment from the IPUMS original sample (Column [1]). To overcome the limited availability of CZ level controls, we include the interaction terms between US main region dummies[19] with time dummies to account for any potential region specific trend of patenting activity not driven by the local abstract intensity (Column [2]). Additionally, to take into account other potential CZ level confounding factors, we grouped CZs according to quintiles of the distribution of population size in the initial year, we created dummy variables for each quintile and interacted them with time dummies (Columns [3]). Hinging on the idea that highly populated locations may be endowed with a larger and more diverse set of capabilities which can more easily enhance the inventive activity, these controls are meant to capture the trend in capabilities accumulation and deployment across CZs of different size. In all cases our baseline evidence is confirmed. We further account for the uneven spatial distribution of patent activities within and across the CZs by adding an auto-regressive spatial term to our baseline specification: we report the findings when we include the average of the total number of granted patents at time t_0 to the CZs that are contiguous to CZ i (Column [4]); next, we consider the patent activity in all the CZs other than i and weight them according to the inverse of the distance between each one of them and i (Column [5]), or according to the

[19] Regions are Northeast, Midwest, South and West.

inverse of the squared distance between each one of them and i (Column [6]). In all cases our baseline evidence is confirmed. Additionally, we allow for alternative time lags between local initial conditions and patent grants. In Column [7] we set $\tau = 2$ and, hence, aggregate patents over the 2002-2004, 2007-2009, and 2012-2014 time spans. Alternatively, in Column [8] we set $\tau = 1$ and aggregate patents over the 2001-2003, 2006-2008, and 2011-2013 time periods. Also, in Columns [9] we set $\tau = 1$ and aggregate patents over the five-year aggregations 2001-2005, 2006-2010 and 2011-2015. In all cases the evidence obtained is consistent with the baseline one.

Table O.5: Robustness Checks

Panel A	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
		Including			Separate Tasks			Patents/Pop	With 0s
	No Controls	State Level Controls	CZ level Controls						
$Abstract\_Intensity_{t_0}$	56.515***	53.803***	12.675**					13.178***	12.207***
	[3.492]	[4.064]	[5.026]					[3.931]	[3.935]
$Abstract\_Task_{t_0}$				1.343***			1.000*		
				[0.457]			[0.562]		
$Routine\_Task_{t_0}$					-1.079**		-0.625		
					[0.490]		[0.597]		
$Manual\_Task_{t_0}$						-0.482	-0.258		
						[0.751]	[0.837]		
Observations	2,163	2,163	2,163	2,163	2,163	2,163	2,163	2,163	2,223
PseudoR2	0.0777	0.0882	0.145	0.15	0.149	0.148	0.15	0.0193	0.147
α	3.347	3.106	2.018	1.945	1.953	1.972	1.94	3.154	1.827
Chi2	287.2	451.4	1310	1157	1239	1335	1304	338.8	1166
P-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Panel B	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
	No Self-employment	Heterogeneous Trends			Spatial Lag		Alternative Lags& Aggregation		
		By Region	By Size Quintiles				$\tau = 2$	$\tau = 1$	$\tau = 1$ & $patents_{i\ t/t+4}$
$Abstract\_Intensity_{t_0}$	13.537***	10.381***	14.953***	16.182***	17.534***	17.411***	12.954***	13.396***	13.195***
	[4.813]	[3.442]	[3.862]	[3.892]	[4.067]	[3.826]	[4.241]	[4.188]	[4.028]
$Patents_{t_0}^{contiguous}$				0.344***					
				[0.097]					
$Patents_{t_0}^{distance}$					1.200***				
					[0.366]				
$Patents_{t_0}^{distance^2}$						0.608***			
						[0.134]			
Observations	2,163	2,163	2,163	2,163	2,163	2,163	2,163	2,163	2,163
PseudoR2	0.149	0.154	0.152	0.153	0.152	0.154	0.148	0.149	0.143
α	1.953	1.872	1.916	1.893	1.913	1.884	1.965	1.914	1.809
Chi2	1195	1712	2339	1270	1114	1204	1161	1148	1196
P-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets clustered at level of the Federal State. Specifications of Columns [1]-[3] in Panel B respectively include region-time, and CZs' size quartiles-time and deciles-time dummies all the remaining specifications include time dummies.

Columns [1]-[3] of Panel A respectively include no controls, State-level baseline controls only and CZ-level baseline controls only. All the remaining specifications include both State- and CZ-level baseline controls.

In Columns [4]-[8] of Panel A, $Abstract\_Task_{t_0}$, $Routine\_Task_{t_0}$ and $Manual\_Task_{t_0}$ respectively measure the corresponding task scores available from Autor and Dorn (2013). In Columns [4]-[6] of Panel B $patents_{t_0}^{contiguous}$ measures the number of patents granted in the CZs contiguous to CZ i, $patents_{t_0}^{distance}$ measures the weighted average number of patents granted in the CZs other than i with weights equal to the inverse of the distance between the CZ i and each of the other CZs, $patents_{t_0}^{distance^2}$ measures the weighted average number of patents granted in the CZs other than i with weights equal to the inverse of the squared distance between the CZ i and each of the other CZs.

O.2.1 Additional Checks

Table O.6: Abstract intensity and patent count in US CZs - occupational composition - region-specific trends

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
							Pooled					
$Abstract\_Intensity_{t_0}$		12.643***		13.033**		10.443***		10.323***		10.921***		10.424***
		[4.791]		[5.861]		[3.400]		[3.396]		[3.524]		[3.592]
$Abstract\_sh_{t_0}$	1.027	-2.165										
	[1.723]	[2.290]										
$CoreCreative\_sh_{t0}$			3.13	-1.439								
			[3.100]	[3.493]								
$ProfessionalCreative\_sh_{t0}$			2.918*	-1.444								
			[1.641]	[2.737]								
$Bohemian\_sh_{t_0}$			4.88	2.628								
			[8.274]	[8.600]								
$STEM\_sh_{t_0}$					-0.341	0.134						
					[0.919]	[0.934]						
$Techies\_sh_{t_0}$							-0.578	-0.184				
							[1.039]	[1.052]				
$Professional\_sh_{t_0}$									-0.022	-0.454		
									[0.576]	[0.572]		
$Whitecollar\_sh_{t_0}$											0.675	-0.041
											[0.712]	[0.710]
Observations	2,163	2,163	2,163	2,163	2,163	2,163	2,163	2,163	2,163	2,163	2,163	2,163
PseudoR2	0.153	0.155	0.154	0.154	0.153	0.154	0.153	0.154	0.153	0.154	0.153	0.154
α	1.888	1.868	1.879	1.871	1.888	1.872	1.888	1.871	1.889	1.871	1.887	1.872
Chi2	1389	1831	1775	1898	1337	1712	1369	1712	1398	1801	1595	1993
P-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets clustered at level of Federal State. Baseline controls and region-time dummies included in all the specifications.

Table O.7: Abstract intensity and patent count in US CZs - task composition - region-specific trends

	[1]	[2]	[3]	[4]	[5]	[6]
					Abstract Intensity from O*NET Scores	
$Abstract\_Intensity_{t_0}$				16.851***		
				[4.219]		
$Abstract\_Intensity_{t_0}^{O*NET}$					6.571*	24.194***
					[3.890]	[7.637]
$Cognitive_{t_0}$		64.450*		38.28		68.108
		[36.585]		[82.533]		[78.470]
$Interactive_{t_0}$	16.263			-66.136**		-116.974***
	[17.957]			[33.459]		[39.933]
$STEM_{t_0}$			94.749**	84.857*		88.430*
			[36.985]	[46.801]		[48.543]
Observations	2,163	2,163	2,163	2,163	2,163	2,163
PseudoR2	0.153	0.154	0.155	0.156	0.154	0.156
α	1.887	1.881	1.869	1.845	1.883	1.855
Chi2	1520	1404	1499	1788	1581	1773
P-value	0.00	0.00	0.00	0.00	0.00	0.00

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets clustered at level of Federal State. Baseline controls and region-time dummies included in all the specifications. $Cognitive_{t_0}$, $Interactive_{t_0}$ and $STEM_{t_0}$ respectively measure the CZ's level of cognitive, interactive and STEM tasks computed according to equation 1 when the abstract intensity is alternatively substituted by the remaining two task measures.

Table O.8: Abstract intensity and patent count in US CZs - CZ-level task scores

	[1]	[2]	[3]	[4]
$Abstract\_Tasks_{t_0}$	1.639***	1.789***	1.678***	36.089**
	[0.564]	[0.554]	[0.567]	[17.122]
$Cognitive\_Tasks_{t_0}$	-35.826		46.486	92.273
	[42.328]		[88.611]	[91.449]
$Interactive\_Tasks_{t_0}$		-29.122	-47.049	-78.864*
		[19.412]	[41.233]	[40.493]
$Wage\_Income_{t_0}$	0.698	0.603	0.531	0.734
	[0.503]	[0.528]	[0.593]	[0.574]
Pop_{t_0}	0.830***	0.842***	0.837***	0.821***
	[0.064]	[0.060]	[0.063]	[0.065]
$Empl\_sh_{t_0}^{High-Tech}$	9.258***	8.767**	8.314**	9.309***
	[3.539]	[3.535]	[3.354]	[3.404]
$Graduate\_sh_{t_0}$	17.535***	19.468***	19.837***	22.105***
	[5.420]	[5.799]	[6.022]	[5.909]
$R\&D\_GDPsh_{t_0}^{State-Business}$	29.237***	28.473***	28.062***	28.765***
	[9.248]	[9.444]	[9.590]	[10.167]
$R\&D\_GDPsh_{t_0}^{State-Public}$	-0.086	-0.092	-0.093	-0.088
	[0.067]	[0.067]	[0.068]	[0.070]
$ln(\alpha)$	0.664***	0.662***	0.662***	0.670***
	[0.058]	[0.058]	[0.058]	[0.060]
Observations	2,163	2,163	2,163	2,163
PseudoR2	0.15	0.15	0.15	0.149
α	1.943	1.939	1.938	1.955
Chi2	1149	1226	1275	1285
P-value	0	0	0	0

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets clustered at the level of Federal State.

O.3 Comparing the abstract task measure to other tasks definitions from the literature

The literature on the task approach to the labour market has produced different task measures. Beyond tasks meant to capture the extent of substitutability between labour and capital, other works have focused on the evolution of the overall cognitive versus manual intensity of jobs to explain the gender gap evolution in the US (Bacolod and Blum, 2010; Yamaguchi, 2018), and on the different specialisation of immigrants and natives in manual and communication-language tasks (Peri and Sparber, 2009). Hence, further measures of cognitive and interactive tasks have been developed on the basis of the scores recorded by the DOT and O*NET surveys to grasp specific abilities required by different jobs.

Although our abstract task measure is expected to be related to other existing measures of cognitive work, as previously mentioned, the former should especially capture non-routine cognitive abilities - i.e. analytical and coordination capacities - that are essential for the process of innovation and may be not adequately captured by existing measures that looks at workers' individual skills, or which focus on job tasks, but then consider overall cognitive task intensity. Indeed, occupations that are classified as highly cognitive on the basis of workers' abilities could actually reflect a low deployment of analytical and coordination capacities as measured on the basis of work activities. On the other hand, occupations with high cognitive content based on work tasks may require the completion of routine activities and, thus, also imply a low engagement in abstract tasks. To validate these expectations and compare our abstract task measure to the cognitive and interactive ones based in work abilities we hinge on the cognitive task definition by Yamaguchi (2018)[20] and on the definition of interactive tasks by Peri and Sparber (2009),[21] and contrast the level of abstract versus cognitive/interactive tasks. Across all 330 occupations included in the Autor and Dorn's job classification, the rank correlation between the abstract task score and the cognitive and interactive ones is 0.68 in both cases. Then, the ranking of occupations in terms of their abstract content is not coincident with their ranking in terms of the two further task definitions. We explore this issue by plotting the nexus between the task indicators under scrutiny for major occupational groups in Figure O.1. It emerges that as the skill intensity of jobs declines, the average abstract, cognitive and interactive task content of major occupational groups declines. Nonetheless, the evolution of the three task measures across the occupational groupings does not coincide: in some cases, as the cognitive content of jobs increases/declines a decline/increase in abstract content of the job is observed - e.g. Health Assessment/Treatment; Librarians, Archivists, and Curators;

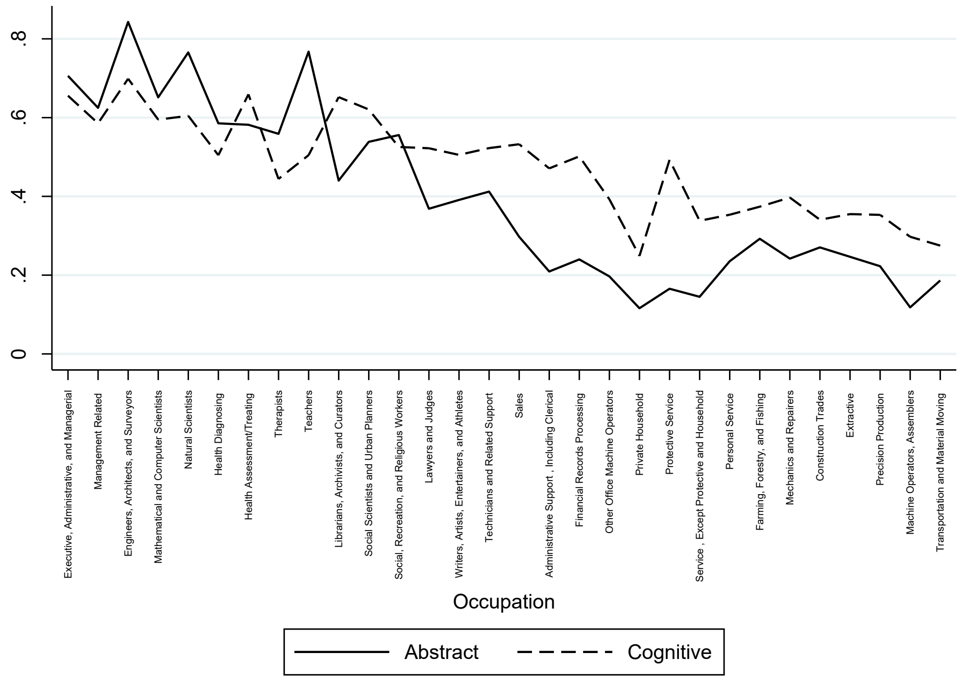
[20]This definition accounts for the following set of abilities available from O*NET 2000: Fluency of Ideas, Originality, Problem Sensitivity, Deductive Reasoning, Inductive Reasoning, Information Ordering, Category Flexibility, Mathematical Reasoning, Category Flexibility, Number Facility, Memorization, Speech Recognition and Clarity.

[21]This definition accounts for the following set of abilities available from O*NET 2000: Written Comprehension, Oral Expression, Written Expression.

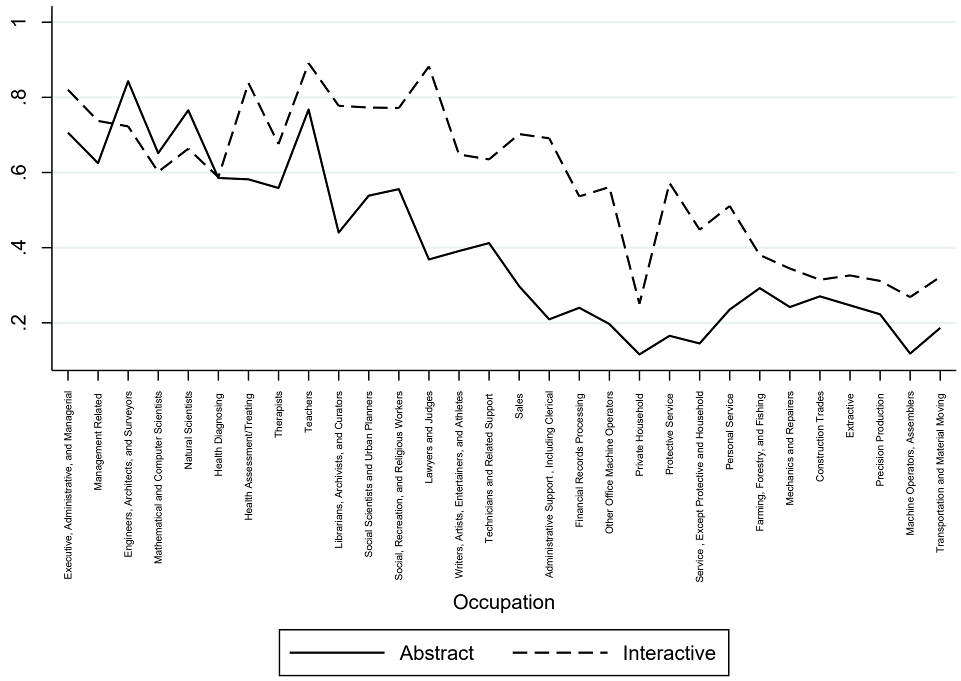
Judges and Lawyers; Machine Operators, Assemblers and Transportation and Material Moving Operators - and a similar pattern emerges from the comparison of the abstract and interactive task content of jobs. Figures O.2 and O.3 enter into the detail of two specific occupational groups showing that some highly cognitive jobs, such as those belonging to the group "Executive, Managerial and Administrative", may display lower levels of abstract tasks while some low cognitive intensive jobs, such as those in the group "Transportation and Material Moving Operators", can display high levels of abstract tasks. By the same token, across narrowly defined occupations, high levels of abstract tasks not always coincide with high levels of interactivity.

Hence, we have shown that the abstract intensity of jobs captures more general and comprehensive features of work activities, that is, neither strictly related to a job's content of specific cognitive activities, nor strictly dependent on a direct involvement in innovation-related activities. In fact, high levels of abstract intensity are observed also for jobs which are not closely related to innovation. Then, it is highly unlikely that the occupational sorting of workers, particularly a higher incidence of "abstract workers", may be driven by the local level of inventive/innovation activities as proxied by patents. Indeed, these latter, unlike the adoption of new technologies, do not necessarily affect/explain the composition of employment in terms of occupations and tasks. All in all, this piece of evidence corroborates a causality direction that we contend in the paper.

Figure O.1: Abstract vs Cognitive and Interactive Tasks - Major Occupational Groups



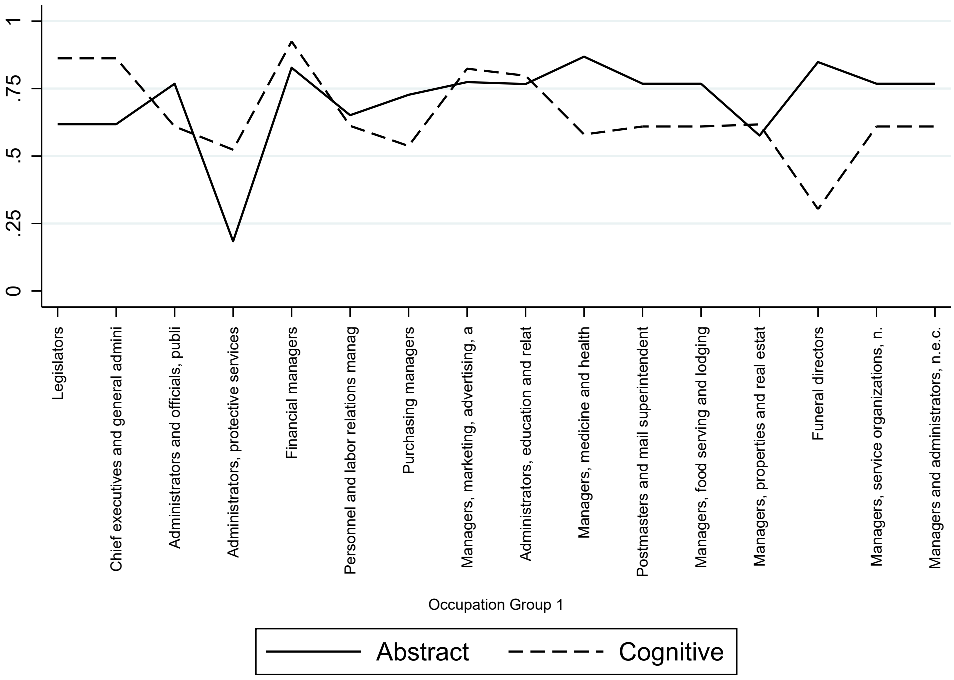
(a) Abstract vs Cognitive



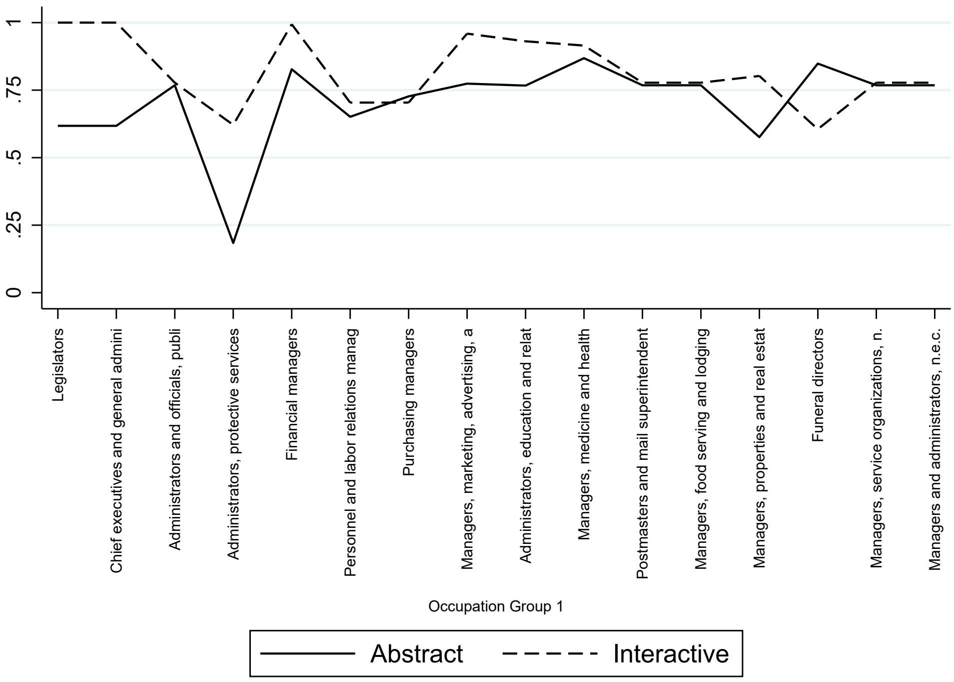
(b) Abstract vs Interactive

Source: IPUMS, Autor and Dorn (2013), O*NET. Own calculations.

Figure O.2: Abstract vs Cognitive and Interactive Tasks - Executive, Administrative, and Managerial



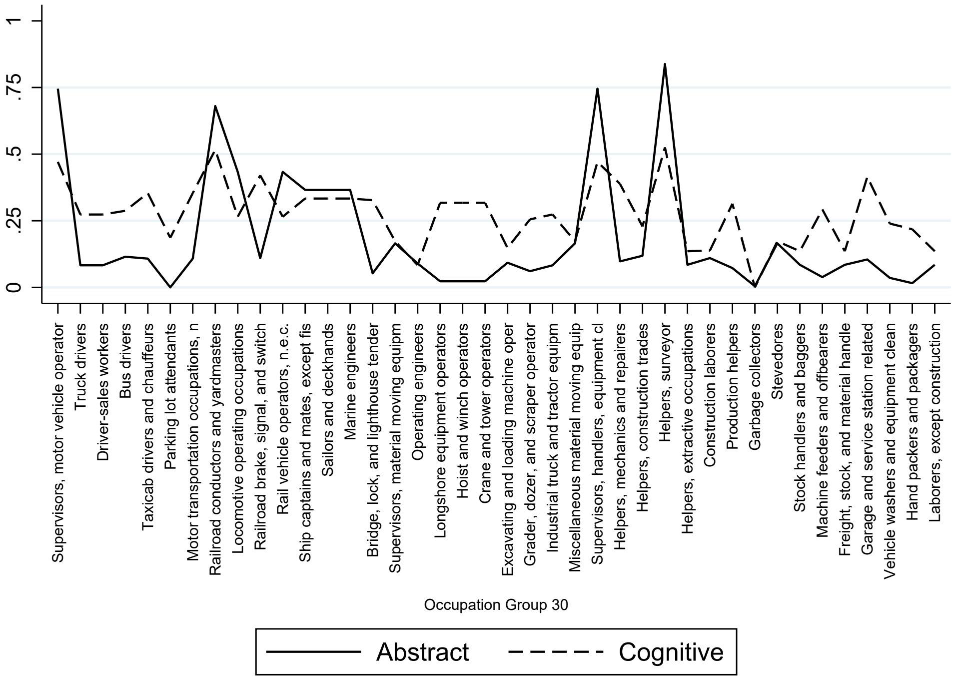
(a) Abstract vs Cognitive



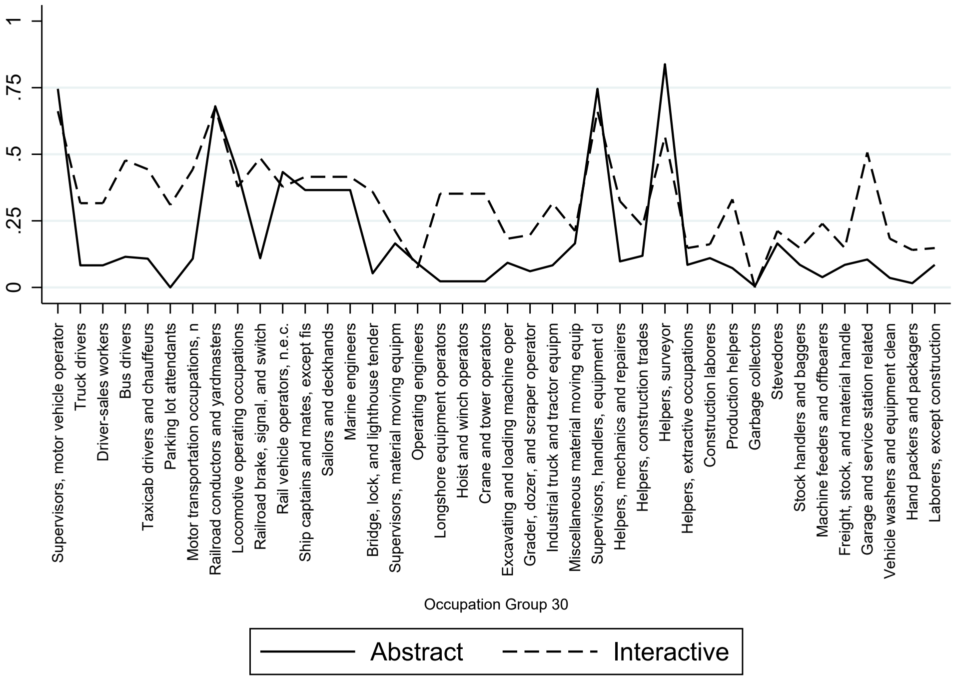
(b) Abstract vs Interactive

Source: IPUMS, Autor and Dorn (2013), O*NET. Own calculations.

Figure O.3: Abstract vs Cognitive and Interactive Tasks - Transportation and Material Moving Operators



(a) Abstract vs Cognitive

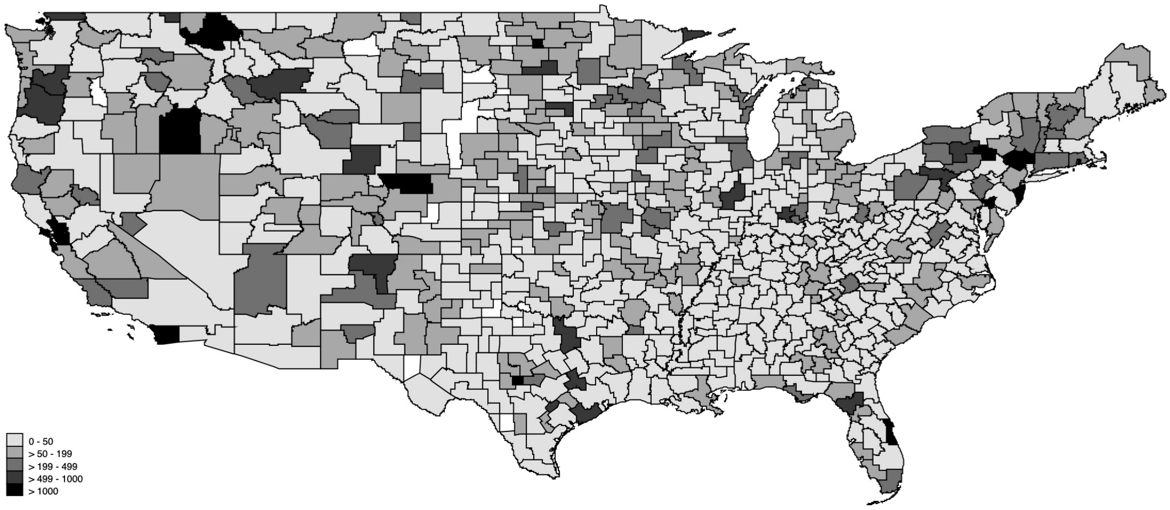


(b) Abstract vs Interactive

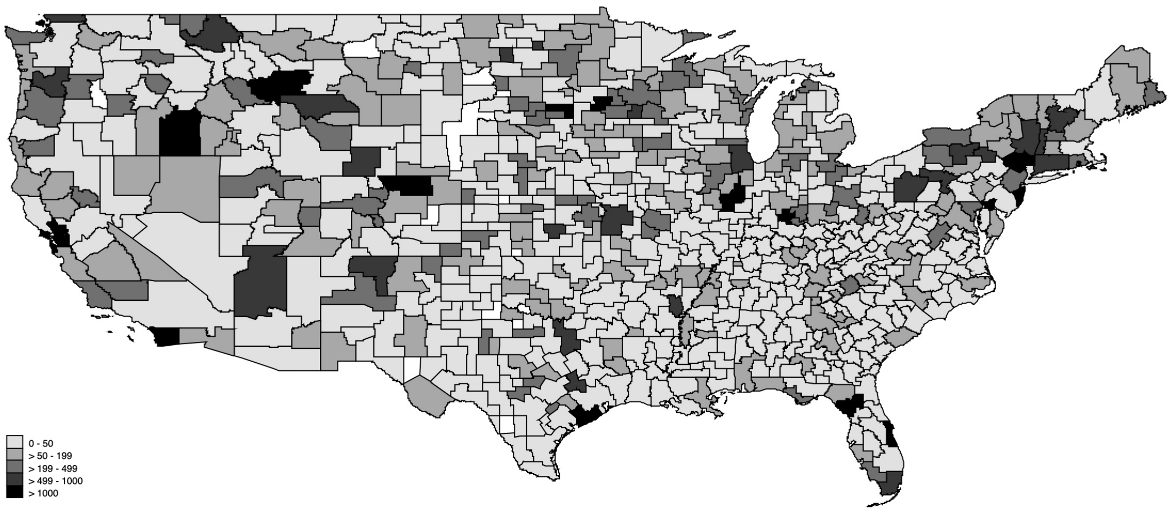
Source: IPUMS, Autor and Dorn (2013), O*NET. Own calculations.

O.4 Additional Figures

Figure O.4: Patents count over population across US CZs in 2000 and 2010



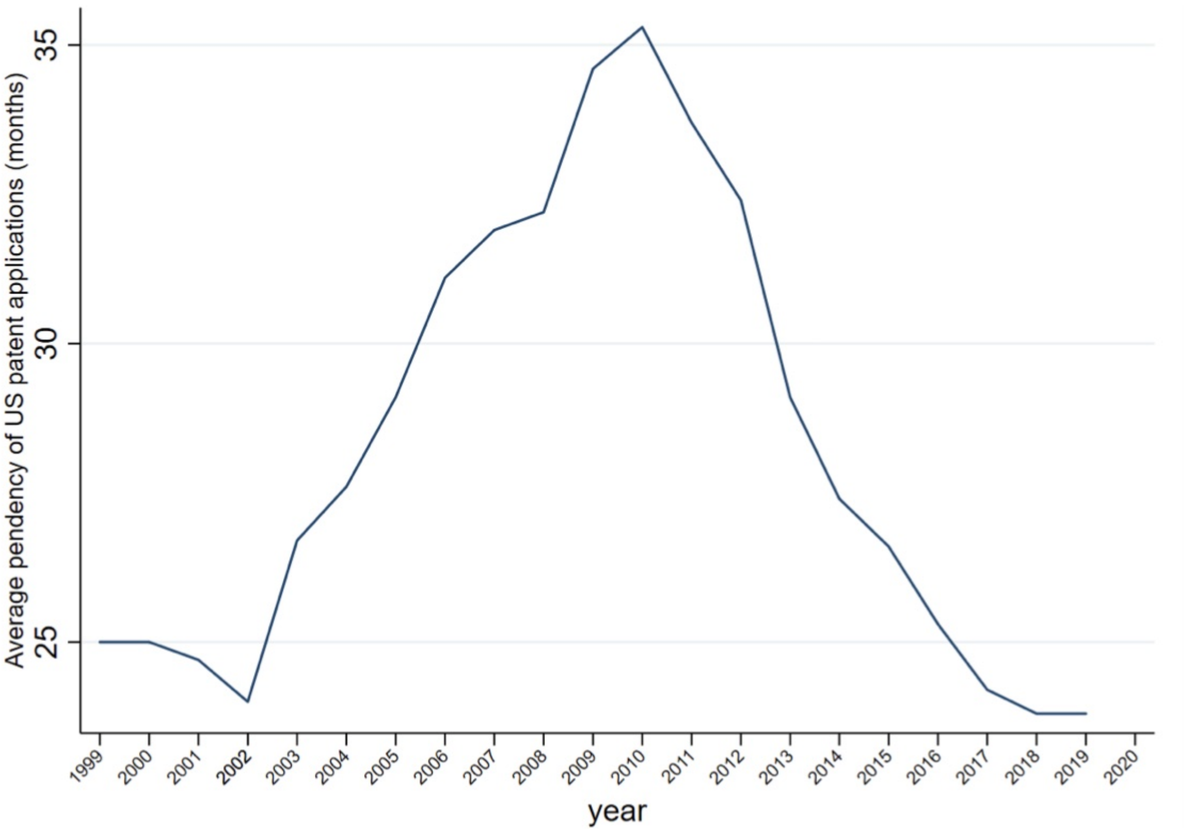
(a) Patents over population 2000



(b) Patents over population 2010

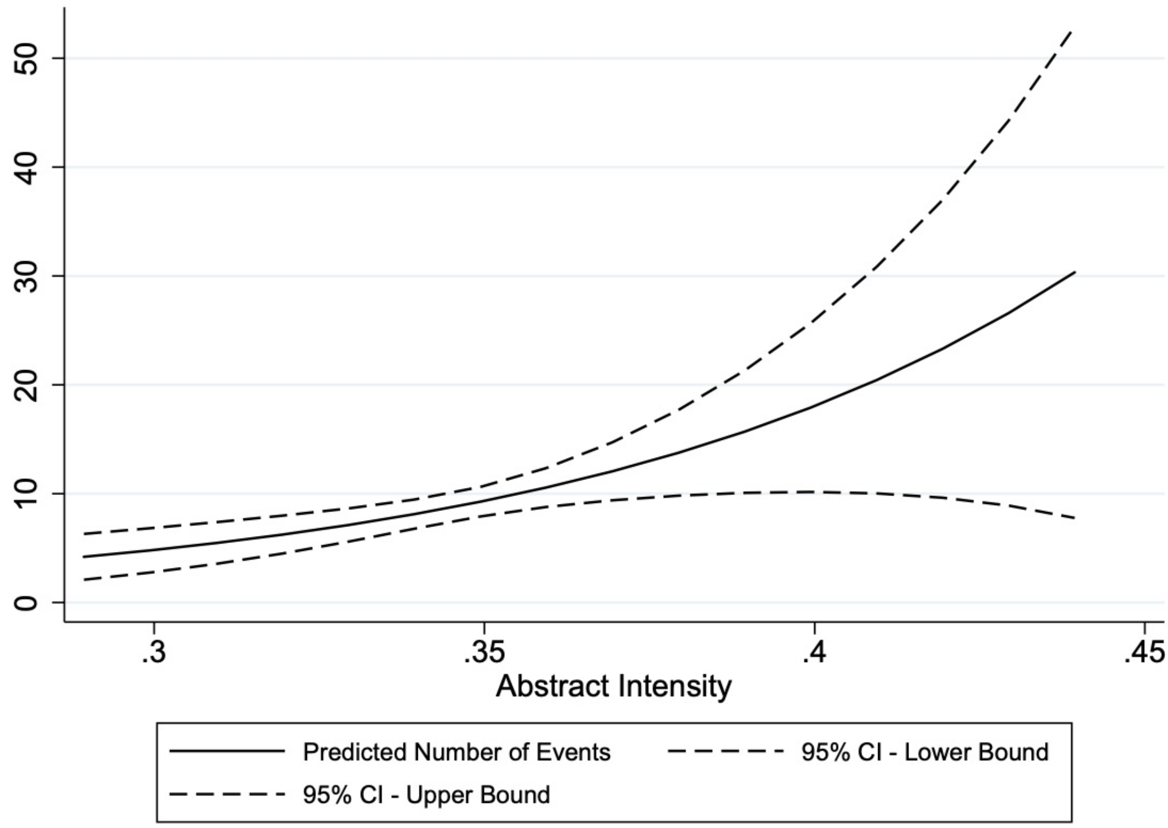
Source: IPUMS, USPTO. Own calculations. For a better readability, we have excluded Alaska and Hawaii from the maps.

Figure O.5: Average pendency of US patent applications



Source: USPTO, Performance and Accountability Report (various years). The average pendency is the estimated time in months from filing a patent application to patent granting.

Figure O.6: Marginal effects at the means of covariates



Source: USPTO, IPUMS and BLS. Own calculations.