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SKILL ENDOWMENT, ROUTINISATION AND DIGITAL TECHNOLOGIES: EVIDENCE FROM U.S. METROPOLITAN AREAS

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Skill endowment, routinisation and digital technologies: Evidence from U.S. Metropolitan Areas

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ABSTRACT

Scholars and policy makers frame the debate on labour market polarisation by emphasising the role of key drivers such as international trade and of technological change. The present paper explores these themes from a different perspective, and inquires whether de-routinisation has harmed local innovation capacity. Our empirical study builds on the literature on learning-by-doing and incremental innovation, and focuses on advanced manufacturing technologies (AMTs) in US Metropolitan Statistical Areas over the period 1990-2012. Results provide support to the hypothesis that de-routinisation is associated with a generalized decline of local innovation performance, especially in AMTs.

JEL: O33; J24; O14; L23.

Keyword: Innovation; Routine skills; Polarisation; Manufacturing; Digital Technology

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1. Introduction

The advent of digital technologies has rejuvenated the debate on the economic and social effects of innovation. The so-called digital transformation is widely regarded as a discontinuity emanating from the Information and Communication Technology (ICT) revolution that gained momentum in the 1990s and that has triggered significant changes both in employment levels and in the structure of labour markets (OECD, 2016; World Bank, 2016; Van Roy et al., 2018).

A growing strand of research on employment and innovation analyses the labour market outcomes associated with the computer revolution. Contributions from innovation studies argue that indirect income and price effects can offset the direct effect of job destruction due to the adoption of new machinery and equipment. Whether and to what extent these compensation mechanisms work, and whether price or income effects dominate, depends on institutional factors that circumscribe the validity of empirical findings (Freeman and Soete, 1987; Pianta, 2005; Vivarelli, 1995, 2014; Piva and Vivarelli, 2018). Other studies in labour economics argue that technological change is skill-biased, and therefore that job creation and job destruction reflect a positive relation between workers' skill levels – often proxied by years of schooling – and labour market returns (Autor et al., 1998; Chennels and van Reenen, 1999; Acemoglu, 2002). The predictions based on these approaches, however, do not match observed patterns of changes in labour demand. Rather, the evidence indicates that in the wake of the ICT revolution the bulk of job destruction occurred in the middle of the skill spectrum and not in the bottom part as the skill-biased technical change (SBTC) tenet predicts (Autor et al, 2003; Goos and Mannig, 2007; Goos, Manning and Salomons, 2014). Upon closer inspection, technology has had a dual effect on labour demand: it substituted for routine (cognitive and manual) tasks that are more intensive among mid-skill jobs – e.g. clerks and machine operators – while increasing the productivity of, and the demand for, occupations at the opposite ends of the employment spectrum, namely high- and low- jobs that entail primarily non-routine (cognitive and manual) activities. This process is known as de-routinisation, or job polarisation. Recent studies find that technology is not only job destroying and that expanded possibilities, in the form of new products and processes, can create demand for new occupations (Bessen, 2018; Acemoglu and Restrepo, 2019; Gregory, Salomons and Ziehran, 2016; Klenert, Fernández-Macías and Antón, 2020). Overall, the evidence reveals a more complex picture than the dominant narrative 'robots are coming for workers' would suggest.

This intense debate revolves around the question of whether technological change affects employment, and how much. The starting point of the present paper is that such a relationship is not only controversial for what concerns the balance between compensation and substitution effects, but also in regards to the directionality. A large body of literature, for example, suggests that labour market dynamics shape innovative performance. On the one hand, empirical studies show that flexibility and deregulation can hinder innovation due to the crowding out of firms' core capabilities (Kleinknecht et al., 2014; Michie and Sheehan, 2003; Wachsen and Blind, 2016; Zhou et al., 2011). On the other hand, for similar reasons, excess worker turnover is likely to have a negative impact on firms' innovation dynamics (Grinza and Quatraro, 2019).

We maintain that these considerations are also relevant for the current debate on job polarisation, albeit in a way that differs from what has become the standard framing. While the literature looks mainly at how digital technologies trigger de-routinisation, the question of whether and to what extent the loss, or of the diminished availability, of routine skills may have affected innovation capacity has been disregarded. What's more, and central to the present paper, blue-collar work tasks and the attending skills are essential for productivity and innovation. Two streams of empirical literature provide support to this intuition. The first is based on Rosenberg's (1974) classic critique to the debate on innovation, which focused excessively on the creative leaps that enable new technologies to stem out of basic research while it disregarded incremental 'downstream' improvements and the importance of other knowledge sources. A second domain of applied literature shows evidence that production, mid-skill workers are crucial to achieve incremental innovation (Waeyenbergh and Pintelon, 2002; Alsyouf, 2007; Kukla, 1983; Sohal et al, 2001; Deivanayagam, 1992).

Building on the above, the present paper empirically analyses whether and to what extent the decline of mid-skill routine employment has been detrimental to innovation capacity in Metropolitan Areas (MSAs) of the United States (US). Specifically, this question is addressed in relation to innovation patterns in manufacturing sectors over the period 1990-2012. In line with recent trends, we look at patenting dynamics in advanced manufacturing technologies (AMT). This is a group of integrated hardware-based and software-based solutions used in the design, manufacture or handling of products (OECD, 2012). We hypothesize that routine workers are crucial to incremental experimentation and problem-solving that stand at the core of incremental innovation. Because of the specific features of this process, we further submit that the prolonged decline of demand for routine jobs observed in the United States has undermined the ability to innovate in organisational ecosystems that revolve around AMTs.

The main finding is that a 1% loss in routine-intensive occupations is negatively associated with a reduction in the local patenting capacity by around 4%. This negative association is larger when we focus specifically on AMTs wherein the decline of patenting is around 7%. Interestingly, the decrease of cognitive- and manual-routine skills are negatively associated to local innovation capacity in general and to AMTs in particular. In fact, the latter reduce more when routine jobs decrease due to losses in manual-repetitive occupations. Our contribution to the literature is threefold. First, we add to the empirical work on the task-based approach by underlining that accounting for task heterogeneity allows capturing important variance in innovation dynamics. Second, we enrich the debate on the relationship between digital technologies and labour market dynamics by showing that it is important to invert the direction of the link. Third, we elaborate upon the importance of a specific set of technologies, i.e. AMTs, that are crucial not only because of their productivity-enhancing effect, but also due to their innovation-enabling role.

The rest of the paper is organized as follows. After a review of the relevant literature in Section 2, we detail the main data sources and the procedures used for the construction of the main variables in Section 3. This is followed by the empirical analysis of Section 4. The last section concludes and summarizes.

2. Theoretical Background

2.1. On innovation and labour market dynamics

Academic scholars and policy makers have recently become more alert to the nature and the extent of the structural changes that are transforming the labour market, and to their relationship with the current wave of technological change in the digital domain.

The technological discontinuities that followed the ICT revolution has brought the relationship between innovation and employment back at the core of the policy and academic debates. In innovation studies, empirical analysis focuses on the existence and extent of substitution and compensation effects, the former consisting of job displacement the latter by the counterbalancing job creation due to productivity gains and new job creation (Vivarelli, 2014; Piva and Vivarelli, 2018; Vivarelli and Pianta, 2000; Cirillo, 2017). The generality of the various findings is often controversial due to the influence of institutional factors such as e.g. regulation that affect the degree of market competition.

While many investigate the impact of ICTs on overall employment growth, considerations about the specific kinds of jobs that these technologies would have displaced, as well as the types of jobs that they would have promoted have enriched the debate on the effects of the ICT revolution. If on the one hand ICTs would have accelerated the obsolescence of some occupations, on the other hand their diffusion would have required an increase in the demand of some other (complementary) occupations. According to the SBTC tenet, ICTs would affect the demand for workers depending on their skill level, thereby favouring high-skilled occupations and hindering low-skill ones (Autor et al., 1998; Chennels and van Reenen, 1999; Acemoglu, 2002). At the same time, recent literature on the impact of robots' adoption on wages or employment points to mixed evidence due to a variety of reasons – i.e. differences across datasets, heterogenous time-spans (Klenert et al, 2020).

The most recent chapter of the analysis of the employment effects associated to technological change emerged out of empirical analysis showing that in the US and many OECD economies labour demand had grown for both high- and low-skill jobs and that the decline mostly concerned mid-skill ones. Although there still is controversy over the timing and the degree of the so-called employment polarisation, broad consensus exists on the underlying mechanics. The decline of demand for mid-skill occupations is in effect capital-labour substitution due to both falling prices of computing power and higher efficiency of automated processes in carrying out routine work tasks (Autor, Katz and Krueger, 1998; Autor, Levy and Murnane, 2003; Goos and Mannig, 2007; Goos, Manning and Salomons, 2014; Gregory, Salomons and Ziehran, 2016).[1] A new approach stemming from the pioneering work of Autor, Levy and Murnane (2003) (ALM henceforth) focused directly on job skills and tasks, rather than inferring them through proxies such as a worker's years of education. In this framework, occupational task content is understood as the ensemble of work activities that are necessary for a job to produce a unit of output. Compared to the traditional human capital theory, this approach affords a more nuanced view of how advances in technologies, changes in skill supplies, or the emergence of trade and off-shoring opportunities affect the division of

[1] As Cortes, Jaimovich and Siu (2017) point out, the issue is far from being settled for what concerns, first, the workings of the process by which routine occupations have declined and, second, the magnitude of aggregate decline of routine employment that can be ascribed to progress in automation technology. For critical views on polarisation, see Mishel et al (2013) and Hunt and Nunn (2017).

labour between workers and machines, the relevance of particular job tasks and, ultimately, the demand for skills (Acemoglu and Autor, 2011).

In the ALM framework occupations are defined by the main work tasks. Accordingly, routine tasks (i.e. executing codified instructions with minimal discretion) are characteristic of middle-skilled jobs that entail repetitive cognitive (i.e. clerks) or manual (i.e. blue-collar) duties. Because routine tasks exist in the forms of rules and instructions, and since the quality of computer and communication technologies has increased while their price has declined, routine tasks are prone to be reassigned to machines or, alternatively, to be performed by low-wage workers in offshore locations. The second main category includes 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, computers accrue productivity benefits to these workers by facilitating the transmission, organisation, and processing of information. This is why technology tends to complement, rather than substituting, these occupations. 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 concentrated in low-skill service jobs such as food preparation, catering, driving and cleaning. Given the significant challenges entailed in automating these activities, workers in these jobs are relatively unscathed by the computer revolution.

The empirical literature in this strand focuses primarily on the contractionary impacts of international trade and of technology on employment, especially in manufacturing industries. These studies however disregard the effect of the loss, or of the diminished availability, of routine skills.

2.2. The importance of routine jobs for innovation

In spite of the profound transformations of manufacturing, blue-collar workers, and their skills, are still central to production activities (Piva et al, 2011). No doubt, the diffusion of information technology together with pressures from international competition have altered the organisation and, a fortiori, the demand for specific skills. In highly automated factories and production sites of the United States workers are expected to command know-how that is considerably more specialized than it would have been a few decades ago (Dietz and Orr, 2006). At the same time, there is evidence on factories that opt for retraining the old workforce after implementing continuous processing and control systems (Fernandez, 2001). This is, we argue, because at the core of routine tasks embedded in blue-collars is a type of technical labour that stands at the interface between engineering and manufacturing, and consists in tacit skills heavily reliant on experience of translating the requirements of each group for the other (Barley, 1996; Barley and Bechky, 1994). The responsibilities of factory floor blue-collar workers entail combined use of physical and conceptual dexterity and blending technical knowledge with practical experience (Drucker, 1999). While in the factory of the past these hands-on skills were primarily involved in the physical manipulation of specific equipment, in the modern-era factory floor employees operate ensembles of machines using routine manual skills such as assembling, maintaining and coordinating. According to the technical literature, the importance of these skills has increased together with the complexity of automated production whereby factory floor workers are now committed to high standards of performance over efficiency, quality, on-time delivery, safety, and plant cost effectiveness (Al-Najjar, 2000; Riis et al., 1997; Mckone and Elliott, 1998).

Further and central to the argument of the present paper, blue-collar type of routine tasks, and the attending skills, are essential for productivity and innovation. Two streams of empirical literature support this claim. The first stems from the classic Rosenberg's (1976) critique that the debate on innovation has focused excessively on the creative leaps that enable new technologies to stem out of basic research while it has neglected the role of other, less formal, knowledge sources and of incremental 'downstream' improvements. A few instances of the latter are the design of new products, testing and evaluating their performance through prototypes, implementing new production processes. Common to this wide range of activities is that they consist of minor modifications that better integrate design and production, establish new feedback channels between users and suppliers, and ultimately tune existing production methods. While taken individually each of these modifications may yield small improvements in performance, their cumulative effects have been observed to be massive in domains as different as agriculture, machine production and aeronautics (Rosenberg and Steinmueller, 2013). According to this literature, blue-collars have the potential to develop useful knowledge, ideas and competences that contribute to a firm's innovation capacity. As Bradley et al. (2017) point out, this class of workers can have an impact on innovation for different reasons. A first channel consists of knowledge inputs originating among production workers and flowing up to the management. Moreover, floor workers often serve as supporting staff for researchers and scientists. Indeed, according to Hayek (1945), the specific knowledge developed by floor workers can be useful to firm's innovation performance only if they are actively involved in these dynamics.

A second stream of applied literature is also relevant in that it provides evidence on the extent to which incremental improvements can be ascribed to the tacit know-how of factory floor workers. These improvements include reducing downtime, limiting costs and increasing equipment productivity across a wide range of industries (Waeyenbergh and Pintelon, 2004; Alsyouf, 2007) as well as new product (Kukla, 1983; Sohal et al, 2001) and process development (Deivanayagam, 1992). Last but not least, there is evidence of growing importance of blue-collar workers for knowledge-bridging across functional departments, including those performing R&D, of the modern factory (Langowitz, 1988; Hoopes and Postrel, 1999).[2]

Based on these arguments, our first hypothesis is:

H1: *De-routinisation is associated with decreasing innovation performance.*

2.3. Routine jobs and advanced manufacturing technologies

Our empirical analysis focuses on innovation in Advanced Manufacturing Technologies (AMTs), a group of integrated hardware-based and software-based solutions for the design, manufacture or handling of products (OECD, 2012). While traditional manufacturing technologies enhance process efficiency mostly through rigid and mechanized design, AMTs improve the overall effectiveness of a production system. Computer-integrated manufacturing, flexible manufacturing systems, computer-aided design and computer-aided manufacturing networks are classic instances of these technologies. Early adoption of AMTs dates back to the 1970s, spread widely in the 1980s and has since penetrated most manufacturing activities, with varying degrees of intensity and of complexity. These technologies enable higher flexibility in the design of new products, faster delivery and greater product variety at low cost (Nemetz and Fry, 1988; Parthasarthy and Sethi, 1992). Thereby AMTs are not only a means to improve performance in the existing remit but also a vehicle to explore new growth paths such as expanding the product range and contesting new markets (Lei and Goldhar, 1990).

[2] The larger and larger implementation of specific work practices, like job rotation or cross-functions networking, highlights the importance of learning and knowledge diffusion dynamics embedded in firms' human resources (Ortega, 2001; Askenazy and Caroli, 2010).

Flexible organisation designs that enable quick responses to emerging opportunities or to a changing competitive landscape are deemed as the most effective to reap the benefits of AMTs (Leonard-Barton, 1988). Lei et al. (1996) identifies key organisational features for the efficient implementation of AMTs: cultivation of new sources of tacit, organisation-embedded knowledge; cross-functional integration and coordination; flexibility in cooperating with other organisations within the value chain. Crucial to the effective implementation of AMTs, and common to all the above features, stands tacit knowledge, that is, the know-how possessed by individuals or teams that have long-standing experience of working with specific equipment over extended periods (Nonaka, 1991; Itami, 1987; Dougherty, 1992). Since tacit knowledge is highly specialized and sticky, the loss of workers who master this type of know-how represents a potential hazard for productivity and innovation (Badaracco, 1991; Nonaka, 1991). To illustrate, workflows and routines that have been adapted to accommodate process or product modifications are likely to be firm specific, and to rely on cross-functional pathways that have consolidated over repeated iterations (Lawler et al, 1992). Technical tasks like materials handling, coding and calibrating largely depend on personal insight, emerging heuristics and direct experience with equipment. Further, the cross-functional integration of design and production activities is especially important in AMT-intensive environments that rely on continuous feedback loops between management, engineering and the factory floor (Lei et al, 1996).

These peculiar characteristics of AMTs, and the challenges that their deployment entail for the skill base, resonate with the previous discussion on the nature of blue-collar routine tasks. Production environments characterized by a high degree of complexity require high levels of tacit know-how, experience and repeated interaction across different functional domains. Routine workers possess these skills and are therefore crucial to incremental experimentation and problem solving that stand at the core of innovation. By the same token, we conjecture that the prolonged decline of demand for routine jobs observed in the United States has undermined the ability to innovate in organisational ecosystems that revolve around AMTs. These issues have been largely ignored by the extant literature, and our empirical analysis will tackle them to fill the gap.

Accordingly, our second hypothesis is:

H2: *De-routinisation is associated with decreasing innovation performance in the domain of Advanced Manufacturing Technology.*

3. Data and Methods

To investigate the relationship between the de-routinisation of employment and innovation capacity in Advanced Manufacturing Technologies, we collect data on occupational tasks, employment, industrial structure and patenting at the US Metropolitan Statistical Area (MSA) level. According to the US Office of Management and Budget (OMB, 2010), MSAs are statistical areas "associated with at least one urbanized area that has a population of at least 50,000".[3] The OMB further specifies that MSAs comprises a central county (or counties) and adjacent counties with a high degree of economic and social integration (measured through commuting flows). The OMB reviews the standard for delineating the areas every ten years, and constantly revises the delineations to reflect estimates of US Census Bureau population and commuting flows. This implies that the composition and the identification codes of MSA may vary over time. Moreover, some areas may disappear, due i.e. to loss of population below the reference threshold, while new ones may emerge. To ensure comparability and consistency of territorial units over time and across different data sources, we create a crosswalk that allows the unique identification of MSAs over changing county composition. We exclude newly identified areas when the county composition is not identifiable in prior years unambiguously. MAs divided into two or more areas by the OMB revisions have been re-aggregated. This procedure allows us to identify 289 coherent MSAs over time that are the main unit of analysis.

Data on employment, skills, patenting, economic and demographic factors come from different data sources. To construct the indicators of the occupational structure, we rely on the Occupational Employment Statistics (OES) program from the U.S. Bureau of Labor Statistics (BLS), which provides annual employment data by occupation profiles for each MSA. OES BLS does not provide data for the 1990s. Occupational task data are available only for the 1990 from the decennial census program provided by IPUMS USA. Therefore, due to data availability limitation, we restrict the construction of our occupational structure indicators at the first available years, i.e.: 1990 and 2001. The most basic geographic unit identified in IPUMS USA census data is the Public Use Microdata Area (PUMA). In order to map PUMAs to MSAs, we exploit the PUMA detailed county composition to develop a crosswalk.[4] We make use of the US Census Bureau County Business Pattern (CBP) to collect data on the

[3] The OMB 2010 report is available at https://www.govinfo.gov/content/pkg/FR-2010-06-28/pdf/2010-15605.pdf.

[4] Available at https://usa.ipums.org/usa/volii/puma.shtml.

number of establishments and the level of employment by sector of activities (SIC and NAICS codes). The source for county population data is the US Census Bureau, which also provides data on counties land through the Gazeteer Files.[5] We then aggregate this data at the MSA level using the crosswalk mentioned above. Patent data are from the USPTO Patents View Database.[6] Our analysis covers 289 MSAs over the period 1990, 2001-2012.[7]

3.1. Variables

Dependent variable: Our goal is to investigate the association between de-routinisation of local labour markets and local innovation capacity, with a focus on the AMTs domain. To this end, we collect information on patents issued in new digital technologies related to manufacturing processes. To do so, we exploit the Cooperative Patent Classification (CPC) scheme that provides, for each patent issued, a list of technological classes encompassing specific technological domains.[8] To properly select domains related to AMTs, we rely on two main sources. The technical report by Aschhoff et al. (2010) provides a list of IPC classes referring to key enabling technologies and identifies the classes strictly related to AMTs.[9] The report by Ménière et al. (2017) focuses instead on technologies associated to the so-called 4th Industrial Revolution. Among these, we select those strictly connected to manufacturing systems, together with their corresponding CPCs, and add them to the former list. To assign patents to MSAs we rely on information on inventors' addresses,[10] ending up with the number of patents in AMTs, yearly for each MSA. Our main dependent variable thus is given by the percentage change of local AMTs patents from 2002 to 2012.

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[5] Available at https://www.census.gov/geo/maps-data/data/gazetteer.html.

[6] Available at http://www.patentsview.org/download/. It is worth stressing that the distinction between incremental and radical innovation has no impact on the discussion on the reliability of patents as a proxy of innovation. Both incremental and radical innovations can be patented provided they satisfy patent offices' criteria. An important stream of literature relies on the statistical analysis of information contained in patent documents to derive measures to distinguish between breakthrough and incremental innovations (Silverberg and Verspagen, 2007; Castaldi and Los, 2012; Castaldi et al., 2015).

[7] Due to data availability at the MSA level, we collect information on employment, economic and demographic characteristics in 1990, and from 2001 to 2012. Patent data are collected for the period 1990-2012.

[8] The CPC has been established in 2010 to harmonize individual classification systems between the USPTO and the EPO. We exploit the PatentsView database table "cpc_current" to extract information on CPC classes for US patents.

[9] For each IPC contained in Aschhoff et al. (2010) we identify the corresponding CPCs using the concordance table by EPO and USPTO (https://www.cooperativepatentclassification.org/cpcConcordances.html).

[10] Patents filed by multiple inventors residing in different MSAs are locally assigned according to the fraction of inventors residing in each MSA.

De-routinisation index: Our main variable of interest is an index of de-routinisation of local employment, which we build following the occupational task-based framework (ALM, 2003; Autor and Dorn, 2013). We focus on changes in the Metro-Area intensity of routine job employment. The reader will recall that the prototypical mid-skill routine job entails performing repetitive cognitive (i.e. clerks) or manual (i.e. blue-collar) work tasks. To illustrate, routine cognitive tasks are bookkeeping and data entry typical of "Office and Administrative support" occupations while routine manual occupations in "production", "maintenance and repair" entail monitoring activities on the factory floor. The construction of a de-routinisation index requires several steps. First, we merge job task requirements to their corresponding occupation classification to assign task-intensity to individual job titles. Occupations are then identified as routine intensive based on their relative task-intensity as in Acemoglu and Autor (2011). Next, using the OES BLS occupational employment data and IPUMS census data, we calculate the routine employment share for each MSA as follows:

$$\mathrm{RSH}_{\mathrm{rt}} = \left(\sum_{\mathrm{j}=1}^{\mathrm{J}} \mathrm{L}_{\mathrm{jrt}} \cdot 1\left[\mathrm{RTI}_{\mathrm{j}}\right]\right) \left(\sum_{\mathrm{j}=1}^{\mathrm{J}} \mathrm{L}_{\mathrm{jrt}}\right)^{-1} \quad (1)$$

where $\mathrm{RSH}_{\mathrm{rt}}$ is the routine employment share in MSA r at time t; $\mathrm{L}_{\mathrm{jrt}}$ is the employment in occupation j in MSA r at time t and $1\left[\mathrm{RTI}_{\mathrm{j}}\right]$ is an indicator function taking value 1 if the occupation j is routine intense. Our index thus calculates the difference between the share of employment in routine-intensive jobs between two periods. In our preferred specification and due to data availability, we calculate this difference between 1990 and 2001 (i.e. the index increases the higher is the reduction in the MSA r routine-job intensity during the 1990s). Formally, we define the index $\Delta\mathrm{RSH}_{\mathrm{r},1990-2001}$ as follows:

$$\Delta\mathrm{RSH}_{\mathrm{r},1990-2001} = 100 \times \left(\mathrm{RSH}_{\mathrm{r},1990} - \mathrm{RSH}_{\mathrm{r},2001}\right) \quad (2)$$

Our expectation is that MSAs that experienced a stronger decline in routine-intensive jobs during the 1990s did suffer in terms of innovative performance in digital manufacturing technologies in the 2000s. Moreover, we split routine jobs between routine cognitive and routine manual to test for possible differential associations between changes in these two categories and local innovation in AMTs.

3.2. Empirical Strategy

To investigate the relationship between employment de-routinisation and innovative efforts in AMTs at the MSA level, we first estimate the following model:

$$\Delta \mathrm{AMT}_{r,2012-2002} = \beta \Delta \mathrm{RSH}_{r,1990-2001} + \Upsilon X_r' + \epsilon_r \tag{3}$$

where $\Delta \mathrm{AMT}_{r,2012-2002}$ is the percentage change in the number of AMT patents for region r between 2012 and 2002, defined as $100 \times (\mathrm{AMT}_{r,2012} - \mathrm{AMT}_{r,2002})/(0.5\mathrm{AMT}_{r,2012} + 0.5\mathrm{AMT}_{r,2002})$;[11] $\Delta \mathrm{RSH}_{r,1990-2001}$ is the change of employment share in routine jobs for region r between 1990 and 2001, defined as $100 \times (\mathrm{RSH}_{1990} - \mathrm{RSH}_{2001})$;[12] ϵ_r is the error term and X_r' comprises controls for local factors, expressed in term of percentage change between 1990 and 2001, that may affect the capacity of an MSA to patent in AMTs. First, we control for the change in the employment share in high-skilled (abstract) occupations between 1990 and 2001. To calculate the share of employment in high-skill (abstract) jobs at the MSA level, we rely on the ALM task-based framework, then following the same procedure adopted for the share of routine occupations described in Section 3.1. We begin with the identification of abstract-intensive occupations. Typical of professional, managerial, technical and creative occupations, abstract tasks require intuition, creativity and problem solving, and are performed by workers possessing high levels of education and analytical capabilities. Then, by applying formula (1) to abstract-intensive occupations and the employment levels in those occupations, we derive our high-skill employment share at the MSA level. By focusing on skills and tasks rather than just education attainments, the high-skill employment share offers a more precise indicator of human capital, better capturing the role of high-skilled workers for innovation. The percentage change in the share of high-skilled (abstract) jobs is calculated as the difference between the 2001 and the 1990 shares. Second, we include the percentage change in MSAs' number of firms operating in the manufacturing sector between 1990 and 2001, to control for the potential effect of de-industrialization due to a contraction in industrial production – that may have occurred during the 1990s – on local innovation capabilities. We also control for the local existing innovation capabilities by including the percentage change in the MSAs patenting level, between 1990 and 2001. This last variable should control, at least partially, for possible decreasing returns to scale in innovation activities. Lastly, we include a control for the level of population density measured in 2001. Since MSAs show high variability in terms of population

[11] $\Delta \mathrm{AMT}_{r,2012-2002}$ ranges between -200 and 200. In the main analysis, we apply this transformation to include also MSAs that did not patent in AMTs in 2002. According to our data, 65 MSAs did not patent in AMTs in 2002.

[12] It is worth noticing that for each MSA r, the stronger the decline in the employment share of routine jobs during the period 1990-2001, the higher the de-routinisation index. In other words, our de-routinisation index is higher in the MSAs that experienced higher losses in routine-intensive occupations.

and, importantly, patenting capacity, we weight all regressions by the local per-capita level of patenting in 2001 to assign a relatively lower weight to observations with the highest patenting variance (i.e. smaller MSAs). Standard errors are clustered at the State level to account for possible spatial correlation across MSAs.[13]

As anticipated in Section 3.1, we split our occupational routine measure into routine cognitive (RCSH) and routine manual (RMSH) and calculate two de-routinisation indexes accordingly ($\Delta \mathrm{RCSH}_{r,1990-2001}$ and $\Delta \mathrm{RMSH}_{r,1990-2001}$, respectively). Therefore, we estimate the following model:

$$\Delta \mathrm{AMT}_{r,2012-2002} = \beta_1 \Delta \mathrm{RCSH}_{r,1990-2001} + \beta_2 \Delta \mathrm{RMSH}_{r,1990-2001} + \Upsilon X_r' + \epsilon_r \quad (4)$$

To complement the analysis, we also estimate models in equations 3 and 4 on, alternatively, the local percentage change in all patents (ALL) and information and communication (ICT) related patents. To retrieve information on ICT patents we rely on the classification proposed by OECD (2017).

4. Empirical Analysis

4.1. Descriptive statistics

Table 1 offers a synthetic description of the main variables employed in the empirical analysis, while Table 2 contains the descriptive statistics. Figure 1 provides a first glimpse of the association between the documented loss of routine-skill workers during the 1990s and AMTs innovative capability that we will explore in detail. The diagram plots the growth rate of AMT patents between 2002 and 2012 against our index of de-routinisation as per section 3.1. Each dot represents an MSA, the size being proportional to the total number of patents in 2001 in the Metro Area. Figure 1 shows that the raw correlation between the change in the endowment of routine workers and AMT patenting is negative. This suggests that areas characterized by higher losses in the shares of routine-skilled workers in 2001 with respect to 1990 (i.e. a positive value in the de-routinisation index) also experienced a higher decline of

[13] Ideally, a panel modelling strategy covering the period 1990-2012 would have been appropriate for it would allow to control for time-invariant local area characteristics and for temporal structural conditions that affect all the MSAs. Unfortunately, as mentioned in Section 3, yearly information on the local skills composition for the decade 1990-2000 are not available. As an alternative, we ran a series of panel fixed effect regressions that exploit the longitudinal dimension of our data starting from 2001. The findings are in line with our main results (see Section 4.2) and confirm the central role of routine workers for the local innovative capacity in AMTs. Appendix B reports the results. We wish to thank an anonymous referee for suggesting this further test.

AMT patenting during the 2000s, especially areas with lower patenting intensity. This is an initial hint that local labour markets where routine-intensive jobs prevailed were more exposed to labour-for-capital substitution and job polarisation after the uptake of automation in the mid-1990s. In turn, the declining demand for routine jobs and the associated lower endowment of mid-skilled workers is negatively associated to MSAs' patenting in AMTs.

Figure 2 depicts the spatial distribution of changes in local AMTs patenting (our dependent variable) and the de-routinisation index (our main explanatory variable). Each MSA is coloured according to the weighted-quintile rank in the distribution of the relevant dimension. The colour scale in panel (a) indicates the MSAs with larger declines in the number of AMT patents between 2002 and 2012. The figure reveals significant geographical variations, with a higher concentration of declining areas around the rust belt. The geographical distribution of changes in the routine employment share is presented in Figure 2 panel (b). Darker colours indicate metropolitan areas that experienced higher losses in terms of routine jobs during the 2000s.

<<<TABLE 1 ABOUT HERE>>>

<<<TABLE 2 ABOUT HERE>>>

<<<FIGURE 1 ABOUT HERE>>>

<<<FIGURE 2 ABOUT HERE>>>

4.2. Regression Analysis

4.2.1. Baseline models

This section contains the results of the econometric analysis of the long-term relationship between local changes in routine skills and local innovation capacity. Table 3 reports estimates for the percentage change in patenting over the period 2002-2012. Columns I and II refer to changes in AMT patenting, while columns III and IV refer to changes in total patenting (ALL). The last two columns (V and VI) instead refer to the association between de-routinisation and patenting in ICT. All the models include the full set of controls as described in Section 3.2 and are weighted by the 2001 per-capita number of local patents. Standard errors are clustered at the State level.

Focusing on the results reported in Table 3, we find a negative association between the decrease in routine-intensive occupations and local innovative capacity in AMTs. Precisely, a 1% decrease in routine-intensive employment (ΔRSH) during the 1990s is associated with a 7.3% decrease in AMTs between 2002 and 2012 (column I). The negative magnitude of the coefficients largely decreases if we focus on total patenting (column III), reaching around -4%, and it does not reach statistical significance when considering patenting in ICT related technologies as dependent variable (column VI). As reported in column II, local inventive activity in AMTs seems to be correlated more to changes in the employment of repetitive manual work (i.e. blue-collar jobs) than to changes in routine cognitive jobs (i.e. clerks). Indeed, we find a negative and significant coefficient for the reduction in both ΔRMSH (-7.9%) and ΔRCSH (-6.5%).

We also find a negative association between losses in both manual and cognitive routine jobs on the percentage change of local total patenting. As shown in column IV, the reduction in the share of blue-collar (ΔRMSH) and clerical workers (ΔRCSH) is indeed negatively associated with local innovation capacity. In this case, the magnitude of the ΔRMSH coefficient is at -4.2%, slightly higher than the previous estimation, while the magnitude of ΔRCHS is similar (around -3.8%). Turning to ICT patenting, changes in local innovative capability in this domain seems to be not responsive to drops in the share of routine-manual and routine-cognitive workers. Indeed, looking at column VI, we do not find statistically significant coefficients for both ΔRMSH and ΔRCSH.

Looking at the control variables, we find positive and significant coefficients for the change in the high-skilled employment share (though only on AMTs) and for the population density. Conversely, we find a negative coefficient for the change in the total level of patenting that likely reflects decreasing returns to scale in innovation. Lastly, the percentage change in the number of manufacturing firms is not statistically significant.

<<< TABLE 3 ABOUT HERE >>>

4.2.2. Incremental innovation

In Section 4.2.1 we empirically show that the diminished availability of routine workers is associated with decreasing innovative performances, confirming our hypothesis that routine workers' tasks and their attending skills can be essential for productivity and innovation. Indeed, as discussed in Section 2, the fundamental 'downstream' incremental improvements that stand at the core of innovation can be ascribed to the tacit know-how of routine workers and their increasing importance as 'knowledge-bridges' across modern factories functional departments. While our distinction between technology domains helps identifying the association between de-routinisation and AMT innovative efforts, the minor 'downstream' improvements of factory-floor workers, though their cumulative effects can be massive, are still incremental in nature, regardless of the technological domain to which they pertain. Accordingly, we complement the main analysis by looking at incremental innovations to better understanding the crucial role of routine workers on innovative capabilities.[14]

To identify patents related to incremental innovations, several steps are required. Extant empirical literature exploiting patent data has primarily focused on radical and breakthrough innovation. Few studies dealt with the identification of incremental innovations using patent data (e.g. Dutta and Weiss, 1997; Katila, 2000). These works distinguish between radical and incremental invention based on patents score on a radicalness measure, by setting a given distribution threshold (Ahuja and Morris Lampert, 2001; Dahlin and Behrens, 2005). For example, Wu et al. (2009) use patents received citations as radicalness measure and classify as incremental inventions those patents having citations below the top 3% of patent citation frequency.

To categorize incremental inventions for the purposes of the present study we exploit the radicalness measure by Squicciarini et al. (2013) (OECD radicalness henceforth) that relies on patent backward citations. The authors compute such a measure among from a set of patent quality indicators proposed by the OECD every year for both EPO and (only recently) USPTO patents (the "OECD Patent Quality Indicators database, January 2020"). Following the measure originally proposed by Shane (2001), according to Squicciarini et al. (2013): "…the radicalness of a patent is measured as a time invariant count of the number of IPC technology classes in which the patents cited by the given patent are, but in which the patent itself is not classified. […] the more a patent cites previous patents in classes other than the ones it is in, the more the invention should be considered radical, as it builds upon paradigms that differ from the one to

[14] We wish to thank an anonymous referee for suggesting us to more formally extend the analysis to incremental innovation by exploiting more in depth information contained in patent data.

which it is applied" [p. 53]. The radicalness index is, therefore, a continuous indicator, ranging from 0 to 1, that "underlines the dispersion of technology classes in the backward citations and the extent to which they differ from the focal patent" [p. 56]. Therefore, we identify patents belonging to the top 3% in the distribution of OECD radicalness index by patent cohort (patent filing year) and main technology field (Schmoch, 2008), and define them as radical patents. On the other hand, patents below this threshold (bottom 97% by field/cohort) are considered incremental patents.[15]

Table 4 reports the results of the econometric analysis on the long-term association between de-routinisation and local incremental innovative capabilities. The table reports the estimates for the percentage change in incremental patenting over the period 2002-2012, where columns I and II refers to changes in AMT incremental patents, columns III and IV to total incremental patenting, while the last two columns (V and VI) refers to the relationship between de-routinisation and ICT incremental patents. All the models include the full set of controls as described in Section 3.2 and are weighted by the 2001 per-capita number of local patents. Standard errors are clustered at the State level.

Looking at the results in Table 4, we find a negative association between the decrease in routine-intensive occupations and local incremental patenting in AMTs. In particular, a 1% decrease in routine-intensive employment (ΔRSH) during the 1990s is associated with about 7% decrease in incremental AMTs patents between 2002 and 2012 (column I). As in Table 3, the negative magnitude of the coefficients decreases when considering total incremental patenting (column III), estimating a coefficient of around -4%. While the association between de-routinisation and ICT patenting does not reach statistical significance (see column VI in Table 3) when considering only incremental patents in ICT related technologies as dependent variable we estimate a negative and significant coefficient (though only at 1% significance level), with a magnitude close to -3.8%.

Similar to the findings of the previous subsection, also in this case local incremental inventive activity in AMTs seems to be more responsive to changes in the employment share of routine-manual workers than to changes in repetitive cognitive jobs (as reported in columns

[15] In Section 4.3 we provide robustness checks to this analysis by considering different index thresholds used to split patents between incremental and radical, i.e.: 1%, 5% and 10%. We also employ an alternative radicalness measure, following Wu et al. (2019), and categorize incremental innovation in terms of patent forward citation frequency.

II). In particular, we find a negative and significant coefficient for the reduction in ΔRMSH at -7.7%, while the coefficient for ΔRCSH is at around -6%.

The negative association between loss in both manual and cognitive routine jobs and local patenting is confirmed when looking at total incremental patents (column IV). Therein, the estimated coefficients are both negative and statistically significant, exhibiting magnitudes very close to those obtained in column IV, Table 3 (-4.3 and -3.7, respectively, for ΔRMSH and ΔRCSH). Interestingly, looking at column VI we notice that, while the association between de-routinisation and incremental ICT patenting is not statistically significant when considering only routine-manual employment, the coefficient for changes in the employment share of routine-cognitive workers is negative and significant. This indicates that the long-term loss of repetitive cognitive routine jobs may have hindered incremental innovative capabilities also in ICT related technologies.

The estimated coefficients of the control variables are in line with those already discussed in Section 4.2.1.

<<< TABLE 4 ABOUT HERE >>>

4.3. Robustness checks

This section presents several robustness checks. First, we consider the robustness of our empirical analysis to different specifications of the intervals over which the percentage change in our dependent variables are calculated. To this end, we compute the rate of patenting growth over three 3-year time-windows, 2002-2005, 2005-2008 and 2008-2011, to incorporate intermediate information on MSAs patenting behaviour during the decade 2002-2012. Here our main dependent variables are the average growth rate over the three periods of, respectively, AMT patents, total patents and ICT patents. Results are reported in Table A1 (see the Appendix) and qualitatively confirm our main findings.[16] In particular, we find that a 1% decrease in the share of routine workers is associated with a decrease of about 3.4% of the

[16] In an additional robustness check, we use the patenting average growth calculated over two 5-year time windows as dependent variable. Moreover, we also test whether results are robust to changing the starting year and the end year over which the percentage change in patenting is calculated, i.e.: from 2003 to 2011. Both checks yield results in line with our main findings and are available upon request.

average three-year growth in AMT patents (column I). The estimated coefficient reduces in magnitude reaching -0.96% when considering total patenting (column III) and -1.1% in the case of ICT (column V). The higher responsiveness of AMTs to changes in the employment of routine-manual workers (with respect to changes in routine-cognitive jobs) is also confirmed. Indeed, as reported in column II, we estimate a negative and statistically significant coefficient of -4.4% for ΔRMSH, while ΔRCSH, though still negative, is not statistically significant. The loss of routine manual and routine cognitive workers are both negatively associated to the average three-years growth rate in total patenting (column IV), while we find a negative and significant coefficient only for ΔRCSH in the case of ICT (column VI).

As a second robustness test, we add two additional controls to our main specification. The first concerns the impact of labour flexibility on productivity and, in turn, on innovation. According to prior studies (see i.e. Arvanitis 2005; Lucidi, and Kleinknecht 2009), intensive reliance on temporary contracts, a proxy of labour flexibility, can potentially hamper the accumulation of tacit and firm-specific knowledge thus reducing innovative competences (Kleinknecht, and Naastepad 2014). From an empirical point of view, Cetrulo et.al. (2019) focus on five major European economies between 1998 and 2012, finding a negative correlation between temporary contracts and product innovation. In order to account for the potential negative effect of temporary employment, we run several robustness checks adding to the set of control variables also the percentage change in the local share of temporary workers between 1990 and 2000. Unfortunately, an explicit measure of temporary workers is not available for the years covered by our analysis. Therefore, we exploit the IPUMS USA census data and collect data on the weeks worked by individuals in 1990 and 2000. Precisely, we proxy temporary workers by considering those individuals that worked a number of weeks that falls below the average number of weeks nationally worked. Then, we calculate the share of those workers at the MSA level and use the percentage change between 1990 and 2000 as a control variable for the role of temporary workers. The second variable we add concerns the share of highly educated workers. While the inclusion of the share of high-skilled (abstract) employment already accounts for the fundamental role of human capital, as mentioned in Section 3.2, we complement it with a more direct proxy for the level of education of the local workforce. Again, we collect data from the IPUMS USA census database and calculate the share of employed individuals possessing at least a bachelor degree for each MSA. In turn, our control is given by the percentage variation in the share of "bachelor" educated workers between 1990 and 2000. Table A2 in the Appendix reports the results when including the two further control variables described above. Here the focus is only on changes in AMT patenting.[17] Results of these robustness checks are fully consistent with the main results. As for the variations in the shares of both temporary and tertiary educated workers, the estimated coefficients are not significant.

Lastly, we test the robustness of our measure of incremental patents. First, we calculated our dependent variables using an alternative measure of incremental patents. To this end, following Wu et al. (2009), we define ‘incremental’ the complement of the patents in the top 3% in term of 5-year forward citations (since filing), by patent cohort and main technology field. We express then the dependent variables as the percentage variation in the number of incremental AMT, total and ICT patents between 2002 and 2012, respectively. Table A3 (see the Appendix) reports the results of the estimation using the alternative measure of incremental patents. The results are very similar to those presented in Table 4, thus confirming our main results. Second, we run additional estimates to check the robustness of our main incremental patent measure to the choice of the forward citations frequency threshold in defining the incremental patents. Precisely, we test whether results hold when excluding from the radicalness measure, alternatively, the top 1%, 5% and 10% most cited patents (by cohort / technological field). The results of these tests confirm the robustness of the main analysis and are available upon request.

5. Concluding remarks and the way ahead

The relationship between technological change and labour dynamics has received much attention in the last decades. Grounded on the seminal contributions by Smith, Marx and Ricardo, a new wave of theoretical and empirical literature has been stimulated by the well-known ICT revolution that gained momentum in the late 1990s. On the one hand, these studies aimed at assessing the extent to which compensation effects could have offset substation ones, generating a net positive impact. On the other hand, it has become clear that the increasing diffusion of computers in production processes would have affected workers in different ways, depending on the kind of skills. The new recent wave of technological change in the digital domain has renewed the interest in the relationship between innovation and labour markets. The peculiarities of digital technologies and their larger scope of applications has stimulated

[17] We perform the same tests also considering variations in overall patenting and patenting in ICT as dependent variables. Results are fully consistent with the main findings and are available upon request by the authors.

new theoretical efforts towards a framework that better accommodates their manifold nuances and pathways of impact. Starting from a dissatisfaction with the traditional model of human capital, the new framework shifts the emphasis to occupations and their skill content. This has proven effective in accounting for the intrinsic heterogeneity of both capital and labour, as well as the potential related to the expansion of the set of tasks produced by capital (Acemoglu and Restrepo, 2019).

The debate on the socio-economic implications of digital innovation revolves mostly around the effect of automation and digitalisation on the demand for mid-skilled workers. The literature has widely documented increasing labour market polarisation, that is, growing labour demand at the two extremes of the skill distribution accompanied by declining demand for occupations in the middle. The debate that has ensued from the seminal findings of ALM (2003) for the US and of Goos and Manning (2007) for the UK has enlarged the geographical scope of the study of polarisation[18] but has arguably neglected the impact that the loss of middle-skill routine human capital could have on innovation.

This gap is noticeable especially in consideration of the vast literature about the importance of tacit knowledge, learning-by-doing and practical know-how skills that are crucial for incremental innovation (Rosenberg, 1976). The gap is also evident when one turns to the debate among practitioners. Due to the radical transformations that led to job polarisation, therein including technology and trade, manufacturing is changing driven by the integration of highly flexible, data-enabled, and cost-efficient processes that hold the promise of boosting competitiveness and opening new avenues for innovation. The modern factory powered by Advanced Manufacturing Technology relies on a large volume and frequency of information that can achieve higher precision, responsiveness and diversification. As usual, the higher complexity of the technology calls upon the adaptation of the skills base (Vona and Consoli, 2015). In the case at hand, reaping the full benefits of AMTs is contingent to the availability of programming, monitoring and troubleshooting skills to handle and respond to the growing intensity and variety of feedback loops. Put otherwise, in the current stage of the life cycle, the new technology requires a new generation of blue-collar workers – or 'new-

[18] See i.e. Autor and Dorn (2013) on US commuting zones; Senftleben-König and Wielandt (2014) and Dauth (2014) on various territorial disaggregations in Germany; Malgouyres (2017) on French commuting units; Consoli and Sanchez-Barrioluengo (2019) on Spanish provinces.

collar' as per the industry jargon[19] – that can program, operate and maintain an ensemble of computer- and network-driven devices. This equipment has proliferated in manufacturing just as many traditional routine factory jobs have been outsourced or supplanted by the early wave of automation. The message stemming from industry experts is clear: finding, creating and retaining this kind of workers has become a critical bottleneck (Accenture and Manufacturing Institute 2014; Muro et al, 2015; Deloitte and Manufacturing Institute, 2018).

These shortcomings motivated our study on whether and to what extent the loss of routine workers, which is the trademark indicator of job polarisation, is related to the local capacity to innovate. This is clearly a complex issue that will require various iterations of empirical work before any evidence can be considered conclusive. The present paper opens this avenue by framing the analysis at the level of Metropolitan Statistical Area (MSA) in the US during the period 2002-2012. Importantly, our main empirical analysis focuses on the relationship between the prolonged local de-routinisation and innovation in AMTs. The empirical analysis indicates that, on average, the loss of routine-intensive jobs is a negative predictor of local innovative capacity. Precisely, we estimate that a 1% decrease in routine intensive occupations during the 1990s is associated to some 4% reduction in local total patenting during the 2002-2012 period. The coefficient is larger on AMTs, as much as around -7.3%. Further, we observe negative associations between innovation and both kinds of routine macro-tasks, i.e. repetitive cognitive and repetitive manual, with the latter showing more pronounced magnitudes for AMTs.

Our analysis contributes the current debate on the relationship between technological change in the digital domain and economic performance. No doubt, compensation and substitution effects are important to grasp how technologies shape labour market dynamics. It goes without saying that organisational adaptations are a key, if understudied, ingredient in the mix. At the same time, our results shed light on a different, hitherto ignored aspect, namely that in the long-run job polarisation may jeopardise the inventive process, especially those incremental innovations based on learning-by-doing and the accumulation of on-the-job know-how. While radical innovation is important for opening up new paradigms, incremental innovation is essential to consolidate technological trajectories by ensuring continuous improvements within a paradigm. From an evolutionary viewpoint, an implication of our

[19] See i.e. National Association of Manufacturers (NAM) 2018 State of Manufacturing Address: https://www.nam.org/Newsroom/Press-Releases/2018/02/Excerpts--NAM-2018-State-of-Manufacturing-Address

results is that routinisation may undermine technological variety that, coming full circle, narrows future prospects for economic development based on innovation.

These considerations call for further reflections concerning the coordination between innovation, industrial and labour policies. Currently, in many countries these three realms converge towards the creation of an environment favourable to the massive diffusion of digital technologies in production processes. However, especially labour policies should help preserve routine jobs because of their key contribution to the incremental innovation process, which is fundamental in ‘normal science’ periods. We hope that our initial exploration will lay the ground for future empirical research.

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FIGURES AND TABLES

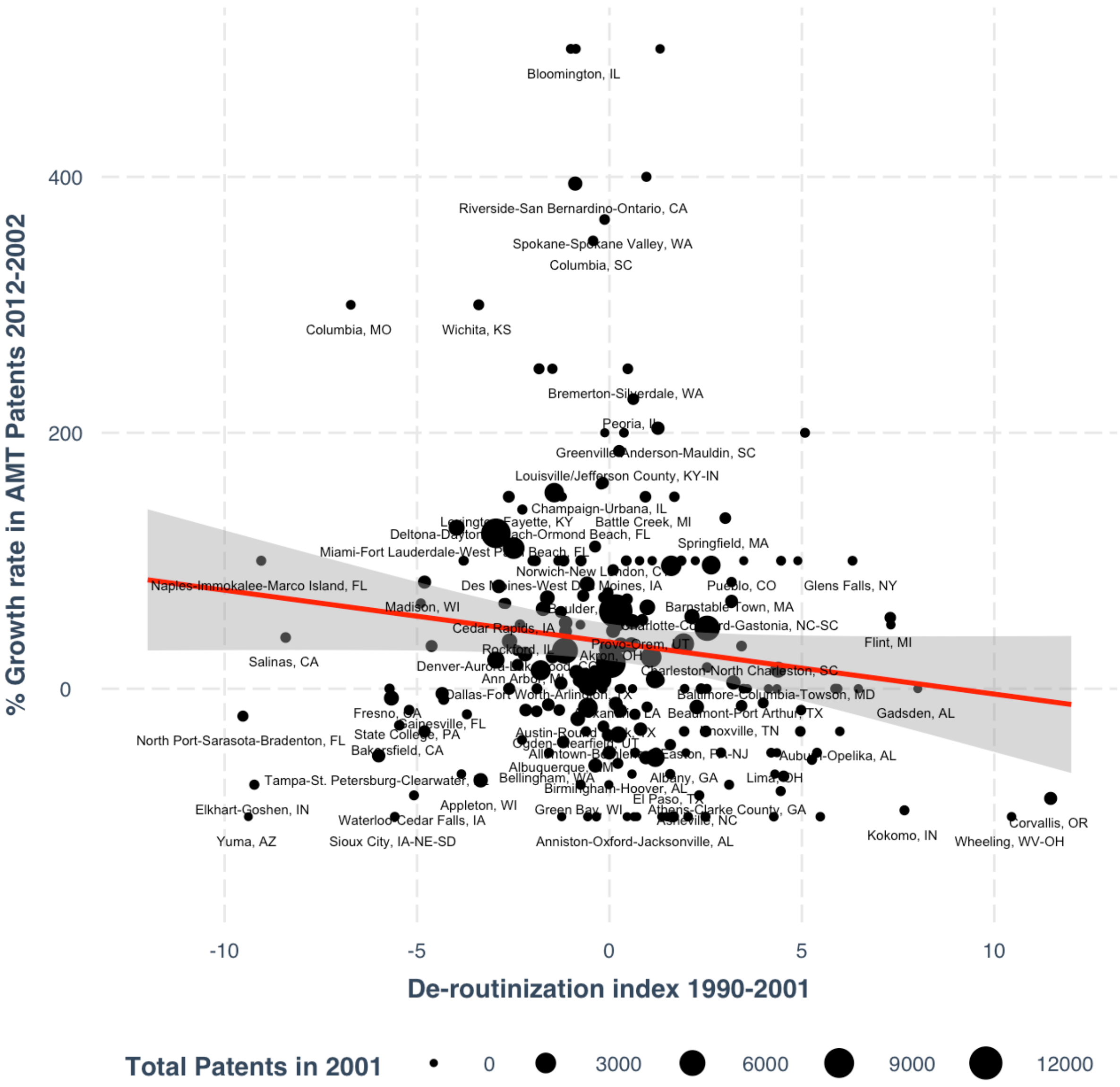
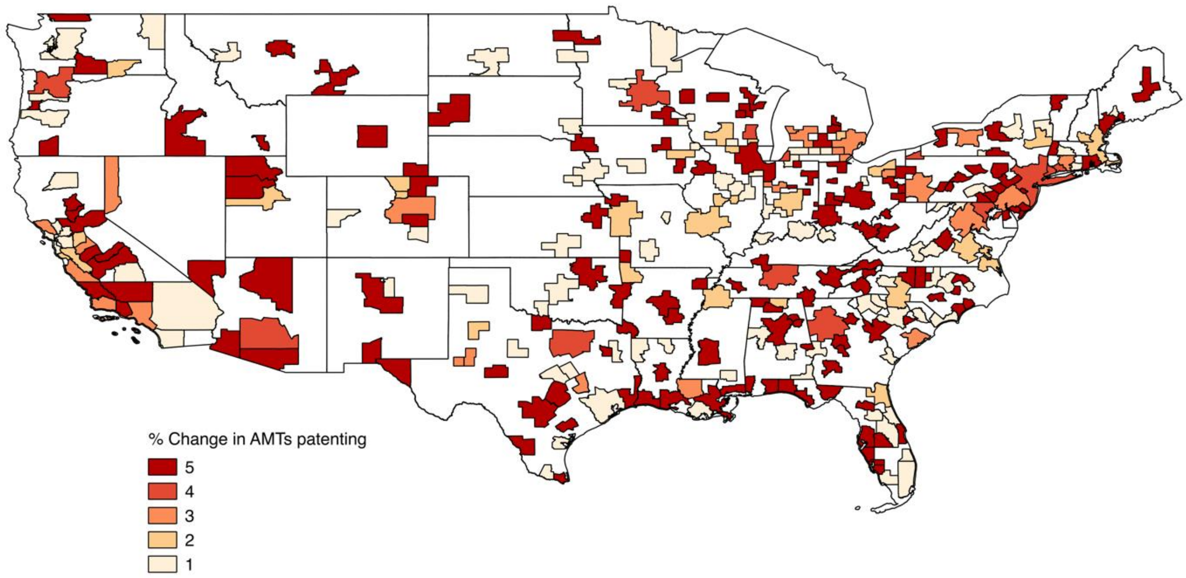


Figure 1. The relationship between the change in routine employment share between 1990 and 2001 (de-routinisation index) and the percentage growth rate in AMT patenting between 2002 and 2012, by MSA.

Note: Observations (MSAs) weighted by the total number of patents in 2001 in the corresponding MSA.

(a) Percentage change in AMTs patenting from 2002 to 2012 (quintiles)



(b) Percentage change in the share of routine jobs from 1990 to 2001 (quintiles)

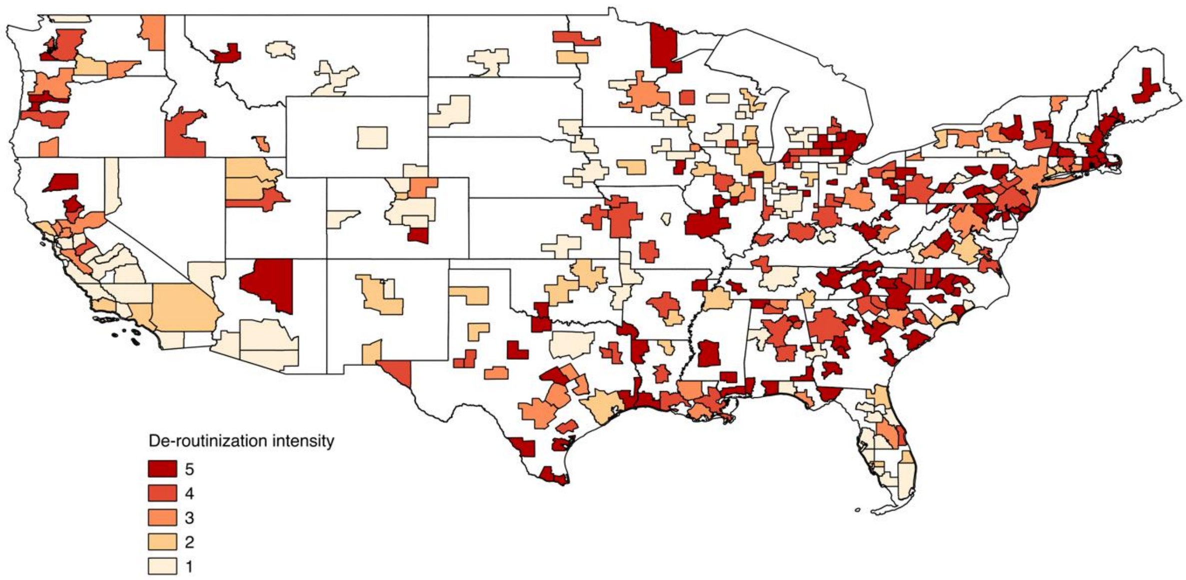


Figure 2. Geographic distribution of the percentage change in AMTs patenting from 2002 to 2012 (panel a), and the de-routinisation index from 1990 to 2001 (panel b).

Note: Quintiles in panel (a) weighted by the MSA total number of patents in 2001. Quintiles in panel (b) weighted by MSA total employment in 1990.

Table 1. Variables description

Variable	Description	Reference Period
ΔAMT	Percentage change in the number of patents in Advanced Manufacturing Technologies between 2012 and 2002	2012-2002
ΔTOT	Percentage change in the number of total patents between 2012 and 2002	2012-2002
ΔICT	Percentage change in the number of patents in ICT between 2012 and 2002	2012-2002
ΔRSH	Percentage change in routine employment share between 2001 and 1990	1990-2001
ΔRMSH	Percentage change in routine-manual (i.e. blue collar workers) employment share between 2001 and 1990	1990-2001
ΔRCSH	Percentage change in routine-cognitive (i.e. clerical workers) employment share between 2001 and 1990	1990-2001
ΔHigh-Skill	Percentage change in high-skilled employment share between 1990 and 2001	2001-1990
ΔN. of man. firms	Percentage change in the number of firms operating in the manufacturing sector between 1990 and 2001	2001-1990
ΔTot patents	Percentage change in the number of patents (log) between 1990 and 2001	2001-1990
Pop dens	Total population divided by MSA land area in 2001	2001

Table 2. Summary Statistics

Variable (N = 289)	Mean	St. dev	Min	Max
ΔAMT	24.2166	98.2488	-200	200
ΔTOT	5.41439	45.3930	-113.0435	158.6592
ΔICT	36.4596	82.3932	-200	200
ΔRSH	0.3070	3.6984	-16.5635	11.4643
ΔRMSH	0.6004	2.2830	-12.8595	10.6377
ΔRCSH	-0.2933	2.8375	-13.4245	8.1072
ΔHigh-Skill	-1.2078	2.5666	-21.5360	5.2599
ΔN. of man. firms (log)	0.6651	14.2951	-36.9747	55.0230
ΔTot patents (log)	0.5673	0.5531	-1.7917	2.5630
Pop dens (log)	2.2784	0.7367	0.1917	4.6122

Table 3. De-routinisation and AMT innovation, total innovation and ICT innovation between 2002 and 2012

	(AMT)	(AMT)	(TOT)	(TOT)	(ICT)	(ICT)
ΔRSH	-7.258**		-3.997***		-2.576	
	(2.799)		(1.315)		(1.918)	
ΔRMSH		-7.950**		-4.171**		-2.073
		(3.149)		(1.599)		(2.244)
ΔRCSH		-6.461*		-3.796**		-3.156
		(3.535)		(1.550)		(2.692)
ΔHigh-Skill	5.631**	5.325*	-0.303	-0.381	-1.323	-1.099
	(2.591)	(2.726)	(1.264)	(1.308)	(1.716)	(1.929)
ΔN. of man. firms	-0.159	-0.145	-0.384	-0.381	-0.194	-0.204
	(0.403)	(0.405)	(0.332)	(0.332)	(0.419)	(0.431)
ΔTot patents	-31.120***	-31.148***	-13.991*	-13.998*	-32.467***	-32.446***
	(10.574)	(10.583)	(7.499)	(7.508)	(8.859)	(8.899)
Pop dens	14.007*	13.864*	11.473**	11.437**	14.782**	14.886**
	(8.227)	(8.217)	(4.560)	(4.546)	(5.932)	(5.914)
Adj. R2	0.171	0.172	0.290	0.290	0.214	0.214
Obs.	289	289	289	289	289	289

Dependent variables: Relative change in AMT patents (Columns I and II), total patents (Columns III and IV) and ICT patents (Columns V and VI). The relative change in patents is defined as the difference in patents over the period 2002-2012, divided by the average number of patents across the two periods 2002 and 2012. ΔRSH, ΔRMSH and ΔRCSH are measured as the difference in the share of employment between 2001 and 1990. Control variables are in delta, measured as the difference between 1990 and 2001. Pop dens is in 2001 levels. Regressions are weighted by the 2001 per-capita number of local total patents. Robust standard errors, in parentheses, are clustered at the State level. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 4. De-routinisation and incremental AMT innovation, incremental total innovation and incremental ICT innovation between 2002 and 2012

	(AMT)	(AMT)	(TOT)	(TOT)	(ICT)	(ICT)
ΔRSH	-6.976**		-4.030***		-3.812*	
	(2.786)		(1.334)		(1.916)	
ΔRMSH		-7.753**		-4.268**		-2.402
		(3.104)		(1.602)		(2.305)
ΔRCSH		-6.081*		-3.755**		–5.435**
		(3.608)		(1.579)		(2.213)
ΔHigh-Skill	4.600*	4.255	-0.451	-0.557	-0.307	0.318
	(2.606)	(2.774)	(1.276)	(1.324)	(1.641)	(1.678)
ΔN. of man. firms	-0.149	-0.133	-0.388	-0.383	-0.434	-0.462
	(0.404)	(0.406)	(0.334)	(0.334)	(0.413)	(0.417)
ΔTot patents	-30.558***	-30.590***	-14.620*	-14.629*	-27.843***	-27.786***
	(10.621)	(10.628)	(7.546)	(7.555)	(9.039)	(9.109)
Pop dens	12.323	12.162	11.593**	11.544**	11.230*	11.522**
	(7.942)	(7.914)	(4.573)	(4.555)	(5.636)	(5.696)
Adj. R2	0.163	0.164	0.297	0.297	0.234	0.239
Obs.	289	289	289	289	289	289

Dependent variables: Relative change in incremental AMT patents (Columns I and II), incremental total patents (Columns III and IV) and incremental ICT patents (Columns V and VI). Incremental patents are defined as the complement of the top 3% radical patents in terms of OECD radicalness measure, by main technology field and cohort. The relative change in patents is defined as the difference in patents over the period 2002-2012, divided by the average number of patents across the two periods 2002 and 2012. ΔRSH, ΔRMSH and ΔRCSH are measured as the difference in the share of employment between 2001 and 1990. Control variables are in delta, measured as the difference between 1990 and 2001. Pop dens is in 2001 levels. Regressions are weighted by the 2001 per-capita number of local total patents. Robust standard errors, in parentheses, are clustered at the State level. * $p < .1$, ** $p < .05$, *** $p < .01$

APPENDIX A

Table A1. Robustness: De-routinisation and AMT innovation, total innovation and ICT innovation (average growth rates over three 3-year windows)

	(AMT)	(AMT)	(TOT)	(TOT)	(ICT)	(ICT)
ΔRSH	-3.341**		-0.964**		-1.105*	
	(1.291)		(0.383)		(0.594)	
ΔRMSH		-4.431***		-0.943**		-0.754
		(1.172)		(0.461)		(0.702)
ΔRCSH		-2.086		-0.989*		-1.509**
		(1.350)		(0.494)		(0.686)
ΔHigh-Skill	2.214	1.731	0.106	0.116	0.336	0.492
	(1.459)	(1.412)	(0.357)	(0.387)	(0.430)	(0.468)
ΔN. of man. firms	-0.425*	-0.403*	-0.131	-0.132	-0.121	-0.128
	(0.238)	(0.225)	(0.099)	(0.099)	(0.140)	(0.139)
ΔTot patents	-7.076	-7.121	-6.014***	-6.013***	-11.970***	-11.956***
	(4.400)	(4.401)	(2.223)	(2.227)	(2.539)	(2.542)
Pop dens	-1.235	-1.461	3.240**	3.244**	3.852*	3.925*
	(4.241)	(4.125)	(1.601)	(1.608)	(2.064)	(2.096)
Adj. R2	0.091	0.099	0.240	0.240	0.148	0.149
Obs.	289	289	289	289	289	289

Dependent variables: Relative change in AMT patents (Columns I and II), total patents (Columns III and IV) and ICT patents (Columns V and VI). The relative change in patents is defined as the average growth rate in patents over the 3-year time windows 2002-2005, 2005-2008 and 2008-2011. ΔRSH, ΔRMSH and ΔRCSH are measured as the difference in the share of employment between 2001 and 1990. Control variables are in delta, measured as the difference between 1990 and 2001. Pop dens is in 2001 levels. Regressions are weighted by the 2001 per-capita number of local total patents. Robust standard errors, in parentheses, are clustered at the State level. * $p < .1$, ** $p < .05$, *** $p < .01$

Table A2. Robustness: De-routinisation and AMT innovation between 2002 and 2012, controlling for temporary workers and tertiary educated workers.

	(AMT)	(AMT)	(AMT)	(AMT)	(AMT)	(AMT)
ΔRSH	-7.037**		-7.203**		-6.908**	
	(2.864)		(2.737)		(2.830)	
ΔRMSH		-7.861**		-7.906**		-7.763**
		(3.183)		(3.065)		(3.121)
ΔRCSH		-6.080*		-6.384*		-5.898
		(3.540)		(3.535)		(3.538)
ΔHigh-Skill	5.744**	5.379**	5.573**	5.254*	5.623**	5.233*
	(2.506)	(2.654)	(2.570)	(2.728)	(2.508)	(2.664)
ΔN. of man. firms	0.002	0.021	-0.160	-0.146	0.007	0.028
	(0.399)	(0.395)	(0.405)	(0.406)	(0.403)	(0.397)
ΔTot patents	-31.994***	-32.043***	-31.646***	-31.720***	-33.178***	-33.301***
	(10.204)	(10.189)	(10.506)	(10.551)	(10.043)	(10.053)
Pop dens	10.354	10.116	13.416	13.219	8.898	8.562
	(7.748)	(7.649)	(8.711)	(8.832)	(8.097)	(8.169)
ΔTemporary	4.218	4.294			4.417	4.509
	(3.175)	(3.150)			(3.246)	(3.224)
ΔTertiary			0.482	0.523	1.046	1.109
			(1.626)	(1.681)	(1.500)	(1.570)
Adj. R2	0.180	0.181	0.171	0.172	0.180	0.181

Obs.	289	289	289	289	289	289

Dependent variables: Relative change in AMT patents. The relative change in patents is defined as the difference in patents over the period 2002-2012, divided by the average number of patents across the two periods 2002 and 2012. ΔRSH, ΔRMSH and ΔRCSH are measured as the difference in the share of employment between 2001 and 1990. Control variables are in delta, measured as the difference between 1990 and 2001. Temporary workers and tertiary educated are measured as the variation in the shares between 1990 and 2000. Pop dens is in 2001 levels. Regressions are weighted by the 2001 per-capita number of local total patents. Robust standard errors, in parentheses, are clustered at the State level. * $p < .1$, ** $p < .05$, *** $p < .01$

Table A3. Robustness: De-routinisation and incremental AMT innovation, incremental total innovation and incremental ICT innovation (alternative measures of incremental patents)

	(AMT)	(AMT)	(TOT)	(TOT)	(ICT)	(ICT)
ΔRSH	-7.258**		-3.923***		-4.111**	
	(2.711)		(1.368)		(1.913)	
ΔRMSH		-7.970**		-4.078**		-2.586
		(3.072)		(1.684)		(2.369)
ΔRCSH		-6.438*		-3.746**		-5.868***
		(3.472)		(1.570)		(2.168)
ΔHigh-Skill	4.958*	4.643*	-0.258	-0.327	0.082	0.759
	(2.522)	(2.668)	(1.297)	(1.332)	(1.647)	(1.661)
ΔN. of man. firms	-0.184	-0.170	-0.435	-0.432	-0.481	-0.512
	(0.388)	(0.389)	(0.341)	(0.341)	(0.415)	(0.418)
ΔTot patents	-32.826***	-32.855***	-13.985*	-13.992*	-27.534***	-27.472***
	(10.433)	(10.445)	(7.520)	(7.528)	(9.080)	(9.158)
Pop dens	12.838	12.691	11.169**	11.137**	10.516*	10.831*
	(7.831)	(7.816)	(4.649)	(4.644)	(5.716)	(5.788)
Adj. R2	0.181	0.182	0.277	0.277	0.232	0.237
Obs.	289	289	289	289	289	289

Dependent variables: Relative change in incremental AMT patents (Columns I and II), incremental total patents (Columns III and IV) and incremental ICT patents (Columns V and VI). Incremental patents are defined as the complement of the top 3% radical patents in terms of 5-year forward citations, by main technology field and cohort. The relative change in patents is defined as the difference in patents over the period 2002-2012, divided by the average number of patents across the two periods 2002 and 2012. ΔRSH, ΔRMSH and ΔRCSH are measured as the difference in the share of employment between 2001 and 1990. Control variables are in delta, measured as the difference between 1990 and 2001. Pop dens is in 2001 levels. Regressions are weighted by the 2001 per-capita number of local total patents. Robust standard errors, in parentheses, are clustered at the State level. * $p < .1$, ** $p < .05$, *** $p < .01$

APPENDIX B

Table B5. Panel data regressions of AMT innovation on routine workers share from 2001 to 2012 (1-year lag)

Model	(Neg._Bin.)	(Poisson)	(LPM)
RSH	1.483***	2.026***	1.085**
	(0.063)	(0.045)	(0.506)
High-Skill empl share	2.471***	2.625***	1.546***
	(0.059)	(0.042)	(0.480)
N. of manufacturing firms (log)	-0.167***	-0.217***	-0.162**
	(0.005)	(0.004)	(0.063)
Pop dens	0.033***	-0.007***	0.074*
	(0.003)	(0.002)	(0.038)
Tot patents (log)	0.858***	0.849***	0.602***
	(0.004)	(0.003)	(0.030)
Year FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
Adj. R2			0.163
Obs.	3408	3408	3480

Dependent variables: Number of AMT patents in model I (Neg. Bin.) and in model II (Poisson); log transformed number of AMT patents in model III (LPM). Given the nature of the dependent variable, models I and II estimate count data models. Column I present the results of a Negative Binomial panel regression in order to account for potential over dispersion in the number of AMT patents. A Poisson panel model is estimated in model II, while column III presents the results of linear probability panel regression after the logarithmic transformation of the number of AMT patents. All independent variables have been lagged by 1 year. *RSH* and *High-Skill empl share* are measured, respectively, as the yearly share of routine employment and high-skill employment by MSA. *N. of manufacturing firms* and *Tot patents* are expressed in log, *Pop dens* is in levels. All regression control for year and MSA fixed effects and cover the period from 2001 to 2012. Robust standard errors are in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Table B2. Panel data regressions of AMT innovation on routine workers share from 2001 to 2012 (2-years lag)

Model	(Neg._Bin.)	(Poisson)	(LPM)
RSH	0.848***	1.978***	1.195**
	(0.068)	(0.046)	(0.531)
High-Skill empl share	1.192***	2.110***	0.373
	(0.065)	(0.043)	(0.504)
N. of manufacturing firms (log)	-0.103***	-0.316***	-0.189***
	(0.005)	(0.004)	(0.067)
Pop dens	0.039***	-0.031***	0.009
	(0.003)	(0.002)	(0.040)
Tot patents (log)	0.697***	0.618***	0.473***
	(0.004)	(0.003)	(0.032)
Year FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
Adj. R2			0.114
Obs.	3102	3102	3190

Dependent variables: Number of AMT patents in model I (Neg. Bin.) and in model II (Poisson); log transformed number of AMT patents in model III (LPM). Given the nature of the dependent variable, models I and II estimate count data models. Column I present the results of a Negative Binomial panel regression in order to account for potential over dispersion in the number of AMT patents. A Poisson panel model is estimated in model II, while column III presents the results of linear probability panel regression after the logarithmic transformation of the number of AMT patents. All independent variables have been lagged by 2 years. *RSH* and *High-Skill empl share* are measured, respectively, as the yearly share of routine employment and high-skill employment by MSA. *N. of manufacturing firms* and *Tot patents* are expressed in log, *Pop dens* is in levels. All regression control for year and MSA fixed effects and cover the period from 2001 to 2012. Robust standard errors are in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$