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Workers' replacements and firms' innovation dynamics: New evidence from Italian matched longitudinal data

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ABSTRACT

In this paper, we explore the impact of a firm's workers' replacements on innovation performance by using rich matched employer–employee panel data for the Veneto region of Italy. We take the well-known resource-based theory of the firm as our departure point, and develop a set of hypotheses which we test empirically with negative binomial regressions. We find that workers' replacements significantly dampen innovation performance, coherently with the idea that they generate losses in the tacit knowledge base of the firm. We also find that workers' replacements are especially detrimental to large and young firms, possibly because large companies benefit comparatively less from 'diaspora' effects and because innovative capabilities in young firms are mostly dependent on specific human capital. Finally, our results show that firms' location in industrial districts significantly mitigates the negative impact of workers' replacements, and that a similar picture emerges when firms are more exposed to knowledge spillovers, particularly of related knowledge.

1. Introduction

The relationship between firms' innovation activities and labor market dynamics has received much attention in economics, from both a theoretical and empirical viewpoint.

The debate has focused on a number of distinct and yet related issues. First, there has arisen in the literature broad and animated discussion about the impact of innovation on employment. On the one hand, innovation is expected to negatively affect employment because of replacement effects. On the other hand, indirect mechanisms are expected to engender compensation effects that ultimately result in employment growth (Pianta, 2005; Piva and Vivarelli, 2018). Second, following the well-known skill-biased technological change hypothesis, many studies have investigated the relationship between technological change and the composition of the labor force in terms of skills within firms and local areas (Acemoglu and Autor, 2011; Autor et al., 2003; Moretti and Thulin, 2013; Vona and Consoli, 2015). A third set of studies have focused on the impact of labor market dynamics on firms' innovation performance, paying particular attention to the effects of labor market deregulation and flexibility on firms' ability to successfully carry out more or less formalized innovation activities (Kleinknecht et al., 2014; Michie and Sheehan, 2003; Wachsen and Blind, 2016; Zhou et al., 2011).

Within the latter strand of analysis, a large debate about the relationship between labor mobility and firms' innovation performance has gained momentum in the past decade. This issue was mainly tackled from a geographical viewpoint. In fact, the mobility of highly-qualified personnel is regarded as one of the main channels whereby knowledge spillovers across different locations materialize (Agrawal et al., 2006; Simonen and McCann, 2008). This literature has focused much on the role of social ties and the interplay among spatial, technological, and cognitive proximities in shaping the effectiveness of labor-driven knowledge flows. Firm-level studies have also investigated this issue from a strategic viewpoint. In fact, inter-firm labor mobility can be a source of knowledge externalities which may involve the transmission of important and confidential knowledge to competitors. These dynamics affect firms' human resources strategic management, which aims to minimize workers' separations and information leakage, and to improve innovation performance by increasing the hiring of highly-qualified human capital (Herstad et al., 2015; Kaiser et al., 2015; Maliranta et al., 2009; Parrotta and Pozzoli, 2012).

While the benefits of hiring knowledge-intensive workers have been largely documented, how labor mobility affects firms' innovation performance through the combination of hirings and separations has been less investigated. Yet, substitutions of workers are likely to affect firms' performance in many respects. Workers' replacements have been found

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to affect firms' financial and economic performance, especially in regard to firm productivity (Grinza, 2016). Instead, there is much less evidence on the relationship between workers' replacements and firms' innovation outcomes, and that which exists mostly focuses on the replacement of R&D personnel (Braunerhjelm et al., 2015; Cooper, 2001; Eriksson et al., 2014; Müller and Peters, 2010).

Our paper intends to contribute to this strand of literature by investigating the impact of workers' replacements on firms' innovation performance. To this end, we take the well-known resource-based theory of the firm as our departure point. In this theoretical framework, the firm is regarded as the locus of competence accumulation, wherein technological and organizational knowledge develops through the integration of formalized R&D activities and learning processes (Foss, 1997, 1998; Penrose, 1959). The importance of the learning process in the generation of tacit organizational knowledge makes firms' human resources key to the achievement of strategic objectives and the preservation of competitive advantage (Peteraf, 1993). Moreover, the emphasis on learning dynamics allows appreciating the importance of all of the firms' workers in the generation of new competencies leading to new knowledge. While R&D activities are mostly related to the generation of codified knowledge, learning dynamics are related to the generation of tacit knowledge, which is very likely to remain attached to the people who developed it (von Hippel, 1994). We also hypothesize that other key drivers of firms' innovation performance, including firm-level and local-level characteristics, moderate the impact of workers' replacements. To the best of our knowledge, this paper is the first analysis of the effect of workers' replacements on innovation performance within such a broader theoretical and empirical framework.

We carry out the empirical analysis on rich administrative matched employer–employee data covering the entire private sector of the Veneto region of Italy over a seven-year period. These data have the unique feature of providing a monthly-level history of job matches which make it possible to construct a detailed dynamics of firms' workers' replacements. They are merged with other data sources to gather financial and patent information on firms. Balance sheet data are taken from the Bureau van Dijk's *Analisi Informatizzata delle Aziende Italiane* (AIDA) data set. Instead, we obtain information on firms' innovative performance and local knowledge stock from the PATSTAT and OECD REGPAT data sets. To match patent data at the firm level, we draw on the procedure proposed by Lotti and Marin (2013).

The results of our empirical analyses show that workers' replacements are detrimental to firms' innovation performance, consistently with the idea that they cause the loss of important tacit knowledge repositories. We also find that firm age and size are two important factors that mediate the relationship between workers' replacements and innovation performance. Large and young firms are those that suffer from workers' replacements. On the one hand, large firms are likely to be particularly penalized by 'competence drain' effects engendered by separating workers, which positive 'diaspora' effects are not able to compensate for. On the other hand, young firms are likely to pay for the fact that they rely closely on the innovative capabilities of specific workers rather than on practices rooted in the organization. Moreover, we show that factors external to firms' boundaries are crucial moderators of the impact of workers' replacements on innovation performance, too. Features such as being located in industrial districts and in areas characterized by high knowledge spillovers (especially of related knowledge) considerably mitigate the negative impact of workers' replacements, thus pointing to the importance of thicker social relationships and better integrated local labor markets.

The rest of the paper is structured as follows. Section 2 outlines the theoretical framework linking workers' replacements to innovation performance. Section 3 presents the empirical model. Section 4 describes the data and the variables used and sets out relevant summary statistics. Section 5 shows and discusses our results, while Section 6 reports several robustness checks. Finally, Section 7 concludes.

2. Theory and hypotheses development

2.1. Innovation and workers' replacements

A large body of theoretical and empirical literature has documented a positive impact of innovation dynamics on firms' economic and financial performances. Instead, studies on the relationship between innovation and employment have yielded controversial results. While the impact of technological and organizational change on employment has attracted close attention, how labor market dynamics affect firms' innovation performance has received relatively scant consideration.

Former treatments of the impact of labor mobility on firms' innovation dynamics can be found in the sociological literature. In this context, the main envisaged effect of labor mobility on innovation was consistent with the so-called 'learning-by-hiring' hypothesis. The basic argument was that labor mobility favors the flow of knowledge across competing firms, leading to a more balanced distribution of innovation capabilities (Gilfillan, 1935; Price, 1977).

Subsequent works have elaborated on this hypothesis, proposing that the management of hirings can be of strategic importance for firms wanting to extend the scope of their knowledge base in order to enact radical innovations (Ettlie, 1980, 1985). More recent literature has further stressed the importance of hiring strategies for firms wanting to extend their knowledge base and to reposition their portfolios of technologies. In so doing, strategic hiring allows firms to go beyond local search constrained by path-dependent innovation capabilities (Almeida and Kogut, 1999; Lacetera et al., 2004; Rao and Drazin, 2002; Rosenkopf and Almeida, 2003; Tzabbar, 2009).

The literature discussed above has focused exclusively on the positive effects of labor mobility for the hiring firms (i.e., firms receiving inflows of new knowledge). The viewpoint of firms experiencing workers' separations (i.e., outflows of knowledge) has instead been mostly neglected. On the one hand, these firms can be negatively affected by labor mobility because of 'brain drain' effects depleting firms' knowledge base. On the other hand, they can nonetheless obtain advantages related to a sort of 'diaspora' or 'brain bank' effect. Accordingly, mobile workers can be a channel for knowledge spillovers from the destination to the origin firms (Agrawal et al., 2011; Crane, 1969; Kerr, 2008; Oettl and Agrawal, 2008).

In this regard, the resource-based view of the firm provides a valuable framework within which to appreciate the overall impact of workers' replacements on firms' innovation performance, whereby two opposite flows simultaneously occur: hirings and separations. The emphasis on learning dynamics allows indeed combining the arguments about the above-mentioned positive effects driven by hirings or 'brain bank' effects, with the negative ones driven by separations.

According to Penrose (1959), firms are bundles of resources and competencies. Distinctive competitive advantage emerges from the possession of idiosyncratic resources and competencies, and the ability of firms to combine them in unique and effective ways (Mahoney, 1995). Improvements in the management of resources and new ways to combine competencies enable firms to generate new knowledge and innovations. In this framework, dynamic capabilities are firms' abilities to combine internal and external competencies, achieve new configurations, address challenges from rapidly changing environments. In other words, dynamic capabilities concern firms' ability to set up innovative dynamics (Teece et al., 1997).

Learning processes play a major role in enhancing the way in which firms manage and combine resources and competencies to achieve competitive advantages (Arrow, 1962). In this sense, organizational knowledge is cumulative, in that it builds upon the previous experience and entails the development of routines, which are in turn the pillars of competencies and capabilities (Dosi and Grazzi, 2010; Nelson and Winter, 1982). Organizational routines concerning the creation of novelty at the firm level can thus be regarded as the constituents of firms' dynamic capabilities.

A basic issue concerns the extent to which these routines (and the competencies originating from them) are codified to preserve the organizational memory and provide the building blocks for future changes and innovations, or are rather embodied in tacit skills of relevant actors, that is, firms' employees (Dosi and Grazzi, 2006, 2010). Since the seminal contribution by Polanyi (1966), tacit knowledge has received large attention in innovation studies. Knowledge is said to be tacit when actors, even the most competent and experienced, are not able fully to articulate the "procedures by which 'things are done', problems are solved, behavioral patterns are formed" (Dosi and Grazzi, 2010, p.176). An important property of tacit knowledge is its 'stickiness', that is, the difficulty with which it can be transmitted to other parties. Significant resources have to be committed to making a person's tacit knowledge transferable and usable by others. This makes tacit knowledge attached to the place in which it is produced, as well as to the actors that developed it through learning dynamics (von Hippel, 1994).

Because of the importance of learning processes for the accumulation of organizational knowledge enabling successful innovation dynamics, firms' strategic decisions have to deal with the need to deploy competencies and tacit skills to generate novelties (Neffke and Henning, 2013). In view of the tacit dimension of knowledge emerging from learning dynamics, strategic decisions also involve the management of human capital (Delery and Shaw, 2001; Shaw et al., 2013). Consequently, workers' replacements driven by separations can be regarded as a factor hindering the development and the preservation of organizational routines. This can be particularly harmful to innovation performance, which depends to a large extent on learning and knowledge accumulation (Nelson and Winter, 1982). On the contrary, and consistently with the 'learning-by-hiring' hypothesis, the localized nature of learning dynamics makes the injection of external competencies crucial for diversification through radical innovation (Kogut and Zander, 1992).

These arguments lead us to spell out our first set of hypotheses.

Hypothesis 1a. The effect of workers' replacements on firms' innovation performance is positive if the 'learning-by-hiring' and 'brain bank' mechanisms prevail.

Hypothesis 1b. The effect of workers' replacements on firms' innovation performance is negative if the 'brain drain' mechanism prevails.

2.2. *The role of firm-level characteristics*

The empirical literature on the determinants of innovative output at the firm level has investigated how key features such as firm age and size affect the capacity to generate new knowledge and, eventually, new technologies. While these characteristics are expected to have a direct impact on firms' innovation performance, they are also likely to influence the relationship between workers' replacements and innovation, because of how these features affect firms' reliance on idiosyncratic human capital and organizational routines.

As regards age, the empirical evidence is ambiguous, depending on how innovation outcomes are proxied. Hansen (1992) found that it is negatively associated with innovation when it is measured as the number of new products. Instead, Sørensen and Stuart (2000) found that age has a positive impact when innovation is measured by patent applications. These results are evidently influenced by the changing nature of firms' innovation efforts across their life-cycle (Utterback, 1994).

As for the interplay with effects of workers' replacements, previous analyses have stressed that young firms tend to rely mostly on the skills possessed by younger workers because of their stronger attitude to creativity and novelty. In these firms, innovative capabilities are thus prevalently dependent on specific human capital, rather than on organizational routines that are institutionalized in the organization. Young firms are thus expected to be harmed by workers' replacements more than old firms, because negative effects stemming from separations are more disruptive for them (Aubert et al., 2006; Coad, 2018; Ouimet and Zarutskie, 2014). In view of these considerations, we propose the following hypothesis:

Hypothesis 2a. Workers' replacements are expected to affect (negatively) young firms more than old firms.

The evidence on the relationship between size and innovation is also mixed. According to the Schumpeterian tradition, large firms are expected to have an advantage in producing innovations (Galbraith, 1958; Schumpeter, 1942). This is attributable to a number of reasons, including financial structure and access to a wider range of knowledge and human capital skills (Rogers, 2004). Yet a number of studies have stressed that both small and large firms show comparative advantages in innovation, depending on the proxy that is used in the empirical analyses. Large firms, in particular, exhibit a clear advantage when measures of formalized innovation efforts are considered (Vaona and Pianta, 2008). Instead, one significant advantage of small firms, as compared to large companies, is their capacity to recognize new opportunities promptly and adjust their plans in research and production activities. Moreover, small firms may find it easier to allow less rigid management structures as compared to large companies.

As regards the mediating impact of firm size in the relationship between workers' replacements and innovation, small firms may be more resilient than large companies to negative effects stemming from workers' replacements (Rogers, 2004), and possibly even experience an overall positive effect for a number of reasons. Most importantly, small firms seem to benefit comparatively more than large firms from exchanges of knowledge with other (possibly larger and/or more productive) firms. In a recent study on R&D labor mobility, Braunerhjelm et al. (2015) consistently show that small firms benefit more than the large ones from the 'learning-by-hiring' effect, in line with the idea that intakes of new knowledge are crucial for small firms to enrich their competence base. At the same time, the authors find that separations tend to have a positive impact on small firms, too. This suggests that the 'brain bank' effect is more important than the 'brain drain' effect for such companies. Through migration of own workers to other firms, in fact, new valuable networks of relations can emerge and there might materialize important spillovers of knowledge, which small firms may find it hard to acquire in other ways. In the cited study, large firms are shown to benefit from 'learning-by-hiring', as small firms do. Yet, differently from small companies, large firms seem to experience an overall negative impact from separations. The authors suggest that this is due to a sort of 'competence drain' effect, whereby the firm bears a loss of (tacit) knowledge and competencies that scratch its knowledge base. Thus, in large firms, the positive effects of separations engendered by the 'diaspora' effect seem to be comparatively less important than for small firms. In view of these considerations, we propose the following hypothesis:

Hypothesis 2b. Workers' replacements are expected to yield differential effects on small firms *vis-à-vis* large companies. The effect is positive for small firms. The effect is negative (positive) for large firms if the separation (hiring) effect dominates.

2.3. *The role of local externalities*

According to a large number of studies, firms' economic and innovation performances are affected by place-specific external conditions because of the role of technical, pecuniary, and knowledge externalities (Antonelli and Colombelli, 2017; Antonelli et al., 2011). On the basis of the seminal work by Glaeser et al. (1992), it is possible to identify two main classes of externalities: the Marshall–Arrow–Romer (MAR) and the Jacobs' externalities. MAR externalities arise from the spatial concentration of firms within a specific industry. Spatial proximity may enhance firms' performance because of three key channels: (i) input-output linkages, (ii) labor market dynamics, and (iii) knowledge spillovers (Marshall, 1890).

The second point is especially relevant to the relationship between workers' replacements and innovation. Indeed, labor market pooling is deemed a major source of agglomeration externalities. According to Marshall (1890), spatial concentration matters in that it provides constant markets for skills. Overman and Puga (2010) provided empirical evidence on the relationship between industries' degree of spatial concentration and employment volatility shocks, supporting the labor market pooling hypothesis. Spatial concentration enables firms to cope with employment shocks because of the ease of replacing skilled workers. Division of labor entails specialization and favors the emergence of local markets for specialized competencies. Besides the pooling effect, agglomeration economies from the labor market can stem from matching dynamics. Spatial concentration, in fact, favors the alignment of competencies between labor demand and supply as well as learning by interacting, and it also reduces frictions related to information asymmetries (Duranton and Puga, 2004). Based on these arguments, we can state the following hypothesis:

Hypothesis 3a. Firms' location in industrial districts moderates the effects of workers' replacements.

Agglomeration externalities are also generated by knowledge spillovers. Several empirical studies have evidenced the important role of external knowledge in firms' innovation performance. Since Griliches (1992), the role of knowledge spillovers has been found to be significant in many different empirical settings. Knowledge spillovers increase the productivity of knowledge generation activities for a given budget because of the access to knowledge inputs generated by other firms. Spatial proximity has been found to be crucial for external effects to take place in this case (Audretsch and Feldman, 1996; Jaffe et al., 1993; Quatraro and Usai, 2017). According to this evidence, the larger the amount of knowledge produced by co-located firms, the larger the productivity of innovation activities of each firm in the area. *Ceteris paribus*, it is therefore to expected that high levels of knowledge spillovers can mitigate the negative effects of workers' replacements driven by separations, or augment the positive effects driven by 'learning-by-hiring', because of overall productivity gains in the knowledge generation function (Antonelli and Colombelli, 2015a,b). This leads us to state the following hypothesis:

Hypothesis 3b. The availability of knowledge spillovers moderates the effects of workers' replacements on firms' innovation dynamics.

Jacobs' externalities are also important in innovation dynamics. In fact, not only does the local stock of knowledge matter but also its composition. Jacobs' externalities are traditionally associated with the variety of firms and industries in a specific area. Recent theoretical and empirical studies have extended the notion of Jacobs' externalities to the analysis of knowledge spillovers, stressing the importance of knowledge variety for the rate of creation of new knowledge. In this respect, the difference between 'related' and 'unrelated' technological variety is important to qualify local knowledge spillovers as well as their effects on firm innovation (Antonelli and Colombelli, 2017; Frenken et al., 2007). Previous studies have shown that an increasing variety of related technologies leads to higher rates of innovation, because of the closeness of the competencies on which they impinge. By contrast, recombining unrelated technologies is more complicated because of the heterogeneity of the competencies on which they impinge (Antonelli and Colombelli, 2015a; Nesta and Saviotti, 2005; Quatraro, 2010).

The 'related variety' of local knowledge is a proxy for the degree of coherence or specialization of technological activities, while 'unrelated variety' is a proxy for diversification. Consistently with our contention concerning the moderating effect of location in an industrial district, when local knowledge bases are characterized by high levels of related variety the impact of workers' replacements is expected to augment the positive effects driven by hirings and mitigate the negative ones driven by separations. Indeed, the high degree of integration of technological activities is likely to ease the replacement of the lost competencies or the introduction of new competencies that fit well with the hiring firm's activities.[1] These arguments lead to our last hypothesis:

Hypothesis 3c. The high degree of related (unrelated) knowledge variety positively (negatively) moderates the effects of workers' replacements on firms' innovation dynamics.

The rest of the paper is devoted to the empirical test of the three sets of hypotheses elaborated above. The next section presents our empirical methodology.

3. The empirical model

To investigate the relationship between a firm's innovation performance and workers' replacements, we used a knowledge production function (henceforth, KPF). The concept of KPF was introduced by Pakes and Griliches (1980), and a first empirical analysis was carried out by Hausman et al. (1984). It represents to date the standard way to estimate the association between a variety of factors, including workforce characteristics, and innovation output (e.g., Bronzini and Piselli, 2016).

In its most general specification, a KPF takes the following form:

$$\text{Innovation output} = f\,(\text{Innovation inputs}). \tag{1}$$

It relates a firm's innovation output to a vector of innovation inputs. Innovation inputs include investments in R&D and an array of other variables which influence innovation performance, such as industry- and province-specific features and human resources characteristics. We include workers' replacements, our object of interest, in the set of innovation inputs. In the previous section, we highlighted several mechanisms in which workers' replacements can influence innovation performance. Estimating Eq. (1) will give us an empirical test of this.

Since, as is standard in the literature, we measured a firm's innovation capability through the number of patent applications, we used count data models and estimation methods. They are more appropriate than linear models when dealing with dependent variables that assume non-negative integer values, as in our case. We modeled the expected number of patent applications of firm i in year t, P_{it}, as follows:

$$E\,[P_{\text{it}}\,|R\&D_{\text{it}-1},\,\text{EWTR}_{\text{it}-1},\,X_{\text{it}-1}] = \lambda_{\text{it}} = \exp(\beta R\&D_{\text{it}-1} + \theta\text{EWTR}_{\text{it}-1} + \gamma X_{\text{it}-1}). \tag{2}$$

$R\,\&\,D$ are R&D investments; *EWTR* is the excess worker turnover rate, our measure of workers' replacements (see Section 4.3); and X is a series of other workforce and firm characteristics and several fixed effects, included as controls. To help reduce the risks of spurious relationships, we lagged all the explanatory variables by one year. This is a standard practice in the literature, and also has the advantage of capturing dynamics in the impact, which generally takes time to materialize because producing innovation is a relatively long-run process (Nesta and Saviotti, 2005).[2]

We estimated this model by using maximum likelihood for the negative binomial distribution. We preferred negative binomial models to Poisson models because the equality between the mean and variance of the dependent variable assumed by Poisson models was not verified in our data. The distribution of the number of patent applications, in fact, was substantially over-dispersed: the variance was about 4 times higher

[1] We thank an anonymous referee for her suggestions on the articulation of this hypothesis.

[2] Appendix A shows robustness checks with the use of the two-year, rather than one-year, lags.

Table 1
Sample summary statistics: general information.

Variable	Notes	Mean	Std. dev.	25th P.tile	Median	75th P.tile	Min	Max
Dependent variable								
Firm's patent applications	Capitalized using the perpetual inventory method with a constant depreciation rate of 0.15	0.604	2.325	0	0	0	0	30.769
Independent variables								
Excess worker turnover rate	See Table 2	0.286	0.177	0.16	0.248	0.379	0	0.968
Net job creation rate	See Table 2	0.048	0.113	−0.014	0.035	0.093	−0.804	1.404
log R&D intensity	R&D intensity is R&D expenditures over revenues; distribution shifted by one unit	0.003	0.011	0	0	0.0003	0	0.166
log Revenues	1000 Euros (2000 prices)	9.732	0.885	9.141	9.633	10.180	7.681	13.661
Firm age	Years	18.036	7.577	11.417	20	24.583	1	31.75
Share of female workers	Monthly weighted	0.177	0.157	0.081	0.124	0.206	0	0.990
Share of foreign workers	Monthly weighted	0.043	0.049	0.015	0.030	0.055	0	0.477
Average age of the workforce	Monthly weighted, years	35.292	3.446	33.194	35.324	37.732	23.371	44.86
Share of managers	Monthly weighted	0.026	0.031	0	0.018	0.037	0	0.323
Share of white-collar workers	Monthly weighted	0.294	0.132	0.203	0.272	0.361	0	0.832
Share of blue-collar workers	Monthly weighted	0.651	0.144	0.575	0.676	0.745	0.090	1
Share of apprentices	Monthly weighted	0.022	0.042	0	0.003	0.027	0	0.419
Share of temporary workers	Monthly weighted	0.039	0.057	0	0.018	0.056	0	0.594
Share of part-timers	Monthly weighted	0.024	0.027	0.004	0.016	0.034	0	0.237
Other variables								
Employees	Monthly weighted	153.015	219.640	64.583	86.917	143	50	2342.333
Revenues	1000 Euros (2000 prices)	29,060.390	59,652.810	9332	15,258	26,380	2167	856,853
R&D expenditures	1000 Euros (2000 prices)	70.884	320.574	0	0	5	0	5,544
Profit margin	Net profits over revenues	0.025	0.064	0.003	0.015	0.040	−1.270	1.378
Average tenure of the workforce	Monthly weighted, years	7.597	3.137	5.058	7.404	9.874	0.787	18.435
Firm-year observations	1565							

Source: VWH-AIDA-PATSTAT data set (years: 1995–2001).
All the variables listed in the 'independent variables' section were lagged by one year. For consistency, also the variables in the 'other variables' section were lagged by one year.

than the mean (see Table 1). Moreover, Vuong tests of zero-inflated *versus* standard negative binomial models speak in favor of the standard version. Similarly, Vuong tests for hurdle models suggest that standard negative binomial models furnish a better description of the data generating process.

4. The data

4.1. The Veneto case

In the analysis reported in this paper, we used data for Veneto, an administrative region in the North-East of Italy with around 5 million people. During the 1970s and 1980s, Veneto underwent a fast industrialization process that transformed it into one of the richest Italian regions. Veneto firms are typically small and operate in the manufacturing industry, particularly in the sectors of chemicals, metal-mechanics, and electronics. Veneto is characterized by the division of the territory into industrial districts, in which firms belonging to similar sectors share much in terms of knowledge and network base.

Italy has traditionally been considered a country with strict employment protection rules (Kugler and Pica, 2008). Yet, the degree of labor mobility in Italy has been in line with that of other countries known for their labor market flexibility, such as the UK (Contini et al., 2009). As highlighted by Contini et al. (2009), the causes of this reside in widespread illegal practices, fragile control systems, and contradictory laws. Interestingly, the Veneto labor market has been even more mobile (Tattara and Valentini, 2003). This feature makes our Veneto data a valuable basis for estimating the economic impacts of worker flows (Serafinelli, 2018).

4.2. The data sets

Our data were the result of the match of three separate data sources: Veneto Workers History (VWH), *Analisi Informatizzata delle Aziende Italiane* (AIDA), and PATSTAT together with OECD REGPAT.

Giuseppe Tattara and his team at the University of Venice constructed VWH by drawing on administrative data of the Italian Social Security System. The VHW data set collects labor market histories between 1975 and 2001 of *all* employees working for at least one day in the Veneto private sector (except for agriculture). It is organized into three parts. There is the worker archive, which gathers personal information on the worker (e.g., gender, age, and place of birth); the job archive, which contains job information (e.g., hiring date, separation date, if applicable, contract type); and the firm archive, which stores information on the firm (e.g., the firm's national tax number, used as a firm identifier, location, and industry). This structure makes VWH a longitudinal matched employer-employee data set.[3]

Unfortunately, VWH does not include financial information on firms. However, Bureau van Dijk provides AIDA yearly since 1995. It contains detailed information on balance sheets of all (non-financial and non-agricultural) incorporated private companies in Italy with annual sales above 500 thousand Euros. The AIDA variables include R&

[3] See Tattara and Valentini (2010) and http://www.frdb.org/page/data/scheda/inps-data-veneto-workers-histories-vwh/doc_pk/11145 for details on VWH. Note, however, that both documents refer to a restricted version of the data, which only covers the Veneto provinces of Treviso and Vicenza. A list, as complete as possible, of published (or in press) papers using the VWH data set is the following: Bartolucci et al. (2018), Battisti (2017), Card et al. (2013), Chan (2018), Devicienti et al. (2018), Gianelle (2014), Leonardi and Pica (2012), Serafinelli (2018), Tattara and Valentini (2010).

D expenditures, revenues, and the firm's national tax number.[4]

Through the firms' national tax number it is possible to match worker and job information in VWH with balance sheet information in AIDA. David Card, Francesco Devicienti, and Agata Maida conceived and conducted this match, which they thoroughly describe in Card et al. (2013). The result is a longitudinal matched employer–employee data set, VWH-AIDA, which covers the period 1995–2001 and collects job histories of all employees in all the (non-financial and non-agricultural) incorporated private Veneto firms with revenues greater than 500 thousand Euros.

The third source of information – that related to a firm's innovation output and local knowledge stock – derives from PATSTAT and OECD REGPAT, respectively. The former is the well-known patent data set provided by the European Patent Office. It collects a wealth of patent information, including when the patent application was filed and who the applicants were. The second data set, distributed by the OECD and obtained starting from PATSTAT, provides aggregate information on knowledge stocks of local areas at a fine-grained level. To match patent information from PATSTAT with VWH-AIDA, we drew upon the matching procedure between PATSTAT and AIDA firms developed by Lotti and Marin (2013).

4.3. The variables

In the empirical analysis, we measured a firm's innovation output with the (capitalized) number of patent applications filed by the firm.

A firm's workers' replacements were measured through the excess worker turnover, also referred to as 'excess worker reallocation' or 'worker churning' (Burgess et al., 2000a). Technically, the excess worker turnover is the number of hirings and separations over and above those necessary to accommodate for the firm's job creation or destruction, and it results from the following definitions (for a detailed description on job and worker flows, see also Burgess et al., 2000a):

- number of workers hired between $t-1$ and t;
- number of workers separated between $t-1$ and t;
- sum of hirings and separations between $t-1$ and t;
- difference between the number of employees at t and $t-1$;
- difference between worker turnover and the absolute value of net job creation.

An example clarifies these definitions. Let us consider a company with 50 employees at the beginning of the year, which hires 5 workers immediately afterward and does not separate from any worker during the rest of the year. The number of workers at the end of the year is 55. This firm experiences 5 hirings, 0 separations, worker turnover equal to 5 (5 hirings + 0 separations), and excess worker turnover equal to 0, as worker turnover compensates exactly for job creation. Let us consider another firm, with 50 employees at the beginning of the year, which hires 10 workers and separates from 5 immediately afterward. Assume that nothing changes for the rest of the year, so that the number of workers at the end of the year is 55, exactly as in the previous case. Here, however, the firm experiences 10 hirings, 5 separations, worker turnover equal to 15 (10 hirings + 5 separations), and excess worker turnover equal to 10 (15 − 5, where 15 is worker turnover and 5 is job creation). While the first firm increases its workforce by simply hiring 5 new workers, the second firm does so by hiring 10 workers and separating from 5. Hence, in the latter case, the firm replaces 5 of its workers with 5 new ones and the excess worker turnover measures this. Note that excess worker turnover is always twice the number of replacements. This is because a replacement converts into two worker flows, one separation and one hiring.[5]

In our regressions, we expressed excess worker turnover in rates, as is common in the literature. We followed Davis et al. (1996) and divided our worker (and job) flow measures, including excess worker turnover, by the average number of workers, computed as the average between the number of workers in January and December of a given year (i.e., at the extremes of our yearly time span). It is vital to express excess worker turnover in rates in the estimating equations because this takes into account the firm's size and the relative weight of workers' replacements (e.g., replacing 10 more workers in a 50-employee company is very different from replacing 10 more workers in a 500-employee firm).

Generally, researchers obtain worker flows on the basis of yearly-level information on the stock of workers in the firm. Instead, we could rely on finer, monthly-level information. Therefore, we could obtain more precise measures of worker flows, which account for work relations that start and end within a year.[6]

4.4. Sample construction and descriptive statistics

In this paper, we focused on manufacturing companies with at least 50 employees operating in the top innovative industries: chemicals, metal-mechanics, electronics, and automotives.[7]

We carried out an essential cleaning of the sample to remove unusable observations or observations representing particular cases that might bias the estimates. The first issue is that VWH refers to establishment-level data (i.e., it reports information for all the Veneto establishments of a firm), while AIDA refers to firm-level data (i.e., possibly including non-Veneto establishments). To alleviate this potential bias, we excluded firms for which the number of employees reported by VWH was less than half that reported by AIDA.[8] Second, we only considered firms established (still alive) at least one calendar year before (after) we observed them. We did this to exclude excess worker turnover due to firm entry (exit), which is not the focus of this paper.[9] Third, we restricted the analysis to firms classified as 'active', thereby excluding firms that were closing down. Finally, we removed a few (outlier) firms with excess worker turnover rates greater than 1, meaning that at least 50% of the workforce was replaced with new employees in a given year.

The data set used in our empirical analysis was the firm-level collapsed version of the (cleaned) matched employer–employee data set. It consisted of 1565 firm-year usable observations (i.e., excluding observations lost due to our use of one-year lags).

Table 1 provides general descriptive statistics about workforce and

[4] See https://www.bvdinfo.com/en-gb/our-products/data/national/aida#secondaryMenuAnchor0 for details on AIDA.

[5] Excess worker turnover is used whenever the object of interest, as in our case, is an employment-neutral measure of worker turnover, whereby only successfully replaced workers are accounted for. Excess worker turnover is the way in which researchers empirically measure a firm's workers' replacements (see, for example, Centeno and Novo, 2012; Devicienti et al., 2007; Ilmakunnas et al., 2005). The concept of excess worker turnover is relatively recent and was originally defined in a series of papers by Julia Lane and colleagues (Burgess et al., 2000a,b, 2001; Lane et al., 1996), who, in turn, built on previous studies on job (and worker) reallocation (e.g., Dunne et al., 1989; Davis and Haltiwanger, 1992; Davis et al., 1996).

[6] Thanks to the monthly-level structure of our data, we could construct a large series of workforce controls (e.g., the shares of females, foreigners, and so on) by weighting workers on a monthly basis. For example, to compute the share of females, a woman who was employed for only four months weighted three times less than a woman employed for the whole year.

[7] These were defined as the top-25% two-digit industries in terms of percentage of firms that innovated (i.e., had at least one patent filed in the year). Note that in Appendix B we show robustness checks with the inclusion of larger numbers of sectors.

[8] Appendix C presents robustness checks that experiment with higher (i.e., more restrictive) thresholds.

[9] For the last year of observation we could not identify which firms closed down in the subsequent year.

Table 2
Sample summary statistics: job and worker flows.

Variable	Mean	Std. dev.	25th P.tile	Median	75th P.tile	Min	Max
Net job creation	5.381	24.099	−1	3	9	−212	521
abs(Net job creation)	10.578	22.348	2	6	11	0	521
Hirings	27.109	45.879	11	17	29	0	620
Separations	21.578	35.141	8	14	22	0	506
Worker turnover	48.688	78.095	20	32	50	0	1106
Excess worker turnover	38.110	68.086	14	24	40	0	1012
Net job creation rate	0.048	0.113	−0.014	0.035	0.093	−0.804	1.404
abs(Net job creation rate)	0.081	0.092	0.025	0.056	0.105	0	1.404
Hiring rate	0.207	0.140	0.110	0.179	0.273	0	1.5
Separation rate	0.160	0.094	0.098	0.138	0.209	0	0.810
Worker turnover rate	0.367	0.210	0.217	0.324	0.478	0	1.596
Excess worker turnover rate	0.286	0.177	0.16	0.248	0.379	0	0.968
Firm-year observations	1565						

Source: VWH-AIDA-PATSTAT data set (years: 1995–2001).
The excess worker turnover rate and net job creation rate were lagged by one year. For consistency, also the other variables were lagged by one year.

firm characteristics. On average, firms in the sample had 0.6 patents filed each year and invested around 0.3% of their revenues in R&D. They employed about 153 workers and earned about 29 million Euros per year in revenues. The average firm was about 18 years old and obtained 25 Euros of net profits out of 1000 Euros of revenues. In the average company, only 17.7% of the workers were females, consistently with the fact that the industries on which we focused are predominantly male industries; 4.3% were foreigners; employees were, on average, about 35 years old; and a few of them were employed on a part-time basis (2.4%) or were temporary workers (3.9%). In the average firm, the vast majority of employees were blue- (65.1%) or white-collar (29.4%) workers. A few of them were apprentices (2.2%) or managers (2.6%). On average, workers stayed in the same firm for about 7.6 years.

Table 2 focuses on job and worker flows. As reported in the top panel, the average firm (with 153 employees) hired 27 workers and separated from 22 in any given year. Hence, it experienced a worker turnover of 49 (27 hirings + 22 separations) and a net job creation of 5 (27 hirings − 22 separations). In principle, the average firm could have accommodated this job creation by hiring 5 workers and separating from none. Instead, it hired 27 workers and separated from 22, thus replacing 22 of its workers with 22 new ones and experiencing an excess worker turnover equal to 44.[10] The second panel of Table 2 reports rates of job and worker flows. On average, firms increased their workforce by 4.8% per year. The average hiring and separation rates were 0.207 and 0.160, respectively, so that the worker turnover rate was 0.367. The average excess worker turnover rate was 0.286, meaning that 14.3% of the workforce was replaced each year.

Finally, Table 3 reports the correlation matrix of the (continuous) variables used in our regressions. Interestingly, the correlation between a firm's innovation output and workers' replacements was negative (−0.122) and significant at the 1% level. This is a first indication that workers' replacements may dampen a firm's innovation output. The following econometric analysis will shed more light on this aspect by accounting for several potentially confounding workforce and firm characteristics and possible simultaneity bias.

5. Results

5.1. Main results

The results of our econometric estimations testing the first set of hypotheses (Hypotheses 1a and 1b) are reported in Table 4. All the estimations included year, industry, and province dummies. Note also that, though not reported in the estimation tables, all the estimations include the constant term. The first column presents the baseline estimations. The coefficient of the excess worker turnover rate is negative and significant.

In Section 2, we discussed the possible impact of workers' replacements on innovation, stressing that this can be positive or negative depending on the relative importance of 'learning-by-hiring' or 'competence drain' effects. Our results show that the negative effect is dominant in our sampled firms. Workers' replacements hinder the dynamics of innovation because of the importance of individual learning dynamics and knowledge embeddedness. When workers leave, they take with them firm-specific knowledge about competencies and routines, as well as about the potential for resource combination for the creation of novelty. The incoming of new replacement workers, with their own tacit knowledge base which might be valuable to the firm, does not appear to compensate for this negative effect.

In Column (2) we show an extended version of the model, which includes several firm-specific controls. The negative and significant effect of excess worker turnover is confirmed also in this setting. First of all, we include two types of variables related to learning dynamics. Firms' age shows a positive and significant coefficient, supporting the importance of dynamic scale economies. As for workers' age, we test for the presence of non-linearities in the impact on innovation. We find that workers' age and firms' innovation are linked by an inverted U-shape relationship. Learning dynamics at the individual level are important, but diminishing returns are likely to emerge because of skill obsolescence. The impact of size is assessed by using the log of firms' revenues. The coefficient of this variable is positive and significant. These results thus show that firm size and age yield direct positive and significant effects on innovation. As regards the other control variables, the coefficient of R&D intensity is positive and significant, as expected.

[10] Table 2 reports the exact numbers. Here we used integer numbers to make the discussion about the 'typical firm' realistic.

Table 3
Sample summary statistics: correlation matrix.

	pat	ewtr	ewtr-sq	ewtr1	ewtr2	ewtr3	njcr	lni	lnrev	f-age	fem	for	age	age-sq	man	wc	bc	app	temp	pt
Firm's patent applications (pat)	1																			
Excess worker turnover rate (ewtr)	−0.122	1																		
Excess worker turnover rate – squared (ewtr-sq)	−0.094	0.951	1																	
Excess worker turnover rate – when low (ewtr1)	0.088	−0.370	−0.232	1																
Excess worker turnover rate – when medium (ewtr2)	−0.013	−0.394	−0.438	−0.300	1															
Excess worker turnover rate – when high (ewtr3)	−0.090	0.930	0.901	−0.223	−0.699	1														
Net job creation rate (njcr)	−0.050	0.225	0.202	−0.156	−0.016	0.183	1													
log R&D intensity (lni)	0.003	0.008	0.001	−0.000	0.008	0.002	0.005	1												
log Revenues (lnrev)	0.355	−0.164	−0.140	0.036	0.091	−0.162	−0.024	−0.035	1											
Firm age (f-age)	0.081	−0.142	−0.136	0.058	0.010	−0.112	−0.152	−0.076	0.036	1										
Share of female workers (fem)	0.131	0.098	0.083	−0.044	−0.056	0.099	0.042	−0.063	−0.046	−0.092	1									
Share of foreign workers (for)	−0.016	0.345	0.336	−0.110	−0.144	0.323	0.014	0.047	−0.020	−0.008	0.037	1								
Average age of the workforce (age)	0.144	−0.407	−0.350	0.205	0.107	−0.359	−0.297	−0.041	0.190	0.306	−0.250	−0.065	1							
Average age of the workforce – squared (age-sq)	0.148	−0.404	−0.344	0.212	0.099	−0.355	−0.297	−0.046	0.184	0.297	−0.238	−0.072	0.998	1						
Share of managers (man)	0.281	−0.210	−0.176	0.133	0.055	−0.188	−0.093	−0.008	0.342	0.000	0.096	−0.049	0.261	0.262	1					
Share of white-collar workers (wc)	0.108	−0.189	−0.183	0.024	0.131	−0.197	−0.031	0.118	0.191	−0.048	−0.054	−0.119	0.121	0.114	0.326	1				
Share of blue-collar workers (bc)	−0.151	0.150	0.142	−0.016	−0.095	0.152	0.024	−0.107	−0.189	0.089	−0.058	0.137	−0.052	−0.054	−0.461	−0.915	1			
Share of apprentices (app)	−0.060	0.294	0.268	−0.102	−0.139	0.283	0.104	0.023	−0.224	−0.103	0.094	−0.026	−0.445	−0.424	−0.180	−0.189	−0.086	1		
Share of temporary workers (temp)	−0.037	0.352	0.344	−0.126	−0.148	0.331	0.167	−0.000	0.002	−0.070	0.151	0.210	−0.276	−0.271	−0.060	−0.134	0.087	0.182	1	
Share of part-time workers (pt)	0.105	−0.062	−0.038	0.064	−0.027	−0.039	−0.063	−0.043	−0.048	0.046	0.369	0.046	0.099	0.105	0.030	−0.008	−0.015	0.009	0.014	1
Firm-year observations	1565																			

Source: VWH-AIDA-PATSTAT data set (years: 1995–2001).
All the variables except the firm's patent applications (pat) were lagged by one year.

Table 4
Impact of workers' replacements on firm innovation: main results.

Dependent variable: firm's patent applications						
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Excess worker turnover rate	−1.355***	−1.024**	−1.080**	−0.952*	−2.107*	
	(0.474)	(0.521)	(0.526)	(1.182)	(1.182)	
Excess worker turnover rate – squared					1.389	
					(1.510)	
Excess worker turnover rate * firm with low excess worker turnover rate (< 0.10)						−0.256 (3.419)
Excess worker turnover rate * firm with medium excess worker turnover rate (≥0.10 ∧ ≤0.30)						−1.875* (1.151)
Excess worker turnover rate * firm with high excess worker turnover rate (> 0.30)						−1.196** (0.617)
Net job creation rate	−0.526	−0.205	−0.241	−0.143	−0.202	−0.176
	(0.612)	(0.751)	(0.749)	(0.750)	(0.749)	(0.741)
log R&D intensity	8.318	9.776*	8.263*	8.422*	8.332*	8.029
	(5.383)	(5.008)	(4.872)	(4.897)	(4.891)	(5.050)
log Revenues		0.870***	0.897***	0.902***	0.893***	0.899***
		(0.066)	(0.069)	(0.068)	(0.070)	(0.070)
Firm age		0.018**	0.018**	0.018**	0.018**	0.017*
		(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Industrial district		2.734***	2.746***	2.718***	2.801***	2.736***
		(0.536)	(0.536)	(0.533)	(0.522)	(0.538)
Share of female workers		2.449***	2.190***	2.024***	2.232***	2.199***
		(0.469)	(0.475)	(0.509)	(0.475)	(0.480)
Share of foreign workers		3.795***	4.564***	4.692***	4.501***	4.493***
		(1.363)	(1.368)	(1.365)	(1.372)	(1.365)
Average age of the workforce		0.835***	1.145***	1.115***	1.218***	1.212***
		(0.313)	(0.351)	(0.357)	(0.356)	(0.351)
Average age of the workforce – squared		−0.012***	−0.016***	−0.016***	−0.017***	−0.017***
		(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Share of managers			−5.814**	−5.675**	−5.923**	−6.008**
			(2.473)	(2.449)	(2.491)	(2.485)
Share of white-collar workers			−4.008**	−4.096**	−4.138***	−4.055**
			(1.600)	(1.603)	(1.615)	(1.596)
Share of blue-collar workers			−4.676***	−4.702***	−4.819***	−4.762***
			(1.562)	(1.558)	(1.579)	(1.564)
Share of temporary workers				−1.743		
				(1.532)		
Share of part-time workers				3.070		
				(2.292)		
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes
Firm-year observations	1565					

Source: VWH-AIDA-PATSTAT data set (years: 1995–2001).
Estimation method: negative binomial regressions. Robust standard errors in parentheses. All the independent variables were lagged by one year. The reference category for the job distribution was the share of apprentices. The average excess worker turnover rates were 0.064 (std. dev. 0.027), 0.199 (std. dev. 0.056), and 0.470 (std. dev. 0.146) in the groups of firms with low, medium, and high excess worker turnover rates, respectively. The moderating analysis in Column (6) refers to interaction terms (i.e., we did not split the sample). We report the interaction effects for all the *n* relevant interaction categories (i.e., these are direct effects and not differential effects).

* The 10% significance level.
** The 5% significance level.
*** The 1% significance level.

Moreover, the dummy variable indicating location within an industrial district is characterized by a positive and significant coefficient. This is in line with findings in the literature emphasizing the role of externalities in innovation dynamics. Agglomeration economies favor the access to external knowledge produced by co-located firms, which, in turn, is used as an input in the firm-level generation of innovation. The shares of both female and foreign workers are accompanied by positive and significant coefficients.

In Columns (3) and (4), we further extend the set of control variables, finding a persistent negative and significant coefficient of the excess worker turnover rate. In Column (5), we check for possible u-shaped non-linearities in the effect of our variable of interest, but our results do not support their existence, the coefficient of the quadratic term not being statistically significant. Finally, in Column (6), we examine whether the impact of workers' replacements is different depending on the magnitude of the firm's replacement activity. To do so, we first constructed three dummy variables indicating whether the level of the excess worker turnover rate in the firm was low (below 0.10), medium (between 0.10 and 0.30), or high (above 0.30). We then interacted these three dummy variables with the actual excess worker turnover rate in the firm (i.e., a continuous variable).[11] We find that the impact of workers' replacements on innovation is small and not significant when the firm experiences a few replacements. Whereas, when the firm experiences higher levels of replacements (i.e., in the medium and high categories), the negative impact of workers' replacements becomes high and statistically significant. This suggests that the effect of workers' replacements is stronger, the higher the replacement activity.[12]

5.2. Innovation, workers' replacements, and the role of firm characteristics

Overall, this first set of estimates provide robust support to our Hypothesis 1b, according to which excess worker turnover negatively affects firms' innovation dynamics. Hence, in our sample, workers' replacements hinder innovation.

Consistently with previous literature, we find that age and size are positively associated with the outcomes of formalized innovation activities. Yet, age and size are also expected to moderate the impact of excess worker turnover on innovation. In particular, the literature discussed in Section 2 suggests that young firms are expected to be more sensitive to excess worker turnover than old firms, while small firms are likely to be more resilient to workers' replacements than large firms.

We tested the expectations of our Hypotheses 2a and 2b by running additional estimations, the results of which are reported in Table 5. Note that all the regression results from now on use the same set of controls as Specification (3) of Table 4.

The top panel of Table 5 shows the results for the moderating role of firm age. We followed two distinct strategies. First, we interacted the excess worker turnover rate with firm age (continuous variable). We obtained a positive and significant coefficient. This suggests that, other things being equal, the older the firm, the smaller the overall (negative) impact of excess worker turnover on innovation. Second, we created three age classes (below 5, between 5 and 20, and above 20 years of age), built the corresponding dummy variables, and multiplied each of them by the excess worker turnover rate. These interactions, therefore, give the impacts of workers' replacements in young firms, medium-aged firms, and old firms. We obtained consistent results. In particular, the impact for old firms is predicted to be not significant, while the impact for medium-aged and especially young firms is negative and significant. It should also be noted that the impact for firms in the lowermost age class (i.e., below 5 years) is ten times larger than that for firms in the intermediate class (i.e., between 5 and 20 years).

Table 5
Impact of workers' replacements on firm innovation: diversified impacts by firm age and size.

Firm age		
Differentiated impact by firm age (1)		
Excess worker turnover rate	−4.243***	(1.137)
Excess worker turnover rate * firm age	0.172***	(0.054)
Differentiated impact by firm age (2)		
Excess worker turnover rate * firm established less than 5 years before	−11.089***	(1.607)
Excess worker turnover rate * firm established between 5 and 20 years before	−1.439**	(0.643)
Excess worker turnover rate * firm established more than 20 years before	−0.142	(0.673)
Firm-year observations	1565	
Firm size		
Using number of employees to control for firm size		
Standard regression		
Excess worker turnover rate	−0.946*	(0.526)
Differentiated impact by firm size		
Excess worker turnover rate * firm with 50–250 employees	−0.397	(0.510)
Excess worker turnover rate * firm with 250+ employees	−6.142***	(1.197)
Using revenues to control for firm size		
Standard regression		
Excess worker turnover rate	−1.080**	(0.526)
Differentiated impact by firm size		
Excess worker turnover rate * firm with revenues lower than or equal to 50 million Euros	−0.571	(0.512)
Excess worker turnover rate * firm with revenues greater than 50 million Euros	−4.664***	(1.791)
Firm-year observations	1565	

Source: VWH-AIDA-PATSTAT data set (years: 1995–2001).
All the estimations included the same set of controls as Specification (3) of Table 4. All the moderating analyses refer to interaction terms (i.e., we did not split the sample). We report the interaction effects for all the *n* relevant interaction categories (i.e., these are direct effects and not differential effects). For the rest, see the footnote of Table 4. The average excess worker turnover rates were 0.363 (std. dev. 0.204), 0.305 (std. dev. 0.182), and 0.261 (std. dev. 0.164) in firms established less than 5, between 5 and 20, and more than 20 years before, respectively. The average excess worker turnover rate was 0.297 (std. dev. 0.178) in firms with 50–250 employees, and 0.210 (std. dev. 0.151) in firms with 250+ employees.

[11] This and the following analyses on diversified impacts (e.g., young *versus* old firms, small *versus* big companies, being located *versus* not being located in an industrial district) refer to interaction effects (i.e., we did not split the sample). We always show interaction effects in the form of direct effects (i.e., we show the effects for the excess worker turnover rate interacted with each of the *n* relevant interaction categories). This is a strategy algebraically equivalent to showing the effects for the non-interacted excess worker turnover rate and its interactions with only $n-1$ interaction categories (i.e., in the form of differential impacts). We prefer displaying results in this way as they directly show the impacts for each category of firms without needing additional algebraic computations to get direct effects. An example illustrates this point. Considering the case of industrial districts, we proceeded in this way. We first created two dummy variables, one indicating whether the firm was located within an industrial district and another one indicating whether the firm was located outside. These dummies are opposite each other. When the first is 0, the second is 1, and *vice versa*. We then interacted the excess worker turnover rate with these two dummy variables. Two new variables were then created. The first one, "Excess worker turnover rate * firm belonging to an industrial district", takes the value of the actual excess worker turnover rate when the firm belongs to an industrial district and the value 0 otherwise. The second variable, "Excess worker turnover rate * firm not belonging to an industrial district", takes the value of the actual excess worker turnover rate when the firm does not belong to an industrial district and the value 0 otherwise. The first variable, therefore, tells us the effect of excess worker turnover for firms located in industrial districts, whereas the second variable tells us the effect of excess worker turnover for firms located outside. This strategy is equivalent to inserting in the regression the excess worker turnover rate and the excess worker turnover rate interacted with being located in an industrial district (or outside, one of the two). The interaction term, let us suppose it is chosen the interaction category "being located within an industrial district", tells us the differential effect of being located within an industrial district. The coefficient associated with the non-interacted excess worker turnover rate tells us the impact on the residual category (in our example, being located outside an industrial district). This way, the regression output is in terms of differential impacts, in the sense that the different effects of excess worker turnover for firms belonging and for those not belonging to industrial districts are left implicit and can be derived by applying simple algebraic steps. The implicit approach says that the impact in firms belonging to industrial districts is 5.135 units bigger (i.e., this is the coefficient associated with the interaction between the excess worker turnover rate and being located in an industrial district) than the overall impact, which is, −5.523 (i.e., this is the coefficient associated with the non-interacted excess worker turnover rate). This means that the impact on firms belonging to industrial districts is $-5.523 + 5.135 = -0.388$, the same number found in the explicit approach (see Table 6). The impact on firms not belonging to industrial districts, being the residual category (i.e., that not interacted), is given by the coefficient associated with the excess worker turnover rate, −5.523, which is the same as the one obtained under the explicit approach (see Table 6).

[12] As suggested by an anonymous referee, whom we thank, this feature could call for the excess worker turnover rate expressed in logs. In Appendix D, we provide robustness checks on this.

In the bottom panel of Table 5, we instead report evidence about the moderating effect of size. This latter was measured by using either revenues (as in Table 4) or employment. We start with the case of size measured through revenues. The coefficient of the excess worker turnover rate in the standard regression is indeed −1.080, as in Column (3) of Table 4. The moderating effect of size was obtained by interacting revenues with the excess worker turnover rate. Specifically, we built two dummy variables distinguishing small *versus* large firms on the basis of revenues, and interacted them with the excess worker turnover rate. To distinguish between small and large firms, we followed the standard thresholds proposed by the European Commission and set the threshold for small firms at (less than) 50 million Euros of revenues per year.[13] The results suggest that large firms are much more sensitive than small companies to the effect of workers' replacements, as signaled by the marked difference between the two coefficients, as well as by the fact that the interaction with the uppermost revenue class shows a statistically significant coefficient, while the other interaction does not. We also checked the robustness of these results by using the number of employees as a proxy for firm size. The results are very similar to those obtained by using revenues and, in fact, the two variables (i.e., revenues and employment) show a substantial correlation (0.855). The coefficient of the interaction with the dummy variable identifying small firms (with 250 or fewer employees - also here we follow the classification of the European Commission) is not statistically significant in this case either. Conversely, the effect on large firms (with more than 250 employees) is large and significant.

Overall, these results provide support to our Hypotheses 2a and 2b. First, old firms are less damaged by workers' replacements than young firms, because the latter strongly rely on individual capacity and specific human capital in their innovative dynamics. Second, small firms are more resilient to workers' replacements than large firms. This is consistent with the idea that exchanges of knowledge with other firms, engendered by hirings and separations, are comparatively more important for small firms.

5.3. Innovation, workers' replacements, and the role of external factors

The first set of results confirm our hypothesis about the negative impact of excess worker turnover on firms' innovation output. They also shed light on the moderating role of two important variables, age and size, which are well-known major sources of heterogeneity in firms' economic and innovative performances.

In Section 2, we stressed that also factors external to firms' boundaries can influence the impact of workers' replacements on innovation. First, we put forward the hypothesis that firms within industrial districts suffer less (in the case of separation-driven effects) or gain more (in the case of 'learning-by-hiring' effects) from workers' replacements compared to firms outside industrial districts (Hypothesis 3a). This is because of labor pooling dynamics and job matching effects.

Our previous results suggest that separation-driven effects are dominant in our sample. According to Hypothesis 3a, in this context, spatial clustering and localized industrial specialization should increase the probability of replacing workers that have abandoned the firms with new workers possessing the requisite (and lost) competencies.

We investigated the moderating impact of location in industrial districts by building two dummy variables covering firms within districts and firms that are outside them, and interacting these dummies with the excess worker turnover rate.[14] The results of the estimations are reported in the first panel of Table 6. While the effect of workers' replacements on innovation is not significant in firms located within industrial districts, firms located outside those areas significantly suffer from workers' replacements. The coefficient of the excess worker turnover rate for these latter firms is indeed large and significant.

Next, we investigated whether the impact of workers' replacements varies with the availability of knowledge spillovers in the areas in which firms locate (Hypothesis 3b). Knowledge spillovers were measured by aggregating all the Veneto firms' patent stock at the NUTS-3 level (i.e., provinces). In areas with large amounts of available knowledge stock, the general efficiency of firms' innovation activities was expected to be high, as compared to areas characterized by scarcity of external knowledge. Moreover, the high spatial concentration of knowledge increases the likelihood that local human capital accesses and absorbs place- and industry-specific competencies that can be useful for co-located firms. In contexts characterized by the dominance of 'competence drain' effects, like the Veneto region, these dynamics render workers' replacements less harmful for firms operating in areas with high levels of aggregate knowledge stock. As previously, to explore this issue, we constructed two dummy variables capturing firms' location in provinces with high *versus* low levels of knowledge spillovers. Provinces with high (low) levels of knowledge spillovers were defined as those above (below) the median level of aggregate firms' patent stocks. We then interacted these two dummy variables with the excess worker turnover rate to measure the impact of workers' replacements in the two different settings (i.e., high *versus* low availability of knowledge spillovers). As regards agglomeration externalities, the effect of workers' replacements in firms located in areas characterized by high knowledge externalities is not significant. Conversely, workers' replacements largely dampen innovation performance when firms cannot access high knowledge externalities (second panel of Table 6).

Finally, we hypothesized that knowledge variety can moderate the effects of workers' replacements on innovation. The dispersion of individual technological competencies across a wide array of fields impedes the matching between firms' needs and human capital specialization. We also hypothesized that this negative moderation is driven by unrelated *versus* related technological variety (Hypothesis 3c). We report the results of our estimations in the third and fourth panels of Table 6. As before, we created relevant dummy variables identifying the different contexts in which the firms are located, and interacted these dummy variables with the excess worker turnover rate. The degree of knowledge variety of an area was measured by the information entropy at the NUTS-3 level. The degree of unrelated and related knowledge variety was measured by the between and within information entropy rates, respectively, again measured at the NUTS-3 level. In the regressions, we inserted the ratio between the unrelated and related components of knowledge variety. As before, we split between high and low categories based on whether relevant values were above or below the median. First, as expected, firms located in areas with high technological variety experience a negative and significant effect of workers' replacements. Conversely, firms located in areas with low levels of knowledge variety are not significantly affected by excess worker turnover (third panel of Table 6). The breakdown of variety into its related and unrelated components is also in line with expectations. For firms operating in areas with high levels of the unrelated/related ratio (i.e., featured by the prevalence of unrelated variety), workers' replacements significantly harm innovation performance. Conversely, for firms located in areas with low levels of this indicator (i.e., characterized by the prevalence of related variety), the negative impact of workers' replacements vanishes.

Overall, this second set of estimates confirms that the features of the external environment in which firms operate largely influence the impact of excess worker turnover on innovation dynamics. The channel is the distribution of skills and technological components among individuals in local labor markets.

[13] For details, see http://ec.europa.eu/eurostat/statistics-explained/index.php/Archive:Small_and_medium-sized_enterprises.

[14] We identified industrial districts from the list issued by the *Osservatorio Nazionale dei Distretti Industriali* (the Italian monitoring center of industrial districts). For a detailed list, see http://www.osservatoriodistretti.org/category/regione/Veneto.

Table 6
Impact of workers' replacements on firm innovation: local networks.

Industrial districts		
Excess worker turnover rate * firm belonging to an industrial district	−0.388	(0.516)
Excess worker turnover rate * firm not belonging to an industrial district	−5.523***	(1.515)
Firm-year observations	1565	
Stock of innovative capital in the province		
Excess worker turnover rate * firm belonging to a province with high stock of innovative capital	−0.579	(0.582)
Excess worker turnover rate * firm belonging to a province with low stock of innovative capital	−1.742**	(0.857)
Firm-year observations	1565	
Information entropy (IE) in the province		
Excess worker turnover rate * firm belonging to a province with high information entropy	−1.355**	(0.553)
Excess worker turnover rate * firm belonging to a province with low information entropy	−0.827	(0.650)
Firm-year observations	1565	
Between/within entropy ratio (IEB/IEW) in the province		
Excess worker turnover rate * firm belonging to a province with high between/within entropy ratio	−1.279**	(0.593)
Excess worker turnover rate * firm belonging to a province with low between/within entropy ratio	−0.844	(0.571)
Firm-year observations	1565	

Source: VWH-AIDA-PATSTAT data set (years: 1995–2001).
All the estimations included the same set of controls as Specification (3) of Table 4. All the moderating analyses refer to interaction terms (i.e., we did not split the sample). We report the interaction effects for all the *n* relevant interaction categories (i.e., these are direct effects and not differential effects). For the rest, see the footnote of Table 4. The high (low) categories referred to values above (below) the median. The average excess worker turnover rate was 0.283 (std. dev. 0.172) in firms located in industrial districts, and 0.300 (std. dev. 0.196) in firms located outside. It was 0.307 (std. dev. 0.179), 0.290 (std. dev. 0.177), 0.297 (std. dev. 0.180) in firms located in provinces with high stocks of innovative capital, high levels of information entropy, and high between/within entropy ratios, respectively. It was instead 0.271 (std. dev. 0.173), 0.284 (std. dev. 0.177), 0.274 (std. dev. 0.172) in firms located in provinces with low stocks of innovative capital, low levels of information entropy, and low between/within entropy ratios, respectively.

6. Robustness checks

Several checks were conducted to test the robustness of our results and to gain a finer-grained picture of the mechanisms involved. In this section we report additional estimations dealing with (i) endogeneity issues; (ii) the differential effects of hirings and separations; (iii) the differential role of job categories and job tenure.

6.1. Endogeneity

Although using lagged independent variables can contribute to obtaining a more reliable estimation of the true impact, there may still be a potential for reverse causality to occur. A firm hit by a bad demand shock may plan to invest less in innovative activities, which is likely to result in subsequent lower innovation performance. At the same time, this may also condition the firm's current replacement activity, because more talented workers may want to quit and the firm would have to replace them with other workers to keep a constant workforce. This is only one example among others showing that reverse causality problems can emerge despite the use of lagged independent variables. While inserting lagged regressors is an important precaution, only proper instrumental variable estimation can give a sound solution to endogeneity. For this reason, we also experimented with instrumental variable regressions.

For an instrument to be usable, two main conditions must hold: (i) the instrument should be significantly correlated with the endogenous regressor, and this correlation should hold conditional on all the other (exogenous) explanatory variables used in the regression; (ii) it should not directly explain/determine the dependent variable. We used an instrument which seemed to satisfy both criteria. We instrumented the excess worker turnover rate in the firm with the average worker turnover rate of relevant surrounding firms (excluding the firm itself). In particular, we resorted to the categorization of local labor markets according to so-called 'local labor systems' (*Sistemi Locali del Lavoro* or SLLs, in Italian). These SLLs are basically geographical portions of the country defined by the Italian statistical office (Istat), wherein a local labor market unfolds. Put differently, SLLs are self-contained local labor pools. We also considered other dimensions which we deemed relevant: industry and firm size. The idea behind our instrument is simple. A firm's replacement activity is directly influenced, among other things, by the degree of labor mobility in the relevant local labor market, that is, the one constituted by firms belonging to the same SLL, industry, and size category. If a firm is expanding its workforce by hiring massively, it is possible that some of the other firms' employees quit and move to the expanding firm, thereby obliging the origin firms to replace them with other employees. For this to happen, of course, firms need to be somehow connected; and location in the same local labor market, being involved in similar activities, and having similar size are important conditions.[15] Therefore, worker mobility, captured by (overall) worker turnover rate, in surrounding firms is seen as a valid predictor of a firm's replacement activity.[16] This is testified by our first-stage regression (shown in the first panel of Table 7), which evidenced that other relevant firms' worker turnover positively and significantly influences a

Table 7
Impact of workers' replacements on firm innovation: dealing with endogeneity through instrumental variable estimation.

First-stage instrumental variable estimation		
Other relevant firms' average worker turnover	0.076**	(0.033)
Second-stage instrumental variable estimation		
Excess worker turnover rate	−11.703**	(5.348)
Firm-year observations	876	
Standard estimation – comparison		
Excess worker turnover rate	−1.432*	(0.832)
Firm-year observations	876	

Source: VWH-AIDA-PATSTAT data set (years: 1995–2001).
All the estimations included the same set of controls as Specification (3) of Table 4. For the rest, see the footnote of Table 4.

[15] There is an established body of literature reporting that workers employed in smaller *versus* larger companies are different in various respects, including education, experience, and talent (see, for instance, Headd, 2000; Oi and Idson, 1999; Schmidt and Zimmermann, 1991). Note that we also experimented with not including the size category to identify relevant surrounding firms, and found no change in the results.

[16] Note that we used the (overall) worker turnover of surrounding firms as an instrument for the firm's replacement activity (i.e., excess worker turnover), because also job creation/destruction of surrounding firms matters for determining the firm's level of replacements, as the example provided above (that of an expanding surrounding firm) clearly shows.

firm's workers' replacements, given all the other (exogenous) independent variables, with a first-stage *F*-statistic well above conventional levels (21.59).

On the other hand, for the instrument to be valid, worker mobility in the relevant surroundings should not *directly* influence the firm's innovation performance. While the degree of worker mobility among other relevant firms can influence the firm's innovation performance (e.g., through knowledge spillovers), it seems not to influence it directly, because knowledge spillovers can only materialize to the extent that some worker enters or exits the firm, factors already accounted for by the degree of the firm's workers' replacements and net job creation (which was controlled for in our regressions). As the second panel of Table 7 shows, the negative and significant impact of workers' replacements on innovation performance is confirmed in this instrumental variable setting. On comparing the estimated impact in the instrumental variable estimation with that from standard estimation performed on the same sample (see the third panel of the table), it emerges that the IV estimate is much larger in magnitude compared to the standard estimate. This suggests that the true impact of workers' replacements on innovation performance is higher (in absolute terms) than what we have found. Hence, the results set out in Table 4 should be seen as an upward estimate of the impact, which, if anything, suggests that workers' replacements are likely to be more detrimental to innovation outcomes than we have already found. To empirically check the validity of our instrumental variable results, we would need at least one more instrument. Although a two-year lag of worker mobility in the relevant surroundings could have been a suitable additional instrument, unfortunately, convergence failed to be achieved in this case, so that we could not empirically assess the validity of our instrument. Nevertheless, despite the absence of over-identification tests and, especially, of a natural experiment that imposes a truly exogenous shift on workers' replacements, we are confident that the overall conclusion that workers' replacements hurt innovation performance holds, as the various robustness checks that we performed (and the underlying theoretical framework) indicated.

6.2. Hirings and separations

In Section 2 we conducted an extensive discussion of the literature dealing with the impact of workers' replacements on innovation. Existing studies, on the one hand, stress the positive effects due to the so-called 'learning-by-hiring' hypothesis. This argument stresses the impact of hirings while it neglects any possible effect driven by separations. Workers' replacements positively affect innovation performances because of the injections of new competencies in the organization, leading to a higher probability that novelty will be created (Ettlie, 1980; Price, 1977). On the other hand, we have stressed that a more composite framework based on the resource-based theory of the firm would make it possible to combine positive and negative effects of workers' replacements by stressing the importance of learning dynamics and hence of firm-specific tacit knowledge embodied in workers. Separations appear in this case to constitute a factor hindering innovation, insofar as they imply the loss of tacit knowledge relevant to the organization. Separations may prove to have a positive impact when the so-called 'brain bank' effect offsets the 'competence drain' effects (Kerr, 2008; Oettl and Agrawal, 2008).

In this section, we report additional estimations that checked whether our results were driven by separations or hirings. Our previous discussion induces the expectation that the negative sign of the excess worker turnover variable is actually driven by separations. Results from Table 8 seem to suggest that what really hurts the firm in a worker's replacement is the separation of the worker rather than the hiring of the substitute worker, which is consistent with the idea that what really hurts the firm is the loss of tacit firm-specific knowledge and competencies.

It should be stressed, however, that while splitting inflows and outflows of workers may be helpful for grasping whether separations or hirings (or both) drive the overall impact of workers' replacements, relying too closely on this estimate may be misleading. In fact, in this paper, we have been interested in the effect of *replacements* of workers. They entail hirings and separations, but not *all* of the firm's hirings or separations, since there are hirings or separations which are not meant to replace anyone in the firm, but only to increase or decrease the firm's workforce. As discussed above, excess worker turnover gives a measure of the firm's replacement activity, which is purged of those hirings or separations that only modify the firm's number of employees. That said, it is a fact that most of the hirings and separations of firms are done to replace workers rather than simply to increase or decrease the firm's workforce. In our sample, as much as 77% of hirings and separations occurred to replace workers (i.e., the ratio between excess worker turnover and worker turnover was 0.77). We tried to purge the effect from hirings and separations that simply increase or decrease the workforce by only considering firms that underwent a period close to job stability (whereby the relative weight of replacements to total turnover was high – more than 70% or 80%), and obtained very consistent results. We can thus confidently conclude that the overall effect of workers' replacements stems from separations rather than hirings, a result that one would legitimately expect.

6.3. Innovation, workers' replacements, and the role of workforce characteristics

The empirical evidence that we have provided indicates that in the Veneto region workers' replacements hinder firms' innovation performance, and that this effect is driven by separations. Our results therefore suggest that the negative effects due to the loss of relevant tacit knowledge embodied in separating workers outperform any possible positive effects engendered by 'brain bank' or 'learning-by-hiring' dynamics. These latter did not prove to be significant at all.

In this context, given the importance of learning dynamics in our theoretical framework, and in the interpretation of the empirical results, it would be useful to check if finer-grained analyses of the differential effects of workers' replacements by job category and job tenure yield consistent results. On the one hand, since the seminal contribution by Arrow (1962), several studies have stressed that blue-collar workers' 'learning-by-doing' dynamics are important for firm-level innovation performances (Aoki, 1990; Pieroni and Pompei, 2008; Piore, 1968). Moreover, the extant literature stresses the role of managers in the preservation and transmission of organizational knowledge, as well as the orientation of the decision-making process in directions consistent with the firm's core capabilities (Nonaka, 1994; Nonaka et al., 2006). Higher replacement rates in these categories are therefore expected to exert negative effects on innovation.

On the other hand, the emphasis on sticky knowledge gained through learning dynamics calls for an explicit account of the time that mobile workers have spent within the firm's organizational boundaries. Extant theory suggests that the historical process of competence

Table 8
Impat of workers' replacements on firm innovation: isolating the impact of hirings and separations.

Hirings and separations		
Hiring rate	−0.025	(1.077)
Separation rate	−2.115*	(1.206)
Firm-year observations	1565	

Source: VWH-AIDA-PATSTAT data set (years: 1995–2001).
The estimation included the same set of controls as Specification (3) of Table 4. For the rest, see the footnote of Table 4. Instead of using the net job creation rate as a control, we inserted three dummies indicating whether the firm was in a period of job creation, destruction, or stability. We could not insert the net job creation rate as it is by construction perfectly collinear with hiring and separation rates (net job creation rate = hiring rate − separation rate).

Table 9
Impact of workers' replacements on firm innovation: diversified impacts by job categories and tenure of separated workers.

Job categories		
Excess worker turnover rate of blue-collar workers	−1.122**	(0.546)
Excess worker turnover rate of white-collar workers	0.658	(0.465)
Excess worker turnover rate of managerial workers	−0.553**	(0.259)
Firm-year observations	1104	
Tenure		
Excess worker turnover rate * relative weight of separations of high-tenured workers is low	−0.807	(0.631)
Excess worker turnover rate * relative weight of separations of high-tenured workers is high	−1.694**	(0.742)
Firm-year observations	1558	

Source: VWH-AIDA-PATSTAT data set (years: 1995–2001).
All the estimations included the same set of controls as Specification (3) of Table 4. For the rest, see the footnote of Table 4. The average excess worker turnover rate of blue-collar workers was 0.253 (std. dev. 0.199), whereas the average excess worker turnover rates of white-collar workers and managers were 0.198 (std. dev. 0.160) and 0.095 (std. dev. 0.316), respectively. The moderating analysis in the second panel refers to interaction terms (i.e., we did not split the sample). We report the interaction effects for all the *n* relevant interaction categories (i.e., these are direct effects and not differential effects).

accumulation is characterized by increasing returns due to dynamic irreversibilities (Antonelli, 2001; Nelson and Winter, 1982). The mobility of high-tenured workers is therefore expected to have a higher impact than that of low-tenured ones.

We report the results of these estimations in Table 9. To recover excess worker turnover rates by job category, we computed the excess worker turnover for blue-collar workers, white-collar workers, and managers separately. We then obtained rates by dividing such figures with the relevant employment levels. Therefore, these are within-job-category rates. This implies that we had to remove firms that did not employ any worker in at least one of the three categories. No firm in the sample did not employ blue-collar or white-collar workers, but some of them did not employ any workers with a managerial contract.[17]

To understand whether replacements impact on the firm's innovation output differently according to whether they stem from separations of high- or low-tenured workers, we proceeded as follows. We interacted the firm's excess worker turnover rate with two dummies indicating whether the share of separated high-tenured workers was high or low. Whether a separation stemmed from a high-tenured or a low-tenured worker was expressed as a function of the firm's average workers' tenure. In practice, if the separated worker's tenure was above the workers' average tenure, then this was a separation of a high-tenured worker. Conversely, if it was below the average workers' tenure, then this was a separation of a low-tenured worker. We then computed the relative weight of separated high-tenured workers as the proportion of separations of high-tenured workers over the total number of separations. Finally, the firm's relative weight of high-tenured separations was classified as low (high) depending on whether it was below (over) the median.[18] The average relative weight of high-tenured separations was 0.223 (std. dev. 0.163). This means that, on average, 22.3% of a firm's total separations were attributable to high-tenured workers.[19]

These results on job tenure should, however, be treated with a certain amount of caution. In fact, we do not know *which* separated workers (i.e., whether high- or low-tenured) are replaced and which instead are not (i.e., just decrease the firm's number of employees). This implies that these results are valid to the extent that the relative proportions of high- and low-tenured separated workers do not systematically differ between those workers who are replaced and those who are not. Yet, the fact that workers' replacements (i.e., excess worker turnover) constitute the great majority (about 80%) of the firm's total worker turnover should much attenuate the potential problem.

The empirical results are in line with the expectations, and consistent with a theory of excess worker turnover and innovation focusing on the relevance of learning dynamics. Indeed, the findings reported in the upper part of Table 9 show that replacements of blue-collar workers and managers significantly dampen the firm's innovation performance. We do not find any significant effect as far as the replacements of white-collar workers are concerned.

In the lower part of Table 9 we show instead the results of the estimations discriminating between the effects of high- and low-tenured workers. According to our findings, when the proportion of workers' replacements stemming from separations of high-tenured workers is relatively high, the impact of replacements on innovation output is large and significant. Conversely, when replacements stem mostly from separations of low-tenured workers, their impact on innovation is not significant.

In sum, these additional estimations indicate that workers' replacements are more likely to hinder firm-level innovation performances when they involve types of workers that are crucial to the development and preservation of organizational knowledge. The intersection of job categories and job tenure allows identifying high-tenured blue-collar workers and managers as the most important human resources in this respect.

7. Conclusions

In this paper, we have investigated the impact of workers' replacements, captured by excess worker turnover, on firms' innovation dynamics. Our main argument has hinged on the resource-based view of the firm and the importance of workers' learning dynamics in the accumulation of tacit knowledge and in the development of organizational routines, which are major drivers of firms' innovation. Workers' replacements imply the loss of organizational knowledge embodied in individuals and accumulated over time through on-the-job learning. This, in turn, is likely to hinder firms' innovation outcomes. Moreover, we have investigated the moderating role of factors both internal and external to the firm. The former concerns firm age and size, while the latter includes agglomeration externalities, knowledge spillovers, and technological variety.

Our empirical investigation was based on matched employer–employee data for the Veneto region of Italy in the period 1995–2001. These data were merged with other information sources: Bureau van Dijk's AIDA and the PATSTAT and OECD REGPAT data sets. We implemented negative binomial estimations to assess the impact of excess worker turnover rate, as well as the influence of hypothesized moderating factors.

Our results confirm that excess worker turnover is negatively associated with firms' innovation outcomes. This result is persistent across all the implemented models, including instrumental variable estimation. As regards the interacting factors, we find that both firm age and size play an important role. In particular, our results suggest that young and large firms are more sensitive to the negative effects of workers' replacements on innovation. Moreover, agglomeration externalities can mitigate the effect of workers' replacements, and the same applies to the availability of local knowledge spillovers. Instead, variety is found to amplify the negative impact of excess worker turnover on innovation. We grounded the interpretation of these results on

[17] We did not consider excess worker turnover of apprentices (which we also observe) in this regression because also considering apprentices would have reduced the sample size too much for meaningful conclusions to be drawn (observations used in the estimation would be only 464 in this case). This is because many firms do not have at least one employee in each of the four job categories (i.e., blue-collar, white-collar, managerial, apprenticeship).

[18] To perform this estimation, we had to remove (a few) firms experiencing no separations since we could not calculate relative weights for them.

[19] We experimented with different ways of defining high- and low-tenured separated workers (e.g., more or less than 5 years of tenure, more or less than 10 years of tenure), with no change in the results.

the basis of the theory discussed in Section 2, which identifies labor pooling dynamics as the main channel driving the influence of external factors on the relationship between workers' replacements and innovation.

Like many other empirical investigations, also this one requires some caveats. First, the geographical coverage is limited to the Veneto region. Though it is part of the more advanced North-East regions in Italy, Veneto cannot be considered as representative of country dynamics. Yet, our data have the unique advantage of referring to the entire population of Veneto firms, thus furnishing a complete view of a self-contained labor market. Second, the time coverage is limited to the early 2000s, leaving aside the most recent years, which are characterized by more aggressive technology-based competition. While both these limitations are due to data constraints, it should also be stressed that we performed our estimations on a selected sample which collected top innovative sectors. If, on the one hand, we limited the analysis to top innovative industries in order to better individuate the effects of excess worker turnover on innovation performance, on the other hand, it is also true that some of the effects that we found could be diluted when considering larger inclusions of sectors. Due to this concern, we also pursued several robustness checks (shown in Appendix B) by including more industries. We found that the main result that workers' replacements are detrimental to innovation performance is strongly robust, and that the results from the various moderating effects remain largely unchanged, thus delivering a very consistent and robust picture. Moreover, it is worth noting that although we control for the average age of firms' workers, in the construction of our dependent variable separations also include retirements, the effect of which on innovation is deemed ambiguous.

Nevertheless, the study has important implications from both a strategic management and policy perspective. As regards the former, our results suggest that workers' mobility is detrimental to firms' innovation dynamics. This would seem to be at odds with the findings reported in Grinza (2016), wherein excess worker turnover is found to have a positive impact on firm productivity. On the contrary, this latter can be interpreted as an outcome of imitation externalities. Firms wanting to increase their productivity by means of replication of competitors' routines and technologies will benefit from worker mobility. Conversely, firms that want to stand competitive by means of innovation should devise measures to encourage experienced workers to stay instead of migrating to other firms. Experienced workers indeed represent a crucial asset for innovative firms because they are repositories of organizational knowledge and routines, and, for this reason, they are to be regarded as a source of opportunities to generate novelty that enhances firms' core competencies.

From the viewpoint of labor policies, this paper suggests that one-size-fits-all solutions cannot be supported. Moreover, these results challenge the idea that labor mobility is positive in absolute. Clearly, policy makers are not expected to obstruct labor mobility to promote innovation. Our results instead imply that some firms in specific places and industries would benefit from labor mobility more than others. Therefore, the promotion of labor mobility should be especially targeted on areas characterized by low innovation performances, and stronger reliance on imitation strategies.

This study opens up stimulating avenues for further research. First, from the viewpoint of firms' innovation strategies, it would be interesting to assess the differential impact of excess worker turnover on exploration *versus* exploitation strategies. Moreover, our results call for further refinements of the analyses to gain a better understanding of the factors behind the negative impact of workers' replacements on innovation, by exploiting the information on workers' histories, and, in particular, by looking at their previous employment and qualifying their experience in terms of sectoral and technological variety as well as of relatedness to their current activity. Finally, further investigations will focus on disentangling the effects of different kinds of separations.

Appendix A. Robustness checks: using two-year lags

While in the estimations presented in the paper all the (time-varying) regressors were lagged by one year, we also experimented with the inclusion of the longer two-year lags.

The estimation presented in Table A.1 replicated Specification (3) of Table 4, but, in this case, all the independent variables were lagged by two years.[20] Restricting the sample to firms with at least three years of observations significantly decreased the sample size, which passed from 1565 to 1173 observations that could be used in the estimations. Having a relatively short (seven-year) panel data set is, in fact, the main reason why we used one-year lags in this paper. Nevertheless, experimenting with longer time lags is important for two reasons. First, it allows further preserving the estimation from potential reverse causality, providing an additional check over the more tenuous one-year lags. Second, it allows better grasping longer-run dynamics, which are likely to be important as innovation is usually pursued over a medium-/long-run horizon.[21] As Table A.1 shows, the main result that workers' replacements dampen firm innovation was preserved. Note that we also ran the other specifications/regressions presented in the paper (e.g., moderating effects of firm age and size, location, etc.), and found that results were broadly unaffected by using two-year lags.[22]

Table A.1
Robustness checks: using two-year lags.

Excess worker turnover rate at $t-2$	−1.122*	(0.609)
Firm-year observations	1173	

Source: VWH-AIDA-PATSTAT data set (years: 1995–2001).
All the estimations included the same set of controls as Specification (3) of Table 4. For the rest, see the footnote of Table 4.

[20] Note that instead of three-digit industry dummies, those that we used throughout the paper's regressions, here we inserted two-digit dummies, because using three-digit dummies impeded convergence of the estimation.

[21] We thank an anonymous referee for having raised these issues.

[22] These additional results (and the others related to the robustness checks described below) are available upon request.

Appendix B. Robustness checks: experimenting with different thresholds to identify top innovative industries

As discussed in the paper, we constructed our estimation sample by considering the top-25% innovative industries, which resulted in the selection of four industries: chemicals, metal-mechanics, electronics, and automotives. While the rationale for this (somewhat strict) threshold was to avoid having a huge proportion of firms that did not innovate at all (and for which dynamics about workers' replacements and innovation performance were not relevant because they did not pursue innovation), experimenting with larger inclusions of industries is nonetheless important to better assess the generalizability of our results.[23]

Table B.1 reports results for these checks. All the estimations presented in the table replicated Specification (3) of Table 4, but using alternately different threshold levels (and, therefore, different samples) to identify top innovative industries. As mentioned in the paper, a threshold level of *x*% corresponded to selecting the top-*x*% two-digit industries in terms of percentage of firms that innovated (i.e., had at least one patent filed in the year). To check the sensitivity of our results, we tested two different thresholds: 75% and 50% (whereas in the paper we used the more restrictive 25% threshold). As Table C.1 shows, the main results were unchanged: workers' replacements were still predicted to have a negative and significant impact on innovation performance. We also experimented with the other specifications/regressions of the paper and found very consistent results using both thresholds (i.e., 75% and 50%).

Note that further increasing the threshold (e.g., at the 90% level or considering all the two-digit industries) was not feasible as convergence could not be achieved in any of our regressions in those cases. Indeed, the percentage of firms that innovated (i.e., for which the dependent variable was greater than zero) decreased substantially as the threshold approached 1. While the percentage of firms having at least one patent filed in the year was around 10% when top-25% innovative sectors were considered, it lowered to around 7% and 5% when top-50% and top-75% sectors were considered, respectively. When top-90% or all sectors were included, this percentage further decreased to less than 4%.

Table B.1
Robustness checks: top innovative industries.

Threshold at 75%			
Excess worker turnover rate	−1.045***		(0.374)
Firm-year observations		4703	
Threshold at 50%			
Excess worker turnover rate	−1.333***		(0.415)
Firm-year observations		3550	

Source: VWH-AIDA-PATSTAT data set (years: 1995–2001).
All the estimations included the same set of controls as Specification (3) of Table 4. For the rest, see the footnote of Table 4.

Appendix C. Robustness checks: experimenting with different threshold levels to identify multiple-plants firms

We also pursued robustness checks concerning the identification and consequent removal from the sample of multiple-plants firms. As discussed in the paper, for such firms the worker-level information from VWH was not aligned with the firm-level information from AIDA if they also included non-Veneto establishments.

Table C.1 shows three different estimations, all replicating Specification (3) of Table 4, but using alternately different threshold levels (and, therefore, different samples) to identify and remove multiple-plants firms. As mentioned in the paper, threshold levels were defined as the number of employees in VWH over the number of employees in AIDA. While in the paper we applied a more tenuous 50% threshold, here we experimented with stricter cutoffs. In particular, three thresholds were tested to check the sensitivity of our results: 70%, 75%, and 80%. As Table C.1 shows, the main results remained unchanged. Workers' replacements were still predicted to dampen innovation performance. As for the other robustness tests, we also experimented with the other specifications/regressions presented in the paper, and found very similar results.

Table C.1
Robustness checks: multiple-plants firms.

Threshold at 70%			
Excess worker turnover rate	−0.924*		(0.546)
Firm-year observations		1472	
Threshold at 75%			
Excess worker turnover rate	−0.960*		(0.570)
Firm-year observations		1424	
Threshold at 80%			
Excess worker turnover rate	−0.992*		(0.605)
Firm-year observations		1354	

Source: VWH-AIDA-PATSTAT data set (years: 1995–2001).
All the estimations included the same set of controls as Specification (3) of Table 4. For the rest, see the footnote of Table 4.

[23] This point was raised by an anonymous referee, whom we thank.

Note that further increasing the threshold (e.g., at the 90% level) resulted in large drops in the number of observations. Furthermore, when using too high thresholds, more than better identifying multiple-establishment firms, there was a risk of eliminating single-plant firms. In fact, small discrepancies in the reported number of employees between the two data sources are physiological and possibly derive from different timings of data collection of VWH and AIDA.

Appendix D. Robustness checks: expressing excess worker turnover rate in logs

Finally, we carried out robustness tests expressing the excess worker turnover rate in logs rather than levels. In the paper's estimations, we expressed the excess worker turnover rate in levels to conform to the literature on worker flows, which regularly uses levels. Nonetheless, running robustness checks where the excess worker turnover rate is expressed in logs is important, given the tendency of non-linear trends in the impact, as highlighted by Specification (6) of Table 4.

The negative and significant impact of excess worker turnover on innovation output was again confirmed, as shown by Table D.1. As in the previous cases, we also ran several tests with the other specifications/regressions of the paper, and found that results remained broadly unchanged.

Table D.1
Robustness checks: logs.

log Excess worker turnover rate	−0.332***	(0.112)
Firm-year observations	1546	

Source: VWH-AIDA-PATSTAT data set (years: 1995–2001).
The estimation included the same set of controls as Specification (3) of Table 4. For the rest, see the footnote of Table 4. Note that we dropped (a few) observations for which excess worker turnover was equal to zero.

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Is flexible labour good for innovation? Evidence from firm-level data

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Whether the use of flexible workers is damaging to innovation or not depends on the dominant innovation regime in a sector. In sectors with a 'routinised' innovation regime, high shares of low-paid temporary workers have a negative impact on the probability that firms invest in R&D. In sectors that tend towards a 'garage business' regime, however, flexibility has no impact. The two innovation regimes differ in the nature of their knowledge base: reliance on generally available knowledge or dependence on a firm's historically accumulated knowledge base. Innovation in the latter regime benefits from longer job durations. Our results are consistent with findings in macro-level studies that coordinated market economies with rigid labour markets have higher labour productivity gains than liberalised market economies.

Key words: Determinants of R&D, Entrepreneurship, Routinised innovation, Schumpeterian innovation models, Varieties of capitalism
JEL classifications: J53, M51, M54, O31, O32, O33

1. Introduction

The mainstream argues that unemployment is due to labour market rigidities. Examples of labour market rigidities are strong trade unions, generous social benefits, high minimum wages, powerful insiders or firing restrictions. The standard remedy consists of 'structural reforms', which essentially come down to lifting firing restrictions, reducing minimum wages or cutting back on social benefits.

The plea for 'structural reforms' has been supported by evidence that countries with deregulated labour markets tend to have lower unemployment. There are doubts, however, whether this holds true. For example, Vergeer and Kleinknecht (2012) demonstrated that the empirical model in a highly cited article by Nickell *et al.* (2005) is far from robust. Others have demonstrated that evidence provided by 'rigidities cause unemployment' studies can change if observation periods are extended or if new countries are added to a sample (Baker *et al.*, 2005; Baccaro and Rei, 2007; Howell *et al.*, 2007).

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The plea for deregulation of labour markets has also been supported by evidence that the USA experienced higher GDP growth compared with 'Old Europe', at least during the 1990s up to 2007. Meanwhile, we realise that higher growth was driven by an impressive growth of debt related to bubbles in asset markets (Maki and Palumbo, 2001; Palley, 2009). In the long run there is little difference in GDP growth rates between countries that have more rigid or more flexible labour markets, while there is evidence at the macro level that a mix of downwardly flexible wages and wage cost-saving deregulation of labour markets brings down labour productivity growth rates (Vergeer and Kleinknecht, 2011). A series of studies gives theoretical arguments and/or empirical support to the hypothesis that the rigid corporatist labour markets of 'Old Europe' may actually *favour* innovation and labour productivity growth.[1] Some studies, however, argue that the opposite should hold[2] and a single study reports insignificant results (Arvanitis, 2005).

In this paper we argue that some of the divergence in the findings may be explained once we control for the dominant innovation model in a firm's sector of principal activity. We distinguish an 'entrepreneurial' (or garage business) model and a 'routinised' model of innovation. The latter are sometimes called Schumpeter mark I (Schumpeter, 1912) and Schumpeter mark II models (Schumpeter, 1943). Table 1 gives a stylised sketch of the two Schumpeter models. The essential difference between the models relates to the properties of the knowledge base required for innovation. The garage business model

Table 1. *Stylised sketch of the two innovation models by Schumpeter (1912, 1943)*

Schumpeter mark I model: 'garage business innovation'	Schumpeter mark II model: 'routinised innovation'
Starters in high tech; niche players	Mature firms with professional R&D laboratories
Turbulent competition; creative destruction	Monopolistic competition, oligopolies
Frequent market entry and exit	Stable hierarchy of (dominant) innovators
Properties of the knowledge base	
General and generally available knowledge → low entry barriers	Dependence on historically accumulated, often firm specific and idiosyncratic knowledge from experience ('tacit knowledge') → high entry barriers
Properties of the related labour market institutions	
Hiring through external labour markets	Strong reliance on internal labour markets with well-protected insiders

Note: This table is also inspired by Breschi *et al.* (2000).

[1] See, e.g., Acharya *et al.* (2010), Agell (1999), Lucidi & Kleinknecht (2010); Appelbaum *et al.* (2000), Auer *et al.* (2005), Boeri and Garibaldi (2007), Huselid (1995), Kleinknecht *et al.* (2006), Michie and Sheehan (2001, 2003), Buchele and Christiansen (1999), Lorenz (1999), Pieroni and Pompei (2008) or Storm and Naastepad (2012).

[2] See, e.g., Scarpetta and Tressel (2004), Bassanini *et al.* (2009) or Bartelsman *et al.* (2012).

relies more on *generally available* knowledge while the routinised innovation model relies more on *firm-specific and historically accumulated* knowledge, which creates path dependencies: what a firm is 'good' at depends on the knowledge it accumulated in the past. The accumulation of firm-specific (often 'tacit') knowledge creates barriers to entry, thus assuring monopoly profits that give incentives to innovation.

Using firm-level OSA-SCP data, we provide a simple empirical test of two hypotheses:

(i) In firms that operate in sectors that tend towards a routinised Schumpeter II regime, innovation will benefit from more rigid labour relations that imply long-lasting commitments between employers and employees.
(ii) In firms that operate in sectors that tend towards a Schumpeter I garage business model, flexible labour may benefit innovation.

The remainder of this paper is organised as follows. Section 2 discusses opposite arguments found in the literature and in popular discourse about whether flexible labour would enhance or damage innovation. Section 3 introduces our database and indicators. Section 4 provides an empirical test and Section 5 rounds up with discussions and conclusions.

2. Why and how could flexible labour impact on innovation?

2.1 Arguments why flexible labour could favour innovation and productivity growth

First, strong firing protection will slow down the reallocation of labour from old and declining sectors to new and dynamic ones (see, e.g., Nickell and Layard, 1999).

Second, the difficult or expensive firing of redundant personnel can frustrate labour-saving innovations at the firm level (Bassanini and Ernst, 2002; Scarpetta and Tressel, 2004).

Third, well-protected and powerful personnel could appropriate rents from innovation through higher wage claims, thus reducing incentives for taking innovative risks (Malcomson, 1997).

Fourth, firms will more easily engage in risky new ventures if they are sure they can easily dispense with their personnel in the case of failure (Bartelsman *et al.*, 2012).

Fifth, easier firing will increase rates of job turnover, allowing for more 'job matches'. This increases the chance that people will find the jobs in which they are most productive. When scrutinising the economic impact of party programmes for the 1912 national elections in the Netherlands, the Central Planning Office (CPB, The Hague) used this argument, attributing in its models positive productivity effects to proposals towards easier firing.

Sixth, higher labour turnover enhances the inflow of 'fresh blood': people with new ideas and new networks may foster innovation. Moreover, there is less chance that employees will be entrenched in safe jobs, gradually losing their creativity; further, the (latent) threat of easy firing may prevent 'shirking'.

Against such arguments, several objections are possible. As to the first argument, emerging new industries are likely to offer better career opportunities and higher pay than declining industries. Why should we not rely that such incentives will make people move voluntarily into new industries? As to the second argument, rates of job turnover have been estimated as being around 9–12%, thus offering some potential for downsizing without forced leave.[3] Moreover, if firing is difficult, firms have incentives to invest in

[3] Kleinknecht *et al.* (2006) report that, on average, 9–12% of a firm's personnel in the Netherlands leave voluntarily each year, the exact percentage depending on the state of the business cycle. Nickell and Layard (1999, p. 363) report that this figure amounts to more than 10%.

functional flexibility by means of training, which will allow labour to be shifted from old to new activities in internal labour markets. In other words, a lack of *numerical* flexibility will enhance *functional* flexibility.[4] The third argument may indeed be relevant in decentralised wage-bargaining settings typical of Anglo-Saxon labour markets. 'Rhineland'-type labour markets rely more on industry-level bargaining in which wage bargains are often imposed by government on *everyone* in a sector. Moreover, such labour market rigidity may actually enhance innovation, as technological laggards may be forced to make productivity-increasing investments in response to a rise in wages. The fourth argument may be relevant as it allows part of the entrepreneurial risks to be shifted to employees. This may notably encourage garage business innovation in young and fragile firms. The same holds for the 'fresh blood' argument: if firms rely on readily available *general* knowledge in a garage business model, a higher job turnover may be helpful for innovation. It may, however, be counterproductive in a 'routinised' Schumpeter II model when continuous accumulation of (often tacit) knowledge is crucial.

2.2 Arguments why flexible labour could damage innovation and productivity

First, Vergeer and Kleinknecht (2011) demonstrated that, during 1960–2004, the 'rigid' labour markets of 'Old Europe' showed substantially higher real-wage increases compared with 'flexible' Anglo-Saxon type labour markets in which easy firing restricts the power of labour. From this it can be derived that higher labour productivity gains in 'Old Europe' may have been caused by stronger substitution of capital for labour and by vintage effects: old vintages of capital need to be replaced more quickly as they become less profitable with rising wages. Lower wage increases can thus result in a growing age of capital stock, which has been shown to be one of the reasons behind the productivity crisis in the Netherlands after 1984 when trade unions voluntarily sacrificed wages against the promise of more jobs (see Naastepad and Kleinknecht, 2004).

Second, from a Schumpeterian perspective, it can be argued that due to their monopoly rents from innovation, innovators are better able than technological laggards to live with wage increases (or with high adjustment costs due to stricter regulation). Therefore, high real-wage growth and labour market rigidities may enhance the Schumpeterian process of *creative destruction* in which innovators compete away technological laggards (Kleinknecht, 1998). This makes innovation more rewarding. Actually, Vergeer and Kleinknecht (2011) report that, in a sample of 19 OECD countries (1960–2004), a 1% lower wage increase will result in a lower growth of labour productivity by 0.33–0.39%.

Third, easier firing and higher labour turnover shorten the payback period of a firm's investment in manpower training. In addition, workers will be more interested in acquiring *general* skills that increase their employability on the external job market, but may be reluctant to acquire firm-specific skills if there is no long-term commitment to their employers (Belot *et al.*, 2002). A similar conclusion emerges from the hypothesis that highly flexible labour reduces the compression of the wage structure (both within and between firms); note that Acemoglu and Pischke (1999) and Agell (1999) argue that wage compression is a reason for the provision of training by firms.

[4] Acemoglou and Pischke (1999) emphasise that wage compression in rigid German labour markets enhances training for highly educated *and* for low-educated workers, while in the liberalised US system mainly highly educated workers receive training.

Fourth, work by Huselid (1995), Buchele and Christiansen (1999), Lorenz (1999), Michie and Sheehan (2001, 2003) and Naastepad and Storm (2006) shows favourable productivity effects of 'high trust' or 'high road' human resource management practices. Long-lasting working relations and strong protection against dismissal can be interpreted as an investment in trust (see also Svensson, 2011), loyalty and commitment, which favours productivity growth in four ways: (i) it reduces costs of monitoring and control—e.g. Naastepad and Storm (2006, pp. 170–91) demonstrated that firms in low-trust 'Anglo-Saxon' countries typically have much thicker management bureaucracies for monitoring and control compared with 'Rhineland' countries; (ii) the greater loyalty of personnel reduces positive externalities, i.e. the leakage of trade secrets to competitors; (iii) more continuity of personnel favours long-run historical accumulation of (tacit) knowledge in a 'routinised' innovation model (see Table 1); and (iv) better protection against firing will favour critical feedback for bosses from the shop floor. Powerful managers have a tendency to surround themselves by people who hardly contradict them. If this is enhanced by a change of power relations due to easier firing, it can favour conformist attitudes and autocratic management practices.

Fifth, an argument closely related to the previous one comes from Acharya *et al.* (2010), who study patents and patent citations as a proxy for innovation. They argue that stringent labour laws provide firms with a 'commitment device' to not punish short-run failures and this would encourage employees pursuing risky and value-enhancing innovative activities. Exploiting time-series variation in changes of dismissal laws, they find that 'innovation and growth are fostered by stringent laws governing dismissal of employees, especially in the more innovation-intensive sectors. Firm-level tests within the United States that exploit a discontinuity generated by the passage of the federal Worker Adjustment and Retraining Notification Act confirm the cross-country evidence' (Acharya *et al.*, 2010, p. 1).

Finally, Lorenz (1999) has argued that protection against dismissal may enhance productivity performance, as secure workers will be more willing to cooperate with management in developing labour-saving processes and in disclosing their (tacit) knowledge to the firm. More generally, workers who are easy to fire have incentives to hide information about how their work can be done more efficiently. This implies that a flexible firing system is likely to make poor use of (tacit) knowledge on the job floor.

The opposite arguments in favour and against the hypothesis that flexible labour may damage (or enhance) innovation call for empirical tests to be done, as described in the remainder of this paper.

3. Data and indicators

As opposed to all earlier empirical studies, this paper will explicitly control for innovation models. As a proxy for the extent to which an industry is Schumpeter I or II, we use the degree of concentration of R&D budgets in an industry, using the well-known Herfindahl–Hirschman index. In other words, every industry receives a value on a continuous scale between 0 (perfect dispersion of R&D) and 1 (perfect concentration of R&D). Values closer to zero indicate a Schumpeter I garage business model; values closer to 1 indicate a Schumpeter II model in which dominant innovators have erected strong entry barriers thanks to their historical accumulation of (tacit) knowledge. The Herfindahl–Hirschman measure of concentration is calculated from Community

Innovation Survey data available from Statistics Netherlands, taking averages over the years 1998–2008 in 26 manufacturing and commercial service sectors (see the illustration in Table A3; Appendix).

From our database we have chosen two variables that can indicate whether a firm tends more towards 'low road' Human Resources Management (HRM) practices in an Anglo-Saxon style or whether it tends more towards 'high road' practices in a corporatist Rhineland style: the percentage of personnel on temporary contracts (without a perspective of tenure) and the percentage of hours worked in a firm by manpower agency workers. In our estimates, both measures will be interacted with the Herfindahl–Hirschman concentration index in a firm's sector of principal activity, this being our crucial variable of interest. Our firm-level data are from the enterprise survey of OSA-SCP over the years 1987–88.[5]

The OSA-SCP database covers two types of innovation indicators:[6]

(i) A firm has some R&D activities ('yes'/'no' answers).
(ii) A firm describes its R&D activities as occasional or as permanent activities.

As both indicators are given as dummy variables, we estimate logit models. We use firm size and firm age, and dummies for whether a firm underwent a major reorganisation or a merger or an acquisition as control variables. We also introduce a measure of the thickness of management layers, which may be somewhat ambiguous. From what was discussed above, thick management layers may reflect a lack of trust and loyalty and a need for tougher control, which might be frustrating for creative people. On the other hand, innovative projects might be enhanced by extra management efforts.

The firm age variable was insignificant in all preliminary estimates and is omitted from the final versions. As our dependent is a dummy variable, we expect the coefficients for firm size to be highly significantly positive. This does not allow drawing conclusions about the innovativeness of smaller versus larger firms. A positive coefficient simply indicates that larger trees catch more wind and there is an obvious need to correct for this.

4. Results

Before going into detail, it should be mentioned that in all versions of our estimates, the coefficients of manpower agency workers were always close to zero and far from significant. So we can safely conclude that manpower agency work has no relationship with innovation. On the other hand, the temporary workers variable does show a number of significant outcomes. What could explain these different outcomes? The difference is likely to relate to different motives behind the choice between temporary contracts and manpower agency workers. Estimates of firm-level wage equations in the Netherlands show that firms with high percentages of temporary workers pay significantly lower average hourly wages (after controls for age, sex, education, etc.). Independently, person-level wage equations in the Netherlands show that temporary

[5] Available through the web site www.dans.knaw.nl.

[6] A third indicator relates to 'new product' introductions during the past two years. This indicator, however, is dominated by products 'new to the firm' (rather than 'first in the market') and therefore tends to measure imitation rather than innovation. In our data exploration we discovered that many firms reporting such imitative new products do not report R&D activities, suggesting that this indicator covers lots of trivial product improvements. Preliminary estimates suggested that there are no robust relationships between flexible labour and imitative new products, which is consistent with similar findings by Zhou *et al.* (2011). This indicator is therefore omitted from our analysis.

workers earn up to 20% lower wages compared with tenured workers with similar properties (see Kleinknecht *et al.*, 2006). The same does *not* hold, however, for manpower agency workers. The latter may earn less than tenured people, but the firm also has to pay the manpower agency's margin. Ultimately, the wage costs paid by the firm for manpower agency workers do not differ significantly from those of tenured workers. From this we conclude that temporary contracts are primarily used by firms that intend to economise on wage costs, while manpower agency workers fulfil a true need for flexibility (e.g. replacements for maternity leave, etc.). We therefore confine our tables to the former. In other words, percentages of temporary workers reflect a firm's need for wage cost-saving labour flexibility. It can therefore indicate whether a firm's HRM strategy tends towards 'low road' or 'high road' practices.

Turning to the results (see Appendix for descriptive data), we can see that, as expected, in almost all versions of our model, the probability of giving a 'yes' answer rises with firm size. Moreover, management matters: if the percentage of managers in total personnel rises by 1%, the probability that a firm will invest in R&D increases by 3.5–7.5% in the various models in Table 2. Restructuring operations seem to have little impact on innovation, while mergers and acquisitions have, in most cases, a negative impact.

The most interesting outcome relates to the interaction term between a firm's flexible staff and the degree to which its sector of principal activity tends towards a Schumpeter I or rather to a Schumpeter II innovation model (see model B in Table 2). Earlier explorations of the data without using interaction terms revealed that temporary contracts always had a negative sign, which was almost always significant. Only in a single specification did we find weakly significant coefficients. This is consistent with the impression gained from the literature: most contributions report significantly negative coefficients (see footnote 1).

As expected, the interaction term 'Herfindahl*percentage of temporary workers' has a significantly negative sign in Table 2. This indicates that a mix of high concentration of R&D in a sector (as a proxy for a routinised Schumpeter II model) and high shares of wage cost-saving temporary contracts has a strongly negative impact on the probability that a firm would engage in (permanent) R&D. Consistent with our expectations, we see that the weaker form of innovation (i.e. *occasional* R&D activities) has weaker significance levels than the other two (i.e. R&D or permanent R&D). By studying the effects, we observe that the coefficients of the interaction term in Table 2 are not straightforward to interpret. Simulations (data not shown) show that the negative relationship between temporary workers and the probability of conducting (occasional or permanent) R&D is definitely stronger in Schumpeter II industries than in Schumpeter I industries.

As a robustness check and as a more intuitive illustration of the effects, we present in Table 3 an alternative specification. In this case we split the sample into two groups: 13 industries with higher versus 13 industries with lower values of the Herfindahl–Hirschman concentration index. Table 3 gives the separate estimates for the lower concentration ('garage business', or Schumpeter I) industries and for higher concentration ('Schumpeter II') industries.

Table 3 confirms the impression from the interaction term in Table 2: coefficients of temporary workers are *insignificant* in Schumpeter I industries, but highly significantly *negative* in Schumpeter II industries. In other words, in industries that tend towards a high concentration of R&D (i.e. a 'routinised' innovation model), a high share of temporary workers has a significantly negative impact on the probability that R&D takes place. According to Table 3, an increase in the percentage of temporary workers in a

Table 2. *The probability that a firm will invest in R&D (summary of logit estimates)*

	R&D: yes/no?		Occasional R&D (versus no R&D)		Permanent R&D (versus no R&D)	
	Model A	Model B	Model A	Model B	Model A	Model B
Firm size (reference group: 5–9 workers)	–	–	–	–	–	–
10–19 workers	0.620**	0.625**	0.103	0.109	1.083***	1.086***
20–49 workers	1.129***	1.160***	0.689*	0.724*	1.517***	1.547***
50–99 workers	1.502***	1.538***	0.617	0.655	2.206***	2.240***
100–499 workers	2.002***	2.019***	1.093***	1.111***	2.725***	2.740***
≥500 workers	2.330***	2.301***	0.811	0.783	3.281***	3.252***
Share of managers in personnel	0.060***	0.058***	0.036**	0.035**	0.075***	0.073***
Firm underwent restructuring	−0.281*	−0.317*	−0.305	−0.343	−0.271	−0.305
Firm had merger or acquisition	−0.415*	−0.429*	−0.313	−0.331	−0.473*	−0.486*
Herfindahl–Hirschman index in sector of principal activity	−0.226	1.021*	−0.268	1.040	−0.197	1.012
Constant term	−2.360***	−2.553***	−2.280***	−2.487***	−3.670***	−3.856***
Variables of interest:						
Interaction term 'Herfindahl index*percentage of temporary workers'	–	−0.075**	–	−0.077*	–	−0.074**
Percentage of temporary contracts	−0.020***	−0.008	−0.022***	−0.009	−0.019***	−0.007
Number of observations	1216	1216	1216	1216	1216	1216
R^2 (Nagelkerke)	0.17	0.17	0.17	0.18	0.17	0.18

Notes: *10% level of significance; **5% level of significance; ***1% level of significance.
Significance levels are determined using the Wald test.

Table 3. *Separate logit estimates for Schumpeter I[a] and II[b] industries*

	R&D: yes/no?		Occasional R&D (versus no R&D)		Permanent R&D (versus no R&D)	
	Schumpeter I	Schumpeter II	Schumpeter I	Schumpeter II	Schumpeter I	Schumpeter II
Firm size (reference group: 5–9 workers)	–	–	–	–	–	–
10–19 workers	0.563	0.809	0.305	−0.265	0.745	2.687**
20–49 workers	1.078***	1.420**	0.772	0.662	1.292***	2.874**
50–99 workers	1.325***	2.145***	0.80	0.461	1.690***	4.524***
100–499 workers	1.927***	2.303***	1.391***	0.500	2.289***	4.781***
≥500 workers	2.274***	2.422***	0.615	0.529	2.969***	4.961***
Share of managers in personnel	0.063***	0.053**	0.050***	0.003	0.070***	0.101***
Firm underwent restructuring	−0.349*	−0.113	−0.375	−0.103	−0.336	−0.124
Firm had merger or acquisition	−0.456*	−0.545	−0.348	−0.551	−0.516*	−0.514
Constant term	−2.569***	−2.120***	−2.869**	−1.199	−3.491***	−5.320***
Variable of interest:						
Percentage of temporary contracts	−0.008	−0.045***	−0.012	−0.040***	−0.005	−0.048***
Number of observations	803	413	803	413	803	413
R^2 (Nagelkerke)	0.14	0.27	0.14	0.30	0.15	0.30

Notes: *10% level of significance; **5% level of significance; ***1% level of significance.
Significance levels are determined using the Wald test.
[a]'Schumpeter I', the 13 out of 26 industries with the lowest value of the Herfindahl–Hirschman index.
[b]'Schumpeter II', the 13 out of 26 industries with the highest value of the Herfindahl–Hirschman index.

firm's total personnel by 1% reduces the probability of investing in R&D by 4–5%. The apparent differences between Schumpeter I and Schumpeter II industries in Table 3 explain why outcomes of earlier studies were not clear-cut: by lack of control for innovation models, an important variable was missed.

5. Discussion and conclusions

Adherents of 'structural reforms' of European labour markets may be comfortable with our results: the Netherlands has high shares of flexible workers since 'insiders' are strongly protected. So a firm's need for flexibility will increase numbers of 'outsiders'. If structural reforms reduced the protection of insiders, numbers of outsiders might actually decline—and this would result in higher innovation probabilities in our model!

This argument neglects that a major motive behind structural reforms of labour markets is more 'dynamism' in the labour market, i.e. more frequent job matches, which increase the chance that people will find jobs in which they are the most productive. Moreover, lower protection of insiders allows firms to dispense with people more easily if risky innovation projects fail and this encourages risk-taking. Another motive is that people should not be entrenched in safe jobs and firms should have the ability to fire easily in the case of shirking.

The problem with such arguments is that they look at the labour market in isolation from the innovation process. Undoubtedly, from the perspective of Walrasian general equilibrium theory, labour markets can never be flexible enough. Flexible *hire and fire* guarantees (static) allocative efficiency! From a Schumpeterian innovation perspective, however, things look different. The field of innovation is full of market imperfections. For example, knowledge has strong public goods characteristics; hence property rights are hard to protect, resulting in underinvestment in R&D. Moreover, various sorts of information asymmetry can play, for example in the search for suitable collaboration partners. Moreover innovation is subject to strong uncertainty (high failure rates). All this, combined with the sunk-costs character of innovative investments, can leave innovative efforts far below the social optimum.

Recognising that market failures are the rule rather than rare exceptions, we arrive at a pattern of argument that tries to repair for one market imperfection by introducing another. For example, institutions such as trademarks, copyrights or the patent system give a degree of monopoly power to creative people. From a Walrasian general equilibrium perspective, monopoly power is undesirable as it prevents the efficient allocation of scarce resources. From a Schumpeterian perspective, however, a degree of monopoly power is a highly desirable incentive for investment in creative solutions. Or take another example: perfect competition is most efficient for the allocation of scarce resources from a static Walrasian perspective, but it is undesirable from an innovation viewpoint since easy entry would too quickly erode monopoly profits from innovation and hence take away incentives to carry innovative risks. Finally, according to the logic of Schumpeter's (1943) routinised innovation model, labour market rigidities are useful since longer job durations create loyalty and make the long-run accumulation of (tacit) knowledge easier.

Looking at policy implications, we conclude that more flexibility in labour relations appears to be without problems in Silicon Valley-type garage businesses. According to our estimates, flexible working has no impact on innovation among young and small firms. In industries that tend towards a routinised innovation model, however, such flexibility appears to be harmful. 'Structural reforms' aimed at easier firing would probably enhance job hopping, which disturbs knowledge accumulation and is a major channel for positive externalities. To conclude, the above may shed some light on the observation that, in spite of a highly flexible labour market, the USA is doing quite well in industries that have high rates of new-firm foundations, such as IT. Our findings, however, might also explain why, since the Reagan era, many 'classical' industries in the USA (e.g. steel or automobiles) have found it hard to compete against Japanese and German suppliers.

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Appendix

Table A1. *Descriptive statistics*

	Min.	Max.	Mean	Std Dev.
Dependent variables				
R&D yes/no	0.00	1.00	0.330	0.470
Permanent R&D	0.00	2.00	0.533	0.810
Independent variables				
Firm size	1.00	6.00	3.170	1.663
Size of management	0.00	40.00	13.779	8.418
Numerical flexibility (Percentage of employees on temporary contracts)	0.00	100.00	17.457	16.456
Herfindahl–Hirschman index	0.03	1.00	0.150	0.185
Dummy 'reorganisation'	0.00	1.00	0.149	0.356
Dummy 'merger and acquisition'	0.00	1.00	0.069	0.253

Table A2. *Pearson correlations between variables*

	1	2	3	4	5	6	7
1 Firm size	1						
2 Percentage of managers	−0.57**	1					
3 Percentage of temporary workers	−0.33**	0.18**	1				
4 Herfindahl concentration	0.06	−0.09**	−0.14**	1			
5 Interaction Herfindahl/ temporary workers	−0.12**	−0.01	−0.56**	0.72**	1		
6 Dummy 'reorganisation'	0.30**	−0.19	0.11**	0.13**	0.07*	1	
7 Dummy 'merger and acquisition'	0.14**	−0.05*	−0.09**	−0.03	−0.06*	0.15**	1

Note: **Significant at 0.01 level; **significant at 0.05 level (two-tailed tests).

Table A3. *Herfindahl–Hirschman indices by sector*

	Sectors	Herfindahl
1	Mining and quarrying	0.11
2	Food and tobacco	0.03
3	Textile and leather	0.12
4	Wood and paper	0.06
5	Publishing and printing	0.19
6	Oil/chemicals	0.13
7	Rubber and plastics	0.05
8	Concrete, cement and plaster	0.15
9	Metal industry	0.03
10	Mechanical engineering	0.51
11	Computer/electrical/electronics	0.33
12	Medical equipment	0.56
13	Transport equipment	0.67
14	Furniture/other/recycling	0.18
15	Utilities and water	0.27
16	Construction and building industry	0.05
17	Trade, repair, retail, catering	0.26
18	Wholesale and retail trade	0.05
19	Transport services	0.06
20	Transport-related services	0.07
21	Post and telecom	1[a]
22	Financial services	0.07
23	Real estate, rental services	0.26
24	ICT services	0.04
25	R&D laboratories	0.34
26	Other business services	0.08
27	Environmental and other services	0.15
	Mean	0.13
	Standard deviation	0.19
	Minimum	0
	Maximum	1

[a]Omitted from regressions.

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ARTICLE

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 generalised decline of local innovation performance, particularly in AMTs.

KEYWORDS

Innovation; routine skills; polarisation; manufacturing; digital technology

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 triggered significant changes both in employment levels and in the structure of labour markets (Organisation for Economic Co-operation and Development [OECD] 2016; World Bank 2016; Van Roy, Vértesy, and Vivarelli 2018).

A growing strand of research on employment and innovation analyses the labour market outcomes associated with the computer revolution. Innovation scholars argue that indirect income and price effects 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, 2003; Vivarelli, 1995, Vivarelli 2014; Piva and Vivarelli 2018). Studies in labour economics argue that technological change is skill-biased, and that therefore job creation and job destruction reflect a positive relation between workers' skill levels – often proxied by years of schooling – and labour market returns (Autor, Katz, and Krueger 1998; Chennells and Reenen 1999; Acemoglu 2002). The predictions based on

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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, Levy, and Murnane 2003; Goos and Manning 2007; Goos, Manning, and Salomons 2014). Upon closer inspection, technology 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 P. Restrepo 2019; Gregory, Salomons, and Zierahn 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 regard 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, Van Schaik, and Zhou 2014; Michie and Sheehan 2003; Wachsen and Blind 2016; Zhou, Dekker, and Kleinknecht 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 propose 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; Lewis2020a, 2020b).

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 in manufacturing sectors over the period 1990–2012. In line with recent trends, we look at patenting dynamics in advanced manufacturing technologies (AMT), a group of integrated hardware-based and software-based solutions used in the design, manufacture or handling of products (Organisation for Economic Co-operation and Development [OECD] 2012). We hypothesise 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 of around 1.8%. Interestingly, the decrease of cognitive- and manual-routine skills are negatively associated to local innovation capacity both in general and to AMTs in particular. In fact, the latter reduce more when routine jobs decrease due to losses in manual-repetitive occupations. Moreover, we also find a more pronounced negative association between routine-job losses and the local generation of incremental innovation, particularly in AMT fields. Our contribution to the literature is threefold. First, we add to the empirical work on the task-based approach by underlining that task heterogeneity captures important variance in innovation dynamics. Second, we enrich the debate on the relationship between digital technologies and labour market dynamics byinverting the traditional direction of the link between them. Third, we elaborate upon the importance of a specific set of technologies, i.e., AMTs, which are crucianot only because of their productivity-enhancing effect, but also due to their innovation-enabling role.

The rest of the paper is organised as follows. Section 2 reviews the relevant literature and develops the working hypotheses. In Section 3 we detail the main data sources, the main variables and the empirical models adopted. Section 4 presents and discuss the results. The last section concludes and summarises.

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 regulation, that can 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 enrich the debate on the effects of technology. If on the one hand ICTs have accelerated the obsolescence of some occupations, on the other hand their diffusion led to an increase in demand of other 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, Katz, and Krueger 1998; Chennells and 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, Fernández-Macías, and Antón 2020).

An important turning point in this line of research is the emergence of evidence that labour demand has grown for high- and low-skill jobs, and that the decline was mostly concentrated in the middle of the occupational skill spectrum. 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 Manning 2007; Goos, Manning, and Salomons 2014; Gregory, Salomons, and Zierahn 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 offshoring opportunities affect the division of 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 generally complements, 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

[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, Shierholz, and Schmitt (2013) and Hunt and Nunn (2017).

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, Grilli, and Rossi-Lamastra 2011). No doubt, the diffusion of information technology together with pressures from international competition have altered the organisation of job tasks and, a fortiori, the demand for the attendant skills. In highly automated factories and production sites of the United States workers are expected to command know-how that is considerably more specialised 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 collar jobs is a 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, Luxhoj, and Uffe 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 a regrettably scant literature, blue collars have the potential to develop useful knowledge, ideas and competences that contribute to a firm's innovation capacity (see i.e. Lewis 2020a, 2020bb). As Bradley, Kim, and Tian (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 provides relevant 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 (Organisation for Economic Co-operation and Development [OECD] 2012). While traditional manufacturing technologies enhance process efficiency mostly through rigid and mechanised design, AMTs improve the overall effectiveness of production systems. 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).

Flexible organisation designs that enable quick responses to emerging opportunities or to a changing competitive landscape are deemed most effective to reaping the benefits of AMTs (Leonard-Barton 1988). Lei, Hitt, and Goldhar (1996) identifies key organisational

[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).

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 specialised 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, Mohrman, and Ledford 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, Hitt, and Goldhar 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 characterised 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

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

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 290 coherent MSAs over time that are the main unit of analysis.

Data on employment, skills, patents and 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) programme –> from the U.S. Bureau of Labour 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 programme 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 use the US Census Bureau County Business Pattern (CBP) to collect data on the number of establishments and the level of employment by sector of activity (SIC and NAICS codes). The source for county population data is the US Census Bureau, which also provides data on counties land through the Gazetteer 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 290 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 identify AMT-related technologies, we collect information on patents issued in new digital technologies related to manufacturing processes. In particular, we exploit the Cooperative Patent Classification (CPC) scheme that provides, for each patent, 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

[4]Available at https://usa.ipums.org/usa/volii/puma.shtml.
[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, Frenken, and Los 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.

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, Rudyk, and Valdes (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.

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 (Autor, Levy, and Murnane 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:

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

where $\mathrm{RSH}_{\mathrm{rt}}$ is the routine employment share in MSA r at time t; $\mathrm{L}_{\mathrm{jrt}}$ is total employment of occupation j in MSA r at time t and $1\left[\mathrm{RTI}_{\mathrm{j}}\right]$ is an indicator function equal to 1 if occupation$j$ is routine intense. Our index thus consists in the difference between the share of employment in routine-intensive jobs between two periods. In our preferred specification, also 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 $\mathrm{RSH}_{\mathrm{r},1990-2001}$ as follows:

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

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.

[8] The CPC has been established in 2010 to harmonise 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.

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:

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

where $\mathrm{AMT}_{\mathrm{r},2012-2002}$ is the percentage change in the number of AMT patents for region r between 2012 and 2002, defined as $\left(\mathrm{AMT}_{\mathrm{r},2012} - \mathrm{AMT}_{\mathrm{r},2002}\right)/\left(0.5\mathrm{AMT}_{\mathrm{r},2012} + 0.5\mathrm{AMT}_{\mathrm{r},2002}\right)$[11] ; $\mathrm{RSH}_{\mathrm{r},1990-2001}$ 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] ;$_{\mathrm{r}}$ is the error term and $\mathrm{X}'_{\mathrm{r},1990}$ comprises controls for local factors, measured in 1990, that may affect the capacity of an MSA to patent in AMTs. First, we control for the employment share in high-skilled (abstract) occupations. 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. Second, we include the MSAs' number of firms operating in the manufacturing sector, to control for the role of the industrial structure on local innovation capabilities. We also control for the local existing innovation capabilities by including the MSAs total number of patents in 1990. This last variable should control, at least partially, for decreasing returns to scale in innovation activities. Lastly, we include a control for the level of population density measured in 1990. Since MSAs show high variability in terms of population and, importantly, patenting capacity, we weight all regressions by the local per-capita level of patenting in 1990 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 ($\mathrm{RCSH}_{\mathrm{r},1990-2001}$ and $\mathrm{RMSH}_{\mathrm{r},1990-2001}$, respectively). Therefore, we estimate the following model:

$$\mathrm{AMT}_{\mathrm{r},2012-2002} = \beta_1 \mathrm{RCSH}_{\mathrm{r},1990-2001} + \beta_2 \mathrm{RMSH}_{\mathrm{r},1990-2001} + \Upsilon \mathrm{X}'_{\mathrm{r},1990} + {}_{\mathrm{r}} \tag{4}$$

To complement the analysis, we also estimate models in equations 3 and 4 on the local percentage change in all patents (ALL). Moreover, we also focus on the association between long-run changes in the local endowment of routine jobs and the generation of incremental inventions, both overall and AMT-related in particular.

4. Empirical analysis

4.1. Descriptive statistics

Table 1 synthetically describes the main variables employed in the empirical analysis, while Table 2 reports 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 characterised 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 AMT patenting during the 2000s, especially areas with lower patenting intensity. This is an initial hint that local labour markets wherein 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).

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
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
High-Skill	Share of high-skilled employment over total employment in1990 (x100)	1990
N. of man. firms	Number of firms operating in the manufacturing sector in 1990	1990
Tot patents	Total number of patents (log) in 1990	1990
Pop dens	Total population divided by MSA land area in 1990	1990

[11] $AMT_{r,2012-2002}$ 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.

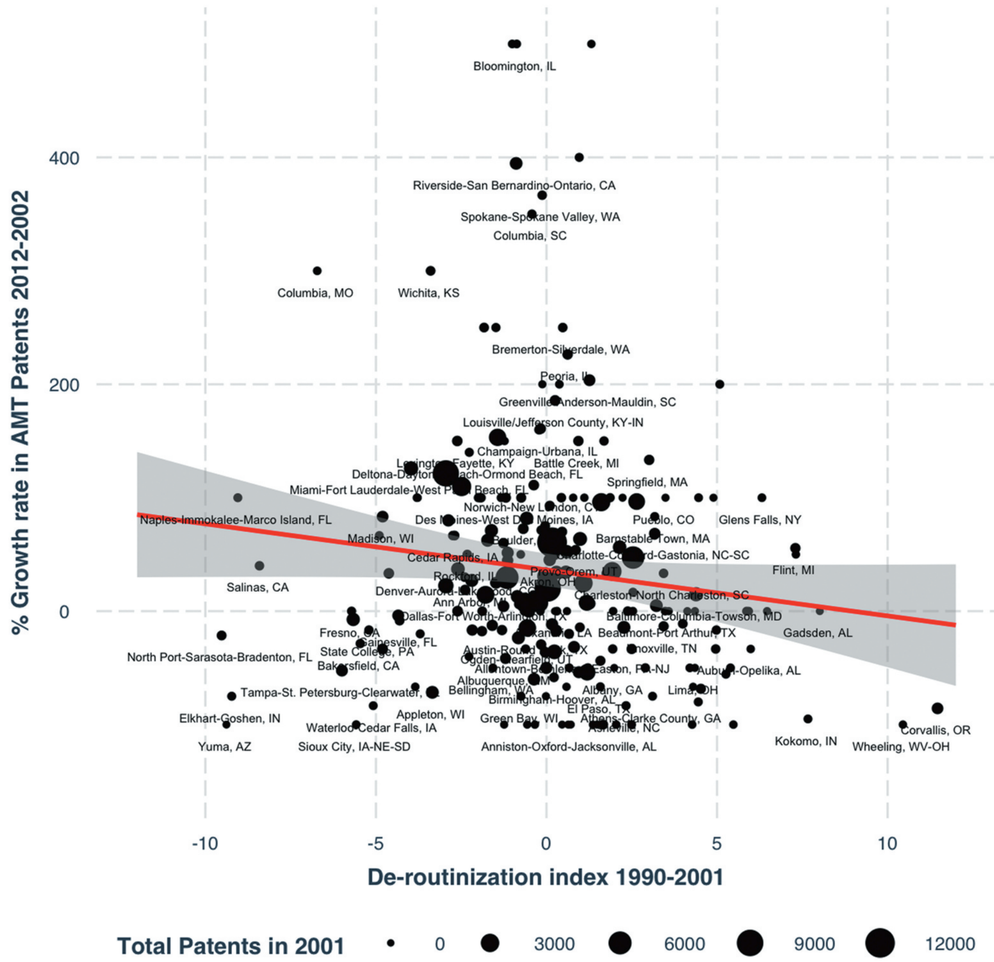

Figure 1. The relationship between the change in routine employment share between 1990 and 2001 (de-routinisation index) and the percentage growth rate in AMT patenting between 2002 and 2012, by MSA. Note: Observations (MSAs) weighted by the total number of patents in 2001 in the corresponding MSA.

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 variation, with 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.

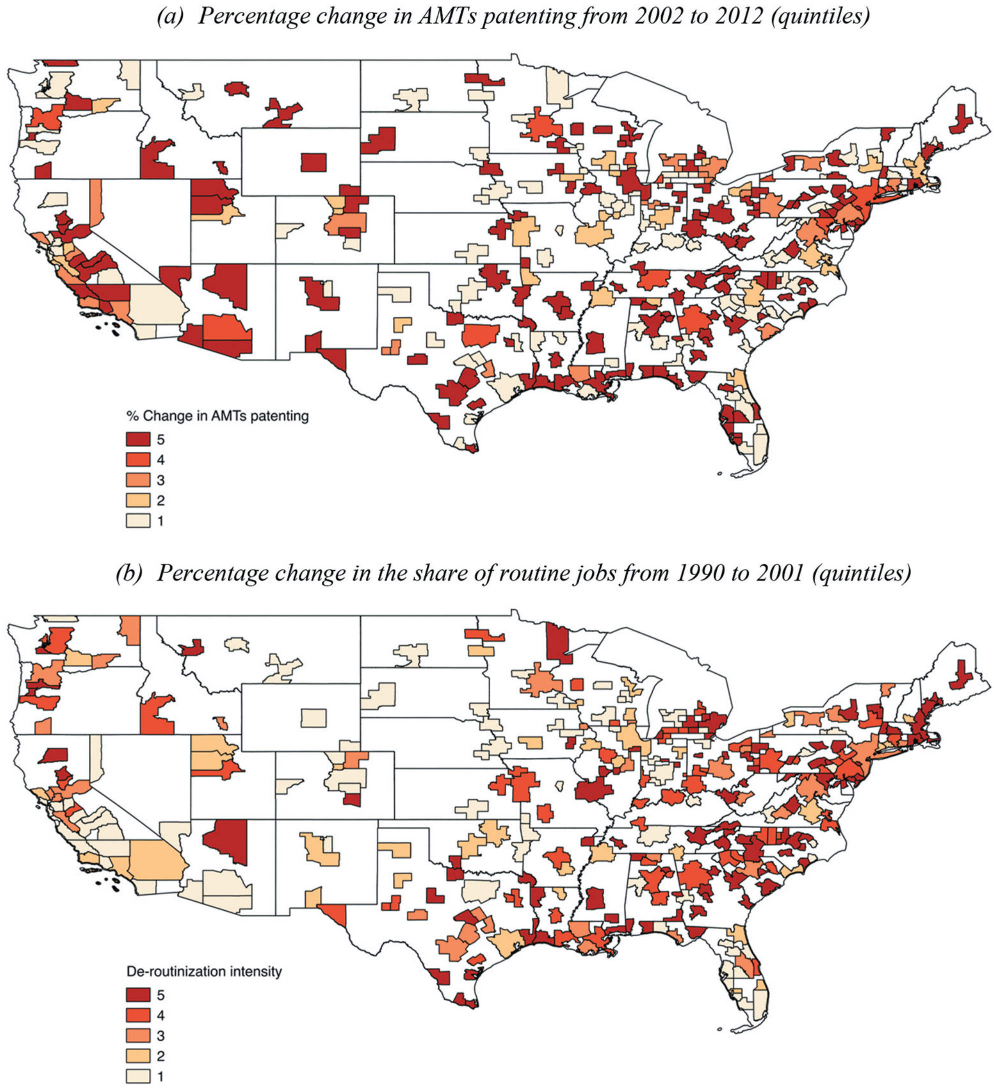

Figure 2. Geographic distribution of the percentage change in AMTs patenting from 2002 to 2012 (panel a), and the de-routinisation index from 1990 to 2001 (panel b). Note: Quintiles in panel (a) weighted by the MSA total number of patents in 2001. Quintiles in panel (b) weighted by MSA total employment in 1990.

4.2. Regression analysis

4.2.1. Baseline models

This section presents 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 local 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). All the models include the full set of controls as described

Table 2. Summary Statistics.

Variable (N = 289)	Mean	St. dev	Min	Max
ΔAMT	24.217	98.249	−200	200
ΔTOT	5.414	45.393	−113.043	158.659
ΔRSH	0.307	3.698	−16.563	11.464
ΔRMSH	0.600	2.283	−12.859	10.638
ΔRCSH	−0.293	2.837	−13.424	8.107
High-Skill	10.645	1.122	8.758	14.611
N. of man. firms (log)	8.972	1.091	7.359	12.982
Tot patents (log)	3.946	1.524	0.693	8.455
Pop dens (log)	10.696	11.376	0.175	89.896

Table 3. De-routinisation and innovation (AMTs and Total patents).

	(AMT)	(AMT)	(TOT)	(TOT)
ΔRSH	−1.562		−1.811**	
	(2.049)		(0.819)	
ΔRMSH		−4.731**		−2.787**
		(2.151)		(1.213)
ΔRCSH		0.922		−1.047
		(2.355)		(0.920)
High-Skill $_{r,t=1990}$	3.512**	3.732**	3.204***	3.272***
	(1.627)	(1.557)	(0.700)	(0.699)
N. of man. firms $_{r,t=1990}$	33.300***	34.574***	14.810***	15.203***
	(10.482)	(10.052)	(5.212)	(5.351)
Tot patents $_{r,t=1990}$	−27.576***	−28.849***	−15.062***	−15.454***
	(9.699)	(9.319)	(4.750)	(4.820)
Pop dens $_{r,t=1990}$	0.003	−0.038	0.154	0.141
	(0.279)	(0.262)	(0.160)	(0.165)
Adj. R2	0.066	0.079	0.149	0.154
Obs.	289	289	289	289

Dependent variables: Relative change in AMT patents (Columns I and II) and total patents (Columns III and IV). 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 measured in 1990. Regressions are weighted by the 1990 per-capita number of local total patents. Robust standard errors, in parentheses, are clustered at the State level. * $p < .1$, ** $p < .05$, *** $p < .01$

in Section 3.2 and are weighted by the 1990 per-capita number of local patents. Standard errors are clustered at the State level to account for possible spatial correlation across MSAs.

Focusing on the results reported in Table 3, the decrease in routine-intensive employment does not reach statistical significance on local innovative capacity in AMTs (column I), while we find a negative association between the decrease in routine-intensive occupations and local innovative capacity when focusing on total patenting. In particular, our estimates indicate that a 1% decrease in routine-intensive employment (ΔRSH) during the 1990s is associated with a 1.8% decrease in total patenting between 2002 and 2012 (column III). In line with expectations, we find a strong and negative association between losses in

[13]Ideally, an empirical analysis of the period 1990–2012 would have been appropriate 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 qualitatively in line with our baseline results (see Section 4.2) and confirm the negative association with the loss in routine jobs and local patenting in AMTs. Table B1 in Appendix B reports the results. We wish to thank an anonymous referee for suggesting this further test.

Table 4. De-routinisation and innovation (AMTs and Total patents).

	(AMT)	(AMT)	(TOT)	(TOT)
ΔRSH	−2.808		−2.948***	
	(1.985)		(0.788)	
ΔRMSH		−5.782***		−3.708***
		(2.109)		(1.110)
ΔRCSH		−0.604		−2.385**
		(2.244)		(1.055)
N. of man. firms $_{r,t=1990}$	27.573***	28.412***	9.585**	9.800**
	(9.631)	(8.974)	(4.564)	(4.719)
Tot patents $_{r,t=1990}$	−18.714**	−19.373**	−6.977*	−7.146**
	(8.297)	(7.727)	(3.494)	(3.507)
Pop dens $_{r,t=1990}$	0.125	0.095	0.265*	0.257
	(0.281)	(0.264)	(0.154)	(0.160)
Adj. R2	0.050	0.061	0.093	0.096
Obs.	289	289	289	289

Dependent variables: Relative change in AMT patents (Columns I and II) and total patents (Columns III and IV). 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 measured in 1990. Regressions are weighted by the 1990 per-capita number of local total patents. Robust standard errors, in parentheses, are clustered at the State level. * $p < .1$, ** $p < .05$, *** $p < .01$

manual routine jobs on the percentage change of AMT patenting. Indeed, as reported in column II, the reduction in the share of blue-collar workers (ΔRMSH) is associated with a 4.7% decrease in local innovative capacity in AMTs. For what concerns the share of clerical workers (ΔRCSH), changes in local innovative capability in this domain seems to be not responsive to drops in the share of routine-cognitive workers. Likewise, we find that total local inventive activity is correlated more to changes in the employment of repetitive manual work (i.e., blue-collar jobs) than in routine cognitive jobs (i.e., clerks). Thereby, as reported in column IV, we estimate a negative and significant coefficient for the reduction in ΔRMSH, while the coefficient for ΔRCSH is not statistically significant. In this case, the magnitude of the ΔRMSH coefficient is at −2.8%, lower than the coefficient estimated when considering changes in local AMTs patenting. Turning to the control variables, we find positive and significant coefficients for the share of high-skill workers and for the number of manufacturing firms. Conversely, we find a negative coefficient for the total level of patenting in 1990 that likely reflects decreasing returns to scale in innovation. Lastly, the control for population density is not statistically significant.

As discussed in the theoretical section, prior studies report that de-routinisation is rooted in the so-called job polarisation effect of technology on labour demand. Accordingly, if, on the one hand, technology substituted for routine tasks, on the other hand it increases the demand for high and low skill jobs. Thus, the de-routinisation process and the consequent decrease in the share of routine-intensive occupations might have resulted in an increase in the share of high-skilled employment. In our empirical framework, this implies that controlling for the share of high-skilled employment might, in principle, bias the estimated association between the change in routine-intensive employment and the local innovation capacity. Though measuring the high-skilled employment share in 1990 should limit the potential bias, we also adopt a more conservative approach and estimate the baseline model excluding the share of high-skilled occupations from the set of control variables.[14] Results are reported in Table 4 and are consistent with respect to the baseline analysis summarised by Table 3. Precisely, the ΔRSH coefficient is at ~ −2.9% when considering changes in total patenting, while it does not show statistical significance in the case of AMTs. Importantly, we fully confirm the prominent association between drops in ΔRMSH and drops in patenting activity, more pronounced in the AMT case (−5.8%, column II) than for overall innovation (−3.7%, column IV). Moreover, we also estimate a negative coefficient for ΔRCSH in column III (−2.4%). As for the control variables, we find positive and significant coefficients for the number of manufacturing firms, and negative coefficients for the number of total patents at the starting point of the series. Lastly, coefficients for population density show tiny statistical significance only in column III.

4.2.2. Incremental innovation

As presented in Section 4.2.1, the long-run reduction of routine workers is associated with decreasing innovative performances at the local level, especially in AMTs, confirming our hypothesis that routine workers' tasks and their attending skills are important for productivity and innovation. Indeed, as discussed in Section 2, the necessary '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 role of routine workers on innovative capabilities.[15]

To identify patents related to incremental innovations, several steps are required. Prior 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 (Dutta and Weiss 1997; Katila 2000), relying on ad hoc patent radicalness measures to distinguish between radical and incremental inventions (Ahuja and Morris Lampert 2001; Dahlin and Behrens 2005). For example, Wu et al. (2009) use patents received citations as a radicalness measure and consider incremental inventions those patents that belong to the top 3% of patent forward citation frequency.

For the purposes of the present subsection, we exploit the radicalness measure proposed by Squicciarini, Dernis, and Criscuolo (2013) – *OECD radicalness* henceforth – that relies on patent backward citations. The authors compute such a measure among a set of different patent quality indicators 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, Dernis, and Criscuolo (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 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

Table 5. De-routinisation and incremental innovation (AMTs and Total patents).

	(AMT)	(AMT)	(TOT)	(TOT)
ΔRSH	−3.072		−2.063**	
	(1.833)		(0.878)	
ΔRMSH		−4.955**		−2.939**
		(2.098)		(1.308)
ΔRCSH		−1.597		−1.376
		(2.298)		(1.064)
High-Skill $_{r,t=1990}$	3.303**	3.433**	3.417***	3.477***
	(1.518)	(1.480)	(0.729)	(0.743)
N. of man. firms $_{r,t=1990}$	35.764***	36.521***	17.315***	17.667***
	(9.256)	(9.044)	(5.339)	(5.548)
Tot patents $_{r,t=1990}$	−28.238***	−28.995***	−17.344***	−17.696***
	(8.934)	(8.753)	(5.026)	(5.187)
Pop dens $_{r,t=1990}$	−0.046	−0.071	0.117	0.105
	(0.248)	(0.240)	(0.168)	(0.173)
Adj. R2	0.081	0.085	0.155	0.158
Obs.	289	289	289	289

Dependent variables: Relative change in incremental AMT patents (Columns I and II) and incremental total patents (Columns III and IV). 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 measured in 1990. Regressions are weighted by the 1990 per-capita number of local total patents. Robust standard errors, in parentheses, are clustered at the State level. * $p < .1$, ** $p < .05$, *** $p < .01$

which they differ from the focal patent' [p. 56]. We identify patents belonging to the top 3% in the distribution of *OECD radicalness* 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 of *OECD radicalness*) are considered 'incremental'.[16]

Table 5 reports the results of the econometric analysis on the association between de-routinisation and local incremental innovative capabilities. It reports the estimates for the percentage change in incremental patenting over the period 2002–2012, where columns I and II refer to changes in AMT incremental patents and columns III and IV to total incremental patents. In all the specifications we include the full set of control variables as described in Section 3.2. Regressions are weighted by the 1990 per-capita number of local patents and standard errors are clustered at the State level.

We find a negative association between the decrease in routine-intensive occupations and local incremental patenting. In particular, a 1% decrease in routine-intensive employment (ΔRSH) during the 1990s is associated with about 2.1% decrease in incremental patents between 2002 and 2012 (column III). While statistically insignificant, the negative magnitude of the coefficient increases to −3.1% when considering AMT incremental patenting (column I). Similar to the findings of the previous subsection, also in this case our dependent variables are more responsive to changes in the employment share of routine-manual workers than to changes in repetitive cognitive jobs (columns II and IV). In particular, we find a negative and significant coefficient for a 1% reduction in ΔRMSH at about −5% when AMT incremental patenting is under scrutiny (column II), and at about −2.9% when considering total incremental patenting changes (column IV). The coefficient for ΔRCSH is instead not statistically significant in both cases.

[14]We wish to thank an anonymous referee for this suggestion.

As for the control variables, our estimates return coefficients qualitatively in line with those already discussed in Section 4.2.1. Precisely, we document positive associations between the share of high-skill occupations and local patenting performances, the opposite for the total number of patents in 1990, and insignificant coefficients for population density.

4.3. Robustness checks

This section presents selected robustness checks. First, we test the robustness of our results to a different structure of our control variables. In accordance with our main explanatory variables, we express control variables in terms of percentage changes between 1990 and 2001, with the exception of population density. In so doing we control for the potential association between de-routinisation and de-industrialisation and to account for the contraction/expansion of the local industrial production. Results are reported in Table A1 in the Appendix and highly confirm our main findings. First, we estimate a negative and significant coefficient for ΔRSH on both AMT (column I) and total patenting (column III). Negative changes in local patenting associated with a drop in routine jobs are more pronounced for AMTs (−7.2%) than for the average patenting activity (−3.7%). Second, we find negative and statistically significant coefficients for the drop in ΔRMSH and ΔRCSH, both on total and AMTs local patenting, with changes correlated more to the reduction in the employment share of repetitive manual works (i.e. blue-collar jobs) than to the drop in routine cognitive jobs (i.e. clerks). Again, for both types of routine occupations, we estimate larger coefficients in the case of local AMT patenting.

Then, we test the robustness of our empirical analysis to different specifications of the intervals over which the percentage change in local patenting in AMTs is calculated. To this end, we compute the rate of patenting growth over three 3-year time-windows (i.e., 2002–2005, 2005–2008 and 2008–2011) to incorporate intermediate information on MSAs patenting performance during the decade 2002–2012. Here our main dependent variable is the average growth rate of AMT patents over the three periods. Results, reported in Table A2 in Appendix A, confirm the robustness of our main findings reported in Table 3, columns I and II and in Table 4, columns I and II.[17] In particular, we find that a 1% decrease in the share of routine workers is associated with a significant decrease of about 1.8% of the average three-year growth in AMT patents (column I). The estimated coefficient raises in magnitude to −2.1% when we exclude the 1990 share of high-skill workers from the set of control variables (column III). 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 ~ −4.1% for ΔRMSH, while ΔRCSH, though negative, is not statistically significant.

[15]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 documents.

[16]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 test an alternative measure, following Wu et al. (2019), categorising incremental innovation in terms of patent forward citation frequency.

Similar results are reported in column IV, where we estimate a coefficient for ΔRMSH at around −4.4%.

As a third 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, Van Schaik, and Zhou 2014). From an empirical point of view, Cetrulo, Cirillo, and Guarascio (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 add to the set of control variables also the share of temporary workers in 1990. 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. 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 in 1990 as a control variable for the role of temporary workers. The second variable we add concerns the share of highly educated workers in 1990. While the inclusion of the share of high-skilled (abstract) employment should largely account for the fundamental role of human capital, as mentioned in Section 3.2, we substitute this variable 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 with at least one year in college for each MSA. In turn, our control is given by the share of these workers in 1990. Table A3 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.[18] Results of these robustness checks are consistent with the main results. Reductions in repetitive manual occupations is in fact negatively correlated (ΔRMSH), with robust statistical significance, with the local generation of AMTs. As for the share of temporary workers, we find negative and significant coefficients in all the model specifications, qualitatively in line with previous empirical evidence. On the contrary, as expected, the coefficients for the share of highly educated workers turn out to be positive and significant. Again, the presence of high-skill worker is central for innovation performances.

Lastly, we test the robustness of our measure of incremental patents. First, we calculate our dependent variables using an alternative measure of incremental patents. To this end, following Wu et al. (2009), we define 'incremental' the complement to the patents in the top 3% distribution of forward citations in a five-year window 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 patents and incremental total patents between 2002 and 2012, respectively. Table A4 in the Appendix reports the

[17]In additional robustness tests, 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.: 2002–2010, 2002–2011, 2003–2010 and 2003–2011. These tests yield robust results and are available upon request.

results of the estimation using this alternative measure of incremental patents. The results are qualitatively similar to those presented in Table 5. In fact, we find a negative and significant coefficient for ΔRMSH, stable across specifications. Second, we run additional estimates to further check the robustness of our measure of 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 has 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 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 P. 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 Autor, Levy, and Murnane (2003) for the US and of Goos and Manning (2007) for the UK has enlarged the geographical scope of the study of polarisation[19] 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

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

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-collar' as per the industry jargon[20] – 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 The 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 further research. . The present paper opens a novel avenue by focusing on the relationship between de-routinisation and innovation in AMTs in US Metropolitan Statistical Area during the period 2002–2012. The empirical analysis indicates that, on average, the loss of routine-intensive jobs is a negative predictor of local innovative capacity. In particular, we find that a 1% decrease in routine intensive occupations during the 1990s is associated to some 1.8% reduction in local total patenting during the 2002–2012 period. Further, we observe negative associations between innovation and both kinds of routine macro-tasks – repetitive cognitive and repetitive manual – with the latter showing more pronounced magnitudes. This result is larger for AMTs than the average total patenting activity. A 1% reduction in routine manual occupations is in fact significantly associated to some 4.7% reduction in local AMT patenting. Finally, we also document a negative association between de-routinisation and local incremental innovations, especially in AMTs again. Those results are robust to several tests on the construction of both dependent and independent variables, and to different econometric strategies.

Our study 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 under-studied, 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

[19]See i.e. Autor and Dorn (2013) on US commuting zones; Senftleben-König and Wielandt (2014) and Dauth (2014) on German local labour markets; Malgouyres (2017) on French commuting units; Consoli and Sánchez-Barrioluengo (2019) on Spanish provinces.

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 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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APPENDIX A

Table A1. Robustness I: De-routinisation and innovation (AMTs and Total patents).

	(AMT)	(AMT)	(TOT)	(TOT)
ΔRSH	−7.185**		−3.685***	
	(2.748)		(1.140)	
ΔRMSH		−7.867**		−3.831**
		(3.126)		(1.353)
ΔRCSH		−6.429*		−3.524**
		(3.537)		(1.570)
ΔHigh-Skill	5.422**	5.145*	−0.846	−0.905
	(2.610)	(2.706)	(1.296)	(1.356)
ΔN. of man. firms	−4.019	−3.759	−8.365	−8.310
	(9.485)	(9.726)	(5.765)	(5.903)
ΔTot patents	−33.099***	−32.985***	−18.347*	−18.323*
	(11.746)	(11.759)	(9.708)	(9.757)
Pop dens	14.170	13.995	12.274**	12.236**
	(8.842)	(8.873)	(5.134)	(5.135)
Adj. R2	0.172	0.172	0.294	0.294
Obs.	289	289	289	289

Dependent variables: Relative change in AMT patents (Columns I and II) and total patents (Columns III and IV). 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 A2. Robustness II: De-routinisation and AMT innovation.

	(AMT)	(AMT)	(AMT)	(AMT)
ΔRSH	−1.827*		−2.150*	
	(1.051)		(1.089)	
ΔRMSH		−4.066***		−4.367***
		(0.873)		(0.880)
ΔRCSH		−0.072		−0.508
		(0.953)		(0.974)
High-Skill $_{r,t=1990}$	0.913	1.068		
	(0.697)	(0.666)		
N. of man. firms $_{r,t=1990}$	14.194***	15.095***	12.706***	13.331***
	(3.361)	(2.996)	(3.363)	(2.733)
Tot patents $_{r,t=1990}$	−10.298***	−11.198***	−7.994**	−8.485***
	(3.513)	(3.304)	(3.268)	(2.823)
Pop dens $_{r,t=1990}$	−0.130	−0.159	−0.098	−0.121
	(0.149)	(0.130)	(0.150)	(0.132)
Adj. R2	0.071	0.097	0.066	0.091
Obs.	289	289	289	289

Dependent variables: Relative change in AMT patents. 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 measured in 1990. Regressions are weighted by the 1990 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 III: De-routinisation and AMT innovation.

	(AMT)	(AMT)	(AMT)	(AMT)	(AMT)	(AMT)
ΔRSH	−1.832		−1.733		−1.213	
	(1.957)		(2.064)		(2.025)	
ΔRMSH		−4.504**		−5.139**		−4.388*
		(2.076)		(2.295)		(2.227)
ΔRCSH		0.069		0.877		1.121
		(2.216)		(2.175)		(2.164)
N. of man. firms $_{r,t=1990}$	33.087***	33.576***	33.227***	34.465***	36.231***	37.039***
	(10.132)	(9.565)	(10.295)	(9.618)	(10.848)	(10.234)
Tot patents $_{r,t=1990}$	−26.856***	−27.066***	−27.712***	−28.896***	−32.050***	−32.663***
	(9.144)	(8.696)	(9.427)	(8.717)	(10.158)	(9.552)
Pop dens $_{r,t=1990}$	0.107	0.081	0.174	0.141	0.154	0.126
	(0.283)	(0.266)	(0.283)	(0.262)	(0.289)	(0.268)
Temporary $_{r,t=1990}$	−3.978***	−3.797***			−2.784*	−2.482*
	(1.287)	(1.311)			(1.403)	(1.449)
Tertiary $_{r,t=1990}$			2.203***	2.306***	1.870**	2.000**
			(0.683)	(0.683)	(0.736)	(0.747)
Adj. R2	0.075	0.083	0.091	0.105	0.102	0.114
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. Temporary workers are measured as the share of workers at the MSA level in 1990 with a number of weeks worked falling below the average number of weeks nationally worked. Tertiary educated workers are given by the share of employed individuals with at least one year in College for each MSA in 1990. Other control variables are measured in 1990. Regressions are weighted by the 1990 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 A4. Robustness IV: De-routinisation and incremental innovation (AMT and Total patents).

	(AMT)	(AMT)	(TOT)	(TOT)
ΔRSH	−2.018		−1.550*	
	(1.959)		(0.862)	
ΔRMSH		−5.099**		−2.489*
		(2.103)		(1.311)
ΔRCSH		0.396		−0.814
		(2.253)		(0.949)
High-Skill $_{r,t=1990}$	3.320**	3.533**	3.339***	3.404***
	(1.591)	(1.557)	(0.682)	(0.689)
N. of man. firms $_{r,t=1990}$	32.464***	33.703***	15.591***	15.968***
	(10.243)	(9.855)	(5.320)	(5.471)
Tot patents $_{r,t=1990}$	−28.406***	−29.643***	−15.734***	−16.111***
	(9.830)	(9.462)	(4.836)	(4.923)
Pop dens $_{r,t=1990}$	0.113	0.073	0.164	0.152
	(0.261)	(0.250)	(0.177)	(0.182)
Adj. R2	0.069	0.081	0.143	0.148
Obs.	289	289	289	289

Dependent variables: Relative change in incremental AMT patents (Columns I and II) and incremental total patents (Columns III and IV). 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 measured in 1990. Regressions are weighted by the 1990 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 B1. Panel data regressions.

	(AMT)	(AMT)	(AMT)
RSH $_{r,t-1}$	0.288*	0.664***	0.441**
	(0.164)	(0.208)	(0.178)
High-skill $_{r,t-1}$		0.583***	
		(0.198)	
High-skill $_{r,t-2}$			−0.130
			(0.157)
N. of man. firms $_{r,t-1}$	0.076***	0.065**	0.050*
	(0.026)	(0.026)	(0.027)
Tot patents $_{r,t-1}$	0.863***	0.852***	0.934***
	(0.027)	(0.027)	(0.029)
Pop dens $_{r,t-1}$	0.116***	0.112***	0.097***
	(0.016)	(0.016)	(0.016)
Adj. R2	0.402	0.404	0.379
Obs.	3480	3480	3190

Dependent variables: Local stock of AMT patents (log). All models are estimated using panel OLS regressions controlling for year and MSA fixed effects and cover the period from 2001 to 2012. All independent variables have been lagged by 1 year with the exception of high-skill in columns III, lagged by two years. RSH and High-Skill are measured, respectively, as the yearly share of routine employment and high-skill employment by MSA. N. of man. firms and Tot patents are expressed in log, Pop dens is in levels. Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$