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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. Coherently with our theoretical framework, we find that workers' replacements significantly dampen innovation performance, because 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, because large companies have more hierarchical rigidities and innovative capabilities in young firms are mostly dependent on specific human capital. Finally, our results show that firms' localization 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.

Keywords: Workers' replacements, excess worker turnover, innovation performance, tacit knowledge, knowledge spillovers, employer-employee matched longitudinal data.
JEL: J63, O30.

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1. Introduction

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

The debate focused on a number of distinct and yet related issues. First, a large and controversial debate about the impact of innovation on employment established in the literature. 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 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; Vona and Consoli, 2015; Moretti and Thulin, 2013). A third set of studies focused on the impact of labor market dynamics on firms' innovation performance, with particular attention to the effects of labor market deregulation and flexibility on firms' ability to successfully carry out more or less formalized innovation activities (Michie and Sheehan, 2003; Zhou et al., 2011; Kleinknecht et al., 2014; Wachsen and Blind, 2016).

Within the latter strand of analysis, a large debate about the relationship between labor mobility and firms' innovation performance gained momentum in the last 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 for knowledge spillovers across different locations to materialize (Agrawal et al., 2006; Simonen and McCann, 2008). This literature focused much on the role of social ties and the interplay between spatial, technological, and cognitive proximity in shaping the effectiveness of labor-driven knowledge flows. Firm-level studies 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 relevant 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 high-qualified human capital (Maliranta et al., 2009; Parrotta and Pozzoli, 2012; Herstad et al., 2015; Kaiser et al., 2015).

While the benefits of hiring knowledge-intensive workers were largely documented, how labor mobility affects firms' innovation performance through the combination of hirings and separations was less investigated. Yet, the churning of workers likely affects firms' performance in many respects. Workers' replacements were found to affect firms' financial and economic performance, especially with respect to firm productivity (Grinza, 2016). Instead, there is much more scant evidence on the relationship between workers' replacements and firms' innovation outcomes, which mostly focused on the churning of R&D personnel (Müller and Peters, 2010; Cooper, 2001; Eriksson et al., 2014; Braunerhjelm et al., 2015).

Our paper contributes to this strand of literature by investigating the impact of workers' replacements on firms' innovation performance. In doing this, we take the well-known resource-based theory of the firm as a 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 (Penrose, 1959; Foss, 1997, 1998). 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). The relevance of 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). To the best of our knowledge, this paper represents the first attempt to look at 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, which cover the entire private sector of the Veneto region of Italy over a 7-year period. These data have the unique feature of providing a monthly-level history of job matches, which allows constructing a detailed dynamics of firms' workers' replacements. They are merged with other data sources to gather financial and patent information of firms. Balance sheet data are taken from the Bureau van Dijk's *Analisi Informatizzata delle Aziende Italiane* (AIDA) data set. Instead, we recover 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 upon the procedure proposed by Lotti and Marin (2013).

The results of our empirical analyses provide support to our main hypothesis according to which workers' replacements are detrimental to firms' innovation performance, because of the loss of important tacit knowledge repositories. We also find that firms' 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 penalized by more rigid hierarchical structures and lower capabilities to adapt to fast-changing environments. On the other hand, young firms pay for the fact that they rely much on 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 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 presents relevant summary statistics. Section 5 shows and discusses our results. Finally, Section 6 concludes.

2. Theory and hypotheses development

A wide body of theoretical and empirical literature documented a positive impact of innovation dynamics on firms' economic and financial performance. Instead, studies on the relationship between innovation and employment provided controversial results. While the impact of technological and organizational change on employment aroused much attention, how labor market dynamics affect firms' innovation performance received relatively scarce consideration.

The resource-based view of the firm provides a valuable framework to appreciate the impact of workers' replacements on firms' innovation performance. According to Penrose (1959), firms are bundles of resources and competencies. Distinctive competitive advantage emerges from the ownership 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 allow firms to generate new knowledge and innovations. In this framework, dynamic capabilities are firms' ability 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 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 the building blocks of competencies and capabilities (Nelson and Winter, 1982; Dosi and Grazzi, 2010). 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 relates to the extent to which these routines, and the emanating competencies, are codified to preserve the organizational memory and provide the building blocks for future changes and innovations, or they rather are embodied in tacit skills of relevant actors, that is, firms' employees (Dosi and Grazzi, 2006, 2010). Based on the seminal contribution of Polanyi (1966), tacit knowledge received large attention in innovation studies. Knowledge is said to be tacit when actors, even the most competent and experienced, are not able to fully articulate the "procedures by which 'things are done', problems are solved, behavioral patterns are formed" (Dosi and Grazzi, 2010, p.176). An important attribute of tacit knowledge is its stickiness, that is, the difficulty with which it can be transmitted to other parties. Relevant 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 confront 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 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). These arguments lead us to spell out our first hypothesis.

Hypothesis 1: Workers' replacements are negatively associated with firms' innovation performance.

The empirical literature on the determinants of innovative outputs at the firm level investigated how key features such as firms' age and size affect the capacity to generate new knowledge and, eventually, new technologies. Empirical evidence is ambiguous, depending on how innovation outcomes are proxied. Hansen (1992) found that age 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). Similarly, the evidence on the relationship between size and innovation is non-univocal. According to the Schumpeterian tradition, large firms are expected to have an advantage in producing innovations (Schumpeter, 1942; Galbraith, 1958). 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 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). These arguments lead us to the following hypothesis:

Hypothesis 2a: Firms' size and age are positively associated with the outcome of formalized innovation activities.

While size and age 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. On the one hand, previous analyses 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 expected to be harmed by workers' replacements more than old firms (Aubert et al., 2006; Ouimet and Zarutskie, 2014; Coad, 2018). On the other hand, one advantage of small firms, as compared to large companies, is the capacity to promptly recognize new opportunities and to adjust their plans in research and production activities. Small firms may also find it easier to allow less rigid management structures. Hence, thanks to lower hierarchical rigidities, small firms may be more resilient than large companies to worker churning (Rogers, 2004). In view of these considerations, we propose the following hypothesis:

Hypothesis 2b: Firms' size and age moderate the effect of workers' replacements on innovation performance. Workers' replacements are expected to affect young firms more than old firms, while they are expected to affect small firms less than large companies.

According to a large number of studies, firms' economic and innovation performance is affected by place-specific external conditions, because of the role of technical, pecuniary, and knowledge externalities (Antonelli and Colombelli, 2017; Antonelli et al., 2011). Based on the seminal work by Glaeser, Kallal, Scheinkman, and Shleifer (1992), it is possible to identify two main classes of externalities: the Marshall-Arrow-Romer (MAR) and the Jacobs' externalities. MAR externalities emerge 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 for 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 of the relationship between industries' degree of spatial concentration and employment volatility shocks, supporting the labor market pooling hypothesis. Spatial concentration allows firms to cope with employment shocks because of easiness in 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 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 spell out the following hypothesis:

Hypothesis 3a: Firms' localization in industrial districts mitigates the negative effects of workers' replacements.

Agglomeration externalities are also generated by knowledge spillovers. Several empirical studies provided support to the important role of external knowledge in firms' innovation performance. Since Griliches (1992), the role of knowledge spillovers was 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 was found to be crucial for external effects to take place in this case (Jaffe et al., 1993; Audretsch and Feldman, 1996; Quatraro and Usai, 2017). According to this evidence, the larger the amount of knowledge produced by co-localized firms, the larger the productivity of innovation activities of each firm in the area. *Ceteris paribus*, one thus expects that high levels of knowledge spillovers can mitigate the negative effects of workers' replacements, because of overall productivity gains in the knowledge generation function (Antonelli and Colombelli, 2015a,b). This leads us to the following hypothesis:

Hypothesis 3b: The high (low) availability of knowledge spillovers mitigates (augments) the negative effects of workers' replacements on firms' innovation dynamics.

Jacobs' externalities are also important in innovation dynamics. In fact, not only the local stock of knowledge matters but also its composition. Jacobs' externalities are traditionally associated with the variety of firms and industries in a specific area. Recent theoretical and empirical contributions extended the notion of Jacobs' externalities to the analysis of knowledge spillovers, stressing the relevance of knowledge variety for the rate of creation of new knowledge. These studies are conceptually grounded on the recombinant knowledge theory (Weitzman, 1998; Fleming and Sorenson, 2001). According to this view, the creation of novelty is the outcome of a dynamics in which agents combine existing pieces of knowledge in new and unprecedented ways, or they rather combine brand new pieces of knowledge. The degree of relatedness among these components is likely to affect the knowledge generation process, in such a way that the higher the relatedness, the higher the likelihood to engage in successful novelty creation (Nesta and Saviotti, 2005; Quatraro, 2010; Antonelli and Colombelli, 2015a). An increasing variety of related technologies leads to higher rates of innovation, because of the closeness of the competencies they impinge upon. On the contrary, recombining unrelated technologies is more complicated, because of the heterogeneity of the competencies they impinge upon. For this reason, successful exploitation of loosely related knowledge requires deep familiarity with a firm's routines and capabilities, in order to spot fruitful recombination opportunities fitting firms' resources and innovation potential. These arguments lead us to our last hypothesis:

Hypothesis 3c: The high (low) degree of related knowledge variety mitigates (augments) the negative effects of workers' replacements on firms' innovation dynamics.

The rest of the paper is dedicated 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 use 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:

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

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 Equation (1) will give us an empirical test of this.

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

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

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

We estimate this model by using maximum likelihood for the negative binomial distribution. We prefer negative binomial models over Poisson models as the equality between the mean and variance of the dependent variable assumed by Poisson models is not verified in our data. The distribution of the number of patent applications, in fact, is substantially over-dispersed: the variance is about 4 times higher than the mean (see Table 1). Moreover, Voung 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 offer a better description of the data generating process.

4. The data

4.1. The Veneto case

In this paper, we use data for Veneto, an administrative region in the Northeast 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 as a country with strict employment protection rules (Kugler and Pica, 2008). Yet, despite Italian politicians have long aimed to limit workers' movements, the degree of labor mobility in Italy was in line with that of other countries known for their labor market flexibility, such as the UK (Contini et al., 2008). The causes of this reside in widespread illegal practices, fragile control systems, and contradictory laws. Interestingly, the Veneto labor market was even more mobile (Tattara and Valentini, 2003). This feature makes our Veneto data a valuable ground for estimating economic impacts of worker flows (Serafinelli, 2018).

4.2. The data sets

Our data are 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 starting from administrative data of the Italian Social Security System. The VHW data set collects labor market histories between 1975 and 2001 of *each* employee working for at least one day in the Veneto private sector (except for agriculture). It is organized in three parts. There is the worker archive, which gathers personal information of 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.[1]

[1]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.

Unfortunately, VWH does not include financial information of firms. Yet, 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&D expenditures, revenues, and the firm's national tax number.[2]

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 carefully 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' innovation output and local knowledge stock, derives from PATSTAT and OECD REGPAT, respectively. The first 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 aggregated information on knowledge stock of local areas at a fine-grained level. To match patent information from PATSTAT with VWH-AIDA, we draw upon the matching procedure between PATSTAT and AIDA firms developed by Lotti and Marin (2013).

4.3. The variables

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

As Davis et al. (1996), we measure a firm's workers' replacements through the excess worker turnover, expressed as follows:

hirings: number of workers hired between $t-1$ and t;

separations: number of workers separated between $t-1$ and t;

worker turnover: sum of hirings and separations between $t-1$ and t;

net job creation: difference between the number of employees at t and $t-1$;

excess worker turnover: difference between worker turnover and the absolute value of net job creation.

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

An example clarifies these definitions. Let us consider a company with 50 employees at the beginning of the year, which hires 5 workers immediately after and does not separate from anyone 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 after. 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.[3]

In our regressions, we express excess worker turnover in rates (Davis et al., 1996). We divide 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). 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 much 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 can bank on a finer, monthly-level information. Therefore, we can get more precise measures of worker flows, which account for work relations that start and end within a year.[4]

4.4. Sample construction and descriptive statistics

In this paper, we focus on manufacturing companies with at least 50 employees operating in the top innovative industries: chemicals, metal-mechanics, electronics, and automotive.[5]

We carry out an essential cleaning of the sample to remove unusable observations or observations representing particular cases that can 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

[3]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.

[4]Thanks to the monthly-level structure of our data, we can 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 is employed for only four months weights three times less than a woman employed for the whole year.

[5]These are the top-25% 2-digit industries in terms of percentage of firms that innovate (i.e., have at least one patent filed in the year).

a firm), while AIDA refers to firm-level data (i.e., possibly including non-Veneto establishments). To alleviate this potential bias, we exclude firms for which the number of employees reported by VWH is less than a half compared to that reported by AIDA. Second, we only consider firms established (still alive) at least one calendar year before (after) we observe them. We do this to exclude excess worker turnover derived from firm entry (exit), which is not the focus of this paper.[6] Third, we restrict the analysis to firms classified as 'active', thereby excluding firms that are closing down. Finally, we remove a few (outlier) firms with excess worker turnover rates greater than 1, meaning that at least 50% of the workforce is replaced with new employees in a given year.

The data set used in our empirical analysis is the firm-level collapsed version of the (cleaned) matched employer-employee data set. It consists of 1,565 firm-year observations.

Table 1 provides general descriptive statistics about workforce and firm characteristics. On average, firms in the sample have 0.6 patents filed each year and invest around 0.3% of their revenues in R&D. They employ about 153 workers and earn about 29 million Euros per year in revenues. The average firm is about 18 years old and gets 25 Euros of net profit out of 1,000 Euros of revenues. In the average company, only 17.7% of the workers are females, consistently with the fact that the industries in which we focus are predominantly male industries; 4.3% are foreigners; employees are, on average, about 35 years old; and a few of them are employed on a part-time basis (2.4%) or are temporary workers (3.9%). In the average firm, the vast majority of employees are blue- (65.1%) or white-collar (29.4%) workers. A few of them are apprentices (2.2%) or managers (2.6%). On average, workers stay in the same firm for about 7.6 years.

INSERT TABLE 1 AROUND HERE

Table 2 focuses on job and worker flows. As reported in the top panel, the average firm (with 153 employees) hires 27 workers and separates from 22 in any given year. Hence, it experiences 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 accommodate this job creation by hiring 5 workers and separating from none. Instead, it hires 27 workers and separates from 22, thus replacing 22 of its workers with 22 new ones and experiencing an excess worker turnover equal to 44.[7] The second panel of Table 2 reports rates of job and worker flows. On average, firms increase their workforce by 4.8% per year. The average hiring and separation rates are 0.207 and 0.160, respectively, so that the worker turnover rate is 0.367. The average excess worker turnover rate is 0.286, meaning that 14.3% of the workforce is replaced each year.

INSERT TABLE 2 AROUND HERE

[6] For the last year of observation we cannot identify which firms close down in the subsequent year.

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

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 appears to be 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, by accounting for several potentially confounding workforce and firm characteristics and possible simultaneity bias.

INSERT TABLE 3 AROUND HERE

5. Results

5.1. Main results

The results of our econometric estimations are reported in Table 4. All the estimations include year, industry, and province dummies. The first column presents the baseline estimations. The coefficient of the excess worker turnover rate is negative and significant, as predicted by our Hypothesis 1. Workers' replacements hinder the dynamics of innovation, because of the importance of individual learning dynamics and knowledge embeddedness. When workers leave, they bring with themselves 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 this negative effect.

INSERT TABLE 4 AROUND HERE

In Column (2) we show an extended version of the model, which includes several firm-specific controls. 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 support Hypothesis 2a, according to which firms' size and age are expected to yield direct positive and significant effects on innovation. The negative and significant effect of excess worker turnover is confirmed also in this setting.

As for the other control variables, the coefficient of R&D intensity is positive and significant, as expected. Moreover, the dummy variable indicating the location within an industrial district is characterized by a positive and significant coefficient. This is in line with the literature emphasizing the role of externalities in innovation dynamics. Agglomeration economies favor the access to external knowledge produced by co-localized firms, which, in turn, is used as an input in firm-level generation of innovation. The shares of both female and foreign workers are featured by positive and significant coefficients.

In Columns (3) and (4), we 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 non-linearities in the effect of our variable of interest, but our results do support only the existence of a linear effect, the coefficient of the quadratic term not being statistically significant. Finally, in Column (6) we substitute our focal regressor and introduce three dummy variables indicating low, medium, and high levels of excess worker turnover rate, respectively. We find that the coefficient of the lowermost class is not statistically significant, while the coefficient for medium and high levels of excess worker turnover rate is negative and significant. This suggests that the effect is stronger the higher is the replacement activity.

Overall, this first set of estimates provides robust support to our Hypotheses 1 and 2a, according to which excess worker turnover hinders firms' innovation dynamics, while size and age are positively associated with the outcomes of formalized innovation activities.

Yet, size and age 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 test these expectations 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. In the top panel of Table 5, we report evidence about the moderating effect of size. This latter is measured by using either revenues (as in Table 4) or employment. Let us 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 is obtained by interacting revenues with the excess worker turnover rate. Specifically, we build two dummy variables distinguishing firms with low *versus* high revenues. We follow the standard threshold for large firms proposed by the European Commission and set at 50 million Euros of revenues per year.[8] 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 check the robustness of these results by using the number of employees as a proxy of firm size. The results are very similar to those obtained by using revenues and, in fact, the two variables show a sensible correlation (0.855). The coefficient of the interaction with

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

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, too. Conversely, the effect on large firms (with more than 250 employees) is large and significant.

INSERT TABLE 5 AROUND HERE

The bottom panel of Table 5 shows, instead, the results about the moderating role of firm age. We follow two distinct strategies. First, we interact the excess worker turnover rate with firm age (continuous variable). We obtain a positive and significant coefficient. This suggests that, other things being equal, the older is the firm, the smaller is the overall impact of excess worker turnover on innovation. Second, we create three age classes, build the correspondent dummy variables, and multiply each of them by the excess worker turnover rate. We obtain consistent results. In particular, the coefficient for firms in the uppermost age class is not significant, while the coefficients for firms in the intermediate and lowermost age classes are negative and significant. It must also be noted that the coefficient for firms in the lowermost age class is ten times larger than that for firms in the intermediate class.

Overall, these results provide support to our Hypothesis 2b. First, small firms are more resilient to workers' replacements than large firms. This is because of the higher flexibility and capacity to adjust their plans that characterize small firms. Second, 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.

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

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

In Section 2, we stressed that also factors external to firms' boundaries can influence the impact of workers' replacements on innovation.

First, we set forth the hypothesis that firms within industrial districts suffer less from workers' replacements compared to firms outside industrial districts (Hypothesis 3a). This is because of labor pooling dynamics and job matching effects. Spatial clustering and localized industrial specialization increase the probability to replace workers that abandoned the firms with new workers holding the requested (and missed) competencies. We investigate the impact of localization in industrial districts by building two dummy variables covering firms within districts and firms that are outside.[9] The results of the estimations are reported in the first panel of Table

[9] We identify industrial districts from the list given 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`.

6. While the effect of workers' replacements on innovation is not significant in firms localized within industrial districts, firms localized outside these areas significantly suffer from workers' replacements. The coefficient of the excess worker turnover rate for these latter firms is indeed large and significant.

INSERT TABLE 6 AROUND HERE

Next, we investigate whether the impact of workers' replacements varies with the availability of knowledge spillovers in the areas in which firms localize (Hypothesis 3b). Knowledge spillovers are 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 is 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 access and absorb place- and industry-specific competencies that can be useful for co-localized firms. These dynamics render workers' replacements less harmful for firms operating in areas with high levels of aggregate knowledge stock. As before, to explore this issue we build up two dummy variables capturing firms' location in areas with high *versus* low levels of knowledge spillovers. As for 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 to 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 makes more difficult 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 create relevant dummy variables identifying the different contexts in which the firms are located. The degree of knowledge variety of an area is measured by the information entropy at the NUTS 3 level. The degree of unrelated and related knowledge variety is measured by the between and within information entropy rates, respectively, again measured at the NUTS 3 level. In the regressions, we insert the ratio between the unrelated and related components of knowledge variety. 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 in 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., featured 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.

6. Conclusions

In this paper, we investigated the impact of workers' replacements, captured by excess worker turnover, on firms' innovation dynamics. Our main argument hinges 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 investigated the moderating role of factors both internal and external to the firm. The former concerns firm's age and size, while the latter includes agglomeration externalities, knowledge spillovers, and technological variety.

Our empirical investigation is 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 of the implemented models. As for the interacting factors, we find that both firms' size and age 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 allow mitigating the effect of workers' replacements, and the same applies to 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 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.

As many other empirical investigations, also this one presents some caveats to be mentioned. First, the geographical coverage is limited to the Veneto region. Though it is part of the more advanced North-East regions in Italy, it 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 allowing us to have 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 fiercer technology-based competition. Both these limitations are due to data constraints. Moreover, 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.

Yet, the study brings about important implications from both a strategic management and policy perspective. As for 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 workers 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 willing to increase their productivity by means of replication of competitors' routines and technologies will benefit from workers' mobility. Conversely, firms' willing to stand competitive by means of innovation should find out measures to promote experienced workers to stay instead of migrating to other firms. Experienced workers represent indeed 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 valorizes firms' core competencies.

From the viewpoint of labor policies, this paper suggests that one-size-fits-all solutions cannot be supported. Also, these results challenge the idea that labor mobility is positive in absolute. Clearly, policy makers are not expected to obstacle labor mobility to promote innovation. Our results rather imply that some firms in specific places and industries would benefit from labor mobility more than others. Therefore, the promotion of labor mobility should especially be targeted towards 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 workers turnover on exploration *versus* exploitation strategies. Moreover, our results call for further refinements of the analyses to better understand the channels 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 the differential effect of replacements of white- *versus* blue-collar workers, and on disentangling the effects of different kinds of separations.

Table 1: **Sample summary statistics: general information**

Variable	**Notes**	**Mean**	**Std. dev.**
	Dependent variable		
Firm's patent applications	Capitalized using the perpetual inventory method with a constant depreciation rate of 0.15	0.604	2.325
	Independent variables		
Excess worker turnover rate	See Table 2	0.286	0.177
Net job creation rate	See Table 2	0.048	0.113
log R&D intensity	R&D intensity is R&D expenditure over revenues	0.003	0.011
log Revenues	1,000 Euros (2000 prices)	9.732	0.885
Firm age	Years	18.036	7.577
Share of female workers	Monthly weighted	0.177	0.157
Share of foreign workers	Monthly weighted	0.043	0.049
Average age of the workforce	Monthly weighted, years	35.292	3.446
Share of managers	Monthly weighted	0.026	0.031
Share of white-collar workers	Monthly weighted	0.294	0.132
Share of blue-collar workers	Monthly weighted	0.651	0.144
Share of apprentices	Monthly weighted	0.022	0.042
Share of temporary workers	Monthly weighted	0.039	0.057
Share of part-timers	Monthly weighted	0.024	0.027
	Other variables		
Employees	Monthly weighted	153.015	219.640
Revenues	1,000 Euros (2000 prices)	29,060.390	59,652.810
R&D expenditure	1,000 Euros (2000 prices)	70.884	320.574
Profit margin	Net profit over revenues	0.025	0.064
Average tenure of the workforce	Monthly weighted, years	7.597	3.137
			Firm-year observations: 1,565

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

Table 2: **Sample summary statistics: job and worker flows**

Variable	**Mean**	**Std. dev.**
Net job creation	5.381	24.099
abs(Net job creation)	10.578	22.348
Hirings	27.109	45.879
Separations	21.578	35.141
Worker turnover	48.688	78.095
Excess worker turnover	38.110	68.086
Net job creation rate	0.048	0.113
abs(Net job creation rate)	0.081	0.092
Hiring rate	0.207	0.140
Separation rate	0.160	0.094
Worker turnover rate	0.367	0.210
Excess worker turnover rate	0.286	0.177
		Firm-year observations: 1,565

Source: VWH-AIDA-PATSTAT data set (years: 1995-2001)
Excess worker turnover rate is lagged by one year. For consistency, also the other variables are lagged by one year.

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: 1,565

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

Table 4: **Impact of workers' replacements on firm innovation; estimation method: negative binomial regressions**

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 - when low: less than 0.10						-0.256
						(3.419)
Excess worker turnover rate - when medium: between 0.10 and 0.30						-1.875*
						(1.151)
Excess worker turnover rate - when high: below 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: 1,565						

Source: VWH-AIDA-PATSTAT data set (years: 1995-2001)
Robust standard errors in parentheses; ***, **, and * denote, respectively the 1%, 5%, and 10% significance level. All the independent variables are lagged by one year. The reference category for the job distribution is the share of apprentices. The average excess worker turnover rate is 0.064 (std. dev. 0.027), 0.199 (std. dev. 0.056), and 0.470 (std. dev. 0.146) in the group of firms with low, medium, and high, excess worker turnover rates, respectively.

Table 5: **Impact of workers' replacements on firm innovation: diversified impacts by firm size and age; estimation method: negative binomial regressions**

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 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)

Source: VWH-AIDA-PATSTAT data set (years: 1995-2001)
All the estimations include 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 is 0.297 (std. dev. 0.178) in firms with 50-250 employees, and 0.210 (std. dev. 0.151) in firms with 250+ employees. It is 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.

Table 6: **Impact of workers' replacements on firm innovation: local networks; estimation method: negative binomial regressions**

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)
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)
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)
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)

Source: VWH-AIDA-PATSTAT data set (years: 1995-2001)
The high (low) categories refer to values above (below) the median. All the estimations include 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 is 0.283 (std. dev. 0.172) in firms that belong to industrial districts, and 0.300 (std. dev. 0.196) in firms that do not. It is 0.307 (std. dev. 0.179) in firms that belong to provinces with high stock of innovative capital, and 0.271 (std. dev. 0.173) in firms that do not. It is 0.290 (std. dev. 0.177) in firms that belong to provinces with high information entropy, and 0.284 (std. dev. 0.177) in firms that do not. It is 0.297 (std. dev. 0.180) in firms that belong to provinces with high between/within entropy ratio, and 0.274 (std. dev. 0.172) in firms that do not.

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