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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.

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 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 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 abovementioned 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, 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 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:

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

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.

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

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:

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

$R\&D$ are R&D investments; $EWTR$ 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 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 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.

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

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&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

[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).

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

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):

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.

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]

[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

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 1,565 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 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 1,000 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.

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) 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

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.

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.

INSERT TABLE 2 AROUND HERE

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.

INSERT TABLE 3 AROUND HERE

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.

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

INSERT TABLE 4 AROUND HERE

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. 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

[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

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.

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.

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).

INSERT TABLE 5 AROUND HERE

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,

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

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 our 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

[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`.

worker turnover rate for these latter firms is indeed large and significant.

INSERT TABLE 6 AROUND HERE

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.

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

INSERT TABLE 7 AROUND HERE

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

[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.

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.

INSERT TABLE 8 AROUND HERE

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 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)

[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).

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.

INSERT TABLE 9 AROUND HERE

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.

[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.

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 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.

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	1,000 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	2,342.333
Revenues	1,000 Euros (2000 prices)	29,060.390	59,652.810	9,332	15,258	26,380	2,167	856,853
R&D expenditures	1,000 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: 1,565

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.

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	1,106
Excess worker turnover	38.110	68.086	14	24	40	0	1,012
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:	1,565

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.

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 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: 1,565

Source: VWH-AIDA-PATSTAT data set (years: 1995-2001)
Estimation method: negative binomial regressions. Robust standard errors in parentheses; ***, **, and * denote, respectively, the 1%, 5%, and 10% significance levels. 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).

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: 1,565		
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: 1,565		

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.

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: 1,565	
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: 1,565	
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: 1,565	
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: 1,565	

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.

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.

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: 1,565		

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: 1,104		
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: 1,558		

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).

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Appendices

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 1,565 to 1,173 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, ...), 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: 1,173	

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.

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)

[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.

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%).

Table B.1: **Robustness checks: top innovative industries**

Threshold at 75%		
Excess worker turnover rate	-1.045***	(0.374)
	Firm-year observations: 4,703	
Threshold at 50%		
Excess worker turnover rate	-1.333***	(0.415)
	Firm-year observations: 3,550	

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.

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%.

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

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:	1,472
Threshold at 75%		
Excess worker turnover rate	-0.960*	(0.570)
	Firm-year observations:	1,424
Threshold at 80%		
Excess worker turnover rate	-0.992*	(0.605)
	Firm-year observations:	1,354

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.

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.

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: 1,546	

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.