Worker Flows, Reallocation Dynamics, and Firm Productivity: New Evidence from Longitudinal Matched Employer-Employee Data

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Worker Flows, Reallocation Dynamics, and Firm Productivity: New Evidence from Longitudinal Matched Employer-Employee Data

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Abstract

This paper investigates the impact of the worker flows of a firm on productivity by using unique longitudinal matched employer-employee data. The analysis has split a firm's total worker flows into three components: workers' replacements (excess worker flows), hirings introduced to increase the firm's employment level (net hirings), and separations of workers intended to decrease the firm's workforce (net separations). This has allowed the impact of workers' replacements, which represent the most prominent and compelling feature of worker mobility, to be isolated from the other two components. Endogeneity has been dealt with by using a modified version of Ackerberg et al.'s (2015) control function method, which explicitly accounts for firm fixed effects. The main findings are that (i) excess flows have an inverted U-shape impact on productivity, (ii) net hirings foster firm productivity, and (iii) net separations damage it. The impacts are heterogeneous and vary widely on the basis of the types of replacements, the categories of workers involved, and the types of firms experiencing such flows. Overall, the findings of this paper highlight the importance of reallocation dynamics to obtain better employer-employee matches, and call for a reconsideration of policies concerning the flexibility of the labor market.

Keywords: Worker flows, excess worker flows, firm productivity, semi-parametric estimation of production functions, longitudinal matched employer-employee data.
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1. Introduction

A ubiquitous feature of labor markets is that workers move extensively in and out of firms (Davis and Haltiwanger, 1999). When firms want to expand their workforce, they hire new workers, thereby experiencing the net inflow of workers. When they want to decrease their workforce, they separate from some of their workers and experience a net outflow of workers. However, most of the workers' movements in and out of firms take place "in excess" of job creation or destruction (Burgess et al., 2000a, 2001; Lazear and McCue, 2017). Firms often face a simultaneous inflow and outflow of workers. Workers separate from firms for a variety of reasons, and firms have to replace such separated workers with new workers if they want to maintain a particular job slot.

Inflows and outflows of workers can affect a firm's productive performance significantly. For instance, an inflow of new workers can introduce valuable knowledge and a new network of connections, but also substantial inefficiencies due to the initial learning phases. When workers separate from a firm, the firm might lose relevant (firm-specific) knowledge, but it might also free itself from an underperforming worker. Productive performance is a crucial determinant of sustained and sustainable economic performance. Understanding whether and how worker flows have an impact on firm productivity is, therefore, an essential task for researchers.

In recent years, a line of literature has emerged in which the productivity impact of several labor-related issues is studied through large matched employer-employee or firm-level data (e.g., Devicienti et al., 2018; Garnero et al., 2014; Vandenberghe, 2012). However, the productivity impact of worker flows is still a scarcely explored territory. Some studies exist in the management literature on the relationship between worker mobility and organizational performance (e.g., Glebbeek and Bax, 2004; Huselid, 1995; Siebert and Zubanov, 2009). On the one hand, they generally rely on either single-firm case studies or on very particular samples that can compromise the external validity or generalizability of the findings. On the other hand, they usually adopt simple OLS estimation techniques that do not allow for robust interpretations of the results.

Moreover, the extant empirical works on worker mobility and organizational performance have not differentiated between net and excess flows. They have instead focused on total worker flows (also referred to as "worker turnover").[1] This is a crucial aspect as the creation

[1] The results on the relationship between worker turnover and firm performance that emerge from these studies are somewhat heterogeneous. Some of them found a negative association (e.g., Huselid, 1995; Ton and Huckman, 2008); some others reported a non-linear correlation (e.g., Glebbeek and Bax, 2004; Siebert and Zubanov, 2009); while others separately looked at the (total) hirings and separations (e.g., Bingley and Westgaard-Nielsen, 2004, who found that separations are associated with increased profits and hirings are

of new matches is necessary when a firm expands its workforce: if the firm wants to grow, it must hire someone. Similarly, the dissolution of existing matches is necessary when the firm wants to reduce its workforce: if the firm wants to become smaller, it must separate itself from someone. Therefore, from the single firm viewpoint, net inflows or net outflows represent events that are necessary to reach a given employment level. Conversely, the simultaneous creation and destruction of matches embodied in workers' replacements are, in this sense, not necessary: in this case, there is no expansion or contraction of employment. From the single firm perspective, workers' replacements thus represent a genuine reallocation of matches.

The net and excess components of a firm's workers' movements thus respond to structurally different processes, and this calls for their separate analysis (Burgess et al., 2000a). Isolating excess flows also makes it possible to gauge the effects of reallocation dynamics, which represent the most prominent and compelling feature of worker flows (Centeno and Novo, 2012). The fact that workers' movements "in excess" of job creation or destruction are so abundant in free labor markets must originate from something that is different from relatively rare events, such as retirements or withdrawals from the labor market. As theorized by Jovanovic (1979), replacements must take place as the result of a reallocation process of employer-employee combinations that is aimed at searching for better, more productive matches. Whether this reallocation process succeeds remains to be seen. While new matches (i.e., replacement workers) can be important for the firm, the dissolution of matches (i.e., separated workers) entails the loss of firm-specific knowledge, which takes time and resources to acquire (Becker, 1964).

These contrasting mechanisms behind reallocation dynamics likely have a different importance in different contexts, and, as a result, diversified impacts might emerge. For instance, the replacements of workers in small firms may create staffing difficulties during job vacancy periods, whereas this might be less of an issue in larger firms. The replacements of high-skilled workers might be a more delicate matter than the replacements of low-skilled workers. The labor market pool for high-skilled workers is more limited than that of low-skilled workers, and the firm-specific knowledge acquired by the former workers might be relatively more important for the firm (e.g., the knowledge of a firm's processes and routines in leadership roles is crucial to achieve a sustainable competitive advantage). In high-tech sectors, the

linked to reduced profits). Most of these studies focused on the association between worker turnover and such variables as customer satisfaction and accounting firm performance indicators. The only exceptions are the studies by Huselid (1995) and by Siebert and Zubanov (2009), who focused on firm productivity (i.e., they made use of a production function). For a detailed review of this literature, see Mawdsley and Somaya (2016) and Shaw (2011).

inflows of new and updated knowledge are of utmost importance and may overcompensate for the losses of firm-specific human capital. The reasons behind replacements, departing workers' tenure, firm age and location (e.g., in business clusters), and the characteristics of the sending firms (i.e., the firms from which the replacement workers come from) are also likely to play critical roles in shaping the effect of reallocation dynamics.

This paper contributes to the extant literature on several fronts. First, it answers a set of research questions that have not yet been fully explored. What is the impact of net and excess worker flows on a firm's productivity? How does the productivity impact of reallocation dynamics unfold in different contexts? What are the primary sources behind the productivity impact of excess flows? Second, to answer these questions, I have used a large, longitudinal, matched employer-employee data set. This data set, which refers to the Veneto region in the North East of Italy and covers the 1995-2001 period, is based on administrative records, and it has allowed a detailed, monthly-level history of the worker flows in different firms to be reconstructed. Moreover, it encompasses much of the Veneto worker and firm population, thus furnishing a comprehensive view of a self-contained labor market. Third, the paper addresses endogeneity problems, stemming from unobserved firm heterogeneity and reverse causality, by adopting state-of-the-art econometric techniques. It uses a modified version of Ackerberg et al.'s (2015) control function approach, recently developed by Lee et al. (2019), which explicitly removes firm fixed effects.

The Veneto region represents an excellent case study. It is one of the wealthiest and most dynamic regions in Italy, and is comparable with the other most advanced industrialized countries and regions. During the period under investigation, it was characterized by nearly full-employment (Tattara and Valentini, 2010). Excess worker flows thus genuinely reflected a pure reallocation process rather than dynamics linked to abnormal job destruction in (specific sectors of) the economy. Moreover, despite the standard view, Italy has a mobile labor market, on par with other generally acknowledged mobile countries, such as the UK (Contini et al., 2008). As part of such a national context, Veneto has an even higher degree of labor mobility, thus allowing the effects and dynamics associated with net and excess worker flows to be understood more clearly (Tattara and Valentini, 2003). The Veneto region is also characterized by the aggregation of firms in industrial districts (Sforzi, 1989). This makes it possible to assess how net and excess worker flows impact productivity in such an interesting setting, where the typical labor market pooling of spatial concentration provides constant markets for skills.

The findings show that (i) the net inflows of workers have a positive effect on productivity, whereas (ii) the net separations harm it. Instead, (iii) the excess flows have an inverted U-shape effect on a firm's productivity, and a net positive impact emerges until the point at which the replacement activities become substantial (i.e., when around 47% of the workforce is replaced with new workers). The reallocation of matches thus appears vital for a firm to achieve better, more productive employer-employee combinations. However, when replacements reach very high levels, detrimental effects, related to a loss of (firm-specific) knowledge, prevail. The results point to (iv) a substantial heterogeneity in the productivity impact of replacement activities. The observed effects of reallocation dynamics stem from the replacement of workers who make job-to-job transitions, which is compatible with voluntary resignations, and workers who drop out of the sample around the age of retirement, which is compatible with retirements. While excess flows of low-skilled workers introduce clear benefits to productivity, the estimated impact for high-skilled workers is negative, albeit small and not significant. Reallocation dynamics are associated with lower productivity gains as the separated workers' tenure increases. High-tech firms and firms located in industrial districts experience much higher benefits from excess flows than low-tech firms and firms located outside industrial districts. Small and young firms instead fail to capture the benefits of reallocation dynamics. Additional results also point out that the sources of gains from excess flows are mainly industry-specific, and that reallocation dynamics enhance productivity irrespective of the relative "quality" of the sending firms. Nevertheless, increased (relative) performances of the sending firms are found to significantly and substantially reinforce the beneficial effects stemming from the reallocation of the employer-employee matches.

The rest of the paper is structured as follows. Section 2 presents the conceptual framework and discusses how excess flows can impact productivity in a differentiated way according to different contexts. Section 3 describes the Veneto region case. Section 4 reports the definitions and formulas related to the worker flow measures. Section 5 discusses the empirical model and the identification strategy. Section 6 describes the data, discusses some measurement issues, and presents the relevant descriptive statistics. Section 7 presents and discusses the results for the impacts of net and excess flows on productivity, and for the presence of heterogeneities in such impacts according to the dimensions outlined in Section 2. Finally, Section 8 concludes and draws up some policy implications.

2. Conceptual framework and mechanisms

2.1. Worker flows and firm productivity

A firm's inflow and outflow of workers can affect its productive performance to a great extent. The various mechanisms that can explain this effect primarily unfold along with the effects of a variation in the firm's knowledge and skill base, due to the modification of the existing employer-employee matches. Two concepts are crucial in this respect: the concept of firm-specific human capital (Becker, 1964) and the concept of tacit knowledge (Polanyi, 1958, 1966). Firm-specific human capital, acquired by a worker through firm-specific training and on-the-job learning processes, is that particular bundle of competences that is only valuable to the firm (Lazear, 2009). As Dosi and Grazzi (2010) stated, “tacitness refers to the inability by the actor(s) implicated, or even by sophisticated observers, to explicitly articulate the sequences of procedures by which “things are done”, problems are solved, behavioural patterns are formed, etc.”. Such a conceptual framework is useful because it allows a variety of “side” mechanisms to be encompassed. For example, worker flows also modify a firm’s knowledge base by affecting its network of connections, which is known to play a relevant role in determining a firm’s productivity (Broschak, 2004; Shaw et al., 2005; Somaya et al., 2008).

An inflow of workers means an inflow of knowledge. Tacit knowledge, about the routines and practices of the sending firms, can be precious for the recipient firms. The inflow of new workers can also affect a firm’s knowledge base by modifying its network of connections. For example, new workers may lead to productive forms of collaboration with their sending firms. At the same time, hiring a new employee entails the cost of making him/her acquire firm-specific human capital. This cost is both a direct burden on a firm, due to the necessity of firm-specific training, and an indirect burden, as a result of lower productivity during the learning process.

On the other hand, an outflow of workers means an outflow of knowledge. When a worker separates from a firm, the firm loses its firm-specific human capital and tacit knowledge. As tacit knowledge resides in the mind of the individual and cannot be formalized or communicated, it goes away with the separated worker (Grant, 1996; Nonaka, 1994). However, a worker’s separation might also be good for a firm, in that it allows the firm to free itself of an underperforming worker (i.e., a bad match). Moreover, a firm’s productive relational capital can deteriorate when a worker separates from the firm. This happens, for instance, when a separated worker introduces a former client to a (destination) competing firm. However, a firm’s network of connections can also benefit from the outflow of workers, for example, when the separated worker moves to a client/supplier/competitor and this leads to a closer relationship between the two firms.

A net worker flow entails the flow of workers in only one direction: either a firm is expanding its workforce, thereby undergoing a net inflow, or it is contracting its employment level, thereby undergoing a net outflow. In the case of net inflows, a firm undergoes the creation of new matches. In the case of net outflows, a firm undergoes the dissolution of existing matches. The productivity impact of these new or dissolved matches originates from the combination of the various previously mentioned mechanisms relative to the inflow or outflow of workers, respectively. Excess flows (i.e., workers’ replacements) instead entail two simultaneous worker flows, one away from the firm, that is, workers' separations, and one into the firm, that is, replacement hirings. Workers' replacements thus imply that a firm undergoes a simultaneous dissolution and constitution of matches. Hence, the productivity impact of excess flows is the result of two different impacts, one stemming from an outflow of workers and the other stemming from an inflow.

However, net worker flows represent necessary events for a firm that wants to expand or contract its workforce, and they stem from the evaluation of firms regarding their optimal level of employment. Excess flows are instead the result of an ongoing re-evaluation of matches by a firm and by its workers (Burgess et al., 2000a). From the firm perspective, excess flows represent a reallocation of matches, and the fact that they are so high, ubiquitous, and extremely persistent within firms suggests that they are the result of an equilibrium phenomenon (Burgess et al., 2000a; Lazear and McCue, 2017).

Jovanovic (1979) developed a theoretical model in which excess flows are the mechanism through which employer-employee matches can be reallocated more efficiently as better information becomes available to the parties. Three assumptions underpin this theory (see Jovanovic, 1979, for details). First, each worker performs different jobs with different productivity levels. Second, employers and workers can bargain over wages, on an individual basis, and renegotiate the wage as better information on the quality of the match becomes available. Third, both workers and employers have imperfect information about the exact location of the most productive match. For a given job slot, workers' heterogeneity in productivity levels, the possibility to bargain over wages according to the quality of the match, and imperfect information make workers and employers engage in the search for optimal matches. From the firm's viewpoint, the reallocation process embodied in excess flows could be the way to obtain better matches as better information becomes available. In short, reallocation dynamics could improve a firm's productivity by removing poor matches, which could justify their widespread existence in the real world.

However, this positive aspect might be reduced or even offset by other mechanisms. Recruiting a new worker as a replacement may not be an easy process. Apart from the direct recruitment costs, job vacancy periods can impose productivity losses, since it may not be easy for the remaining workers to perform the extra work previously done by the separated worker (Hom and Griffeth, 1995).

The idea that the productivity impact of workers' replacements is simply the sum of the impacts of two worker flows, one out and one into the firm, is thus defective if it is not considered that workers' replacements stem from reallocation dynamics, which (i) seem to arise from an equilibrium phenomenon, and (ii) might impose organizational inefficiencies due to job vacancy periods.

The coexistence of these opposing mechanisms behind workers' replacements could lead to an inverted U-shape impact, whereby a certain number of excess flows is beneficial for a firm's productivity, but too many flows become detrimental. The positive effects stemming from inflows of new knowledge and reallocation dynamics might emerge up to a certain point, or at least up to the point at which bad employer-employee matches are removed. When a firm replaces a massive proportion of its workforce, losses of significant parts of firm-specific knowledge and organizational problems caused by job vacancies might prevail and offset the positive effects.

The management literature has theorized the existence of a positive optimal number of workers' replacements, whereby an inverted U-shape relationship between excess flows and productivity would emerge. Abelson and Baysinger (1984) argued that workers' replacements lead to costs and benefits for a firm and that an inverted U-shape impact might be the net result of these. The optimal number of workers' replacements is the one that minimizes the net cost of replacements, which is the sum of the costs associated with the retention of workers and those associated with their replacements. The costs associated with the retention of workers are a decreasing function of the replacement rates, whereas those associated with replacements increase as the replacement levels increase. Therefore, the net replacement costs are a U-shaped function of replacements, and the optimal level of the replacement rate is the minimum point of that function. Lower replacement rates, as well as higher replacement rates, are sub-optimal. If the replacement rate is lower than the optimal rate, increases in excess flows are beneficial. Conversely, if the replacement rates are higher than the optimal rate, increases in excess flows are harmful (see Abelson and Baysinger, 1984, p. 333).

The emergence of an inverted U-shape relationship could also depend on the type of work system in force (Siebert and Zubanov, 2009). The costs linked to workers' replacements are higher in "high-involvement" work systems, which can motivate a firm to adopt more careful selection practices and, contextually, lower degrees of replacements to remove bad matches. The range of excess flow levels that lead to positive net effects should thus be limited, so that it is possible to expect a negative impact to prevail across the whole excess flow distribution in this case. Instead, the costs associated with workers' replacements in "low-involvement" work systems are generally low, which results in less careful personnel selection practices, and contextually higher degrees of replacements to remove bad matches. The range of replacement rates that guarantees a positive impact is relatively high before the adverse effects prevail. In this case, a clear inverted U-shape relationship between replacement rates and productivity would thus emerge.

It is an arduous task to *a priori* infer whether the overall productivity effects of net inflows, net outflows, and excess flows are negative or positive, and whether there might be an inverted U-shape impact in the case of excess flows. Subsection 7.1 presents and discusses the empirical results for these effects.

2.2. The contingency role of the worker- and firm-level characteristics

The numerous mechanisms at stake likely play different importance roles, depending on a variety of worker- and firm-level aspects, which could result in differentiated impacts. This subsection discusses some potentially relevant dimensions of heterogeneity, which are then empirically assessed in Subsection 7.2. While Subsection 7.2 presents the results of the differentiated impacts of the three distinct worker flows (i.e., net inflows, net outflows, and excess flows), the discussion here concentrates on excess flows.

First, workers' replacements are either the result of a firm's decision or a worker's decision (Burgess et al., 2000a), except for particular cases, such as retirement or forced withdrawal from the labor market. The productivity impact of a worker's replacement may be different, depending on whether the firm has chosen or not to dissolve a match and constitute a new one. However, the resulting impacts are not easy to predict.

Let us first consider the case of resignations. When a worker decides to leave a firm, the firm may suffer a certain amount of damage (e.g., if the worker is not easily replaceable). However, a worker that resigns from a firm might have a poor match with it. The meta-analysis performed by McEvoy and Cascio (1987) found support for the latter circumstance: poor performers (i.e., those with bad matches) are those who are far more likely to leave. If this is the case, the replacements of workers who have left might lead to productivity enhancements. In the case of dismissals, the picture is likewise intricate. While a firm that chooses to replace a worker arguably does so to remove a poor match, the lengthy bureaucratic procedures associated with dismissals and the possible obstructive behavior of dismissed workers during the period of notice could attenuate the positive effects to a great extent. A third possibility, which is much less frequent, is when a firm has to replace a worker who retires. In this case, the firm knows that the retiring worker will leave at a specific point in time (i.e., retirement is predictable). Possible organizational problems are thus reduced, and the resulting impact might boil down to whether the productivity levels of younger, newly-hired workers can offset the loss of the firm-specific knowledge of the retiring workers.

Another relevant dimension of differentiation is whether excess flows involve high- or low-skilled workers. Firm-specific human capital plays a fundamental role for high-skilled workers (Parsons, 1972). Moreover, finding suitable workers for high-skilled positions may be complicated, as the pool of workers with the required bundle of skills is more limited

(Cappelli, 2015). These downside aspects could offset the positive effects stemming from the possibility of finding better matches. In the case of low-skilled workers, firm-specific knowledge is less crucial, and the workers' pool is more abundant. Therefore, the potential for positive effects seems higher for low-skilled workers than for high-skilled ones. The tenure of a departing worker is also important, as more tenured workers accumulate more firm-specific human capital than workers with a lower tenure. Therefore, any benefit from excess flows is likely reduced in the case of replacements of high-tenure workers.

The productivity impact of workers' replacements unravels as part of the trade-off between the acquisition of new knowledge and the loss of acquired knowledge. The technology of a firm is likely to have a substantial effect on the relative importance of these two dimensions. The acquisition of new knowledge about specific technologies seems crucial for high-tech firms. This so-called "learning-by-hiring" effect in high-tech firms has emerged in a large number of empirical studies (e.g., Herstad et al., 2015; Parrotta and Pozzoli, 2012; Tzabbar et al., 2013). In high-tech firms, which generally compete in fast-changing environments, the gains from the inflows of new knowledge can thus significantly offset the losses from the outflows of (perhaps outdated) knowledge. For low-tech firms, instead, the benefits from the inflows of new knowledge might not completely compensate for the costs associated with replacements.

The location of a firm in industrial districts also appears to be a critical contingency factor. The potential for reallocation dynamics to find better matches depends on the availability of suitable workers for the replacement matches. Firms operating in the same district share much, in terms of production processes and goods produced. The spatial concentration that is typical of industrial districts creates a specialized labor market pool that firms can easily tap into (Overman and Puga, 2010). Furthermore, workers move across firms in the same district (Serafinelli, 2019). Therefore, replacement workers can represent a unique way of acquiring valuable tacit knowledge about the processes and practices of other firms in the same district and of enlarging the firm's network of connections with them. These factors can overcompensate for the costs associated with excess flows. It is thus possible to expect that the potential for positive effects is maximized in the presence of industrial districts. Conversely, for firms located outside industrial districts, the potential for positive effects is more limited, and negative forces associated with excess flows might play a more preponderant role.

The age of a firm is another relevant moderating factor. Excess flows in newly established firms are generally higher than those of well-established companies, thus reflecting the fact that new firms undergo a period of intense experimentation of matches (Haltiwanger et al., 2012). Whether this higher replacement activity among new firms materializes into positive or negative impacts is unclear. On the one hand, it may be that new firms can obtain substantial benefits from the replacement of workers. There might be more room, in the early stages of life of a firm, to improve employer-employee matches. Finding suitable matches at the first try might be very unlikely, and more attempts might prove advantageous for the firm. On the other hand, newly established firms have to "practice with the market" and consolidate their understanding of internal processes, and workers' replacements can prevent these objectives from being achieved, thus hindering a firm's productive performance.

Finally, the size of a firm likely moderates the impact of excess flows on productivity. Very small firms are likely to enjoy fewer benefits associated with excess flows, because they typically have more difficulties in recruiting new workers, especially highly-qualified ones (OECD, 1997). Moreover, during job vacancy periods, it could be more problematic for very small firms to reallocate the workforce in order to perform the extra work previously done by the workers who have left (Pauly et al., 2002).

These are only some of the aspects that may shape the productivity effect of excess flows. Other potentially relevant dimensions of heterogeneity, related to the characteristics of the sending firms, are presented and discussed in Appendix D, where, using a sub-sample of the original data set, the roles of the industry of the sending firms and productivity gaps between the receiving and sending firms are explored.[2]

3. The Veneto case: labor mobility and employment protection legislation

Italy is traditionally a country with one of the strictest employment protection legislation (EPL) regimes in the world (Kugler and Pica, 2008).[3]

During the early 1980s, new workers could only be hired through open-ended contracts, except for a few very particular cases where firms could use temporary workers. Firms had to almost exclusively select blue-collar workers from the list of unemployed people rather than through a direct selection mechanism. Individual dismissals, for firms employing more than 15 workers, were only allowed for a "just cause". Dismissed workers had the right to appeal to a judge. If the judge ruled that the dismissal had been unfair, the firm was obliged to reinstate the worker and to pay any forgone wages (*tutela reale*, Law No. 300 of 1970, Article 18).

As part of a constant (if slow) trend toward a general liberalization and modernization of

[2] I am indebted to two anonymous referees for their helpful comments and suggestions on the construction of this conceptual framework.

[3] EPL refers to the laws that regulate hirings and individual and collective dismissals. This section does not discuss rules on collective dismissals, since firms that were closing down have been removed from the analysis.

the labor market, starting from the mid-1980s, EPL has been somewhat reduced, particularly on the entry side of the market (i.e., hirings). In 1984, the law introduced temporary work-training contracts (*contratti di formazione-lavoro*), aimed at encouraging firms to hire young workers. In 1987, temporary contracts also started to be regulated by sectoral collective agreements, and no longer only (and strictly) be the law. The early 1990s marked the full liberalization of the direct selection mechanism. From that moment on, until the early 2000s (i.e., throughout the observation window of this paper, 1995-2001), nothing changed, except for the introduction of the so-called *Pacchetto Treu*, which introduced additional (mild) deregulations on hirings in 1997 (e.g., it legalized the use of temporary work agencies and introduced the use of internship programs). Despite these liberalizations, the use of temporary contracts remained negligible until the early 2000s. Only from the end of 2001 did the standard open-ended contract lose importance in favor of the fixed-term contract. Indeed, in September 2001, Law No. 368 fully liberalized the use of temporary work: the mediation of sectoral collective agreements was no longer needed, and temporary work was admitted "for any technical, productive, organizational reason, or to replace temporarily absent workers".

In the considered period, Italy was thus characterized by a rigid EPL, concerning both the entry and exit sides of the labor market. Nevertheless, the degree of labor mobility (and excess flows) was in line with that of other countries generally known for their labor market flexibility, such as the UK (Contini et al., 2008). As part of such a national context, the Veneto labor market was even more mobile (Tattara and Valentini, 2003). The causes of such a stark contrast between law provisions and reality may be attributed to the diffusion of illegal practices, the frailty of the control system, and contradictions in the law (Contini et al., 2008). For instance, the "just cause" rule, which had the potential to sharply limit workers' dismissals (and consequently worker flows), was seldom applied. As Garibaldi et al. (2003) pointed out, only about 2% of the individual dismissals went to court *and* ended up with the reinstatement of the unfairly dismissed worker. In the vast majority of cases, the reinstatement was bypassed either legally, through extrajudicial settlements with severance pay, or illegally, in the form of forced resignations. Therefore, firms had a vast degree of freedom in hiring and dismissing workers.

4. Worker flows: definitions and formulas

Before moving on to the description of the empirical model and identification issues, it could be useful to clarify the concepts of worker flows used in this paper.

The employment level of firm i at time t is denoted as E_{it}. Net worker flows, denoted as NWF_{it}, refer to a change in the firm's employment. Therefore, $NWF_{it} = E_{it} - E_{it-1}$ is the net variation in the number of workers in the firm between t and $t-1$. Net worker flows can either be positive or negative (or null). When they are positive, the firm experiences net hirings (NH_{it}), that is, it is expanding its workforce. When net worker flows are negative, the firm experiences net separations (NS_{it}), that is, it is contracting its workforce. Therefore, $NH_{it} > 0$, if $NWF_{it} > 0$, otherwise $NH_{it} = 0$; similarly: $NS_{it} > 0$, if $NWF_{it} < 0$, otherwise $NS_{it} = 0$.

The total worker flows, denoted as TWF_{it}, are defined as the sum of hirings (H_{it}) and separations (S_{it}); therefore, $TWF_{it} = H_{it} + S_{it}$. The net change in employment is the difference between hirings and separations; therefore, $NWF_{it} = H_{it} - S_{it} = E_{it} - E_{it-1}$. The total worker flows can thus be written as $TWF_{it} = |NWF_{it}| + EWF_{it}$, where $|NWF_{it}| = NH_{it}$, if $NWF_{it} > 0$, and $|NWF_{it}| = NS_{it}$, if $NWF_{it} < 0$. The total inflows and outflows of workers can thus be split into a net component and an excess component. The net component of the total worker flows, $|NWF_{it}|$, represents those hirings or separations that serve to increase or decrease the workforce. The excess component, EWF_{it}, represents the hirings and separations that do not serve to increase or decrease the workforce but, on the contrary, reflect a churning activity. Excess flows thus reflect workers' replacements (Burgess et al., 2000a).[4]

A simple example can help to appreciate the different types of worker flows. Let us consider a firm with 10 employees at time $t-1$, which hires 2 workers and does not separate from any workers between $t-1$ and t. This implies that the number of workers at t is 12. This firm experiences 2 hirings plus 0 separations, and has a total worker flow equal to 2 (2 hirings + 0 separations) and an excess worker flow equal to 0. In this case, the firm's hirings serve only to expand its workforce. Let us now consider the same firm, with 10 employees at time $t-1$, but now hiring 4 workers and separating from 2 between $t-1$ and t. The number of workers at t is 12, as in the previous case. However, the firm now experiences 4 hirings plus 2 separations, and has a total worker flow equal to 6 (4 hirings + 2 separations) and an excess flow equal to 4 (6 − 2, where 6 stands for the total worker flow and 2 for the absolute value of the net flow). In the former case, the firm increases its workforce by 2 workers and undergoes only net inflows. In the latter case, the firm also increases its workforce by 2

[4]The concept of (and emphasis on) excess flows is relatively recent and was originally proposed 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 net worker flows (e.g., Dunne et al., 1989; Davis and Haltiwanger, 1992; Davis et al., 1996). It should be noted that different names are used in the literature for the same concepts. For instance, net worker flows are sometimes referred to as "job flows" (e.g., in Burgess et al., 2000a) or "net job creation" (e.g., in Davis et al., 1996). Net hirings and net separations are equivalent to "job creation" and "job destruction" in Burgess et al. (2000a). Excess worker flows are sometimes referred to as "excess worker turnover" (e.g., in Centeno and Novo, 2012) or "worker churning" (e.g., in Burgess et al., 2000a).

workers. Therefore, it also undergoes a net inflow of workers, as in the first case. However, it also experiences a worker flow that does not affect the employment level of the firm, and only indicates a replacement activity. In short, it replaces 2 of its workers with 2 new ones.

According to the work of Davis et al. (1996), I divided all the worker flows by the average level of employment, $N_{it} = \frac{E_{it} - E_{it-1}}{2}$. In this way, I defined, among the other variables, the net hiring rate ($NHR_{it} = \frac{NH_{it}}{N_{it}}$), the net separation rate ($NSR_{it} = \frac{NS_{it}}{N_{it}}$), and the excess worker flow rate ($EWFR_{it} = \frac{EWF_{it}}{N_{it}}$). The net hiring rate represents the number of workers, relative to the (average) workforce, who are hired by a firm to expand its workforce (i.e., the net inflow of workers). The net separation rate is the number of workers, relative to the (average) workforce, who separate from a firm to reduce the firm's employment level (i.e., the net outflow of workers). The excess worker flow rate gives the proportion of workers, relative to the (average) workforce, who separate from and join a firm to reallocate job matches while leaving the firm's employment level unaffected (i.e., the replacement of workers). It is of utmost importance to include the worker flows expressed in rates in the estimating equations to take into account the size of the firm and the relative weight of the worker flows (e.g., replacing a worker in a firm with 10 employees is different from replacing a worker in a firm with 100 employees).

What is defined (and identified) as net flows and excess flows depends on the level of analysis and the granularity of the data.[5] If the information at the task level were available, it would be possible to define any time a firm creates a new job task and hires a new worker to perform that task as job creation. Similarly, job destruction could be defined as any time a firm eliminates a given job task and separates from the worker who performed that task. On the contrary, excess flows could be defined as any time, for a given job task, the firm replaces the worker who performed that task with another worker, and, in this way, the job task is neither created nor destroyed. This means that, in such a case, a firm could simultaneously experience job creation and job destruction. For instance, citing an example from Davis et al. (1996), a firm may destroy 10 assembler jobs and create 10 robotics technician jobs. In practice, researchers do not have information at the job task level, and, as a result, generally define net and excess flows at a firm's workforce level, as specified in the above formulas (e.g., see Burgess et al., 2000a; Centeno and Novo, 2012; Davis et al., 1996). Worker flows have thus implicitly been defined on the basis of the notion of jobs being contractual relationships between workers and firms, that is, employer-employee matches, rather than bundles of tasks (Burgess et al., 2000a). With the available data, the simultaneous creation and destruction of job tasks in the example above would end in the count of excess flows, rather than in

[5]I would like to thank an anonymous referee for having raised this issue.

net hirings and net separations, respectively. Therefore, from the job task perspective, the result is that net flows are understated, and excess flows are overstated.[6]

5. Empirical model and identification

In order to assess the impact of net and excess flows on productivity, this paper uses the following augmented log-linear value-added Cobb-Douglas production function:

$$y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + \theta_1 NHR_{it} + \theta_2 NSR_{it} + \theta_3 EWFR_{it} + \gamma F_{it} + u_{it}. \tag{1}$$

The variables y_{it}, l_{it}, and k_{it} denote, respectively, the logarithms of value added and labor and capital usage of firm i at time t. The term α is the average productivity of the firms. The coefficients θ_1, θ_2, and θ_3 are the objects of interest in this paper, and express the impact of net inflows (NHR_{it}), net outflows (NSR_{it}), and excess flows ($EWFR_{it}$) on productivity, respectively. The term F_{it} is a vector of workforce and firm characteristics, which may influence productivity, and are included as controls. Finally, u_{it} is the error term, that is, the productivity level of firm i at time t that is left unexplained. It is useful to decompose this term into two parts. The first component, ω_{it}, is the firm's productivity level at t that is not observed by the econometrician, but is partly anticipated at $t-1$ and observed at t by the firm. The second component, ϵ_{it}, is an idiosyncratic error term that is uncorrelated with the regressors.

This empirical setting is generally called "augmented production function". It hinges on the idea that a firm's production output is influenced not only by standard inputs, such as the amounts of labor and capital, but also by other production factors, including the most diverse variables (e.g., workforce composition). It is commonly used in the literature that investigates how a firm's productivity responds to different variables (see, for instance, Parrotta and Pozzoli, 2012, for the case of worker inflows). The coefficients of interest (θ_1, θ_2, and θ_3, in this case) capture the impact of the regressors of interest on the firms' overall productive performance (i.e., their marginal contribution to production output). The discussion in Subsection 2.1 presents various mechanisms through which the different worker flows can affect productivity (e.g., those related to firm-specific human capital, tacit knowledge, reallocation dynamics, coordination inefficiencies). All of these mechanisms have the potential to affect both the intrinsic individual productivity of labor and a more firm-wide productive efficiency (for example, when job vacancies interfere with the effective usage of

[6]Defining worker flows at the job category level (e.g., high- *versus* low-skilled workers) instead of at the overall firm's workforce level is another way of refining the identification of net and excess flows (see the analyses presented in Subsection 7.2).

capital inputs). Disentangling these mechanisms and their impacts on the intrinsic productivity of labor *versus* firm-wide productivity is beyond the scope of this paper, which has a more limited, yet important, major task, that is, to assess the impacts of net and excess worker flows on the overall productive performance of firms, what coefficients θ_1, θ_2, and θ_3 in fact capture.[7]

Therefore, it is crucial to consistently estimate θ_1, θ_2, and θ_3. To this end, the empirical analysis needed to address some endogeneity issues.

The first issue is referred to as “simultaneity of inputs”. This is related to a well-known problem in the estimation of production functions, that is, that inputs are endogenous since they respond to the firm’s productivity level. For example, a highly productive firm will produce more, using more inputs. Similarly, a productivity improvement (e.g., due to the introduction of a process innovation) will lead to an increase in the usage of inputs. This makes inputs correlated with ω_{it}.

A second issue, but which is specific to this paper, is that worker flows are also endogenous. First, there is an omitted variable bias. Some firm characteristics, unobserved by the econometrician, influence both productivity and worker flows. A case in point is the quality of a firm’s management. Firms with good managers generally perform better. At the same time, worker flows are correlated with the quality of managers. Good managers likely lead firms to expansion, which results in positive net hirings. Similarly, firms under good management might experience lower levels of worker churning: good managers are arguably more able to choose the right workers and retain them. The same may hold for other unobserved

[7] Note that Equation (1) is coherent with modeling the production function of the firm as a union between a set of “standard inputs” (e.g., labor and capital) and a total factor productivity term, generally intended as a firm-wide productivity measure, which captures the level of production that is not explained by the standard inputs and which can be modeled with the relevant variables. In practice, a firm’s production function could first be modeled as $Y_{it} = A_{it} L_{it}^{\beta_l} K_{it}^{\beta_k}$, where Y_{it} is value added, L_{it} and K_{it} are labor and capital, and A_{it} is the total factor productivity term. It is then possible to model A_{it} as $A_{it} = exp\{\alpha + \delta_1 NHR_{it} + \delta_2 NSR_{it} + \delta_3 EWFR_{it} + \gamma F_{it} + u_{it}\}$. By using these two equations and taking logarithms, it is possible to obtain the augmented production function in Equation (1), which is the equation that has to be estimated in practice. Equation (1) is also coherent (and can be obtained by following some simple algebraic steps) with assuming that, instead of A_{it}, net inflows, net outflows, and churning workers enter additively a labor aggregate (together with workers who neither join nor separate from the firm, let us call them L_{it}^{stable}), but with a potentially different intrinsic labor productivity, that is, $L_{it} = L_{it}^{stable} + \gamma_1 NH_{it} + \gamma_2 NS_{it} + \gamma_3 EWF_{it}$ (see Hellerstein et al., 1999, for details). In this case, γ_1, γ_2, and γ_3 also capture the combination of both firm-wide productivity effects and the intrinsic differences in individual productivity of the different categories of workers (i.e., net inflows, net outflows, churning workers, and workers who stay). It should be noted that, were it to also be assumed that A_{it} is a linear function of net and excess flow rates, the separate effects of δ_i (i.e., firm-wide productivity effects) and γ_i (i.e., intrinsic differences in individual labor productivity) would not be identified in the context of log-linear Cobb-Douglas production functions. More general production functions might, in principle, allow the two separate effects to be identified. However, in the absence of hard data on the individual productivity of labor, as opposed to firm-wide productivity, this task is rather demanding and is not currently pursued in the literature.

firm characteristics, such as the degree of corporate social responsibility or the firm's culture (broadly defined), which can impact both productivity and worker flows. For instance, a firm that cares about its workers' welfare might be less prone to destructing job positions in a period of crisis, and may thus adopt labor hoarding strategies. This makes the different worker flows correlated with ω_{it}. Second, there is a problem of reverse causality. Worker flows affect productivity and, at the same time, they are influenced by productivity. In bad times (i.e., adverse productivity shocks), firms tend to decrease their workforce, while in good times (i.e., positive productivity shocks), they tend to expand their employment level. Moreover, the job-search theory (see, for example, Burdett and Mortensen, 1998) highlights that low-productivity (low-wage) firms are more likely than high-productivity (high-wage) firms to experience quits and, hence, a higher level of excess flows if they want to maintain a constant level of employment. Again, this makes worker flows correlated with ω_{it}.

In light of these endogeneity issues, an ordinary least squares (OLS) estimation of Equation (1) cannot consistently estimate the coefficients of interest (and the input elasticities, β_l and β_k). A fixed effects (FE) estimation cannot address the issue either, despite it removes the fixed firm-specific productivity level. The FE estimation would deliver consistent estimates only if omitted variable bias derived exclusively from unobserved time-invariant variables and inputs and worker flows did not respond to time-varying unobserved (by the econometrician) productivity levels, which is a somewhat unrealistic picture. Therefore, a method that can control for a more realistic, articulated framework is needed. The control function approach proposed by Ackerberg et al. (2015) (ACF, hereafter), which refines the methods initially developed by Olley and Pakes (1996) and Levinsohn and Petrin (2003), represents a solution to the problem of endogeneity. In a nutshell, ACF proposed using a firm's demand for intermediate inputs to proxy for the unobserved productivity level ω_{it}. The rationale behind this is that intermediate inputs can capture the unobserved productivity level. This is because firms can easily adjust their use of intermediate inputs in response to productivity shocks. This paper uses a modified version of the ACF method, recently developed by Lee et al. (2019) (ACF-FE, hereafter), which extends the ACF procedure by explicitly accounting for (and removing) firm fixed effects. This eliminates unobserved fixed firm heterogeneity. It also further increases the ability of the proxy variable to capture the (fluctuations in the) unobserved productivity level. Appendix A discusses the empirical model and the ACF and ACF-FE methods in detail.

6. Data

The data set used in this paper is the result of the matching of two separate data sources: the Veneto Workers History (VWH) and *Analisi Informatizzata delle Aziende Italiane* (AIDA).

The VWH data set was constructed by a team, led by Giuseppe Tattara, at the University of Venice, and it is based on the Italian Social Security System administrative data. It collects labor market histories for the 1975-2001 period of *each* employee who has worked for at least one day in the private sector (except for agriculture) in Veneto. It is composed of three parts. The first part is the so-called "worker archive", which collects personal information pertaining to a worker (e.g., gender, age, and place of birth). The second part is the "job archive", which contains information on the job held by the worker in a firm (e.g., hiring date, separation date, if applicable, contract type, and qualification). Finally, there is the third part, that is, the "firm archive", which provides information about the firm (e.g., the firm's national tax number, used as a firm identifier, location, establishment date, cessation date, if applicable, and industry). These features make VWH a longitudinal matched employer-employee data set.[8]

However, the VWH data set does not provide any financial details about firms, which are essential to estimate the production function in Equation (1). This information was thus retrieved from a different data source, AIDA. The AIDA data have been provided yearly since 1995 by the Bureau van Dijk and contain comprehensive information about the balance sheets of all (non-financial and non-agricultural) incorporated private firms in Italy with annual sales above 500,000 Euros. The variables in AIDA include revenues, profits, value added, the book value of tangible, intangible, and financial fixed assets, the expenditure on intermediate inputs, and the firm's national tax number.[9]

The firms' national tax number, used as a firm identifier in both VWH and AIDA, was adopted to match the job-year observations in VWH with balance-sheet information in AIDA. The match was conceived and conducted by David Card, Francesco Devicienti, and Agata Maida, who described the detailed procedure in Card et al. (2013). The result is a longitudinal matched employer-employee data set (referred to as "VWH-AIDA") for the 1995-2001 period, which collects the job histories of all the employees in all the (non-financial and non-agricultural) incorporated private Veneto firms with revenues higher than 500,000

[8]For a detailed description of VWH, see Tattara and Valentini (2010). There is also an online description of the data at `http://www.frdb.org/page/data/scheda/inps-data-veneto-workers-histories-vwh/doc_pk/11145`. However, it should be noted that the online version refers to a restricted version of the data, which only covers the Veneto provinces of Treviso and Vicenza.

[9]For a detailed description of AIDA, see `https://www.bvdinfo.com/en-gb/our-products/data/national/aida#secondaryMenuAnchor0`.

Euros.[10]

The output in the empirical analysis is measured with the value added; labor with the total number of full-time adjusted days worked during a year (VWH-AIDA does not provide information on the hours of work); and capital with the book value of tangible fixed assets. Intermediate inputs, which are used in the ACF and ACF-FE procedures to proxy for a firm's unobserved productivity level, are measured with the expenditure on raw materials, consumables, commodities, services, and other ancillary costs. Output, capital, and intermediate inputs are deflated according to the relevant price indexes (see Appendix B.1 for details).

The net hiring rate, net separation rate, and excess worker flow rate are measured on the basis of monthly-level information on the firm's workers (i.e., the data indicate the month in which they joined a firm and, if applicable, the month in which they separated from the firm). This is a unique feature of the VHW-AIDA data set, which allows a more precise computation of worker flows to be obtained, and also accounts for work relations that start and end within a year. Researchers, instead, typically obtain worker flow measures considering yearly-level information on the stock of workers in a firm, so that they know the list of workers of each firm at a given point in a year, but cannot reconstruct within-year worker flows. Appendix B.2 provides details on the measurement of worker flows.[11]

I undertook an essential cleaning of the data set, intended to remove unusable observations or observations representing particular cases that could bias the estimates (see Appendix B.3 for details). Since most of the firms (about 67%) belong to the manufacturing industry, I restricted attention to these firms to ensure a sufficient degree of sample homogeneity. Alternatively, it would be possible to preserve the full sample and perform separate analyses by industry. However, as the remaining firms are split among mining, trade, transportation and telecommunication, services, and construction industries, the sample size would have been too small to draw reliable conclusions for these sectors.

The final data set used in the empirical analysis was the firm-level collapsed version of the

[10]The coverage of the VWH-AIDA data set is the result of the intersection of the coverages of VWH and AIDA, respectively. Although VWH reports data for the 1975-2001 period, AIDA only starts from 1995. Therefore, the matched data set covers the 1995-2001 period. Other studies have used the VWH data set (alone or in the version matched with AIDA). A complete as possible list of published papers, using the VWH data set, is the following: Bartolucci et al. (2018); Battisti (2017); Card et al. (2013); Chan (2018); Devicienti et al. (2019); Gianelle (2014); Leonardi and Pica (2012); Serafinelli (2019); Tattara and Valentini (2010).

[11]The monthly-level structure of the data allows a whole series of workforce controls (e.g., the shares of females, migrants, part-timers) to be constructed and included in the estimating regressions by weighting the workers on a monthly basis. For example, in order to compute the share of females, a woman who is employed for only two months weighs six times less than a woman employed for the whole year.

(cleaned) matched employer-employee data set; it consists of 27,129 firm-year observations for 5,692 firms. Appendix B.4 provides general descriptive statistics on the data set, whereas here the discussion is concentrated on worker flows.[12]

Table 1 shows detailed descriptive statistics on the different worker flows, as defined in Section 4. The first panel of the table reports the flows in levels, that is, in terms of the number of workers (note that the average firm in the sample has 59 employees), whereas the second panel expresses flows in rates (i.e., as a proportion of the average employment). On average, firms increase their workforce by 2.9% in any given year. Some firms undergo job creation, while others undergo job destruction. The former expand their workforce by 6.6%, thus undergoing net inflows of workers, whereas the latter reduce their employment level by 3.8%, thus experiencing net outflows of workers. This implies that, on average, the absolute value of net flows is 10.4%. Coherently with what emerges from the literature (e.g., Burgess et al., 2000a), the sample firms undergo much higher total flows than net flows. On average, the firms hire a number of workers that is equivalent to as much as 22.9% of their average employment level and separate from a number of workers equal to 20.0% of this level. This results in total worker flows equal to 42.9% and excess flows equal to 32.5% (i.e., 42.9%−10.4%), thus pointing to 32.5%/2=16.3% of the average workforce being replaced with new workers in any given year.

Resorting to the complete VWH data set (i.e., that which covers all but agricultural employees of the Veneto private sector), I classified separated workers into three possible categories, depending on their subsequent presence in the (complete VWH) data set. The first category includes workers who made job-to-job transitions. They are separated workers who were observed to have started a new job in the same month of the separation or even in the month following the separation. The second category comprises separated workers who were not observed for a longer period of time (i.e., equal to or greater than two months after the separation) or who were no longer observed in the data (but who were not around retirement age). The third category collects separated workers who were no longer observed in the data and who were around retirement age. I argue that job-to-job transitions most likely represent voluntary quits (of workers willing to change jobs). A worker who voluntarily leaves his/her job (and wants to continue working) likely starts a new job in a short period of time. The workers who dropped out of the sample around retirement age most likely retired. Although workers who exited the sample for a relatively long time or permanently (and were not around retirement age) could have been dismissed, it is somewhat risky to apply this interpretation *tout court*. Such an event is also compatible with withdrawals from the labor

[12]For the sake of brevity, I have often used the term "firms" to indicate "firm-year observations".

market (e.g., to take care of family, for illness reasons), transfers to another region/country or the public sector, or even death.

As shown in the third panel in Table 1, on average, job-to-job transitions represent a substantial fraction of a firm's separations (40.2%), in line with the idea that many workers voluntarily leave their jobs. Coherently with the fact that workers retire only once in a lifetime, on average, the separations of workers around retirement age who dropped out of the sample represented only 4.4% of a firm's total separations. Finally, separated workers who exited the sample for a relatively long time or permanently (and were not around retirement age) were, on average, the majority of a firm's separated workers (55.5%). Even though this category includes a variety of situations, such a large number suggests that dismissals may not be uncommon, coherently with the fact that it was possible for Italian firms to easily circumvent the strict EPL on dismissals.

Finally, the last panel in Table 1 reports the relevant worker flow rates for low- and high-skilled workers separately. It emerges that low-skilled workers, including blue-collar workers and apprentices, are the most replaced (the excess worker flow rate is equal to 0.331). Instead, high-skilled workers, referring to white-collar workers and managers, are replaced 44% less (the excess worker flow rate is equal to 0.187).

7. Results

7.1. Main results: worker flows and firm productivity

What are the overall productivity impacts of net inflows, net outflows, and excess flows? As discussed in Subsection 2.1, in each of the three cases (i.e., net hirings, net separations, and excess flows), some mechanisms push toward a positive impact and others toward a negative one. Moreover, do excess flows have an inverted U-shape impact on productivity? This subsection presents the empirical results for these questions.

Table 2 reports the results of the ACF-FE estimation of Equation (1), in its linear form (first column), including a quadratic term for the excess worker flow rate (second column), and allowing for differential impacts on the basis of different excess flow levels (piecewise linear regression, third column). The vector of controls (F_{it}) collects a large variety of worker and firm characteristics, including the shares of females, migrants, part-timers, and temporary workers, and the workforce distribution across age and job categories. It also includes dummy variables for firm size, year, and year interacted with industry and province, respectively. The ACF-FE estimation also removes firm fixed effects, thereby eliminating unobserved fixed firm heterogeneity. The estimates report firm-level cluster robust bootstrapped standard errors.[13]

It emerges, from the estimation results (first column in Table 2), that the productivity impact of worker flows is differentiated according to the type of worker flow being considered. Net hirings have a positive and significant impact on productivity, while net separations have a negative and significant effect on it. Positive mechanisms, associated with the net inflows of workers, thus prevail over negative ones. Any possible inefficiencies, due to the initial stages of the learning process, are more than offset by the gains resulting from the inflows of new knowledge. Instead, the negative forces associated with the net outflows of workers prevail over positive ones. The loss of knowledge, which likely has a sizable firm-specific component, damages productivity and, on the whole, the fact that underperforming workers might separate from a firm does not compensate for this effect.

When it comes to excess worker flows, the main object of interest in this paper, their estimated overall impact on productivity is positive and significant. An increase of 10 percentage points in the share of replaced workers (i.e., 20 percentage points in the excess worker flow rate) was estimated to raise productivity by 1.05%, that is, $(e^{0.052*0.200} - 1) * 100$. Such an increase, for the average firm with about 59 workers, means replacing about 6 more workers.[14] On the whole, excess flows are thus beneficial for firm productivity. The reallocation process of employer-employee matches, which is pervasive, appears to succeed in its intent of allowing firms to find better matches. Overall, the loss of the (firm-specific) knowledge of separated workers, the learning process of replacement workers, and possible coordination inefficiencies, due to job vacancy periods, are more than offset by the gains stemming from the better employer-employee matching that is reached.

The second column in Table 2 adds a quadratic term in the excess worker flow rate to test the presence of an inverted U-shape impact. The estimated coefficient associated with the excess worker flow rate is positive, higher than in the basic model (0.082), and significant. The estimated coefficient associated with the quadratic term is negative (-0.044) and significant. Therefore, workers' replacements are beneficial up to a certain extent, but they become harmful when there are too many. Notably, the impact was predicted to be positive up to when the excess worker flow rate is very high (equal to 0.932). The excess worker flow rate is below the optimum for about 99% of the firms. Increases in excess flows

[13] Appendix C shows OLS, FE, and ACF estimates for a version of Equation (1) that includes both linear and quadratic terms in the excess worker flow rate (our reference model, see below). All the other results presented in the paper refer to ACF-FE estimations.

[14] The estimated elasticities of labor and capital are 0.873 and 0.091, respectively, values that are comparable with those found in the literature on the estimation of value-added production functions (see, for instance, Van Biesebroeck, 2007). Both estimates are significantly different from zero at any conventional level.

are thus beneficial for most firms, and passing from a zero level of workers' replacements to the optimal level was estimated to boost productivity by as much as 3.89%.

For robustness purposes, the third column in Table 2 examines whether the impact of excess flows is different depending on the magnitude of the firm's replacement activity. First, I constructed three dummy variables that indicated whether the level of the excess worker flow rate in a firm was low (below 0.20), medium (between 0.20 and 0.60), or high (above 0.60). I then interacted these three dummy variables with the actual excess worker flow rate in the firm (i.e., a continuous variable). Consistently with the detected inverted U-shape impact, the effect of excess flows is positive, large, and strongly significant when a firm experiences just a few replacements. It is still positive and significant, though smaller, when the firm has a medium level of excess flows. When a company experiences a high degree of excess flows, the impact becomes negative, even if small in magnitude and not significant.[15] This finding sheds further light on the fact that workers' replacements are not beneficial to firm productivity when a high proportion of the workers is replaced with new employees. Nevertheless, consistently with the results associated with the quadratic model, whereby negative effects of excess flows were estimated to emerge at very high levels, a significantly negative impact does not emerge even when excess flows are substantial (i.e., above 60%).[16]

7.2. Additional results: the contingency role of worker- and firm-level characteristics

The results so far suggest that net inflows of workers enhance productivity, while net outflows of workers damage it. Above all, they show that replacing workers is beneficial for firm productivity, except when the excess flows are very high. As discussed in Subsection 2.2, the diverse mechanisms through which worker flows impact productivity likely play different importance roles, depending on several worker- and firm-level aspects, thereby resulting in differentiated effects. These aspects include the nature of replacements, the categories of workers moving in and out of a firm, in relation to occupation and tenure, and the firm's technology, location, age, and size. The present subsection explores how the productivity effects of the different worker flows vary across these contingency factors.

As the emphasis of the paper is on excess flows, the discussion of these results is focused on these flows. Moreover, the positive impact of net inflows and the negative impact of net outflows were confirmed in all the analyzed worker and firm categories, albeit with varying intensities. On the contrary, the productivity effect of excess flows was more heterogeneous.

[15] It should be noted that different levels for these thresholds (e.g., related to percentile distributions and other arbitrary cut-offs) were tested, but no substantial differences in the results were observed.

[16] Appendix D presents robustness checks which were pursued to control for the productivity levels of the sending firms. As suggested by an anonymous referee, whom I warmly thank, if the productivity levels of the sending and receiving firms are correlated, the regression estimates could be confounded.

Given the existence of the non-linearities detected for the impact of excess flows on productivity (and their theoretical relevance), all the following estimates consider a version of Equation (1) with both linear and quadratic terms in the excess flows.

Table 3 reports the results when the impact of the excess flows is allowed to vary according to the nature of the replacements. To this end, I estimated a modified version of Equation (1), which interacts the excess worker flow rate (and its square) with the relative weights of the different types of separated workers (i.e., those who make job-to-job transitions, those who drop out of the sample for longer periods or permanently and are not around retirement age, and those who drop out of the sample permanently and are around retirement age). These relative weights were measured as the ratios between each category of separated workers and the total number of separated workers in a firm (see the third panel in Table 1). For instance, the relative weight of the job-to-job transitions is a proportion of the job-to-job transitions out of the total number of a firm's separations.

First, the results indicate that the impact of replacing separated workers who make job-to-job transitions has an inverted U-shape (as for the general case, the estimates point to beneficial effects for almost all the support of the excess flow distribution). When the total number of a firm's separations is attributable to job-to-job transitions (i.e., their relative weight is 1), an increase from none to 10% of replaced workers was estimated to raise productivity by 2.20%. Although good workers, that is, those with good matches from the firm's viewpoint, may voluntarily leave (e.g., they "are poached" by higher-productivity firms), this finding indicates a different story. Those workers who voluntarily leave generally seem to be bad workers, that is, those with bad matches from the firm's viewpoint. Reallocation dynamics, stemming from the re-evaluations of matches by workers, seem to enhance a firm's productive performance by releasing the firm from sub-optimal matches and allowing it to obtain better employer-employee combinations. The meta-analysis conducted by McEvoy and Cascio (1987) provides further support to this interpretation. According to their study, poor performers are, in fact, much more likely to voluntarily quit than good performers.

Second, the results show a sizable positive and significant impact (0.293 in the linear term and 0.134 in the quadratic term) when the firm replaces separated workers around retirement age who are no longer observed in the data. This provides evidence that the higher productivity levels of younger replacement workers more than offset the loss of firm-specific knowledge accumulated by retiring workers.[17]

[17]Between 1995 and 2001, the retirement age decreed by law differed, depending on the number of years of work, and between men and women. According to OECD, the average retirement age in Italy in that period was about 57 years for women and 59 for men. A 55-year threshold was here selected. However, different threshold levels, of up to 60 years of age, were tested, but no significant differences were observed in the

As previously discussed, although firms arguably dismiss (very) underperforming workers, dismissing workers might result to be a double-edged sword, if bureaucratic rigidities and other obstacles are at stake. The estimated impact of replacing separated workers who drop out of the sample for a relatively long time or permanently (and are not around retirement age) has an inverted U-shape. However, neither the linear term nor the quadratic term associated with excess flows are significant, thereby suggesting that the rigidities pertaining to dismissals might be relevant. However, this interpretation should be considered with caution. This category of separated workers includes workers who may separate from a firm for other reasons (e.g., because of family commitments or transfers to other regions/countries or to the public sector).[18]

Table 4 estimates whether worker flows have differentiated productivity impacts for high- and low-skilled workers. The results indicate that occupation is indeed a crucial contingent factor for the productivity impact of excess flows. As expected, the benefits associated with excess flows stem from the replacements of low-skilled workers. Although a significant inverted U-shape relationship emerges for these workers, detrimental effects arise outside the support of the excess flow distribution, that is, above 150%). Excess flows of high-skilled workers instead have a negative effect (a negative sign in both the linear and quadratic terms), albeit small and not significant. On the one hand, the firm-specific knowledge accumulated by high-skilled workers appears to play a more prominent role than that of low-skilled workers. On the other hand, high-skilled workers are generally less easily substituted than low-skilled workers, because the pool of workers with the required bundle of specific skills is more limited, thereby preventing beneficial reallocation dynamics to emerge.[19]

Table 5 reports the results pertaining to when the impact of excess flows was allowed to be contingent upon the departing workers' tenure. First, separated workers were classified as being high- or low-tenure employees on the basis of whether their tenure was above or below the median tenure in the separated workers' tenure distribution. Then, for each firm, the proportions of separated workers with high and low tenure were computed and interacted

results.

[18]In order to attenuate these concerns, a different identification strategy for dismissals was tested, whereby only the workers who reappeared in the sample (i.e., were employed in any non-agricultural Veneto firm) within 6 months from separation were included. Although this strategy has the disadvantage of not considering dismissed workers who end up in long periods of unemployment, it excludes workers who are not dismissed, but are separated from the firm for other reasons, such as withdrawals from the labor market or transfers to other places outside Veneto. However, the non-significant inverted U-shape impact remains.

[19]It should be noted that this result is coherent with the theoretical framework presented by Siebert and Zubanov (2009), whereby "low-involvement" work systems (which are more common among low-skilled employees) are associated with inverted U-shape effects, whereas "high-involvement" work systems (more frequent among high-skilled workers) are predicted to feature a negative impact.

with the excess worker flow rate (and its square). As predicted, the benefits associated with excess flows were substantially higher when the departing workers' tenure was lower. In this case, the estimates pointed to an inverted U-shape impact of excess flows that was substantially higher than that predicted when the departing workers' tenure was higher (which nonetheless emerged). The losses of substantial levels of firm-specific human capital and of the tacit knowledge associated with high-tenure workers thus lower the benefits that firms can obtain from excess flows.

Subsection 2.2 discussed the fact that the impact of excess flows likely varies across different types of firm-level aspects, including technology, location, age, and size. Table 6 reports the results for this. Here, the version of Equation (1) with both linear and quadratic terms in excess flows is estimated separately for each category of companies (i.e., these analyses were conducted on split samples).

The first panel in the table reports the results separately for high- and low-tech firms. In order to classify high- and low-tech companies, I adopted the classification proposed by OECD, based on R&D intensities. Among others, high-tech industries include aircraft and spacecraft, chemicals, automotive, and medical instruments (for a detailed list, see the footnote in Table 6). In the sample, 12.9% of the firms are high-tech. The benefits associated with excess flows appear to be accentuated for high-tech firms. In such companies, the acquisition of new knowledge from hirings thus seems to overcompensate to a great extent for losses of the (perhaps outdated) knowledge of departing workers. Passing from a zero to 10% level of workers' replacements in high-tech firms was estimated to raise productivity by 3.15%. Although statistically significant, the impact of the same increase in workers' replacements for low-tech firms is considerably lower (1.30%). Adverse effects linked, for instance, to staffing issues, thus appear to have a greater weight in such companies.

The second panel in Table 6 reports the results separately for firms located in industrial districts and firms located outside these districts. The industrial districts were identified from the list given by the *Osservatorio Nazionale dei Distretti Industriali* (the Italian monitoring center of industrial districts). Among others, they include the eyewear district in Belluno; the ceramic, porcelain, and artistic glass district in Vicenza; the artistic glass district in Murano (Venice); the wood and furniture district, which covers the whole region; the footwear district in Verona; and the mechatronic and innovative mechanical technology district across Veneto.[20] As much as 50.6% of the companies in the sample belong to industrial districts, which is consistent with their widespread diffusion in Veneto. The estimated impact, of an inverted U-shape, on firms located in an industrial district is significant and

[20]For a detailed list, see `http://www.osservatoriodistretti.org/category/regione/Veneto`.

substantially larger than the overall effect (0.153 and -0.071 on the linear and quadratic terms, respectively). Passing from zero to 10% replacements was estimated to raise the productivity of these firms by about 2.81%. Conversely, the impact on firms that do not belong to industrial districts is much smaller and not significant. Highly-specialized labor market pools and high interconnections among the sending and receiving firms, which are typical of industrial districts, thus appear to greatly enhance the potential for reallocation dynamics to foster productivity.

The third panel in Table 6 shows the estimated impact of excess flows contingent upon firm age by splitting the sample between young and old firms. Young firms are defined as those whose panel-average age is lower than or equal to 5 years. Accordingly, old firms are defined as those above 5 years of (panel-average) age. About 9.8% of the firms in the sample are classified as young. According to the estimates, the impact of workers' replacements on young firms is negative (-0.044 and -0.034 in the linear and quadratic terms, respectively), even though not statistically significant. This points to a predominance of harmful mechanisms behind excess flows for the case of young firms. When a firm is in its infancy, workers' replacements could substantially hinder the consolidation of the firm's routines and processes. Old firms, instead, experience the typical inverted U-shape impact associated with excess flows, which is slightly higher than the average impact, thus suggesting that firm age is, in fact, a relevant dimension of differentiation.[21]

Finally, the last panel in Table 6 reports the results separately by firm size, differentiating between very small and larger firms. Very small firms are defined as those whose panel-average number of employees is less than 15. About 12.3% of the companies in the sample are very small. According to the estimates, the benefits associated with excess flows disappear for very small firms. The estimated impact for them is, in fact, very small in magnitude (+0.016 and -0.022 for the linear and quadratic terms, respectively) and not significant. On the contrary, the estimated impact for larger firms has the typical inverted U-shape, thus pointing to substantial benefits across large parts of the excess flow distribution. This suggests that the more severe difficulties involved in recruiting replacement workers and the higher coordination problems associated with job vacancy periods for very small firms significantly hinder the beneficial mechanisms of excess flows, which instead clearly emerge for larger firms.[22] Interestingly, very small firms were estimated to experience no benefits

[21]I performed the estimation using different threshold levels, namely, below 4, 6, and 7 (panel-average) years of age. The results are similar to those of the 5-year threshold. Further decreasing the threshold drastically reduced the size of the group of young firms. For instance, only 2.8% of the firms had a (panel-average) age below 3 years.

[22]I performed the estimation using alternately different threshold levels, namely below 12, 13, and 14 (panel-average) employees. The results are similar to those of the 15-employee threshold.

from excess flows, even though the EPL concerning dismissals was much less binding for them. On the contrary, larger firms, subjected to a more rigid EPL, were estimated to gain a great deal from reallocation dynamics. This highlights the fact that EPL, although rigidly designed, was often circumvented by firms that generally needed positive excess flows to perform better.

8. Conclusions

This paper has investigated the productivity impact of workers' movements in and out of a firm, distinguishing between three structurally distinct worker flows, namely, net inflows, net outflows, and excess flows. The analysis used a matched employer-employee data set, which allowed detailed worker flow dynamics of the manufacturing firms in the Veneto region to be reconstructed over the 1995-2001 period. Endogeneity issues, stemming from unobserved heterogeneity and simultaneity, were addressed by using state-of-the-art semi-parametric methods, based on the use of intermediate inputs to proxy for a firm's unobserved productivity level.

While net inflows and net outflows derive from a firm's evaluation of its optimal employment level and represent necessary events to attain this level, excess flows are, in this sense, not necessary. These flows refer to hirings and separations that do not increase or decrease the workforce, but instead entail the replacement of some workers with new ones. These excess flows are the outcome of a continuous re-evaluation process, by firms and by workers, of the quality of matches. Although this paper has assessed the productivity impact of all of these flows, it has predominantly focused on excess worker flows, that is, the most prominent (and compelling) feature of worker flows.

Firms in Veneto in the 1990s provided an excellent case study. In that period, the Veneto region was characterized by nearly full employment, and it was one of the wealthiest regions in Italy, on par with other industrialized European countries, such as Germany. Excess worker flows arose from pure reallocation dynamics, aimed at searching for more productive matches rather than from pathological job destruction in (specific sectors of) the economy. Despite a strict EPL, Italy (and particularly Veneto) was characterized by a high degree of labor mobility, similar to that of other countries and regions known for their labor market flexibility, such as the UK. Such a dynamic context allowed the effects of reallocation dynamics to be fully captured. The widespread diffusion of industrial districts in Veneto also made it possible to study how the productivity impact of reallocation dynamics unfolded in such a particular industrial setting, which, to various degrees, also characterizes many other industrialized countries and regions (e.g., the Ruhr district in Germany). Furthermore, the fact that the VWH-AIDA data covered a large part of the population of employees and firms made it possible to study the reallocation dynamics of the region considering a self-contained labor market.

Net hirings were estimated to have a positive impact on productivity, thus suggesting that the inflows of new knowledge are of benefit to a firm. Net separations were found to be harmful for productivity, thereby pointing to the fact that outflows of (firm-specific) knowledge damage the productive performance of a firm. Excess flows were found to have an inverted U-shape impact on firm productivity, but were found to be beneficial for large parts of the excess flow distribution. The reallocation dynamics at the core of excess flows, thus, appeared to succeed in allowing firms to find more productive employer-employee matches. Notably, widespread positive effects linked to excess flows emerged, even though there were solid bases for harmful mechanisms to materialize, related, for instance, to the losses in (firm-specific) human capital of the departing workers and to the adjustment phases during the learning processes of the replacement workers, as well as to possible coordination and logistic inefficiencies during job vacancy periods.

The results of this paper have broad managerial and policy implications.

In general, firms should perceive excess flows as an opportunity for productivity enhancement. They should consider that workers' replacements offer the possibility of finding more productive matches, which, in a world of imperfect information, often prove to be sub-optimal. The results also indicate that the excess flows that are not fully controllable by a firm (i.e., those stemming from resignations) are those associated with a higher potential to benefit productivity. Those workers who voluntarily leave a company generally appear to be badly-matched workers. Firms should thus consider quits as a good thing: a worker who judges the match a bad match and leaves the firm is generally right. Moreover, managers should consider that excess flows allow a firm to acquire new knowledge and enlarge its network of connections, which can substantially overcompensate for the losses of human and social capital pertaining to the separated workers. These considerations are especially important for managers who are in charge of high-tech firms and firms located in industrial districts, which were found to benefit substantially from excess flows. The inflows of new knowledge about specific technologies and the practices of sending firms, which likely operate in the same market/district, are precious assets for such firms and substantially overcompensate for the adverse mechanisms associated with workers' replacements.

However, managers should be careful that excess flows do not become dysfunctional for the firm. This happens when workers' replacements involve a substantial share of the firm's employment (i.e., above about 47% of the workforce). At such high levels, harmful effects associated with workers' replacements become preponderant. The damages arising from the loss of firm-specific human capital of separated workers, from the long learning processes of newly hired workers, and from the coordination and logistic problems that emerge during job vacancy periods are the underlying mechanisms of such harmful effects. In these (borderline) cases, managers should invest in more effective recruitment practices and do their best to create working environments in which employees want to remain. Similarly, they should pay more attention to excess flows that involve high-skilled workers and when they are in charge of young or very small firms, as the positive effects were found to disappear in those cases. Successfully replacing high-skilled workers is a difficult task: firm-specific human capital plays a fundamental role, and finding suitable workers with the required bundles of skills is difficult. Young firms need to acquire a certain experience on the market and to enhance their understanding of the internal processes before reallocation dynamics exhibit their positive effects. Very small firms instead suffer from more limited access to the labor market pool and substantial coordination inefficiencies emerging during job vacancy periods. However, it is crucial to stress that even though the excess flows of such workers and in such firms do not boost productivity, the estimates suggested that they were *never* significantly detrimental to productivity.

Policy makers in Italy have traditionally designed laws to limit worker mobility: in the 1990s, and also today, albeit to a lesser extent, Italy was one of the countries with the strictest EPL. The results of this paper call for a reconsideration of this approach, which, to varying degrees, is typical of many European countries. First, apart from increasing the productivity levels of single firms, on an aggregate basis, a certain number of excess flows allows the entire economy to be more productive. Moreover, even though single firms reward knowledge inflows, and not outflows, excess flows allow, on an aggregate basis, knowledge to spread over the whole economy, which is a crucial determinant for the growth of aggregate productivity. Second, reallocation dynamics may also benefit workers, as obtaining a better match can also be an advantage for a worker, who may receive higher wages, better career prospects, and greater gratification from work. This applies, in particular, to policy makers who intervene in economies characterized by a high density of high-tech firms and by a division of the territory into industrial districts. Policy makers could also consider launching programs to help managers who are in charge of firms with dysfunctional rates of workers' replacements to implement more effective recruiting schemes and create better working environments.

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Table 1: **Summary statistics for the worker flows**

Variable	**Mean**	**Std. dev.**
Net worker flows (NWF_{it})	1.429	13.372
Absolute value of the net worker flows ($\|NWF_{it}\|$)	4.808	12.559
Of which:		
Net hirings (NH_{it})	3.119	10.690
Net separations (NS_{it})	1.690	7.348
Hirings (H_{it})	11.624	23.854
Separations (S_{it})	10.194	19.942
Of which:		
Workers who make job-to-job transitions	3.973	7.346
Workers who drop out of the sample for a relatively long time or permanently (and are not around retirement age)	5.760	12.653
Workers who drop out of the sample around retirement age	0.461	1.979
Total worker flows (TWF_{it})	21.818	41.888
Excess worker flows (EWF_{it})	17.009	33.763
Net worker flow rate ($NWFR_{it}$)	0.029	0.166
Absolute value of the net worker flow rate ($\|NWFR_{it}\|$)	0.104	0.132
Of which:		
Net hiring rate (NHR_{it})	0.066	0.106
Net separation rate (NSR_{it})	0.038	0.106
Hiring rate (HR_{it})	0.229	0.165
Separation rate (SR_{it})	0.200	0.149
Of which:		
Rate of workers who make job-to-job transitions	0.082	0.081
Rate of workers who drop out of the sample for a relatively long time or permanently (and are not around retirement age)	0.112	0.107
Rate of workers who drop out of the sample around retirement age	0.007	0.017
Total worker flow rate ($TWFR_{it}$)	0.429	0.267
Excess worker flow rate ($EWFR_{it}$)	0.325	0.222
*Different types of separations**		
Proportion of separated workers who make job-to-job transitions	0.402	0.269
Proportion of separated workers who drop out of the sample for a relatively long time or permanently (and are not around retirement age)	0.555	0.269
Proportion of separated workers who drop out of the sample around retirement age	0.044	0.113
Low-skilled versus *high-skilled workers***		
$EWFR_{it}$ of low-skilled workers	0.331	0.300
NHR_{it} of low-skilled workers	0.076	0.136
NSR_{it} of low-skilled workers	0.044	0.122
$EWFR_{it}$ of high-skilled workers	0.187	0.326
NHR_{it} of high-skilled workers	0.083	0.181
NSR_{it} of high-skilled workers	0.052	0.163
Firm-year observations: 27,129		
Firms: 5,692		

Source: the VWH-AIDA data set

**I removed the firms that did not undergo any separations, which amounted to 1,062, since it was not possible to calculate the proportions of the separated workers in each condition.*

***I first computed the worker flows at the qualification level, that is, for blue-collar workers, apprentices, white-collar workers, and managers. I then summed the worker flows of the blue-collar workers and apprentices (white-collar workers and managers) to obtain the worker flows of the low-skilled workers (high-skilled workers). Finally, I obtained the rates by dividing the worker flows of the low- and high-skilled workers by the relevant employment levels.*

Table 2: **Worker flows and firm productivity: the main results**

Dependent variable: y_{it}						
	Linear model		**Quadratic model**		**PLR***	
l_{it}	+0.873***	(0.053)	+0.861***	(0.055)	+0.863***	(0.048)
k_{it}	+0.091***	(0.008)	+0.096***	(0.011)	+0.094***	(0.014)
$EWFR_{it}$	+0.052***	(0.012)	+0.082***	(0.021)		
$EWFR_{it}$ - squared			−0.044*	(0.023)		
$EWFR_{it}$ ∗ firm with low $EWFR_{it}$ (<0.20)					+0.140***	(0.038)
$EWFR_{it}$ ∗ firm with medium $EWFR_{it}$ ($\geq$0.20 $\wedge$ $\leq$0.60)					+0.024**	(0.010)
$EWFR_{it}$ ∗ firm with high $EWFR_{it}$ (>0.60)					−0.003	(0.013)
NHR_{it}	+0.187***	(0.054)	+0.148***	(0.023)	+0.108***	(0.035)
NSR_{it}	−0.158**	(0.077)	−0.190**	(0.078)	−0.209**	(0.085)
Share of females	−0.048	(0.054)	−0.050	(0.053)	−0.049	(0.054)
Share of migrants	+0.036	(0.063)	+0.035	(0.063)	+0.036	(0.063)
Share of workers under 25	−0.081	(0.059)	−0.081	(0.059)	−0.088	(0.059)
Share of workers aged between 25 and 34	+0.009	(0.052)	+0.008	(0.052)	+0.004	(0.053)
Share of workers aged between 35 and 49	+0.041	(0.048)	+0.041	(0.048)	+0.037	(0.048)
Share of part-timers	+0.053	(0.072)	+0.052	(0.072)	+0.046	(0.072)
Share of temporary workers	−0.024	(0.039)	−0.024	(0.039)	−0.021	(0.039)
Share of blue-collar workers	+0.128	(0.090)	+0.128	(0.090)	+0.134	(0.090)
Share of white-collar workers	+0.009	(0.090)	+0.009	(0.090)	+0.006	(0.090)
Share of apprentices	−0.028	(0.103)	−0.024	(0.102)	−0.017	(0.103)
Firm fixed effects	yes		yes		yes	
Size dummies	yes		yes		yes	
Year dummies	yes		yes		yes	
Year∗industry dummies	yes		yes		yes	
Year∗province dummies	yes		yes		yes	
					Firm-year observations: 27,129	
					Firms: 5,692	

Source: the VWH-AIDA data set

*Estimation method: ACF-FE. Firm-level cluster robust bootstrapped standard errors in parentheses; ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively. The reference group for the shares of blue-collar workers, white-collar workers, and apprentices is the share of managers; for the age distribution, it is instead the share of workers over 50. The size dummies consist of 4 dummies (one for each size category, as defined in Table A.2); the industry dummies, interacted with the year dummies, consist of 114 dummies (one for each 3-digit Ateco 1991 sector); the province dummies, interacted with the year dummies, consist of 7 dummies (one for each Veneto province). Excess worker flow rates below 0.20, between 0.20 and 0.60, and over 0.60 cover around 33%, 54%, and 13% of the firms, respectively.*

* *PLR stands for "piecewise linear regression".*

Table 3: **The impact of excess flows depending on the reason for the separation**

$EWFR_{it}$ $*$ proportion of separated workers who make job-to-job transitions	$+0.121^{***}$	(0.031)
$EWFR_{it}$ - squared $*$ proportion of separated workers who make job-to-job transitions	-0.061^{*}	(0.036)
$EWFR_{it}$ $*$ proportion of separated workers who drop out of the sample for a relatively long time or permanently (and are not around retirement age)	$+0.056$	(0.068)
$EWFR_{it}$ - squared $*$ proportion of separated workers who drop out of the sample for a relatively long time or permanently (and are not around retirement age)	-0.021	(0.042)
$EWFR_{it}$ $*$ proportion of separated workers who drop out of the sample around retirement age	$+0.293^{**}$	(0.140)
$EWFR_{it}$ - squared $*$ proportion of separated workers who drop out of the sample around retirement age	$+0.134^{*}$	(0.076)
NHR_{it}	$+0.115^{**}$	(0.054)
NSR_{it}	-0.257^{***}	(0.073)
		Firm-year observations: 25,616
		Firms: 5,649

Source: the VWH-AIDA data set

Estimation method: ACF-FE. I removed the firms that did not undergo any separations, which amounted to 1,062, since it was not possible to calculate the proportions of separated workers in each condition. The main effects of the proportions of separated workers in each condition were included among the set of endogenous regressors. These estimates include the same set of controls used in Table 2. For other information, see the footnote to Table 2.

Table 4: **The impact of worker flows for low- and high-skilled workers**

$EWFR_{it}$ of low-skilled workers	$+0.099^{***}$	(0.018)
$EWFR_{it}$ - squared of low-skilled workers	-0.033^{***}	(0.010)
$EWFR_{it}$ of high-skilled workers	-0.014	(0.011)
$EWFR_{it}$ - squared of high-skilled workers	-0.008	(0.008)
NHR_{it} of low-skilled workers	$+0.069^{***}$	(0.024)
NHR_{it} of high-skilled workers	$+0.140^{***}$	(0.040)
NSR_{it} of low-skilled workers	-0.152^{***}	(0.052)
NSR_{it} of high-skilled workers	-0.260^{**}	(0.120)
		Firm-year observations: 26,696
		Firms: 5,590

Source: the VWH-AIDA data set

Estimation method: ACF-FE. I removed the firms that did not employ any low- or high-skilled workers, which amounted to 397, since it was not possible to compute the worker flow rates separately for low- and high-skilled workers. For definitions of the high- and low-skilled workers and for the computation of the relative worker flows, see the footnote to Table 1. These estimates include the same set of controls used in Table 2. For other information, see the footnote to Table 2.

Table 5: **The impact of excess flows depending on the departing workers' tenure**

$EWFR_{it}$ $*$ proportion of separated workers with a low tenure	$+0.146^{***}$	(0.045)
$EWFR_{it}$ - squared $*$ proportion of separated workers with a low tenure	-0.066^{***}	(0.021)
$EWFR_{it}$ $*$ proportion of separated workers with a high tenure	$+0.048^{**}$	(0.019)
$EWFR_{it}$ - squared $*$ proportion of separated workers with a high tenure	-0.020^{*}	(0.012)
NHR_{it}	$+0.122^{***}$	(0.033)
NSR_{it}	-0.216^{***}	(0.079)
		Firm-year observations: 25,616
		Firms: 5,649

Source: the VWH-AIDA data set

Estimation method: ACF-FE. I removed the firms that did not undergo any separations, which amounted to 1,062, since it was not possible to calculate the proportions of separated workers by tenure. The main effects of the proportions of separated workers by tenure were included among the set of endogenous regressors. Separated workers with low and high tenures are classified as those with a tenure below and above the median tenure in the separated workers' tenure distribution. The firm-level average proportions of separated workers with a low and a high tenure were 0.350 and 0.650, respectively. These estimates include the same set of controls used in Table 2. For other information, see the footnote to Table 2.

Table 6: **The impact of worker flows for different types of firms**

High-tech firms versus *low-tech firms*		
High-tech firms		
$EWFR_{it}$	+0.159**	(0.064)
$EWFR_{it}$ - squared	−0.020*	(0.012)
NHR_{it}	+0.510***	(0.080)
NSR_{it}	−0.676***	(0.084)
Firm-year observations	3,498	
Low-tech firms		
$EWFR_{it}$	+0.073***	(0.023)
$EWFR_{it}$ - squared	−0.043*	(0.022)
NHR_{it}	+0.100***	(0.027)
NSR_{it}	−0.187**	(0.084)
Firm-year observations	23,631	
Firms located in an industrial district versus *firms located outside a district*		
Firms located in an industrial district		
$EWFR_{it}$	+0.153***	(0.048)
$EWFR_{it}$ - squared	−0.071**	(0.036)
NHR_{it}	+0.273***	(0.085)
NSR_{it}	−0.247**	(0.108)
Firm-year observations	13,719	
Firms not located in an industrial district		
$EWFR_{it}$	+0.027	(0.026)
$EWFR_{it}$ - squared	−0.010	(0.009)
NHR_{it}	+0.025**	(0.010)
NSR_{it}	−0.187***	(0.024)
Firm-year observations	13,410	
Old firms versus *young firms*		
Old firms		
$EWFR_{it}$	+0.096***	(0.034)
$EWFR_{it}$ - squared	−0.040*	(0.021)
NHR_{it}	+0.090***	(0.021)
NSR_{it}	−0.224***	(0.060)
Firm-year observations	24,478	
Young firms		
$EWFR_{it}$	−0.044	(0.064)
$EWFR_{it}$ - squared	−0.034	(0.053)
NHR_{it}	+0.498**	(0.209)
NSR_{it}	−0.196**	(0.094)
Firm-year observations	2,651	
Larger firms versus *very small firms*		
Larger firms		
$EWFR_{it}$	+0.098***	(0.026)
$EWFR_{it}$ - squared	−0.045**	(0.021)
NHR_{it}	+0.120***	(0.035)
NSR_{it}	−0.228***	(0.059)
Firm-year observations	23,784	
Very small firms		
$EWFR_{it}$	+0.016	(0.028)
$EWFR_{it}$ - squared	−0.022	(0.044)
NHR_{it}	+0.085***	(0.022)
NSR_{it}	−0.149*	(0.084)
Firm-year observations	3,345	

Source: the VWH-AIDA data set

Estimation method: ACF-FE. The high-tech sectors include: aircraft and spacecraft; chemicals; office, accounting, and computing machinery; radio, TV, and communications equipment; medical, precision, and optical instruments; electrical machinery and apparatus, n.e.c.; motor vehicles, trailers, and semi-trailers; railroad equipment and transport equipment, n.e.c.; machinery and equipment, n.e.c. I pinpointed firms belonging to an industrial district by looking at those firms that belonged to the 2- or 3-digit Ateco 1991 sector and province which identified an industrial district. Young firms are those that are less than 5 (panel-average) years old. Very small firms are those with less than 15 (panel-average) employees. These estimates include the same set of controls used in Table 2. For other information, see the footnote to Table 2.

Appendices

A. The empirical model and the ACF and ACF-FE estimation methods

The ACF and ACF-FE estimation procedures were designed to estimate firm-level production functions. They are based on the approximation of a firm's unobserved productivity level through a function of observables, called "control function". These methods are based on structural econometric models and are constructed on a number of assumptions, which are discussed in detail in Ackerberg et al. (2015) (ACF) and Lee et al. (2019) (ACF-FE). Within the ACF and ACF-FE frameworks, a researcher can adapt production functions augmented with any variable of interest, such as worker flows. A researcher has relatively limited flexibility concerning the underlying assumptions, and is mainly limited to defining the timing assumptions (e.g., the timing pertaining to the choice of labor and capital and to the realization of the variable of interest). A discussion on the paper's empirical framework, in the context of ACF and ACF-FE estimations, now follows. For details on the here summarized assumptions and their implications, see Ackerberg et al. (2015) and Lee et al. (2019).

As discussed in Section 5, the estimating equation is:

$$y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + \theta_1 NHR_{it} + \theta_2 NSR_{it} + \theta_3 EWFR_{it} + \gamma F_{it} + u_{it}. \tag{A.1}$$

First, it is assumed that the unobserved productivity level, ω_{it}, is regulated by a first-order Markov process, that its realization at t is observed by a firm at t (i.e., contemporaneously), and that it is at least partially anticipated by the firm. Therefore, it is possible to write:

$$E[\omega_{it}|I_{it-1}] = g(\omega_{it-1}) \quad \text{and} \quad \omega_{it} = g(\omega_{it-1}) + \xi_{it},$$

where: I_{it-1} is the information set pertaining to firm i at time $t-1$; $g(\cdot)$ is a general function and $g(\omega_{it-1})$ represents the component of ω_{it} that is predictable by the firm at $t-1$; and ξ_{it} is the innovation in ω_{it}, observed by the firm at t and which, by construction, cannot be predicted by the firm at $t-1$ (i.e., $E[\xi_{it}|I_{it-1}] = 0$). Basically, firms observe ω_{it} at t and form expectations on ω_{it} at $t-1$ using $g(\cdot)$.

Capital is assumed to be a non-perfectly variable input. A firm decides upon the amount of capital to use at t one period earlier, at $t-1$. This reflects the presence of capital adjustment costs, and accounts for the fact that new capital takes time to be ordered, delivered, installed, and put into operation. Labor is instead assumed to be a perfectly variable input. The firm decides upon the amount of labor to use at t in the same period, that is, at t. Consistently, it is assumed that net hirings, net separations, and excess flows at t are also determined at t. This reflects the following situation: (i) at t, the firm decides upon the level of l_{it} (and, therefore, upon NH_{it} and NS_{it}), that is, it decides whether to keep the employment level at the same level of $t-1$, to increase it, through net inflows, or to decrease it, through net outflows; (ii) at t, the firm also decides whether to replace any workers at t; (iii) workers make and communicate, at t, their decision to quit at t; (iv) on the basis of (i), (ii), and (iii), the firm decides, at t, whether to dismiss and/or hire any workers at t.

Moreover, it is assumed that (i) intermediate inputs are perfectly variable inputs, (ii) the firm's demand for intermediate inputs, m_{it}, is a function of labor, capital, the three components of worker flows (i.e., net hirings, net separations, and excess flows, all expressed in rates), and the firm's unobserved productivity level, and (iii) that this function is strictly increasing in ω_{it}:

$$m_{it} = f(l_{it}, k_{it}, NHR_{it}, NSR_{it}, EWFR_{it}, \overset{+}{\omega}_{it}).$$

Intuitively, this amounts to requiring that the higher the unobserved productivity level is, the larger the demand for intermediate inputs. If this (strict) monotonicity assumption on f holds, f can be inverted to deliver an expression of ω_{it} as a function of l_{it}, k_{it}, NHR_{it}, NSR_{it}, $EWFR_{it}$, and m_{it}, which are observable:

$$\omega_{it} = f^{-1}(l_{it}, k_{it}, NHR_{it}, NSR_{it}, EWFR_{it}, m_{it}).$$

This expression for ω_{it} can be substituted in Equation (A.1) to obtain:

$$\begin{aligned} y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + \theta_1 NHR_{it} + \theta_2 NSR_{it} + EWFR_{it} + \gamma F_{it} + \\ + f^{-1}(l_{it}, k_{it}, NHR_{it}, NSR_{it}, EWFR_{it}, m_{it}) + \epsilon_{it}. \end{aligned} \tag{A.2}$$

At this point, ACF proposes a two-step strategy to recover the estimates of β_l, β_k, θ_1, θ_2, and θ_3 (and γ). In the first step, y_{it} is non-parametrically regressed against a function in l_{it}, k_{it}, NHR_{it}, NSR_{it}, $EWFR_{it}$, m_{it}, and F_{it}, which is referred to as $\Phi(\cdot)$.[1] From this regression, it is possible to identify the composite term:

$$\widehat{\Phi}^*_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + \theta_1 NHR_{it} \widehat{+ \theta_2} NSR_{it} + \theta_3 EWFR_{it} + \omega_{it}.$$

[1]Following a practice commonly adopted in the literature, $\Phi(\cdot)$ is approximated with a second-order polynomial in l_{it}, k_{it}, NHR_{it}, NSR_{it}, $EWFR_{it}$, and m_{it}, with F_{it} added linearly. Estimations with higher-order (third- and fourth-order) polynomials were also pursued, but without any notable changes in the results.

It should be noted that these values are just the predicted values of y_{it} from the regression, minus the estimated $\hat{\gamma}F_{it}$. Given guesses of β_l, β_k, θ_1, θ_2, and θ_3, which are denoted as β_l^*, β_k^*, θ_1^*, θ_2^*, and θ_3^*, respectively, it is possible to recover the implied ω_{it}, $\hat{\omega}_{it}(\beta_l^*, \beta_k^*, \theta_1^*, \theta_2^*, \theta_3^*)$[2], as:

$$\hat{\omega}_{it}(\beta_l^*, \beta_k^*, \theta_1^*, \theta_2^*, \theta_3^*) = \widehat{\Phi}_{it}^* - \beta_l^* l_{it} - \beta_k^* k_{it} - \theta_1^* NHR_{it} - \theta_2^* NSR_{it} - \theta_3^* EWFR_{it}. \tag{A.3}$$

Recalling the assumption that ω_{it} follows a first-order Markov process (i.e., $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$) and given $\hat{\omega}_{it}(\beta_l^*, \beta_k^*, \theta_1^*, \theta_2^*, \theta_3^*)$, it is possible to compute the implied innovations, that is, $\hat{\xi}_{it}(\beta_l^*, \beta_k^*, \theta_1^*, \theta_2^*, \theta_3^*)$, as the residuals of a non-parametric regression of $\hat{\omega}_{it}(\beta_l^*, \beta_k^*, \theta_1^*, \theta_2^*, \theta_3^*)$ on $\hat{\omega}_{it-1}(\beta_l^*, \beta_k^*, \theta_1^*, \theta_2^*, \theta_3^*)$.[3] In the second step, the sample analogues of the moment conditions imposed by the model[4] are evaluated:

$$\begin{aligned}
&\frac{1}{N}\frac{1}{T}\sum_i\sum_t \hat{\xi}_{it}(\beta_l^*, \beta_k^*, \theta_1^*, \theta_2^*, \theta_3^*)k_{it} = 0\\
&\frac{1}{N}\frac{1}{T}\sum_i\sum_t \hat{\xi}_{it}(\beta_l^*, \beta_k^*, \theta_1^*, \theta_2^*, \theta_3^*)l_{it-1} = 0\\
&\frac{1}{N}\frac{1}{T}\sum_i\sum_t \hat{\xi}_{it}(\beta_l^*, \beta_k^*, \theta_1^*, \theta_2^*, \theta_3^*)NHR_{it-1} = 0\\
&\frac{1}{N}\frac{1}{T}\sum_i\sum_t \hat{\xi}_{it}(\beta_l^*, \beta_k^*, \theta_1^*, \theta_2^*, \theta_3^*)NSR_{it-1} = 0\\
&\frac{1}{N}\frac{1}{T}\sum_i\sum_t \hat{\xi}_{it}(\beta_l^*, \beta_k^*, \theta_1^*, \theta_2^*, \theta_3^*)EWFR_{it-1} = 0.
\end{aligned} \tag{A.4}$$

The search for β_l^*, β_k^*, θ_1^*, θ_2^*, and θ_3^* continues until the $\hat{\beta}_l$, $\hat{\beta}_k$, $\hat{\theta}_1$, $\hat{\theta}_2$, and $\hat{\theta}_3$ estimates that satisfy Equation (A.4) have been found. These are the ACF estimates of β_l, β_k, θ_1, θ_2, and θ_3.[5]

The ACF-FE estimator only involves a minimal modification of the standard ACF estimation. All the ACF assumptions are maintained, although the stochastic process regulating unobserved productivity is generalized in the ACF-FE setting. Unobserved productivity ω_{it}

[2] They also include the constant term, α, which ends up not having any effect.

[3] Following a practice commonly adopted in the literature, $g(\cdot)$ is approximated with a third-order polynomial in $\hat{\omega}_{it-1}(\beta_l^*, \beta_k^*, \theta_1^*, \theta_2^*, \theta_3^*)$.

[4] Stemming from the assumptions that capital is a non-perfectly variable input, labor is a perfectly variable input, and net inflows, net outflows, and excess flows at t are determined at t, the moment conditions are: $E[\xi_{it}k_{it}] = 0$, $E[\xi_{it}l_{it-1}] = 0$, $E[\xi_{it}NHR_{it-1}] = 0$, $E[\xi_{it}NSR_{it-1}] = 0$, and $E[\xi_{it}EWFR_{it-1}] = 0$.

[5] When more articulated specifications of Equation (1) are estimated, these moment conditions are expanded to include the new endogenous regressors (e.g., squared term in excess flows, interaction terms, etc.).

is assumed to follow a first-order Markov process conditional on a time-invariant random variable η_i:

$$\omega_{it} = E[\omega_{it}|\omega_{it-1}, \eta_i] + \xi_{it}, \tag{A.5}$$

where $E[\xi_{it}|\omega_{it-1}, \eta_i] = 0$ and $E[\epsilon_{it}|\eta_i = 0]$. Lee et al. (2019) considered a version of Equation (A.5), where $E[\omega_{it}|\omega_{it-1}, \eta_i] = \eta_i + g(\omega_{it-1})$, which gives:

$$\omega_{it} = \eta_i + g(\omega_{it-1}) + \xi_{it} \tag{A.6}$$

The first step of the ACF-FE procedure is the same as the first step in ACF, except that a fixed-term effect η_i is added. It is still possible to estimate $\Phi(\cdot)$ from the analogue of Equation (A.2) with added fixed effects. In the second step, it is possible to estimate β_l, β_k, θ_1, θ_2, and θ_3 proceeding as before, but this time including η_i in the stochastic process of the unobserved productivity level, as defined in Equation (A.6), thereby recovering the implied ω_{it}, as in (A.3), and then the implied ξ_{it}, as the residuals of a fixed effects regression of $\hat{\omega}_{it}$ on $g(\hat{\omega}_{it-1})$, with $g(\cdot)$ being approximated with a third-order polynomial (Lee et al., 2019, p.87).

B. Details on data and measurement issues

B.1. Deflation of output and inputs

Value added is deflated with the value-added deflator provided by the Italian National Institute of Statistics (Istat). This deflator is at the 3-digit level of the Ateco 1991 classification of economic activities. The book value of tangible fixed assets is deflated with the deflator for capital goods used in the manufacturing industry, as provided by Istat. Finally, the expenditure on intermediate inputs is deflated with the deflator for intermediate inputs used in the manufacturing industry, as provided by Istat.

B.2. Measurement of worker flows

Researchers can often only observe stocks of employment at a given point in the year (e.g., on the 31st of December), indicated as t for short. A firm's hirings in a given year are then identified by considering the workers employed in the firm at t, but not at $t-1$. Similarly, separations are identified by considering the workers employed in the firm at $t-1$, but not at t. In this case, any employment relationship that begins after $t-1$ and terminates before t does not enter into the count of hirings and separations, even though it represents one hiring by and one separation from the firm in that year. Hence, the worker flows computed with yearly-level information are undercounted. Since VWH-AIDA allows the monthly history of each job held by a worker in a given firm to be observed, it is possible to compute the worker flows more precisely (i.e., in a way that also accounts for the employment relations that start and end within a year). I used two variables that were present in the original version of the VWH data set. One indicates the month and year of a hiring, whereas the other indicates the month and year of a separation, if applicable, for each job. Essentially, if the hiring date is equal to or after January of a given year, it is a hiring. If the separation date is prior or equal to December of a given year, it is a separation.

B.3. Data cleaning

VWH refers to establishment-level data (i.e., it reports information about all the Veneto establishments of a firm), while AIDA refers to firm-level data (i.e., it may include non-Veneto establishments). To alleviate this issue, firms for which the number of employees reported by VWH was less than half that reported by AIDA were excluded from the analysis. Only firms established (still in activity) at least one calendar year before (after) they were observed were considered in the analysis in order to exclude worker flows derived from firm entry (exit).[6] As a further precaution, the analysis was focused on firms classified as "active", thus excluding firms that were closing down. Moreover, firms with less than 10 employees were removed. The rationale was twofold. First, this served to clean the data from systematic actions taken to improve the appearance of the company's balance sheet (e.g., showing tangible fixed assets at their acquisition cost, irrespective of their market value). These practices are common in very small firms, where the accounting procedures are generally less strident (e.g., there is usually no statutory audit). Second, this allowed meaningful worker flow rates to be computed. A few firms with implausibly high excess flow rates (above 1) were removed from the analysis. Lastly, firms with non-positive or missing book values of value added, tangible fixed assets, and expenditure on intermediate inputs had to be excluded from the analysis; moreover, to apply the ACF and ACF-FE methods, the sample had to be restricted to firms observed for at least two consecutive years.

B.4. General descriptive statistics

Table A.1 shows the distribution of firms by the number of consecutive panel observations. About 54% of the firms were observed for at least 5 consecutive years, while 27.2% of them were observed throughout the entire sample period.

Table A.2 reports the distribution of firms, according to industry and size. Consistently with the typical specializations of Veneto manufacturing firms, firms in the ferrous and machinery products, furniture, food and beverage, textile, clothing, and leather sectors are

[6]For the last year of observation, it was not possible to identify which firms closed down in the following year and, consequently, to eliminate them from the sample.

the most numerous in the sample. Moreover, given the diffusion of small- and medium-sized enterprises in Veneto, firms that employ fewer than 50 workers are the most common in the sample (70% of the firms).

Table A.3 presents summary statistics of several workforce and firm characteristics. On average, firms employ about 59 workers, and their revenues amount to about 11 million Euros per year. The average firm is about 16 years old and obtains 14 Euros of net profit from 1,000 Euros of sales. In the typical firm, 29.5% of the workers are females, 6.2% are migrants, 15.8% are under 25, 75% are in the central age category (between 25 and 49 years old), and 9.1% of them are over 50. A few of them are employed on a part-time basis (4.2%) or are temporary workers (3.9%). On average, the vast majority of employees are blue- (69.7%) or white-collar workers (23.7%). Some of them are in a period of apprenticeship (4.4%), and a few fill managerial positions (1.3%). Workers tend to stay in the same firm for about 6.5 years.

C. Worker flows and productivity: the OLS, FE, and ACF estimates

Table A.4 shows the OLS, FE, and ACF estimates of the reference specification where excess flows enter in both linear and quadratic forms. Net hirings and net separations were estimated to have, respectively, a significantly positive and negative impact on productivity across all of the three estimation methods, though with varying intensities. The OLS, FE, and ACF estimates of the impact of excess flows are instead heterogeneous.

The first column in Table A.4 reports the OLS estimates. Although the linear term associated with excess flows is positive, only the quadratic term - which is negative - is significant, thereby suggesting that the impact is essentially negative, though non-linear. When controlling for firm fixed effects (FE estimation, second column in the table), the estimated impact takes on the typical inverted U-shape found in the ACF-FE estimates, although pointing to substantially lower benefits of excess flows. The negative coefficient associated with squared excess flows compared to the positive coefficient associated with the linear term is higher than for the ACF-FE estimates. Either way, the sharp contrast between the OLS and FE estimates points to the substantial role of unobserved firm fixed heterogeneity. However, although the FE estimator removes firm fixed effects, it does not account for time-varying unobserved firm heterogeneity or reverse causality stemming from fluctuations in a firm's unobserved productivity level. Unlike the FE estimation, the ACF method was designed to deal with endogeneity problems due to unobserved firm heterogeneity and reverse causality, but it does not explicitly remove firm fixed effects. According to the ACF estimates (third column in Table A.4), the impact of excess flows is negligible and largely not significant. It is thus crucial to explicitly account for firm fixed effects to obtain an increased precision of the ACF method.

D. The role of the sending firms' characteristics

It has emerged, from recent studies in the literature (e.g., Serafinelli, 2019; Stoyanov and Zubanov, 2014, 2012), that the productivity effect of the inflows of new workers depends on the firms these new workers come from (i.e., the sending firms). This motivates two types of analyses. First, if there is a correlation between the productivity of sending and receiving firms, not accounting for the productivity of the sending firms may confound the regression estimates. Second, the impact of excess flows might be contingent on some critical characteristics of the sending firms. The industry that new replacement workers come from, and the relative "quality" of the sending firms are two crucial dimensions. This appendix presents a set of results with the aim of exploring these issues. As usual, the ACF-FE results of the specifications with linear and quadratic terms in the excess flows are reported.

Table A.5 presents the results of the case in which the productivity levels of sending firms are controlled for.

The steps undertaken to pursue this robustness check can be summarized as follows. First, the productivity estimates of the whole sample of firms in the VWH-AIDA data set were obtained (i.e., these are the firms that could have been the sending firms). I conducted a basic cleaning of this sample, which removed firms that were closing down in the year of observation and firms for which the level of information from AIDA (i.e., firm-level) was likely different from that from VWH (i.e., establishment-level, see Appendix B, Subsection B.3 for this). The productivity estimates for these firms were obtained from the residuals of the ACF-FE estimation of a standard value-added Cobb-Douglas production function with only labor and capital inputs, and year dummies (e.g., see Devicienti et al., 2018). The yearly productivity estimates of the sending firms were then matched with each worker hired in the sampled firms (i.e., by the firms that constitute the sample used in the estimations in the paper). Out of the 317,096 workers hired by the sampled firms, 61,149 (i.e., 19.3%) were matched with the productivity estimate of the sending firms. I was able to retrieve the identity of the sending firms for as many as 227,586 of the 317,096 (i.e., 71.8%) workers hired by the sampled firms using the complete VWH data set. However, I was only able to recover the productivity estimates for a few of the sending firms, because AIDA (i.e., the source of the financial-level information) only gathers a portion of all the firms contained in VWH, as specified in Section 6 (e.g., it only gathers incorporated firms, which are non-financial, with annual sales above 500,000 thousand Euros, and for the years after 1995). The average productivity level of the sending firms was then computed for each firm-year observation, and the collapsed firm-level estimation sample was obtained. This sample provided the average productivity of the firms the newly hired workers came from for each firm-year observation.[7] It should be noted that those firms that did not undergo hirings were dropped, as the productivity of the sending firms for such companies was a missing value. Moreover, a threshold was applied so that the productivity level of the sending firms had to be known for at least 30% of the hired workers. The rationale was to remove situations in which the average productivity of the sending firms was computed on a portion of hired workers that was too small. At the end of this procedure, there were 4,125 firm-year observations for 1,655 firms, that is, only 15.2% of the original estimation sample, which is why the main analysis did not control for the productivity levels of the sending firms.

The first panel in Table A.5 shows the estimation results that control for the average productivity of the sending firms, whereas the second panel presents the estimation results without such a control, for comparative purposes (i.e., the usual specification, with linear and quadratic terms in the excess flows, is estimated on the restricted sample used for this test). The estimated impacts of the different worker flows are very similar in the two specifications, that is, controlling and not controlling for the average productivity levels of the sending firms. A significant inverted U-shape impact of the excess flows is found in both cases. A significant positive correlation of the productivity levels of the sending and receiving firms is detected (the coefficient associated with the productivity levels of the sending firms is positive and significant). However, this does not appear to alter the regression results.

Table A.6 shows the results for the contingency effect of the sending firms' industry. It should be noted that these results, pursued on the previously described restricted sample, also control for the average productivity of the sending firms. This test is relevant to explore the mechanisms behind the impact of excess flows, and to assess the sources of the beneficial effects associated with reallocation dynamics. To what extent do they come from inflows of industry-specific knowledge? To what extent are they linked to general knowledge inflows? In short, to what extent does the potential for reaching better employer-employee matches, enabled by excess flows, depend on the technological-specific knowledge embedded in the replacement workers?

The first panel in Table A.5 uses the 3-digit level in the Ateco 1991 industry classification (114 categories) to define whether a sending firm operates in the same industry as the receiving firm, or not. I constructed two variables that indicated, respectively, the proportions of the hired workers coming from the sending firms operating in the same and in

[7] I computed (and attached) the productivity level that the sending firms had at the time the workers separated from them.

a different 3-digit industry compared to the receiving firm.[8] Such variables were then interacted with the linear and quadratic excess flow terms. The second panel in the table presents the same results, but the definition of the same industry is based on the less strict 2-digit Ateco 1991 level (21 categories). By looking at the first panel, it is possible to see that the benefits from excess flows, although significant, are substantially attenuated when the inflows of knowledge are not from the same 3-digit industry. When all the newly hired workers come from the same 3-digit industry as the receiving firm, the productivity gains, passing from a zero to 10% replacement level, are 3.54%. Conversely, when all the incoming workers come from sending firms not operating in the same 3-digit industry, the effect of such an increase in the excess flows is only 1.33%. The analysis presented in the second panel in the table shows that when the criterion used to define the same *versus* different industry is less strict (i.e., at the 2-digit level), the benefits associated with excess flows involving inflows of knowledge not from the same industry disappear (0.033 and -0.016 are the small and not significant estimated coefficients associated with the linear and quadratic excess flow terms in this case). It thus appears that the benefits from reallocation dynamics mainly materialize when replacement workers share similar industry-specific knowledge (for a similar result, see Stoyanov and Zubanov, 2012). Therefore, industry-specific knowledge seems a crucial condition for employer-employee matches to succeed.

Table A.7 shows the results of the moderating effect of the sending firms' productivity levels relative to the receiving firm. This analysis allows the sources of the benefits stemming from reallocation dynamics to be better gauged. To what extent do the benefits of excess flows stem from the "quality" of the sending firms relative to the receiving firm? How many of these benefits are instead embedded in the workers themselves?

In order to answer these questions, the analysis built upon the empirical method proposed by Stoyanov and Zubanov (2012), who developed an index, called "productivity gap", that synthetically indicates the productivity difference between sending and receiving firms. This index is defined as:

$$\widetilde{gap}_{j,t} = \frac{\sum_{i=1}^{H_{j,t}} (A^s_{i,t-1} - A^r_{j,t-1})}{H_{j,t}} \frac{H_{j,t}}{N_{j,t}},$$

where $A^r_{j,t-1}$ and $A^s_{i,t-1}$ are the productivities of the receiving and sending firms[9] in $t-1$, that is, one year before the hiring; $H_{j,t}$ is the number of hired workers and $N_{j,t}$ is the

[8] These proportions, which sum up to one, were only computed for those hired workers who had been linked to a sending firm (i.e., at least 30% of the firms' total hired workers, see the above discussion).

[9] The productivity estimate of the receiving firm was computed in the same way as that of the sending firms (i.e., as the residual from the ACF-FE estimation of a simple value-added Cobb-Douglas production function with labor and capital, and with year dummies, see above).

(average) total number of workers in the receiving firm. In short, $\widetilde{gap}_{j,t}$ is "the productivity difference between the sending and receiving firm defined for each new worker i, averaged across all the new workers in firm j, and multiplied by their share in total employment ($H_{j,t}/N_{j,t}$)" (Stoyanov and Zubanov, 2012, p. 172). To better assess the contingency role of the relative productivity of the sending firms, I also computed the productivity gap index separately for workers hired from more and from less productive firms than the receiving firm (see Stoyanov and Zubanov, 2012, p. 172). The total productivity gap is divided into the positive productivity gap and the negative productivity gap. The former is the productivity gap between the receiving and sending firms that emerges when only considering the sending firms that are more productive than the receiving firm. The second is the opposite, that is, the productivity gap between the receiving and sending firms that emerge when only considering the sending firms that are less productive than the receiving firm.[10]

The first panel in Table A.7 adds the interaction term between the excess flows and the productivity gap to the usual model.[11] Excess flows were estimated to have the usual inverted U-shape, irrespective of the productivity gap between the sending and receiving firms. However, there is a substantial positive and significant interaction effect, which entails that the benefits associated with workers' replacements are amplified as the gap between the sending and receiving firms becomes greater, that is, as the sending firms' productive performance, relative to the receiving firm's productivity, becomes greater. The second panel in the table further differentiates between the positive and negative productivity gaps, and allows the effect of replacement workers from "better" and "worse" firms compared to the receiving firm to be distinguished. The fact that excess flows have the typical inverted U-shape, regardless of the productivity gaps, is confirmed. The benefits stemming from excess flows are substantially potentiated when new replacement workers arrive from firms with higher productivity than the receiving firm. Interestingly, the same happens, though to a much lesser extent (the interaction term is halved and is only significant at the 10%

[10] As discussed above, it was only possible to link a small proportion of the hired workers to financial-level information on the sending firms. As a result, the averaged productivity difference between the receiving and sending firms (i.e., the first fraction of the formula above) was only computed for those hired workers who had been linked to the productivity estimate of the sending firm. The weight (i.e., share of hired workers to the total firm's workforce) was instead computed considering all the hired workers. In the computation of the positive and negative productivity gaps, I imputed the shares of the two groups of hired workers (i.e., from the more and the less productive firms), relative to the total employment, using the hired workers for which the sending firm's productivity was known.

[11] These estimates were obtained from the restricted sample discussed above. In this case, the first year of observation for each firm could not be used since it was lost to compute productivity gaps (i.e., the productivity gap indexes use productivity levels at $t-1$). Moreover, at least two consecutive observations were needed to perform the ACF-FE estimation. Put together, these two conditions resulted in a significantly reduced sample.

level) when the sending firms are less productive than the receiving company. On the whole, these results suggest that the origin of the benefits from reallocation dynamics resides in the workers themselves as well as in the firms they come from, especially if these are more productive than the receiving company.

Table A.1: **Distribution of the firms by number of consecutive panel observations**

Number of consecutive panel observations	Firms	Observations
2	1,063	2,126
3	824	2,472
4	638	2,552
5	574	2,870
6	1,042	6,252
7	1,551	10,857
Total	5,692	27,129

Source: the VWH-AIDA data set

Table A.2: **Distribution of the firms by industry and size**

Industry*	Observations	Percentage
Food and beverage	1,233	4.5
Textile	1,257	4.6
Clothing	1,422	5.2
Leather and leather goods	2,002	7.4
Wood and wood products (excluding furniture)	871	3.2
Paper and paper products	615	2.3
Printing and publishing	680	2.5
Coke and petroleum products	71	0.3
Chemical products	827	3.1
Rubber and plastics	1,423	5.3
Non-ferrous production	1,833	6.8
Ferrous production	624	2.3
Ferrous products (excluding machinery)	4,212	15.5
Machinery products	3,829	14.1
Office machinery and computers	55	0.2
Electrical machinery	1,226	4.5
Radio, TV, and TLC equipment	298	1.1
Medical equipment and measurement instruments	826	3.0
Motor vehicles	293	1.1
Other transportation equipment	202	0.7
Furniture and other manufacturing industries	3,330	12.3
Total	27,129	100

Size	Observations	Percentage
$[10-20)$ Employees**	7,095	26.2
$[20-50)$ Employees**	11,755	43.3
$[50-250)$ Employees**	7,566	27.9
≥ 250 Employees**	713	2.6
Total	27,129	100

Source: the VWH-AIDA data set
**Industry is defined according to the 2-digit Ateco 1991 classification of economic activities.*
***Monthly weighted.*

Table A.3: **Summary statistics for general firm- and workforce-level characteristics**

Variable	**Notes**	**Mean**	**Std. dev.**
Employees	Monthly weighted	58.791	139.138
Revenues	1,000 Euros (2000's prices)	10,709.700	27,653.470
Profit margin	Net profit over revenues	0.014	0.053
Firm age	Years	15.578	7.853
Share of females	Monthly weighted	0.295	0.237
Share of migrants	Monthly weighted	0.062	0.085
Share of workers under 25	Monthly weighted	0.158	0.112
Share of workers aged between 25 and 34	Monthly weighted	0.384	0.129
Share of workers aged between 35 and 49	Monthly weighted	0.366	0.141
Share of workers over 50	Monthly weighted	0.091	0.077
Average workers' age	Monthly weighted	34.652	3.772
Share of part-timers	Monthly weighted	0.042	0.057
Share of temporary workers	Monthly weighted	0.039	0.056
Share of blue-collar workers	Monthly weighted	0.697	0.166
Share of white-collar workers	Monthly weighted	0.237	0.155
Share of apprentices	Monthly weighted	0.044	0.065
Share of managers	Monthly weighted	0.013	0.029
Average workers' tenure	Monthly weighted, years	6.518	3.176
Value added	1,000 Euros (2000's prices)	2,885.354	8,530.419
log Value added	1,000 Euros (2000's prices)	7.324	0.961
Days worked	FTE adjusted	17,439.500	40,886.290
log Days worked	FTE adjusted	9.284	0.834
Book value of tangible fixed assets	1,000 Euros (2000's prices)	1,703.781	4,984.799
log Book value of tangible fixed assets	1,000 Euros (2000's prices)	6.412	1.411
Expenditure on intermediate inputs	1,000 Euros (2000's prices)	5,930.346	16,597.030
log Expenditure on intermediate inputs	1,000 Euros (2000's prices)	7.767	1.290
			Firm-year observations: 27,129
			Firms: 5,692

Source: the VWH-AIDA data set

Table A.4: **Worker flows and firm productivity: the OLS, FE, and ACF estimates**

Dependent variable: y_{it}	OLS		FE		ACF	
l_{it}	+0.910***	(0.007)	+0.831***	(0.020)	+0.862***	(0.016)
k_{it}	+0.128***	(0.002)	+0.066***	(0.007)	+0.143***	(0.004)
$EWFR_{it}$	+0.042	(0.030)	+0.054**	(0.025)	+0.000	(0.058)
$EWFR_{it}$ - square	−0.089***	(0.034)	−0.048*	(0.028)	−0.015	(0.054)
NHR_{it}	+0.110***	(0.029)	−0.115**	(0.052)	−0.123***	(0.033)
NSR_{it}	−0.335***	(0.032)	−0.175***	(0.030)	−0.236***	(0.068)
Share of females	−0.339***	(0.014)	−0.051	(0.062)	−0.279***	(0.013)
Share of migrants	−0.080***	(0.026)	+0.059	(0.065)	−0.040*	(0.024)
Share of workers under 25	+0.300***	(0.037)	−0.099	(0.071)	+0.206***	(0.035)
Share of workers aged between 25 and 34	+0.276***	(0.030)	−0.015	(0.063)	+0.171***	(0.029)
Share of workers aged between 35 and 49	+0.250***	(0.034)	+0.011	(0.058)	+0.169***	(0.032)
Share of part-timers	+0.014	(0.042)	+0.068	(0.084)	+0.045	(0.036)
Share of temporary workers	−0.067*	(0.038)	+0.010	(0.035)	−0.095***	(0.036)
Share of blue-collar workers	−0.615***	(0.049)	+0.018	(0.127)	−0.491***	(0.046)
Share of white-collar workers	−0.043	(0.052)	+0.099	(0.121)	−0.175***	(0.048)
Share of apprentices	−0.945***	(0.065)	−0.106	(0.137)	−0.814***	(0.061)
Firm fixed effects	no		yes		no	
Size dummies	yes		yes		yes	
Year dummies	yes		yes		yes	
Province dummies	yes		-		yes	
Industry dummies	yes		-		yes	
Year∗industry dummies	yes		yes		yes	
Year∗province dummies	yes		yes		yes	
						Firm-year observations: 27,129
						Firms: 5,692

Source: the VWH-AIDA data set

I computed robust standard errors clustered at the firm level for OLS and FE, and firm-level cluster robust bootstrapped standard errors for ACF. For other information, see the footnote to Table 2.

Table A.5: **The impact of worker flows controlling for the productivity levels of the sending firms**

Model 1: with control for the average productivity of the sending firms		
$EWFR_{it}$	+0.123***	(0.045)
$EWFR_{it}$ - squared	−0.060*	(0.032)
NHR_{it}	+0.119**	(0.052)
NSR_{it}	−0.149**	(0.070)
Average productivity of the sending firms	+0.022**	(0.011)
		Firm-year observations: 4,125
		Firms: 1,655
Model 2: without control for the average productivity of the sending firms		
$EWFR_{it}$	+0.144***	(0.035)
$EWFR_{it}$ - squared	−0.050*	(0.027)
NHR_{it}	+0.115***	(0.030)
NSR_{it}	−0.135*	(0.076)
		Firm-year observations: 4,125
		Firms: 1,655

Source: the VWH-AIDA data set

Estimation method: ACF-FE. These estimates include the same set of controls used in Table 2. For other information, see the footnote to Table 2.

Table A.6: **The impact of excess flows depending on the industry of the sending firms**

Model 1: same/different industry defined at the 3-digit level		
$EWFR_{it}$ $*$ proportion of hired workers from the same industry	+0.190**	(0.085)
$EWFR_{it}$ - squared $*$ proportion of hired workers from the same industry	−0.080**	(0.035)
$EWFR_{it}$ $*$ proportion of hired workers from a different industry	+0.066*	(0.036)
$EWFR_{it}$ - squared $*$ proportion of hired workers from a different industry	−0.022	(0.016)
NHR_{it}	+0.100**	(0.041)
NSR_{it}	−0.156*	(0.088)
Average productivity of the sending firms	+0.028**	(0.012)
Firm-year observations: 4,125		
Firms: 1,655		
Model 2: same/different industry defined at the 2-digit level		
$EWFR_{it}$ $*$ proportion of hired workers from the same industry	+0.204***	(0.069)
$EWFR_{it}$ - squared $*$ proportion of hired workers from the same industry	−0.090**	(0.044)
$EWFR_{it}$ $*$ proportion of hired workers from a different industry	+0.033	(0.058)
$EWFR_{it}$ - squared $*$ proportion of hired workers from a different industry	−0.016	(0.021)
NHR_{it}	+0.115**	(0.045)
NSR_{it}	−0.157**	(0.061)
Average productivity of the sending firms	+0.024**	(0.011)
Firm-year observations: 4,125		
Firms: 1,655		

Source: the VWH-AIDA data set

Estimation method: ACF-FE. The main effects of the proportions of hired workers from the same/a different industry were included among the set of endogenous regressors. When the same/a different industry is defined using 3-digit sectors, the average firm-level proportions of the hired workers from the same and different industries are 0.405 and 0.595, respectively. When the same/a different industry is defined using 2-digit sectors, the average firm-level proportions of hired workers from the same and different industries are 0.476 and 0.524, respectively. These estimates include the same set of controls used in Table 2. For other information, see the footnote to Table 2.

Table A.7: **The impact of excess flows depending on the productivity gap with the sending firms**

Model 1: interaction with the productivity gap		
$EWFR_{it}$	+0.076**	(0.036)
$EWFR_{it}$ - square	−0.042**	(0.021)
$EWFR_{it}$ $*$ productivity gap	+0.224**	(0.110)
NHR_{it}	+0.088**	(0.041)
NSR_{it}	−0.175***	(0.049)
Productivity gap	+0.271**	(0.122)
Firm-year observations: 1,356		
Firms: 541		
Model 2: interaction with positive and negative productivity gaps		
$EWFR_{it}$	+0.077**	(0.033)
$EWFR_{it}$ - squared	−0.041*	(0.025)
$EWFR_{it}$ $*$ positive productivity gap	+0.266**	(0.109)
$EWFR_{it}$ $*$ negative productivity gap	+0.136*	(0.070)
NHR_{it}	+0.087**	(0.044)
NSR_{it}	−0.154***	(0.057)
Positive productivity gap	+0.308**	(0.144)
Negative productivity gap	+0.090	(0.064)
Firm-year observations: 1,356		
Firms: 541		

Source: the VWH-AIDA data set

Estimation method: ACF-FE. The first year of observation for each firm is lost because the productivity gaps are computed on productivities at $t-1$; moreover, at least two observations per firm are needed to perform the ACF-FE estimation. The average productivity gap is 0.058. When negative, the average productivity gap is -0.022. When positive, it is 0.085. These estimates include the same set of controls used in Table 2. For other information, see the footnote to Table 2.