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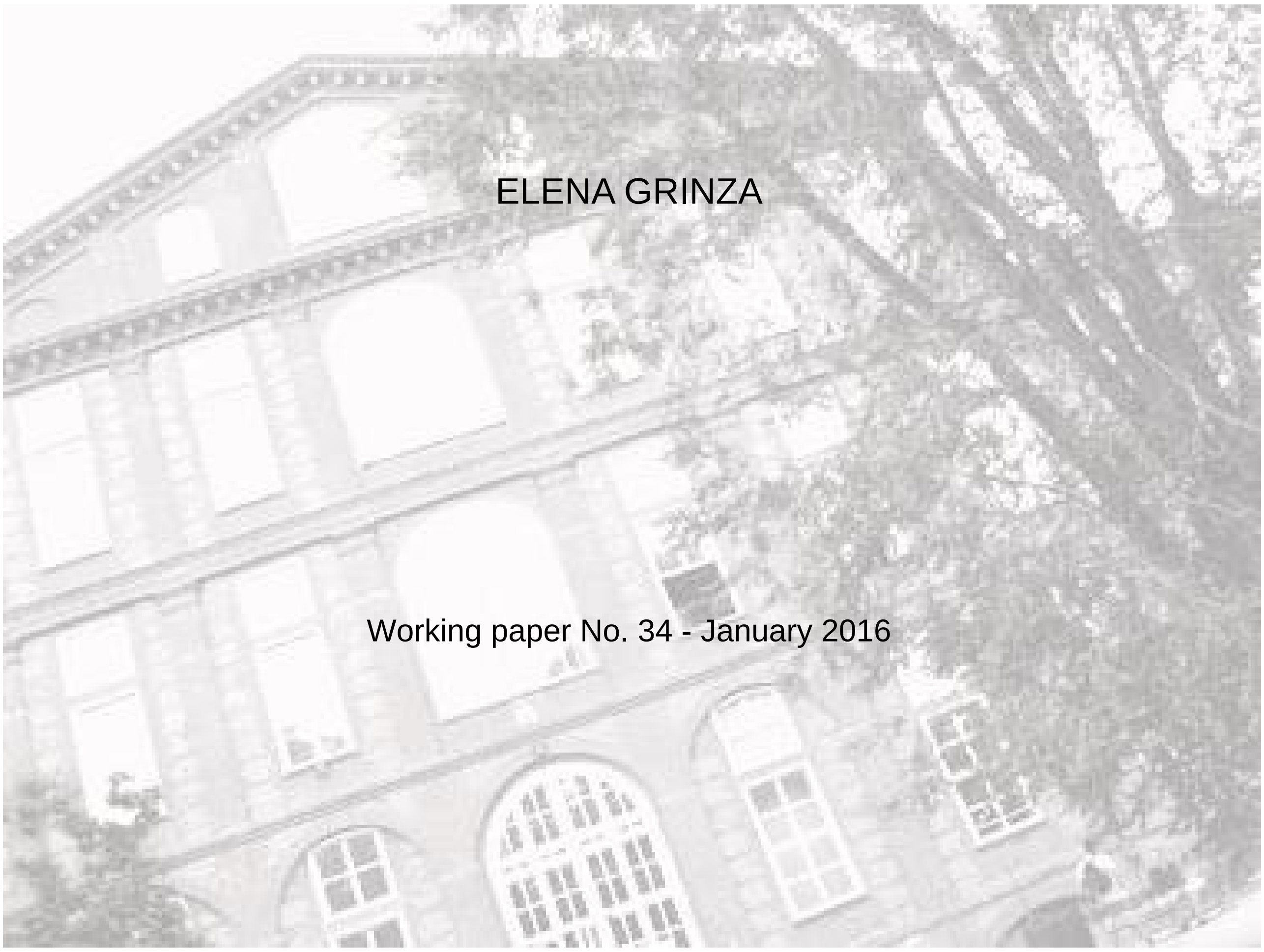

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Replacing Workers: Is It a Boon or a Bane for Firm Productivity?

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Abstract

Using a uniquely rich longitudinal matched employer-employee data set, this paper is the first to investigate the impact of replacing workers, as measured by excess worker turnover, on firm productivity. Using a modified version of the method proposed by Ackerberg et al. (2006), that allows to take into account unobserved heterogeneity, an augmented production function with excess worker turnover entering as the regressor of interest is estimated. The main result is that replacing workers is beneficial to firm productivity. A 1 standard deviation increase in the excess worker turnover rate is estimated to increase productivity by 0.81%. The possibility of finding more suitable employer-employee matches and the presence of knowledge spillover effects are seen as the main determinants of the impact. Robustness checks indicate that the impact has an inverted U-shape, suggesting that, beyond a certain point, replacing workers ends up being harmful. However, since about 90% of firms lie before this point, increases in excess worker turnover are beneficial for the vast majority of them. They also suggest that the effect is diversified across different categories of firms. High-tech firms and firms belonging to industrial districts benefit the most from excess worker turnover. On the contrary, young and very small firms seem to even suffer from it.

Keywords: Workers' replacement, excess worker turnover, job-matching, knowledge spillovers, firm-specific human capital, semiparametric estimation methods, ACF-FE.
JEL: L23, L25, L60.

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1. Introduction

Using a longitudinal matched employer-employee data set for Veneto from 1995 to 2001, I am the first to assess the effect of replacing workers as captured by the excess worker turnover, on firm productivity.

Following Davis et al. (1996), excess worker turnover is defined as the amount of worker turnover (hires plus separations) over and above the level of worker turnover naturally needed to accommodate job creation or destruction. In other words, it measures the extent to which the firm changes the composition of its workforce, replacing separated workers, that is, those who either quit or are fired, with new workers. An example clarifies the point. Suppose the number of workers in the firms is measured two times a year: on the 1st of January and on the 31st of December. Consider a firm with 10 employees on the 1st of January, that hires 2 workers the day after, and does not separate with any worker during the year. This implies that the number of workers on the 31st of December is 12. This firm experiences 2 hires, no separations, worker turnover equal to 2 (2 hires + 0 separations), and excess worker turnover equal to 0, as worker turnover compensates exactly for job creation. Consider the same firm, again with 10 employees on the 1st of January, but now hiring 4 workers and separating with 2 the day after. Assume that nothing changes for the rest of the year so that, on the 31st of December, the number of workers is 12, exactly as in the previous case. Here, the firm experiences 4 hires, 2 separations, with worker turnover equal to 6 (4 hires + 2 separations), and excess worker turnover equal to 4 (6-2, where 6 is worker turnover and 2 is job creation). While in the first case, the firm increases its workforce simply by hiring 2 new workers, in the second case, the firm does so by hiring 4 workers and separating with 2 workers. Hence, in the latter case, the firm *replaces* 2 of its workers with 2 new ones, and the excess worker turnover provides a measure of the degree to which the firm does so.

Worker turnover and excess worker turnover are often confused, both in human resources management and economic literature and among managers. Usually when talking about 'worker turnover', they implicitly mean 'excess worker turnover'. To avoid confusion in this paper, I will keep the distinction clear, so that they are used in the strict sense.

Many look with askance at excess worker turnover. On the one hand, excess worker turnover is regarded as a critical issue in the management of firms by many managers. Most of them fear it; one can realize this by Googling 'worker turnover': there are plenty of sites dictating guidelines on how to retain workers and consequently reduce it. On the other hand, policy makers are often concerned with the reduction of labor mobility, with the purpose of protecting workers' welfare. Nevertheless, it is a fact that excess worker turnover exists, and abundantly. In view of these considerations, it may appear strange that no empirical work has been done to assess whether excess worker turnover is beneficial for firm productivity or not.

Human resources experts have contributed to disseminate the feeling among managers that replacing workers damages the firm; indeed, many theories have been proposed that regard excess worker turnover as harmful for firm performance. They alternatively claim that it is dysfunctional for the business organization (Dess and Shaw, 2001), entailing a loss of human capital that causes the loss of output forgone and the cost of searching for a new employee (Sutherland, 2002), along with the fact that it produces a loss of social capital, since it is disruptive for the morale of the workers who stay (Sheehan, 1993). However, someone has advanced the hypothesis that, at least to a certain extent, excess worker turnover can be beneficial for the firm, such as when underperforming workers voluntarily quit or because it brings some ‘fresh air’ into the firm (Adelson and Baysinger, 1984). Economists, on the contrary, have not paid much attention to the potential effects of excess worker turnover on firm productivity. Essentially, the economic theories modeling the productivity effect of replacing workers are two: the firm-specific human capital theory (FSHC), proposed by Becker (1964), and the matching theory, established, amongst others, by Burdett (1978) and Jovanovic (1979). The FSHC theory predicts that excess worker turnover negatively affects firm productivity because it entails the loss of productive firm-specific human capital acquired by those who are leaving and, at the same time, the ‘waste of time’ to acquire it for new entrants. The matching theory, on the other hand, predicts a positive effect: excess worker turnover allows firms to reach an efficient allocation of employer-employee matches, when the quality of the match is not known *a priori* and is only revealed over time.

As I said previously, this paper represents the first attempt to empirically assess the impact of replacing workers (i.e., of excess worker turnover) on firm productivity. Many empirical works investigate the effect of worker turnover on firm performance (see, for instance, Ton and Huckman, 2008; Huselid, 1995; Mc Evoy and Cascio, 1987; Harris et al., 2006; Siebert et al., 2006). Since excess worker turnover is conceptually (and numerically) different from worker turnover, this prevents me from a direct comparison with remaining literature.

In the empirical analysis, I use the VWH-AIDA data set, a uniquely rich, longitudinal matched employer-employee data set for Veneto, to estimate an augmented production function with excess worker turnover entering as the regressor of interest. Since the VWH-AIDA data set allows me to observe a monthly history of each job held by a worker in a given firm, I can construct an (almost) continuous-time measure of excess worker turnover, whereas discrete-time measures are the norm in literature on worker turnover (a notable exception is represented by Siebert et al., 2006). Following Vandenberghe et al. (2013), I deal with unobserved firm heterogeneity and endogeneity issues through a modified version of the semiparametric approach developed by Ackerberg et al. (2006), that explicitly takes into account firm-specific fixed effects.

The main finding is that excess worker turnover has a significant positive impact on firm productivity. A 1 standard deviation increase in the excess worker turnover rate is estimated to increase firm productivity by 0.81%. The possibility of finding more suitable employer-employee matches and knowledge spillover effects, enhanced by workers' mobility, that is, by excess worker turnover, are regarded as the main determinants of this effect.

The impact of interest is investigated further by allowing non-linearities and diversified effects across several dimensions, seen as potentially relevant. They include: belonging or not to the high-tech industry and to industrial districts and the age and the size of the firm. As expected, the impact is found to have an inverted U-shape, suggesting that there is a point beyond which excess worker turnover becomes harmful. However, since about 90% of the firms in the sample lie before this point, increases in excess worker turnover are beneficial for the vast majority of them. A firm passing from a zero level of excess worker turnover to the optimal one is predicted to experience an increase in productivity by as much as 3.36%. Moreover, high-tech firms, as well as firms belonging to an industrial district, seem to benefit from workers' replacement more than others. On the contrary, young and very small firms seem to suffer from it.

The rest of the paper is structured as follows: Section 2 presents a literature review; Section 3 describes the Italian institutional context; Section 4 discusses the empirical model and the identification strategy; Section 5 describes the data set and the way in which excess worker turnover is computed; Section 6 presents and discusses results; and Section 7 concludes.

2. Literature review

The nature of the impact of excess worker turnover on firm performance and the potential mechanisms behind it have been of great concern in the human resources management literature, whereas the attention devoted by economists has been much less prominent. In both disciplines, however, the theories proposed are contrasting, suggesting that the impact of interest is not trivial and is possibly the result of the interplay of many contrasting forces.

In the human resources management literature, excess worker turnover is mostly regarded as a dysfunctional feature of the firm, essentially because it is costly. From separations, firms suffer the loss of human capital investments and the cost of hiring substitute workers (Sutherland, 2002). Moreover, high excess worker turnover is likely to cause indirect negative effects. Examples include: output forgone during the vacancy period and diminished productivity during the training process of new workers (Sutherland, 2002); organizational disruptions and loss of social capital (Dess and Shaw, 2001); lowered customer satisfaction, as highlighted by Jamal and Kamal (2002) for the retail banking industry; and negative effects on the morale of workers who stay, as argued by Sheehan (1993), who, conducing a controlled experiment, shows that excess worker turnover negatively alters the perception of stayers with respect to the quality of the firm, inducing lower productivity of labor. Yet, there is a strand of literature suggesting that a positive, though small, amount of excess worker turnover can be beneficial to the organization. Adelson and Baysinger (1984) suggest that excess worker turnover is not dysfunctional *per se*, but that it should be evaluated on the basis of the costs and benefits it brings to the firm. For example, excess worker turnover can be beneficial when underperforming workers voluntarily quit, thus making firms save on potentially high firing costs; even when not voluntarily leaving, firing low-performers can be beneficial when firing costs are compensated for by productivity increases of the newly hired workers (Meier and Hicklin, 2007). Moreover, replacing low-performers can bring some ancillary advantages to the firm: it can serve as a motivational push for remaining workers to perform better, as argued by McElroy et al. (2001), and can bring some 'fresh air' into the firm, as Kellough and Osuna (1995) suggest.

The economic literature has proposed two mechanisms through which excess worker turnover may affect firm performance: firm-specific human capital, and job matching.

The firm-specific human capital theory, first proposed by Becker (1964), states that excess worker turnover negatively affects firm productivity because, on the one hand, it entails the loss of productive firm-specific human capital acquired by those who are leaving and, on the other hand, the 'waste of time' to acquire it for the new entrants.

The job matching theory, established, among others, by Burdett (1978) and Jovanovic (1979)[1], conceives excess worker turnover as the mechanism through which, in a world of imperfect information, employer-employee matches can be reallocated in a more efficient way as better information becomes available. This theory hinges on three main assumptions (see Jovanovic, 1979). Firstly, *each* worker performs different jobs with different productivity levels (within-workers heterogeneity). Symmetrically, for *each* job assigned, different workers have different productivity levels (between-workers heterogeneity). Secondly, it is assumed that employers and workers can bargain over wages on an individual basis and renegotiate the wage contract as better information on the quality of the match becomes available. This allows for a signaling of good and poor matches: employers satisfied with the match are willing to pay the worker relatively more than employers who are not. The third assumption

[1]The most representative works in the job matching literature are Mortensen and Pissarides (1994) and Pissarides (2000). However Burdett (1978) and Jovanovic (1979) specifically concentrate on excess worker turnover.

is that both workers and employers have imperfect information about the exact location of the most productive match. Within- and between-workers heterogeneity in productivity, the possibility to set wages on an individual basis according to the quality of the match, and imperfect information make workers and employers engage in the search of optimal matches. Quits, dismissals, and hires, and, consequently, excess worker turnover, are the ways in which optimal matches can be attained as better information becomes available. In short, the job matching theory predicts that excess worker turnover improves firm productivity by removing poor employer-employee matches from the economy.

In addition to the FSHC and the job matching approaches (and closely related to the job matching approach), the theory predicting a positive impact of excess worker turnover on firm performance enhanced by knowledge spillover effects deserves to be mentioned. For instance, Cooper (2000) proposes a 'two-period model of a competitive industry in which workers may capitalize on information acquired on the job by migrating to rival firms and shows that this model implies that a higher excess worker turnover rate is generally associated with an overall greater technological progress. Using the VWH-AIDA data set, Serafinelli (2013) shows that labor mobility contributes to enhancing productivity in firms located near highly productive companies.

This paper is the first to explore empirically the impact of excess worker turnover on firm productivity. Instead, while it remains unclear whether it has been done deliberately or erroneously, many empirical studies have been concerned with the effect of worker turnover on firm performance, thus making this paper unfit to be comparable with them.[2] Indeed, besides incorporating excess worker turnover, the worker turnover comprises all those hires and separations that are *not* meant to replace workers, but only to increase or decrease the number of workers in the firm that are outside the interest of this paper.

Either way, results for the impact of worker turnover on firm performance are contrasting.

Someone finds a negative impact: Ton and Huckman (2008), using 48 months of worker turnover data from the US stores of a major retail chain of entertainment products, find that worker turnover negatively impacts profit margins and customer satisfaction; Tariq et al. (2013), using questionnaires distributed in Mobilink, a telecommunication service provider in Pakistan, show that organizational performance is negatively associated with worker turnover; Huselid (1995), for a sample of about 1,000 large US firms, finds that worker turnover is negatively related to firm productivity and profitability.

Others predict a positive effect. Mc Evoy and Cascio (1987) conducted a meta-analysis

[2] As long as the aim is to investigate the impact of hires and separations on firm performance, it is correct to consider worker turnover. On the contrary, when the aim is to assess the impact of the replacement of some workers with new ones, excess worker turnover (instead of worker turnover) should be considered.

collecting correlations between worker turnover and employees' performance of 24 studies and find that poor performers are more likely to quit, suggesting that worker turnover contributes to enhancing productivity. The meta-analytic work by Williams and Livingstone (1994) further confirms the result of Mc Evoy and Cascio (1987) and suggests that when wage is to some extent set on a performance basis (a major assumption of the matching model by Jovanovic, 1979), the negative correlation between worker turnover and employees' performance is even more pronounced.

Harris et al. (2006) and Glebbeek and Bax (2004) explore the possibility of a non-linear impact, thus assessing whether it exists an optimal amount of worker turnover for the firm. Using a panel of 2,435 small- and medium-sized Australian firms, Harris et al. (2006) find an inverted U-shape link between worker turnover and firm productivity. Glebbeek and Bax (2004), considering a sample of 110 offices of a temporary employment agency, though finding a curvilinear relationship between worker turnover and several accounting performance indicators, can not assert with certainty the existence of an inverted U-shape link.

Bingley and Westgaard-Nielsen (2004) follow a different strategy. Using a panel of 7,118 medium- and large-sized Danish firms, they look at hires and quits separately, finding that quits increase profits while hires reduce them. Also Siebert et al. (2006) examine the separate impact of hires and separations, but on firm productivity, using a sample of 347 shops belonging to a large UK clothing retailer and finding an inverted U-shape for both.

It is worth noting that the bulk of these studies belongs to management literature, thus focusing on the impact of worker turnover on variables such as customer satisfaction and accounting firm performance indicators. The only exceptions are Huselid (1995), Harris et al. (2006) and Siebert et al. (2006), which investigate the effect of worker turnover on firm *productivity*, that is, through the use of a production function, a strategy that is followed here.

As a robustness check, I also perform the estimation using worker turnover instead of excess worker turnover as the regressor of interest, both to make the results comparable with the other papers (Huselid, 1995; Harris et al., 2006; Siebert et al., 2006) and, most importantly, to show that using the 'wrong' regressor for answering the research question of this paper (i.e., worker turnover instead of excess worker turnover) substantially alters the results.

3. The Italian case: employment protection legislation (EPL) and workers' mobility

Italy has traditionally been regarded as one of the most rigid countries in terms of EPL (see, for example, Kugler and Pica, 2008).[3] The OECD, through the provision of synthetic indexes on the EPL intensity, has widely contributed to this view. Though the Italian labor legislation has been a tangle of laws, deliberately aimed at limiting labor mobility, the magnitude of excess worker turnover was in line with that of other countries such as the UK, commonly known for their labor market flexibility (for descriptive statistics on jobs and workers flows, see Contini et al., 2008). Indeed, it is a fact that, for the most diverse causes, that can be found into the diffusion of illegal practices, the frailty of the control system, and the contradictions in the law, the degree of labor mobility in the Italian labor market has been much higher than what one might expect considering only the legislative framework.[4]

During the early 1980s, Italy has experienced the most rigid EPL. On the one hand, hires of new workers could only take place through open-end contracts, except for very particular cases in which temporary work could be used (e.g., for specific projects, seasonal work, or for replacing temporarily absent permanent workers). Blue-collar workers were almost exclusively selected from the list of unemployed people rather than through a direct selection mechanism. On the other hand, for firms employing more than 15 workers, individual dismissals were allowed only under a 'just cause'. Dismissed workers had the right to appeal to the judge. If the judge ruled the dismissal unfair, the firm was obliged to reinstate the worker and to pay forgone wages (*tutela reale*, Law No. 300 from 1970, Article 18). However, as Garibaldi et al. (2003) pointed out, only about 2% of individual dismissals went to court and ended up with a reinstatement of the unfairly dismissed worker. In the vast majority of cases, the reinstatement was bypassed either legally, through extrajudiciary settlements with severance pay, or illegally, in the form of forced quits. Moreover, since small firms (with less than 15 employees) are very common in Italy, the law concerning unfair dismissals did not apply to about 35% of the Italian employees (Contini et al., 2008).[5]

Starting from the mid-1980s, EPL has been markedly reduced, in particular on the entry side of the market, i.e., hires.[6] In 1984, work-training contracts (CFL, *contratti di*

[3] EPL refers to the laws regulating dismissals, either involving an individual worker or a group of workers, and hires. Note that rules concerning collective dismissals are not discussed here because closing firms, that are much involved in collective dismissals, are removed from the analysis.

[4] In Veneto, the labor market was even more mobile. For a discussion on the labor market mobility in this area, see Tattara and Valentini (2003).

[5] Since Veneto is one of the Italian regions featuring the highest proportion of sMall firms, this percentage was even higher there.

[6] The EPL on individual dismissals, on the contrary, has been exacerbated. In 1990, firms with less than

formazione-lavoro) were introduced. These contracts, aiming at favoring the hires of young workers, involved a 50% reduction on social contributions due by firms and, most importantly, were temporary, lasting between 18 and 24 months. At the termination of the contract that was not renewable, the firm had the right, but not the duty, to hire the worker on an open-end contract. In 1988, a partial liberalization of the direct selection mechanism further lessened restrictions on hires. Whereas, in 1991, full liberalization was achieved: since 1991 firms can hire all the workers through a direct selection mechanism. In 1987, temporary contracts were also liberalized. Whereas, prior to 1987, such contracts were strictly and only ruled by the law; after 1987, space has been given to collective agreements. Nonetheless, temporary work remained heavily regulated: it could be only renewed two times, could have a maximum length of 15 months, and could only be used for certain target groups, as specified by the collective agreements (usually, young workers). In 1997, the so-called *Pacchetto Treu* further deregulated hires: it legalized the use of temporary work agencies, even while imposing a maximum number of possible renewals of temporary help workers, it introduced the use of internship programs (*stage* and *tirocinio*) and extended the age limits associated with apprenticeships. However, despite these partial liberalizations on hires, the use of temporary work was negligible until the early 2000s, that is, in all the observation window of the data set used here. Only from the end of 2001 did the standard open-end contract lost importance in favor of the fixed-term. Indeed, in September 2001, Law 368 heavily deregulated the use of temporary work: the mediation of collective agreements was no more needed and was admitted 'for any technical, productive, organizational, or of replacement reason'.

4. Empirical model and identification

Since the aim of the paper is to identify and estimate the causal impact of excess worker turnover on firm productivity, it is sensible to make use of a production function. The data generating process for output produced by firm i at time t is assumed to be given by a production function of the Cobb-Douglas type with the following characteristics:

$$Y_{it} = A_{it} L_{it}^{\beta_l} K_{it}^{\beta_k} \tag{1}$$

where: Y_{it}, L_{it}, and K_{it} denote respectively production and labor and capital usage of firm i at time t; and A_{it}, the total factor productivity (TFP), is modeled as follows:

$$A_{it} = e^{\alpha + \theta EWT_{it} + \gamma F_{it} + \eta_i + \omega_{it} + \epsilon_{it}} \tag{2}$$

15 employees were also subjected to the 'just cause' rule concerning individual dismissals. In case of unfair dismissal, they had to pay severance.

where: α is the average productivity of the firms; θ is the impact of excess worker turnover, EWT_{it}, on (the logarithm of) productivity; F_{it} is a vector of variables influencing the productivity of the firm, included as controls[7]; η_i is a firm-specific fixed effect; ω_{it} is an idiosyncratic productivity shock whose evolution is regulated by a first-order Markov process, whose realization at time t is observed by the firms at time t (i.e., contemporaneously), and which is at least partially anticipated by the firms; and ϵ_{it} is an unforecastable productivity shock or measurement error. The econometrician does not observe either η_i, nor ω_{it}, nor ϵ_{it}.

In this framework, excess worker turnover enters the production function through the TFP. Obviously, it is not a standard input, such as labor and capital; however, it is likely to have a role in determining the firm's output: the potential channels are several and already highlighted in Section 2. They include: decreased productivity due to loss of firm-specific human capital (from the separation) and costly learning process (from the hire); increased productivity if an underperforming worker leaves the firm and if an overperforming worker enters the firm; increased productivity if excess worker turnover is seen as a valuable resource in terms of knowledge spillovers, or decreased productivity if it is seen by remaining workers as a sign of weakness of the firm in retaining workers.

Since ω_{it} is assumed to follow a first-order Markov process, it is possible to write:

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

where: I_{it-1} is the information set of firm i at time $t-1$; $g(\cdot)$ is a completely general function and represents the predictable component of ω_{it}; and ξ_{it} is the innovation in the productivity shock, which, by construction, is unpredictable by the firm, such that $E[\xi_{it}|I_{it-1}] = 0$. The assumption that ω_{it} follows a first-order Markov process, is both an assumption on the stochastic process regulating ω_{it} and an assumption on the firms' information set. Basically, firms observe ω_{it} at t and form expectations on ω_{it} at $t-1$ using $g(\cdot)$.

Labor and capital are assumed to be not perfectly flexible inputs. Intuitively, this means that the amount of labor and capital to be used in the production process at t is actually decided at $t-1$. This assumption is consistent with the presence of capital and labor adjustment costs accounting for the fact that, on the one hand, new capital takes time to be ordered, delivered, installed, and put into operation and, on the other hand, that it takes time to fire and/or hire workers.[8] In the rest of the discussion, this is referred to as

[7] They are: female, migrant, part-time, temporary, apprentice, blue-collar, and white-collar workers' shares, average age of the workforce, and dummies for year, province, sector of economic activity (defined according to the 3-digit Ateco 91 classification), and year interacted by sector of economic activity. For the rest of the discussion, they are assumed to be exogenous.

[8] In a context such as Italy, where EPL is particularly rigid, this assumption is likely to be relevant.

the ‘timing assumption’. Moreover, labor and capital choices are assumed to have dynamic implications. Essentially, this is equivalent to assuming that the choice of labor and capital made at t not only affect profits in $t+1$, as the result of the timing assumption, but also profits in $t+2$, $t+3$, and so on.

In practice, the production function to be estimated is obtained by using Equation (2) and by taking logs in Equation (1):

$$y_{it} = \beta l_{it} + \beta k_{it} + \theta EWT_{it} + \gamma F_{it} + \eta_i + \omega_{it} + \epsilon_{it} \tag{3}$$

where lowercase letters represent natural logarithms.

On the basis of the assumptions on the (composite) error term that one is willing to make, different estimates of θ are obtained. Since the goal is to identify the *causal* effect of excess worker turnover on firm productivity, a discussion on the most realistic assumptions on the error term and, consequently, the most reliable identification strategy will follow.

It is assumed for the moment that each regressor in Equation (3) is not correlated with ω_{it}. This amounts to require that, even though the firm can partially anticipate the productivity shock, it does not react to it by adjusting the level of inputs and that excess worker turnover does not respond to productivity shocks.

If one is willing to assume that η_i is also uncorrelated with each regressor in Equation (3), a simple OLS regression consistently identifies θ and other parameters.

However, there are reasons to believe that η_i is indeed correlated with excess worker turnover. Consider the following example: assuming that η_i is uncorrelated with excess worker turnover means *excluding* that managerial ability, inside η_i, since unobservable and very likely not to vary over time (at least over a short panel like the one used here), has an impact on productivity *and* on excess worker turnover. Indeed, it is possible to conceive situations in which the managerial ability does have an impact on productivity, as better managers reach better productivity results, *and* on excess worker turnover, as better managers may be more able than poorer ones in choosing better employees and in retaining them. If this is the case and if it is not taken it into account, the result is an overestimation of the negative impact of worker turnover on firm productivity. Consider that it is possible to make similar arguments with respect to culture, the degree of internationalization, and other factors which are unobservables and time-invariant (and hence inside η_i). Then, since η_i is most likely correlated with excess worker turnover, a simple OLS regression on Equation (3) does not identify the causal effect of interest. Exploiting the panel nature of the data, it is possible to remove η_i by considering a within-group transformation of Equation (3):

$$\widetilde{y}_{it} = \beta_l \widetilde{l}_{it} + \beta_k \widetilde{k}_{it} + \theta \widetilde{EWT}_{it} + \gamma \widetilde{F}_{it} + \widetilde{\omega}_{it} + \widetilde{\epsilon}_{it} \tag{4}$$

where the tilde operator indicates the within-group transformation: $\widetilde{x}_{it} = x_{it} - \frac{1}{T}\sum_{t=1}^{T} x_{it}$. Thus, as long as one is willing to maintain the assumption of no correlation between regressors and ω_{it}, an OLS regression on Equation (4) identifies the causal effect of interest. This procedure is known as fixed-effects (FE) or within-group regression.

Still, claiming that inputs and excess worker turnover are uncorrelated with the idiosyncratic productivity shock ω_{it} is contrived.

Firstly, this assumption would imply that managers, at $t-1$, when choosing the level of inputs to be used at t (recall the timing assumption), do not consider their prediction of ω_{it} made according to $g(\cdot)$. Such a scenario seems unrealistic, thus pointing to the existence of a positive correlation between inputs and the (predictable part of the) productivity shock, such that the greater the productivity shock is expected to be, the greater the chosen level of inputs to use.[9]

Furthermore, the job-search theory, established, among others, by Burdett and Mortensen (1998), has highlighted that excess worker turnover is higher for low-productivity (and consequently low-wage) firms, and correspondingly lower for high-productivity (and consequently high-wage) ones.[10] Hence, it may happen that not only does excess worker turnover have an impact on firm productivity, as both FSHC theory and matching theory suggest, but also that excess worker turnover itself is influenced by firm productivity, as on-the-job search models point out. If this is the case, excess worker turnover is correlated with the productivity shock ω_{it}, causing it to be endogenous. Failing to account for this results in overestimating the negative impact of excess worker turnover on firm productivity. In particular, it is assumed that excess worker turnover is correlated with the predictable part of ω_{it}, but not with the innovation term, ξ_{it}. This is consistent with the following situation. At $t-1$, when the firm has to choose the amount of labor to be used at t, it decides whether to keep it at the same level of $t-1$, or whether to increase or decrease it. Furthermore, again at $t-1$, the firm decides whether to replace some employees. Workers make and communicate to the firm at $t-1$ their decision to quit or not to quit at t. On the basis of the number of quits, the amount of labor input that the firm has chosen to use at t, and the amount of replacements

[9]In the production function estimation literature, the correlation between inputs and productivity shock is generally referred to as the 'simultaneity problem'.

[10]In equilibrium, low-productivity (low-wage) firms are characterized by high excess worker turnover *exactly* because of the possibility that workers have to keep searching for better jobs while working on the current job.

to be done, the firm decide at $t-1$ whether to hire and/or to fire someone at t. Hence, since the amount of excess worker turnover at t is already settled at $t-1$, it is not correlated with ξ_{it}, which is known by the firm only at t.

These arguments on the endogenous nature of regressors with respect to ω_{it} invalidate the consistency of the fixed-effect estimator.

In view of these considerations, it is possible to remove the endogeneity caused by ω_{it} using the procedure proposed by Ackerberg et al. (2006) (from now on, ACF). In a nutshell, ACF propose to use demand for intermediate goods as a proxy for the unobserved productivity shock. In particular, in the ACF framework, the TFP would be modeled as:

$$A_{it} = e^{\alpha+\theta EWT_{it}+\gamma F_{it}+\omega_{it}+\epsilon_{it}} \tag{5}$$

Note that, in contrast with the previous formulation of TFP in Equation (2), here the fixed firm-specific term η_i is suppressed. The production function in logarithmic form would then become:

$$y_{it} = \beta l_{it} + \beta k_{it} + \theta EWT_{it} + \gamma F_{it} + \omega_{it} + \epsilon_{it} \tag{6}$$

In the ACF method, it is assumed that the demand for intermediate inputs[11], m_{it}, is a function of labor, capital, excess worker turnover (in this particular case), and the time-varying productivity shock and that it is strictly increasing in ω_{it}:

$$m_{it} = f(l_{it}, k_{it}, EWT_{it}, \overset{+}{\omega}_{it}) \tag{7}$$

Intuitively, this amounts to require that the bigger the productivity shock ω_{it}, the larger is the demand for intermediate inputs to be used in the production process. If this (strict) monotonicity on f holds, f can be inverted out to deliver an expression of ω_{it} as a function of l_{it}, k_{it}, EWT_{it}, and m_{it}, which are observables:

$$\omega_{it} = f^{-1}(l_{it}, k_{it}, EWT_{it}, m_{it}) \tag{8}$$

This expression for ω_{it} can then be substituted into Equation (6) to bring:

$$y_{it} = \beta l_{it} + \beta k_{it} + \theta EWT_{it} + \gamma F_{it} + f^{-1}(l_{it}, k_{it}, EWT_{it}, m_{it}) + \epsilon_{it} \tag{9}$$

At this point, ACF proprose a two-step strategy to recover estimates of β_l, β_k, and θ (and γ). In the first step, y_{it} is nonparametrically regressed against a function in l_{it}, k_{it}, EWT_{it},

[11] They are assumed to be perfectly flexible and non dynamic.

m_{it}, and F_{it}, referred to as $\Phi(l_{it}, k_{it}, EWT_{it}, m_{it}, F_{it})$.[12] From this regression, it is possible to identify the composite teRm:[13]

$$\widehat{\Phi}^*_{it} = \widehat{\beta_l l_{it} + \beta_k k_{it} + \theta EWT_{it} + \omega_{it}}$$

Given guesses of β_l, β_k, and θ, respectively denoted with β_l^*, β_k^*, and θ^*, it is then possible to recover implied ω_{it}, i.e., $\hat{\omega}_{it}(\beta_l^*, \beta_k^*, \theta^*)$, as:

$$\hat{\omega}_{it}(\beta_l^*, \beta_k^*, \theta^*) = \widehat{\Phi}^*_{it} - \beta_l^* l_{it} - \beta_k^* k_{it} - \theta^* EWT_{it}$$

Recalling the assumption on the stochastic process regulating ω_{it}, namely, that it follows a first-order Markov process such that $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$, and given the implied $\hat{\omega}_{it}(\beta_l^*, \beta_k^*, \theta^*)$, it is possible to compute the implied innovations $\hat{\xi}_{it}(\beta_l^*, \beta_k^*, \theta^*)$ as the residuals from a non-parametric regression of the implied $\hat{\omega}_{it}(\beta_l^*, \beta_k^*, \theta^*)$ on the implied $\hat{\omega}_{it-1}(\beta_l^*, \beta_k^*, \theta^*)$.[14] Then, the sample analogues of the moment conditions imposed by the model[15] are evaluated:

$$\begin{aligned}
\frac{1}{N}\frac{1}{T}\sum_i\sum_t \hat{\xi}_{it}(\beta_l^*, \beta_k^*, \theta^*)k_{it} = 0 \\
\frac{1}{N}\frac{1}{T}\sum_i\sum_t \hat{\xi}_{it}(\beta_l^*, \beta_k^*, \theta^*)l_{it} = 0 \\
\frac{1}{N}\frac{1}{T}\sum_i\sum_t \hat{\xi}_{it}(\beta_l^*, \beta_k^*, \theta^*)EWT_{it} = 0
\end{aligned} \tag{10}$$

The search over β_l^*, β_k^*, and θ^* continues until $\hat{\beta}_l$, $\hat{\beta}_k$, and $\hat{\theta}$ are found that satisfy Equation (10). These are the ACF estimators of β_l, β_k, and θ.

Therefore, the ACF method represents a solution in dealing with the correlation of inputs and excess worker turnover with the productivity shock ω_{it}. *A* solution; indeed, other methods have been developed that try to solve the simultaneity problem in the framework of semiparametric estimation.[16] However, since the method proposed by Ackerberg et al.

[12] In the empirical analysis, $\Phi(\cdot)$ is approximated with a second-order polynomial in l_{it}, k_{it}, EWT_{it}, and m_{it}, with F_{it} added linearly. I also have tried it with higher-order polynomials (third- and fourth-order). However, this does not alter the results, so that I have chosen to use the second-order approximation.

[13] These are just the predicted values of y_{it} from the regression minus the estimated $\hat{\gamma}F_{it}$.

[14] In the empirical analysis, $g(\cdot)$ is approximated with a third-order polynomial in $\hat{\omega}_{it-1}(\beta_l^*, \beta_k^*, \theta^*)$.

[15] Stemming from the assumption that capital and labor are not perfectly flexible inputs and that quits at t are actually decided by workers at $t-1$, they are: $E[\xi_{it}k_{it}] = 0$, $E[\xi_{it}l_{it}] = 0$ and $E[\xi_{it}EWT_{it}] = 0$.

[16] Olley and Pakes (1996) (OP) have been the first to propose a proxy variable approach, where investment demand serves as a proxy for ω_{it}. Its major drawback is that only observations for which investments are positive can be used in the estimation. Levinsohn and Petrin (2003) (LP) propose to use the demand for intermediate inputs to proxy ω_{it}, since it is more likely to be monotonic in ω_{it} (differently from investments).

(2006) is the most recent and, as such, the one capitalizing from the methods previously developed, the empirical analysis is based on it.

However, what about η_i, which, as discussed before, is most likely correlated with excess worker turnover? To properly account also for unobserved firm-specific fixed effects, I use a modified version of the ACF method (ACF-FE). Following Vandenberghe et al. (2013), it is argued that only the first stage of the ACF procedure needs to be modified to explicitly account for unobserved firm heterogeneity. In this framework, TFP is again modeled as in Equation (2), so that the (logarithmic version of the) production function is again given by Equation (3). It is still assumed that the demand for intermediate inputs is given by Equation (7), so that it solely depends on the amount of labor and capital to be used in t, the amount of excess worker turnover in t, and the productivity shock observed at t. Note that the fact that the demand of intermediate inputs also depends on η_i is excluded. This assumption rules out factors such as management quality, culture, and internationalization of the firm in determining the demand of intermediate goods to be used in the production process. This does not seem an implausible assumption, since it is sensible to believe that the demand of intermediate inputs, which are by assumption perfectly flexible and non dynamic, depends only on time-varying components. Moreover, the assumption that f is invertible in ω_{it} is also maintained. This set of assumptions implies that what is Equation (9) in the ACF framework, becomes, in this case:

$$y_{it} = \beta l_{it} + \beta k_{it} + \theta EWT_{it} + \gamma F_{it} + \eta_i + f^{-1}(l_{it}, k_{it}, EWT_{it}, m_{it}) + \epsilon_{it} \tag{11}$$

As before, setting:

$$\Phi(l_{it}, k_{it}, EWT_{it}, m_{it}, F_{it}) \equiv \beta l_{it} + \beta k_{it} + \theta EWT_{it} + \gamma F_{it} + f^{-1}(l_{it}, k_{it}, EWT_{it}, m_{it})$$

it is possible to write Equation (11) as follows:

$$y_{it} = \Phi(l_{it}, k_{it}, EWT_{it}, m_{it}, F_{it}) + \eta_i + \epsilon_{it} \tag{12}$$

Since η_i is most likely correlated with excess worker turnover, inside $\Phi(\cdot)$, to get a consistent estimate of $\Phi(\cdot)$ itself, η_i should be removed from Equation (12). To this aim, nonparametric FE estimation is proposed.[17] From FE estimation of Equation (12), it is possible to obtain

However, the LP approach has been criticized by Ackerberg et al. (2006), who argue that the first stage of the LP procedure, in which an estimate for β_l is recovered, suffers from collinearity. They propose to identify all the coefficients in the second stage of the estimation, according to the procedure described above.

[17]In the empirical analysis, $\Phi(\cdot)$ is again approximated with a second-order polynomial in l_{it}, k_{it}, EWT_{it},

a consistent estimate of $\Phi^*(\cdot)$, $\hat{\Phi}^*(\cdot)$[18], so that it is possible to proceed to the second stage of the estimation procedure (unchanged with respect to the ACF method) from:

$$\widehat{\Phi}^*_{it} = \widehat{\beta_l l_{it} + \beta_k k_{it} + \theta EWT_{it} + \omega_{it}}$$

In conclusion, according to the set of hypotheses discussed before, it is possible to identify the causal effect of excess worker turnover on firm productivity through the use of the ACF-FE method.

5. The data: VWH-AIDA

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

The VWH data set has been constructed by a team led by Giuseppe Tattara at the University of Venice on the ground of the administrative data of the Italian Social Security System (for an accurate description of the data set, see Tattara and Valentini, 2007, 2010). It collects labor market histories and earning records for the period 1975-2001 of *each* single employee working for at least one day in the private sector (except for agriculture) of Veneto, an administrative region in Italy with a population of around 5 million people. During the 1970s and 1980s, Veneto experienced an industrialization process which made it one of the richest, most dynamic and most export-oriented regions in Italy. The vast majority of firms of Veneto are small- or medium-sized and operate in the manufacturing industry. Among the industries in which these firms specialize are chemistry, metal-mechanics, electronics, food products, wood and furniture, leather and footwear, and textiles and clothing. Typical of Veneto is the division of the territory into industrial districts.[19] Essentially, VWH is made of three parts: a *worker archive*, collecting personal information of the worker (gender, age, and birth place); a *job archive*, containing information on the job held by the worker in the firm (number of days worked and total earnings during the year, contract type, and qualification); and a *firm archive*, containing information about the firm (firm's national tax number, used as firm identifier, name, location, establishment date, cessation date, whenever applicable, and industry, classified according to the Ateco 91 code). These features make VWH a longitudinal matched employer-employee data set.

and m_{it}, with F_{it} added linearly.

[18] As before, these are just the predicted values of y_{it} from the regression minus the estimated $\hat{\gamma}F_{it}$.

[19] For example, the province of Belluno, where Luxottica has production plants, hosts the eyewear district; while the province of Venice hosts the artistic glass district in Murano.

The AIDA data set is provided yearly since 1995 by the Bureau van Dijk and contains comprehensive information on balance sheet data of all (non-financial) incorporated firms in Italy with annual sales above 500,000 Euros. The AIDA variables include revenues, value added, profit, book value of capital, total wage bill, total number of employees, and the firm's national tax number.

Firm's national tax number has then been used to match job-year observations in the VWH with the firm information in AIDA. The merge of the VWH and the AIDA data sets has been conceived and conducted by David Card, Francesco Devicienti, and Agata Maida, who accurately describe the merging procedure in Card et al. (2014). The result is a longitudinal matched employer-employee data set (VWH-AIDA) for the period 1995-2001, collecting job histories and earning records of all employees (with the exception of farm workers) in all (non-financial) incorporated Veneto firms operating in the private sector with revenues greater than 500,000 Euros, for which balance sheet information is available.

As discussed in Section 4, the inputs of the production function are labor and capital. The amount of labor used by a firm in a given year is defined by the total number of full-time adjusted days worked during the year (unfortunately, the data set does not provide information on hours of work); whereas, capital input is measured by the physical capital stock[20]. The intermediate input, to be used in ACF and ACF-FE procedures, is the amount of materials as reported by the 'raw, consumable materials' item. The dependent variable is (deflated) value added.

To obtain a measure of excess worker turnover, the definitions of jobs and workers flows in Davis et al. (1996) are considered:

hires: is the number of workers hired by a given firm between $t-1$ and t;

separations: is the number of workers separating from a given firm between $t-1$ and t; it collects both quits and dismissals;

worker turnover: is the sum of hires and separations in a given firm between $t-1$ and t;

net job creation: is the difference between the number of employees in a given firm at time t and $t-1$;

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

[20]It is computed by a perpetual inventory method (PIM) with constant depreciation rate (0.065). The benchmark at the first year is given by the book value of the 'tangible fixed assets' item; investments are computed as the difference between the tangible fixed assets values as reported in two contiguous balance sheets.

Discrete-time data and, therefore, discrete-time versions of worker turnover measures, are the norm in literature. In practice, the researcher can only observe stocks of employment at discrete points in time, for example on the 1st of January and 31st of December of a given year. Hires in a given firm and in a given year are then identified by looking at workers employed in that firm on the 31st of December but not on the 1st of January of the given year; similarly, separations are identified by looking at workers employed in the given firm on the 1st of January but not on the 31st of December of the given year. In this case, any employment relationship that begins after the 1st of January and terminates before 31st of December of the same year, does not enter the count of hires and separations, even if, to all intents and purposes, it represents one hire and one separation for the firm in that year. Hence, turnover indexes computed with discrete-time data are undercounted.

Since the VWH-AIDA data set allows observation of a monthly history of each job held by a worker in a given firm, it is possible to consider an (almost) *continuous*-time version of the excess worker turnover and of the other worker turnover measures: hires, separations, and worker turnover. In particular, they are calculated on the basis of two variables present in the original version of the VWH data set; one indicating the month of the hire, and the other indicating the month of the separation (if applicable) for each job. Essentially, if the hiring month is equal to or after January of the given year, it is considered as a hire. If the separation month is prior to or during December of the given year, then it is a separation.

Furthermore, having a continuous-time version of the data allows me to *construct* a discrete-time version of them, while the reverse is clearly unfeasible. To show how much the worker turnover measures change when discrete-time definitions are considered and to present results that are comparable with the literature[21], discrete-time measures are also computed. To do this, I act *as if* it would be possible to observe the stock of employment only two times in a given year: in January and December.

Following Davis and Haltiwanger (1992), to express turnover measures in rates, they are divided by the average level of employment, defined as the sum of the number of employees in January and December of a given year, divided by two, that is, $\frac{E_{jan,t}+E_{dec,t}}{2}$.

Finally, some workforce characteristics of the firm, including female, migrant, part-time, temporary, apprentice, blue-collar, white-collar, manager, and under-30 workers' shares, have been constructed by weighting workers on a monthly basis. For example, in the construction of the variable measuring the share of females in the firm, a woman that is employed for only two months weights six times less than a woman employed for the whole year.

[21] The vast majority of empirical works assessing the impact of worker turnover on firm productivity uses discrete-time measures of worker turnover. One notable exception is represented by (Siebert et al., 2006).

To exclude excess worker turnover derived from firm entry or exit, the analysis only considers firms established at least one calendar year before they are observed and firms still alive at least one calendar year after they are observed.[22] As a further precaution, the analysis is restricted to firms classified as 'active', thus excluding closing firms. Firms with non-positive book values of physical capital, materials, and value added are excluded from the sample. The same is done for firms with less than 10 employees (monthly weighted). The rationale behind this is twofold: on the one hand, it cleans the data set from systematic 'window dressing' procedures, usually carried out by very small firms, and, on the other hand, it is required to compute meaningfully the excess worker turnover rate. Moreover, firms with excess worker turnover rate greater than 1 are not considered in the analysis. This has been done to purge the sample from relatively few (about 5%) disturbing outliers. Finally, to apply the ACF and ACF-FE methods, it is necessary to restrict the sample to firms having at least two *consecutive* years of observations.

Since the vast majority of firms (about 70%) belong to the manufacturing industry, for the sake of sample homogeneity, I decided to restrict attention to it. It could as well be possible to preserve the full sample and to perform the analysis by industry. However, the remaining 30% of the sample is split among trade, transportation and telecommunication, services, and construction industries, and the sample size would be too small to draw reliable conclusions for them.

The final data set used in the empirical analysis is the firm-level 'collapsed' version of the matched employer-employee data set; it consists of 27,387 firm-year observations for 5,728 firms.

Table 1 shows the distribution of firms by number of consecutive panel observations: about 56% of the firms are observed for at least 5 consecutive years.[23]

Table 2 shows the distribution of firms by industry, as classified by the 2-digit Ateco 91 classification. Firms producing ferrous and machinery products, furniture, food and beverage, and textile and clothing collect most of the observations.

Table 3 presents basic summary statistics, which, despite the particular sample used in this analysis, are very similar to those in Card et al. (2014).

On average, firms have about 59 employees and obtain 11 million Euros per year in revenues. However, for 50% of the companies, employees are less than 32 and revenue less than 5 million Euros. Each day worked (by each worker) brings on average about 650 Euros

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

[23]For the sake of fluidity, from now on, when referring to 'firm', I actually mean 'firm-year observation'. If needed, I will make the distinction clear.

of revenue, but for 50% of the firms, this figure is less than 470 Euros. The average firm is about 16 years old and gets 20 Euros of net profit out of 1,000 Euros of sales. In the typical firm, 29% of the workers are females, 6% are migrants, 39% are under 30 years of age, and the average age of the workers is 35 years. About 4% of them are employed on a part-time basis and slightly less than 4% are temporary workers. The vast majority of employees in the average firm are blue-collar (70%) or white-collar (24%); some are in a period of apprenticeship (4%) and a few of them fill a managerial position (1%). On average, workers tend to stay in the same firm for 6.5 years and earn about 130 Euros per day before taxes.

Average net job creation rate is 0.03; hiring and separation rates are on average 0.23 and 0.20, so that the mean worker turnover rate is 0.43, and average excess worker turnover rate is 0.33. In any given year, the average firm hires 12 workers and separates from 10 workers, thus experiencing a worker turnover of 22 workers (12 hires + 10 separations) and a net job creation equal to 2.[24] In principle, the average firm could have accommodated the job creation by simply hiring 2 workers and by separating from none. Instead, it has hired 12 workers and, at the same time, separated from 10. It might as well have hired 25 employees and separated from 23. Hence, ideally, all the configurations of hires and separations as long as their difference is 2 would be consistent with the job creation actually observed. Ultimately, the research question here is whether it is better to reach the desired employment level through high or low *excess* worker turnover.

As previously stated, discrete-time turnover measures are also computed. As expected, these figures are significantly lower than their continuous counterparts: average hiring, separation, and worker turnover rates are respectively 0.16, 0.14, and 0.30. Discrete-time excess worker turnover rate is, on average, 0.20. Hence, average excess worker turnover is about 39% lower when considering the discrete- instead of the continuous-time version, suggesting that employment relations starting and ending within a year are indeed common. The turnover measures found in the VWH-AIDA data set are in line with comparable literature: Harris et al. (2006), for an Australian sample of small- and medium-sized firms (like the great majority of Venetian firms), find the discrete-time version of worker turnover rate to be 0.25, whereas, in the VWH-AIDA data set, the corresponding figure is 0.30.[25]

[24] Specifically, average hires are 11.62, average separations are 10.23, average worker turnover is 21.85, and average net job creation is 1.39. Integer numbers are considered to make the discussion about the 'typical firm' realistic.

[25] On the contrary, Huselid (1995), for a US sample of large-sized firms, hardly comparable with the typical Venetian companies, find the discrete-time version of worker turnover to be significantly lower (0.18). Moreover, much of the literature on turnover focuses on service or retail industries, which are not considered here. For example, Siebert et al. (2006), for a sample of 347 shops belonging to a large UK clothing retailer, find that the continuous-time version of excess worker turnover is 0.47. Though not considered in the analysis, this is substantially higher than the corresponding figure for the retail industry in the VWH-AIDA data set,

6. Results

6.1. Main findings

This section presents results from OLS, FE, ACF, and ACF-FE estimations of Equation (3).

In view of the considerations in Section 4, the ACF-FE method is considered to be the most reliable among others described in delivering a consistent estimate of the causal effect of interest (i.e., θ) and, as such, is chosen to be the reference method. Still, OLS, FE, and ACF results are presented to assess their potential bias.

The vector of controls, F_{it}, comprises female, migrant, temporary, part-time, apprentice, blue-collar, and white-collar workers' shares and the average age of the workforce, which may influence both the degree of excess worker turnover and TFP. Moreover, dummies for year, province, industry, and year interacted with industry are included.[26] In ACF and ACF-FE, the function $\Phi_{it}(\cdot)$ is approximated with a second-order polynomial in l_{it}, k_{it}, EWT_{it} and m_{it}, with controls added linearly. Both OLS and FE estimates are robust to heteroskedasticity and the same applies to ACF and ACF-FE, since bootstrapped standard errors are computed.[27]

Results are shown in Table 4. The first column reports the OLS results, the second and the third are for FE and ACF respectively, whereas the forth reports the ACF-FE estimates.

According to the OLS estimates, the impact of excess worker turnover on firm productivity is significantly negative and equal to -0.039; a 1 standard deviation increase in the excess worker turnover rate (0.22) would cause a decrease in productivity by about 0.86%. However, as discussed in Section 4, the OLS estimator is likely to not be able to identify θ, principally because excess worker turnover may be correlated with unobserved heterogeneity (e.g., managerial ability) and with the productivity shock (because of reverse causality coming from on-the-job search).

When controlling for unobserved fixed heterogeneity such as managerial ability (FE estimation), the estimated impact of excess worker turnover changes its sign, becoming significantly positive (0.020). A 1 standard deviation increase in the excess worker turnover rate is predicted to increase productivity by 0.44%. The negative bias of OLS casts light on the negative correlation between unobserved heterogeneity and excess worker turnover. This is consistent with the fact that better managers, while attaining higher productivity

which is 0.35.

[26]Industry is defined on the basis of the 3-digit level Ateco 91 classification. In FE and ACF-FE estimatons, province and industry dummies are obviously omitted, since time-invariant heterogeneity, whether it is observed or unobserved, is, by construction, controlled for.

[27]The STATA code for ACF and ACF-FE methods is written by the author and is available upon request.

levels, systematically reach a lower degree of excess worker turnover, possibly because they are more able than poorer ones in choosing the 'right' workers. However, if, on the one hand, FE is able to deal with unobserved heterogeneity, on the other hand, it does not deal with the simultaneity issue raised by on-the-job search mechanism, that is, with the correlation between excess worker turnover and the idiosyncratic productivity shock.

Contrary to the FE estimation, though not dealing with firm-specific heterogeneity, the ACF method allows to take into account the simultaneity issue. According to the ACF estimates, the impact of excess worker turnover on productivity is negative but lower in magnitude than predicted by OLS (-0.019). A 1 standard deviation increase in the excess worker turnover rate is predicted to decrease productivity by 0.41%. However, this estimate is not statistically different from zero at any conventional significance level. The fact that the ACF estimate is larger than the OLS one (-0.019 *versus* -0.039), sheds light on the relevance of the simultaneity issue. Hence, not only does excess worker turnover impact productivity, but productivity itself contributes to determining the level of excess worker turnover in the firm. As discussed in Section 4, failing to account for reverse causality (as it is for the OLS method) leads to overestimating the negative impact.

When taking into account the simultaneity issue *and* the firm-specific fixed effects, it is possible to get a consistent estimate of θ (ACF-FE method). According to the ACF-FE estimates, the impact of excess worker turnover on productivity is positive and equal to 0.036: a 1 standard deviation increase in the excess worker turnover rate is estimated to increase firm productivity by 0.81%. The estimated coefficient is statistically different from zero at any conventional significance level.

It is worth recalling that the production function inputs are also likely to be correlated with the productivity shock. Hence, over and above the endogeneity of excess worker turnover, one of the inputs has to be taken into account as well, both in itself and in view of the purpose of the paper. In fact, endogeneity of one regressor not only causes inconsistency in its estimation, but also in the estimation of other parameters of the model. This is a further motivation for relying on the ACF-FE estimates instead of on the OLS or FE ones, since they do appropriately deal with the endogeneity of inputs. The ACF-FE estimate of β_l, i.e., the elasticity of the labor input, is 0.799: a 10% increase in the use of labor would increase output by 7.99%, whereas β_k, i.e., the elasticity of the capital input, is estimated to be 0.067: a 10% increase in the physical capital usage would increase output by about 0.67%. These values are in the standard range found in literature on value added production functions (for example, see Van Biesebroeck, 2007). Both the estimates of labor and capital elasticities are significantly different from zero at any conventional level.[28]

Hence, when dealing with the potential sources of bias, data show that replacing workers is beneficial to firm productivity. This result, in sharp contrast with common beliefs, shows that managers should not be *a priori* scared by excess worker turnover. Indeed, they should perceive it as an opportunity of growth of their firms. Firstly, excess worker turnover gives chances to find more suitable workers, especially in a world of imperfect information, where employer-employee matches are often revealed to be not optimal. Secondly, replacing workers allows knowledge to spread out. In particular, for an economy such as Venetos, where industrial districts are the norm, they are likely to play a crucial role. Besides contributing to increased productivity of single firms, excess worker turnover undoubtedly allows, on an aggregate basis, an entire region to be more performing and to grow faster. In this perspective, policy makers should also make their own part concerning workers' mobility: they should try to break away from the cultural heritage that sees it as something to shy away from. Also, considering that, notwithstanding the jumble of laws and bylaws on EPL, workers still move extensively.

6.2. Extensions and robustness checks

As Adelson and Baysinger (1984) suggest, it is possible that, though the average effect of excess worker turnover on productivity is found to be positive, there exists a point after which it becomes harmful. This indicates an inverted U-shape effect, which can be empirically explored by adding a quadratic term in the excess worker turnover rate in Equation (3).

Furthermore, it seems plausible that the impact of interest is diversified across firms. In particular, it is argued that the relevant dimensions are four: belonging or not belonging to the high-tech industry and to industrial districts, and the age and size of the firm.

In the first place, it is possible that the positive effect of excess worker turnover is even more pronounced for the high-tech industry, where optimal matches and spillover effects seem to play a crucial role. Whereas, in the low-tech industry, where their role seems to be less important, it may be that the costs associated with high excess worker turnover (for instance, output forgone when searching for new workers and loss of productivity due to learning process of the newly hired workers) are not greatly compensated for by benefits, unlike in the high-tech industry.

Secondly, it is argued that knowledge spillover effects, enhanced by workers' mobility and, consequently, by excess worker turnover, are mostly relevant for firms belonging to industrial

[28]The estimates of β_l and β_k in the OLS and ACF frameworks are slightly higher than those in the FE and ACF-FE frameworks. This is probably due to measurement error, that, inducing a downward bias in the estimated coefficients, is exacerbated by the within-group transformations.

districts. These firms are in such a strict relationship in terms of production processes and goods produced that knowledge of workers moving from one firm to another one operating in the same district (it is often the case, see Serafinelli, 2013), is spread very easily. Thus, it is expected that the positive impact of excess worker turnover on productivity is substantially higher for such firms.

In the third place, it seems that the age of the firm also represents a relevant dimension according to which the impact of excess worker turnover may differ. Here, however, the argument is less obvious. On the one hand, it may be that young firms benefit from excess worker turnover more than old firms: in the early life of a firm, optimal job matches still have to be reached and excess worker turnover is the only way in which this could be done. On the other hand, it remains a fact that young firms have to 'practice with the world', so that it may be safer, at least for the very first years, to stay with the same workforce to acquire some experience, and, only then, assess whether to replace some workers.

Finally, it is plausible that very small firms may also suffer from excess worker turnover: in general, they have more difficulties than larger firms in recruiting new workers and, during vacancy periods, it is more problematic for them to reallocate the workforce to do the extra job (which was previously done by the separating worker).

Table 5 shows results for these extensions. Since the ACF-FE method is the preferred, the table only reports the corresponding estimates of the relevant coefficients. Moreover, all these models include the usual set of controls.

The first row of Table 5 refers to the non-linear version of the basic model, i.e., with squared excess worker turnover rate added as a regressor in Equation (3). The estimated coefficient associated with the excess worker turnover rate is still positive, though larger than in the basic model (0.107 *versus* 0.036) and highly significant. The coefficient associated with the squared term is estimated to be negative (-0.087) and significant at the 5% level, thus pointing to the existence of an inverted U-shape impact, as expected. The impact is predicted to be positive up to when the excess worker turnover rate is equal to 0.62, becoming negative afterward. Passing from a zero level of excess worker turnover to the optimal level is predicted to increase productivity by as much as 3.36%. Since the excess worker turnover rate is below 0.62 (i.e., the maximum) for about 88% of firms, increases in its level are beneficial for the vast majority of them.

The second row of Table 5 shows results for the case in which it is allowed for differences in the impact of interest between high- and low-tech industries. This is done by interacting excess worker turnover rate with high- and low-tech industry dummies and inserting these new regressors in Equation (3), obviously in place of the excess worker turnover rate. The definition of the high-tech industry is based on R&D intensities and follows the one proposed by the OECD. Among the others, it includes: aircraft and spacecraft, chemicals, automotive, and medical instruments.[29] In the sample, 12.93% of firms belong to the high-tech industry. Results seem to support the argument made before: the estimated impact for the high-tech industry is more than twice that for the low-tech industry (0.076 *versus* 0.030). A 1 standard deviation increase in the excess worker turnover rate is estimated to cause an increase in productivity by as much as 1.07% in the high-tech industry. However, if, on the one hand, the effect for the low-tech industry is statistically significant at (slightly more than) the 5% level, the estimate for the high-tech industry is more imprecise (slightly more than the 10% level). The relatively small number of high-tech firms may be an explanation for this lack of precision.

The third row of Table 5 reports results of a version of Equation (3) in which the impact of interest is allowed to vary depending on whether the firm belongs to an industrial district or not. Industrial districts are identified on the basis of the list given by the *Osservatorio Nazionale dei Distretti Industriali*. Among others, they include: the eyewear district in Belluno, the district of ceramic, porcelain, and artistic glass in Vicenza, as well as the district of artistic glass in Murano (Venice), the district of wood and furniture covering the whole region, the footwear district in Verona, and the district of mechatronic and innovative mechanical technologies across Veneto.[30] In the sample, as much as 50.15% of the firms belong to an industrial district. Then, dummies indicating whether a firm belongs to an industrial district or not are interacted with the excess worker turnover rate and inserted as regressors in Equation (3). Results strongly support what was expected: the impact for firms operating into industrial districts is positive, greater than the overall effect (0.053 *versus* 0.036), and highly significant. For these firms, a 1 standard deviation increase in the excess worker turnover rate is estimated to increase productivity by about 1.18%, whereas firms that do not belong to industrial districts seem to benefit by workers' replacement, but by less (0.015) and not significantly. This result casts light on the major role of knowledge spillover effects in explaining the (positive) impact of excess worker turnover on productivity.

The fourth row of Table 5 shows the results for a model that allows for different impacts on the basis of age of the firm. In particular, the sample is split into two groups: young and old firms. Young firms are defined as ones whose average age in the observation window is lower or equal to 5 years; accordingly, old firms are defined as ones whose average age is over 5 years. About 10% of the sample belongs to the 'young' group. Following the usual procedure, dummies for young and old firms are interacted with excess worker turnover rate

[29] For a detailed list, see footnote of Table 5.

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

and inserted in Equation (3). Results seem to confirm the second conjecture made in this respect, that old firms benefit the most from excess worker turnover. The effect on young firms is estimated to be negative (-0.006), even if small in magnitude, and not significantly different from zero, whereas the effect on old firms is in line with the average effect (0.032).[31]

The last row of Table 5 reports results for the case in which it is allowed for differences in the impact of interest between very small firms and the rest of the firms. Very small firms are defined to be those whose average (over years) number of employees is lower than 15. About 12% of observations belongs to the 'very small' group. Results cast some evidence on the prediction that the benefits from workers' replacement reduce or even disappear for very small firms. The estimated impact for them is -0.004, so that a 1 standard deviation increase in the excess worker turnover rate would cause a decrease, though negligible, in productivity, by about 0.09%. However, the estimated coefficient is not statistically different from zero at any conventional significance level. On the contrary, the impact for other firms is estimated to be positive (0.050) and strongly significant. As in the case of young firms, even if there is some uncertainty on the effect for very small firms, the fact that it is neither positive nor significant is *per se* a result: if, in general, firms benefit from excess worker turnover, the impact on very small firms is less clear and possibly negative.[32] Even if firms with less than 15 employees are subjected to a more favorable EPL concerning dismissals than bigger firms, it is notable that they still suffer from replacing workers. On the contrary, bigger firms, subjected to a more rigid EPL, still benefit from it. This casts further light on the fact that EPL, rigidly designed as it may be, is often circumvented by firms, which need mobility to perform better. It may also be that this does not translate into worsened workers' conditions. In a mobile labor market, workers can earn generally more, because they can find more productive matches.

As a robustness check, and especially for comparative purposes, the same set of estimations presented in Table 4 are performed using the discrete-time measure of excess worker turnover rate instead of continuous-time and (the discrete-time version of) worker turnover, as opposed to excess worker turnover.

When using the discrete-time version of excess worker turnover instead of continous-time,

[31]Since it is not obvious what a 'young' firm is, the estimation has been performed using alternately different threshold levels, below 4, 6, and 7 (average) years old. The results for these thresholds are similar to those for the 5 years. Notice that further decreasing the threshold for young firms drastically reduces the size of the 'young' group. For instance, only 2.5% of the firms have an (average) age below 3 years, thus not allowing to draw reliable conclusions.

[32]As for the case of age, since it is not obvious what a 'very small' firm is, estimation has been performed using alternately different threshold levels, namely below 12, 13 and 14 (average number of) employees. The results are similar to those for the 15 employees threshold.

the main conclusions are preserved, as expected.[33] In particular, the ACF-FE estimate is similar to that for the continuous case (0.039 *versus* 0.036). However, a 1 standard deviation increase in the discrete excess worker turnover rate (0.139) would lead to an increase in productivity by 0.54%, about 30% less than what an increase of 1 standard deviation in the continuous counterpart is estimated to cause (0.81%). Thus, since the (almost) continuous-time version of excess worker turnover is a more accurate measure of the *actual* excess worker turnover experienced by the firm, it is possible to conclude that using the discrete- instead of the continuous-time version leads to underestimate the effect of interest.

If worker turnover instead of excess worker turnover had been mistakenly (obviously: *in relation to* the research question considered here) used, different conclusions would have been drawn. According to the ACF-FE estimates, the effect of worker turnover is negative (-0.008), very small in magnitude, and not statistically different from zero at any conventional level. Considering worker turnover to assess the impact of workers' replacement on productivity leads to erroneously conclude that replacing workers is dangerous for the firms, whereas it is indeed found to be beneficial. Of course, considering worker turnover would be proper if the research question was aimed at assessing the impact of (the whole number of) hires and separations on firm productivity. In this respect, it seems that, overall, they are neutral to firm productivity, possibly hiding contrasting effects of hires and separations which almost equally compensate for each other. However, this goes beyond the object of this paper and would require a further study on the separate impacts of hires and separations (possibly distinguishing between quits and dismissals) on firm productivity.

7. Conclusions

This paper aims at investigating the causal impact of replacing workers, as measured by the excess worker turnover, on firm productivity. Throughout the analysis, endogeneity issues, deriving from both unobserved heterogeneity and simultaneity have been carefully dealt with through the ACF-FE estimation.

The main finding is that excess worker turnover has a significant positive effect on firm productivity. Knowledge spillover effects and the possibility to set more suitable employer-employee matches seem to be the driving forces of this result. By also presenting OLS, FE, and ACF estimates, it is shown that not fully taking into account endogeneity leads to unreliable conclusions. In particular, OLS estimates (as do FE and ACF, although to a lesser extent) prove to be strongly downward biased, suggesting that the unobserved heterogeneity

[33]The other set of estimations (the extensions) have been also performed using the discrete-time measure of excess worker turnover. The main conclusions are maintained.

and reverse causality problems do, indeed, exist.

Moreover, the impact of interest has been further explored by allowing for non-linearities and for different effects across several dimensions, seen as potentially relevant. As expected, results show that the impact has an inverted U-shape, suggesting that replacing workers is beneficial to a certain extent, becoming harmful afterwards. Passing from a zero level of excess worker turnover to the optimal level is predicted to increase productivity by a sizeable 3.36%. Since the great majority of firms are below the maximum, increases in the degree of workers' replacement are beneficial for most of them. The effect of interest is also found to be diversified across firms. High-tech firms seem to benefit from excess worker turnover more than low-tech firms do. This is coherent with the fact that, for high-tech firms more than low-tech ones, reaching optimal job matches as well as taking advantages from knowledge spillover effects is crucial. The same happens for firms belonging to industrial districts as opposed to firms which do not. In this case, it is sensible to believe that knowledge spillover effects enhanced by workers' mobility are the main determinant of this result. Young firms seem not to get any benefit (indeed, there is some evidence that they do suffer) from excess worker turnover and the same is true for very small firms. Young firms, which are experimenting with the market may need some stability in the workforce during their first years, while, only in a second moment should they consider replacing some underperforming workers. For very small firms, the reason of this finding may be that they have more difficulties than bigger ones in recruiting new workers and, during vacancy periods, it is more problematic for them to reallocate the workforce to do the extra job.

Overall, in contradiction with the common beliefs of managers and human resources experts, it is possible to conclude that replacing workers is beneficial to firm productivity, at least for a dynamic region such as Veneto. Firms should, therefore, not be *a priori* afraid of workers' mobility, and the same holds for policy makers, who should depart from the common view that workers' mobility is to be limited. Ultimately, it allows firms, and may also workers, to be better off in terms of productivity enhancements, the firsts, and of consequent wage increases, the seconds.

Moreover, stressing the importance of considering excess worker turnover instead of worker turnover to assess the impact of workers' replacement on firm productivity, this paper tries to clarify what seems to be often confused. Worker turnover is merely the sum of hires and separations experienced by firms, whereas excess worker turnover gives a measure of how much is to replace old workers with new ones, instead of just contributing to increase (decrease) the number of workers in the firm. At the same time, it opens up to a different, although intimately related, research question: what is the separate impact of hires and separations on firm productivity? A matched employer-employee data set like the one used here would be particularly suitable for answering this new question, since it allows to track the job history of each worker.

Table 1: **Distribution of the number of consecutive panel observations**

Number of consecutive observations	Firms	Observations
2	1,045	2,090
3	827	2,481
4	650	2,400
5	575	2,875
6	1,076	6,456
7	1,555	10,885
Total	5,728	27,387

Source: VWH-AIDA data set

Table 2: **Distribution of observations by sector of economic activity (2-digit Ateco 91 industry classification)**

Sector of economic activity	Percentage
Food and beverage	4.53
Textile	4.64
Clothing	5.23
Leather and leather goods	7.39
Wood and wood products (excluding furniture)	3.22
Paper and paper product	2.22
Printing and publishing	2.53
Coke and petroleum products	0.26
Chemical products	3.07
Rubber and plastics	5.24
Non-ferrous production	6.75
Ferrous production	2.32
Ferrous products (excluding machinery)	15.91
Machinery products	13.94
Office machinery and computers	0.21
Electrical machinery	4.57
Radio, TV, and TLC equipment	1.11
Medical equipment and measurement instruments	2.98
Motor vehicles	1.07
Other transportation equipment	0.80
Furniture and other manufacturing industries	12.01
Total	100

Source: VWH-AIDA data set

Table 3: **Sample summary statistics**

Variable	**Notes**	**Mean**	**Std. Dev.**	**1st Q.**	**Median**	**3rd Q.**
Revenues	1,000's Euros (2000 prices)	11,062	29,503	2,524	4,624	10,057
log Revenues	1,000's Euros (2000 prices)	8.60	1.02	7.83	8.44	9.21
Revenues per day worked	FTE adjusted - 1,000's Euros (2000 prices)	0.65	1.03	0.34	0.47	0.72
log Revenues per day worked	FTE adjusted - 1,000's Euros (2000 prices)	-0.68	0.63	-1.09	-0.74	-0.33
Value added	1,000's Euros (2000 prices)	2,965	9,034	764	1,334	2,669
log Value added	1,000's Euros (2000 prices)	7.33	0.97	6.63	7.20	7.89
Days worked	FTE adjusted	17,476	40,892	5,741	9,530	17,490
log Days worked	FTE adjusted	9.28	0.84	8.66	9.16	9.77
Capital	Tangible fixed assets (PIM) - 1,000's Euros	1,746	5,259	237	635	1,565
log Capital	Tangible fixed assets (PIM) - 1,000's Euros	6.41	1.42	5.47	6.45	7.36
Materials	1,000's Euros	6,025	16,737	1,031	2,217	5,350
log Materials	1,000's Euros	7.77	1.30	6.94	7.70	8.58
Number of employees	Monthly weighted	58.89	139.02	19.42	32.17	59.00
Firm's age	Years	15.56	7.86	8.92	15.17	22.92
Profit margin	Net Profit over Revenues	0.02	0.40	0.00	0.01	0.03
Net job creation		1.39	13.56	-1.00	1.00	3.00
Net job creation rate		0.03	0.17	-0.04	0.03	0.10
Abs(Net job creation rate)		0.11	0.14	0.03	0.07	0.13
Hires	Continuous time	11.62	23.76	3.00	6.00	13.00
Separations	Continuous time	10.23	20.02	3.00	6.00	11.00
Worker turnover	Continuous time	21.85	41.80	7.00	13.00	24.00
Excess worker turnover	Continuous time	16.99	33.65	4.00	10.00	20.00
Hiring rate	Continuous time	0.23	0.17	0.11	0.20	0.32
Separation rate	Continuous time	0.20	0.16	0.10	0.17	0.27
Worker turnover rate	Continuous time	0.43	0.27	0.24	0.38	0.58
Excess worker turnover rate	Continuous time	0.33	0.22	0.16	0.29	0.46
Hires	Discrete time	8.36	17.75	2.00	5.00	9.00
Separations	Discrete time	6.98	14.36	2.00	4.00	8.00
Worker turnover	Discrete time	15.34	29.31	5.00	9.00	17.00
Excess worker turnover	Discrete time	10.48	20.67	2.00	6.00	12.00
Hiring rate	Discrete time	0.16	0.13	0.08	0.14	0.22
Separation rate	Discrete time	0.14	0.13	0.07	0.12	0.17
Worker turnover rate	Discrete time	0.30	0.19	0.18	0.27	0.40
Excess worker turnover rate	Discrete time	0.20	0.14	0.10	0.18	0.28
Female workers' share	Monthly weighted	0.29	0.24	0.11	0.20	0.45
Migrant workers' share	Monthly weighted	0.06	0.08	0.00	0.04	0.08

Table 3: **Sample summary statistics - continued**

Variable	**Notes**	**Mean/ Percentage**	**Std. Dev.**	**1st Q.**	**Median**	**3rd Q.**
Young workers' share	Under 30 - Monthly weIghted	0.39	0.17	0.27	0.38	0.50
Part-time workers' share	Monthly weighted	0.04	0.06	0.00	0.02	0.06
Temporary workers' share	Monthly weighted	0.04	0.06	0.00	0.02	0.06
Blue-collar workers' share	Monthly weighted	0.70	0.17	0.62	0.73	0.81
White-collar workers' share	Monthly weighted	0.24	0.16	0.13	0.20	0.30
Managers' share	Monthly weighted	0.01	0.03	0.00	0.00	0.01
Apprentices' share	Monthly weighted	0.04	0.06	0.00	0.02	0.06
Average workers' age	Monthly weighted	34.62	3.76	32.00	34.60	37.30
Average workers' tenure	Years	6.51	3.18	4.10	6.00	8.42
Average workers' gross wage	Euros (2003 prices)	129.53	29.17	109.93	124.95	143.07
						Number of firm-year observations 27,387
						Number of firms 5,728

Source: VWH-AIDA data set

Table 4: **Estimation results; Basic model; Continuous-time excess worker turnover rate; Estimation methods: OLS, FE, ACF, and ACF-FE**

Dependent variable: logarithm of value added (y_{it})								
Variable	**OLS**		**FE**		**ACF**		**ACF-FE**	
l_{it}	0.906***	(0.004)	0.801***	(0.022)	0.912***	(0.013)	0.799***	(0.028)
k_{it}	0.128***	(0.003)	0.053***	(0.006)	0.095***	(0.007)	0.067***	(0.006)
EWT_{it}	-0.039***	(0.011)	0.020**	(0.010)	-0.019	(0.012)	0.036***	(0.012)
Females' share	-0.355***	(0.015)	-0.044	(0.064)	-0.292***	(0.013)	-0.018	(0.044)
Migrants' share	-0.072***	(0.027)	0.090	(0.066)	-0.040	(0.027)	0.040	(0.050)
Employees' average age	-0.006***	(0.001)	0.002	(0.002)	-0.004***	(0.001)	0.005***	(0.002)
Part-timers' share	0.026	(0.046)	0.103	(0.084)	0.081**	(0.038)	0.134**	(0.061)
Temporary workers' share	-0.054	(0.042)	0.000	(0.034)	-0.086**	(0.037)	-0.018	(0.032)
Apprentices' share	-1.042***	(0.065)	-0.076	(0.136)	-0.857***	(0.054)	-0.005	(0.088)
Blue-collar workers' share	-0.658***	(0.051)	0.041	(0.130)	-0.506***	(0.041)	0.134*	(0.078)
White-collar workers' share	-0.006	(0.056)	0.195	(0.122)	-0.169***	(0.044)	0.115	(0.078)
Year dummies	yes		yes		yes		yes	
Province dummies	yes		-		yes		-	
Industry dummies	yes		-		yes		-	
Industry $*$ Province dummies	yes		yes		yes		yes	
Number of firm-year observations 27,387								
Number of firms 5,728								

Source: VWH-AIDA data set

*Robust standard error are used for OLS and FE, while bootstrapped standard errors are computed for ACF and ACF-FE; standard error in parenthesis; ***, **, and * denote respectively, 1%, 5%, and 10% significance level; industry is defined according to the 3-digit Ateco 91 industry classification (it includes 114 categories).*

Table 5: **Estimation results; Extension; Continuous-time excess worker turnover rate; Estimation method: ACF-FE**

Model						
Non-linear	EWT_{it}	0.107***	(0.034)	EWT_{it}^2	-0.087**	(0.038)
High- *vs* low-tech	$EWT_{it} * LT_i$	0.030*	(0.015)	$EWT_{it} * HT_i$	0.076	(0.048)
Ind. districts *vs* not	$EWT_{it} * YID_i$	0.058***	(0.019)	$EWT_{it} * NID_i$	0.015	(0.017)
Young *vs* old	$EWT_{it} * Y_i$	-0.006	(0.054)	$EWT_{it} * O_i$	0.032**	(0.013)
Very small *vs* others	$EWT_{it} * VS_i$	-0.004	(0.041)	$EWT_{it} * OF_i$	0.050***	(0.017)
Number of firm-year observations 27,387						
Number of firms 5,728						

Source: VWH-AIDA data set

*Bootstrapped standard errors in parenthesis; ***, **, and * denote respectively, 1%, 5%, and 10% significance level. LT_i and HT_i are dummies respectively indicating if the firm i belongs to low- or high-tech industry. High-tech industry includes: 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. YID_i (NID_i) is a dummy variable taking the value of 1 if the firm belongs to an industrial district (does not belong to an industrial district). Y_i (O_i) is a dummy variable taking the value of 1 if the mean value over years of the age of the firm is below (over) 5 years old. VS_i (OF_i) is a dummy variable taking the value of 1 if the mean value over years of the number of employees of the firm is below (over) 15.*

Table 6: **Estimation results; Robustness checks; Discrete-time excess worker turnover rate and discrete-time worker turnover rate; Estimation methods: OLS, FE, ACF, and ACF-FE**

Model	OLS		FE		ACF		ACF-FE	
EWT_{it}^D	-0.092***	(0.017)	0.022	(0.013)	-0.055***	(0.018)	0.039**	(0.016)
WT_{it}^D	-0.122***	(0.015)	-0.058***	(0.014)	-0.111***	(0.020)	-0.008	(0.018)
Number of firm-year observations 27,387								
Number of firms 5,728								

Source: VWH-AIDA data set

*Robust standard error are used for OLS and FE, while bootstrapped standard errors are computed for ACF and ACF-FE; standard error in parenthesis; ***, **, and * denote respectively, 1%, 5%, and 10% significance level.*

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