Excess Worker Turnover and Firm Productivity

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Abstract

In this paper we study the impact of excess employee turnover on firm productivity using a uniquely rich longitudinal matched employer-employee dataset for Veneto, an administrative region in Italy, which allows us to construct a continuous time version of excess employee turnover. We perform SYSTEM-GMM estimation (over and above OLS and FE ones) on an 'augmented' production function, in which excess employee turnover enters as the regressor of interest; a strategy allowing us to take into account endogeneity coming from unobservable firm-specific fixed-effects, simultaneity issues concerning excess employee turnover, endogenous nature of the inputs of the production function and measurement errors. The main finding is that excess employee turnover has no significant effect on firm productivity of labor. Moreover, we deeply explore the impact of excess worker turnover on firm productivity by allowing for non-linearities and for different effects across several dimensions which we see as potentially relevant. SYSTEM-GMM estimations still predict that the effect of interest is indeed null. This leads us to conclude that the our primary finding, i.e. that the excess employee turnover has no impact on firm productivity, is not the result of some kind of misspecification or non-accounted-for heterogeneity, but is valid *per se*.

1 Introduction

In this paper we investigate the impact of excess labor turnover on firm productivity. Excess labor turnover the amount of labor turnover over and above the one naturally needed in order

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to accommodate for job creation (or destruction). An example clarifies the point. Suppose that we measure the number of workers in the firms 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, which hires 2 workers the day after and does not fire neither is left by any worker during the year. This implies that the number of workers on the 31st of December is 12. This firm has experienced 2 hires, no separations, employee turnover equal to 2 (2 hires + 0 separations) and excess employee turnover equal to 0, because employee turnover exactly compensates for job creation. Now consider the same firm, with again 10 employees on the 1st of January, but now hiring 5 workers and firing or being left by 3 workers 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. In this case the firm has experienced 5 hires, 3 separations, employee turnover equal to 8 (5 hires + 3 separations) and excess employee turnover equal to 6 (8-2, where 8 is employee turnover and 2 is job creation). We try to identify the causal impact of that *excess* worker turnover on the firm productivity of labor.

Employee turnover and excess employee turnover are often confused, both in the human resources management and economic literature and, to a larger extent, among managers. When talking about 'worker turnover', they implicitly mean 'excess worker turnover'. However, in this paper we are going to keep clear the distinction between 'worker turnover' and 'excess worker turnover', so that we are going to use them in the strict sense.

Excess employee turnover has been and still is regarded as a critical issue in the management of a company by many managers. Most of them fear it; googling 'worker turnover', one can realize this: there is plenty of sites dictating guidelines on how to retain workers and consequently reduce it.

Human resources experts, on the other hand, have contributed to disseminate this feeling: many theories have been proposed that consider excess employee turnover as dangerous, alternatively claiming that it is dysfunctional for the business organization (Dess and Shaw [2001]), that entails a loss of human capital for the firm and that makes the firm suffering the loss of output forgone as well as the cost of searching for a new employee (Sutherland [2002]) and even that produces a loss of social capital since it is disruptive for the morale of the workers who stay (Sheehan [1993]). However, a few of them have advanced the hypothesis that, at least to a certain degree, excess employee turnover can be beneficial to the firm performance, for example when under-performing workers voluntarily quit or because it brings some 'fresh air' into the firm (Adelson and Baysinger [1984]).

Economists have not paid much attention to the effect of excess worker turnover on productivity, despite being an issue of great concern in the real world. Essentially, the economic theories modeling the impact of excess employee turnover on firm productivity are two: the firm-specific human capital theory (FSHC) proposed by Becker [1975] and the matching theory, established, among the others, by Burdett [1978] and Jovanovic [1979]. Firm-specific human capital theory predicts that excess employee 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. Matching theory, on the contrary, predicts a positive effect, since it is focused on its allocative role on employer-employee matches.

Only a few empirical works have been performed to assess the nature of this effect and with quite serious limitations: the regressor of interest is simply employee turnover and not, as it should be, excess employee turnover; empirical specifications are poor and suffer from endogeneity, since estimation methods are simple OLS or, at most, fixed-effects (FE). Results found are diverse and contrasting: Ton and Huckman [2008] and Huselid [1995] find a negative impact; Mc Evoy and Cascio [1987] and Williams and Livingstone [1994], in their meta-analytic studies, find a positive link between employee turnover and firm performance; Harris et al. [2006] and Glebbeek and Bax [2004] find an inverted U-shape link, which permits to define an optimal level of turnover; hires and separations are examined separately by Bingley and Westgaard-Nielsen [2004], which find that separations are beneficial while hires are harmful and Siebert et al. [2006], which find an inverted U-shape for both.

We make use of VWH-AIDA dataset, a uniquely rich longitudinal matched employer-employee dataset for Veneto (an administrative region in Italy) which allows us to construct a *continuous* time version of excess worker turnover, to estimate an 'augmented' production function in which excess employee turnover enters as the regressor of interest.

We perform SYSTEM-GMM estimation (over and above OLS and FE ones), a strategy allowing us to take into account endogeneity coming from unobservable firm-specific fixed-effects, simultaneity issues concerning excess employee turnover, endogenous nature of the inputs of the production function and measurement errors.

The main finding is that excess employee turnover has no significant effect on firm productivity of labor. This result is atypical in the literature, which find both positive and negative, but not null, effects. Moreover, we deeply explore the impact of excess worker turnover on firm productivity by allowing for non-linearities and for different effects across several dimensions which we see as potentially relevant, such as degree of capital intensity, degree of volatility of demand, belonging to the high-tech industry or not and age of the firm. SYSTEM-GMM estimations still predict that the effect of interest is indeed null. This leads us to conclude that the our primary finding, i.e. that the excess employee turnover has no impact on firm productivity, is not the result of some kind of misspecification (i.e. linear instead of non-linear) or non-accounted-for heterogeneity (i.e. different impacts across some relevant dimension).

By also presenting OLS and FE estimates, we show that not fully taking into account endogeneity (i.e. simply considering OLS and/or FE) leads to wrong conclusions. OLS estimates of the causal effect prove to be strongly downward biased. On the other hand (and as expected) FE estimates, taking into account the unobserved fixed heterogeneity, provide more appropriate results, that is more similar to fully robust SYTEM-GMM results, though not totally satisfactory.

The rest is structured as follows: in Section 2 we go through a literature review; Section 3 discusses about the empirical model and our identification strategy; in Section 4 we describe the dataset and the way in which we compute excess worker turnover; Section 5 presents and discusses our results from OLS, FE and SYSTEM-GMM estimations; Section 6 concludes.

2 Literature Review

The impact of excess employee turnover on firm performance has been of great concern in the human resources management literature, whereas the attention devoted to this issue by economists has been much less prominent. In both disciplines theories are contrasting, suggesting that the nature of the impact is not trivial.

In the human resources management literature, excess labor turnover is mostly regarded as a dysfunctional feature of the firm, essentially because it is costly. From quits, firms suffer the loss of human capital investment and the cost of hiring substitute workers (Sutherland [2002]). Moreover, high excess 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 stays, as argued by Sheehan [1993], who, conducing a controlled experiment, shows that excess 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 turnover could be beneficial to the organization. Adelson and Baysinger [1984] suggest that excess labor turnover is not dysfunctional *per se*, but that it should be evaluated on the basis of both costs and benefits that it brings to the firm. For example, excess 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 well, as argued by McElroy et al. [2001] and can bring some 'fresh air' in the firm as Kellough and Osuna [1995] suggest.

The economic literature has proposed two mechanisms through which excess labor turnover affects firm performance: firm-specific human capital and job matching.

Firm-specific human capital theory, first proposed by Becker [1975], states that excess employee 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.

Job matching theory, established by Burdett [1978] and Jovanovic [1979] and many others[1], predicts that excess labor turnover is a mechanism through which employer-employee matches can be reallocated in a more efficient way, as better information becomes available to the parties. The theory of job matching and turnover hinges on three main assumptions (see Jovanovic [1979]). First, *each* worker performs different jobs with different productivity. The same holds for the employer: for *each* job to be assigned, different workers have different productivity. Second, it is assumed that employers and workers can bargain over wages on an individual basis. 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 main assumption is that both workers and employers have imperfect information about the exact location of the most productive match. Between- and within-workers heterogeneity, the possibility to contract wages on an individual basis and imperfect information make workers and employers engaging in the search of optimal matches. And excess turnover is the way in which they can be attained as better information become available. Hence, job matching theory predicts that excess labor turnover improves firm performance by removing poor employer-employee matches from the economy.

In addition to FSHC and job matching approaches (and closely related to job matching), it deserves to be mentioned the theory predicting a positive impact of excess labor turnover on firm performance enhanced by knowledge spillover effects. 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 how this model implies that higher excess turnover rate is generally associated with greater overall technological progress. Using VWH-AIDA dataset, Serafinelli [2013] shows that labor mobility has a positive effect (in terms of enhanced productivity) on firms located near high productivity

[1] We cite, among the others, Pissarides [2000]. However Burdett [1978] and Jovanovic [1979] specifically concentrate on excess employee turnover.

firms.

Capitalizing on theories proposed by both management and economics literature, many studies have tried to empirically assess the effect of employee turnover (and not excess employee turnover, as we try to do) on firm performance. Results are diverse and conflicting.

Among the studies supporting the main prediction of the FSHC theory, it is worth mentioning Ton and Huckman [2008], which use 48 months of turnover data from U.S. stores of a major retail chain of entertainment products and find that turnover impacts negatively on profit margins and customer satisfaction; Tariq et al. [2013] which show, using questionnaires distributed in Mobilink[2] head office, call center and administrative department, that firm performance is negatively associated with employee turnover; Huselid [1995], finding that labor turnover is negatively related to firm productivity and profitability in a sample of about one thousand U.S. firms. Negative effect is also supported by several studies focusing on quits alone: Kersley and Martin [1997] (for establishment-level data from the 1990 U.K. Workplace Employee Relations Survey), Mefford [1986] (for 31 plants of a major multinational manufacturing firm), McElroy et al. [2001] (for a sample of data collected from 31 geographically separated sales regions of a U.S. financial services company) and Batt [2002] (for a sample of U.S. call centers).

Other empirical studies, instead, are in accordance with the job matching theory result. Mc Evoy and Cascio [1987] conduct a meta-analysis collecting reported correlations between turnover and employee performance of 24 studies and find that poor performers are more likely to quit. The meta-analytic work by Williams and Livingstone [1994] further confirms the finding from Mc Evoy and Cascio [1987] and suggests that, when wage is to some extent set on a performance basis, the correlation between turnover and employee performance is even more pronounced. This is consistent with job matching theory, a major assumption of which is the possibility to contract the wage on the basis of the quality of the match.

There is a number of recent studies which do not conceive FSHC and job matching as mutually exclusive and hence competing theories. Following what Adelson and Baysinger [1984] originally suggested, they search for an optimal amount of labor turnover, the one maximizing the net benefit that the firm derives from it.[3] Harris et al. [2006] and Glebbeek and Bax [2004] address this issue by allowing for non-linearities in the empirical specification. Using a panel of 2,435 small and medium size Australian firms, Harris et al. [2006] find an inverted U-shape link between labor turnover and firm performance, suggesting that the FSHC effect dominates when turnover is high, while the job matching one when it is low;

[2]Is a telecommunication service provider and leading cellular operator in Pakistan (http://en.wikipedia.org/wiki/Mobilink).

[3]By 'net benefit' we mean the difference between positive effects from job matching and negative effects from loss of firm-specific human capital.

they find that the optimal turnover rate is about 22% per year.[4] More moderate is the support to this theory in Glebbeek and Bax [2004], which, conducing a study on a sample of 110 offices of a temporary employment agency, find a curvilinear relationship which do not allow to 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 size Danish firms, they look at hires and quits separately, finding that quits increase profit and hires reduce it; something that can be interpreted in terms of a FSHC explanation with respect to the negative impact of hires (costs of training) and of a job matching explanation for what concerns the positive effect of quits (clearing of poor matches).[5]

3 Empirical Model and Identification

Since we are interested in identifying and estimating the causal impact of excess employee turnover on firm productivity, it is sensible to make use of a production function. In particular, we assume that the data generating process for output produced by firm i at time t is a production function of the Cobb-Douglas type with the following characteristics:

$$Y_{it} = A_{it} L_{it}^{\alpha_l} K_{it}^{\alpha_k} M_{it}^{\alpha_m} e^{u_{it}} \qquad i = 1, 2, ..., N; \quad t = 1, 2, ..., T \tag{1}$$

where: Y_{it}, L_{it}, K_{it}, M_{it} denote respectively production and labor, capital and materials usage of firm i at time t; $e^{u_{it}}$ is a measurement error; and A_{it}, the total factor productivity (TFP), is modeled as follows:

$$A_{it} = e^{\theta EET_{it} + \omega_{it}} \tag{2}$$

$$\omega_{it} = \nu_t + \eta_i + \epsilon_{it} \tag{3}$$

where: EET_{it} is excess employee turnover[6] in firm i at time t; ω_{it} can be though of as the total factor productivity of firm i at time t after netting out the excess employee turnover term; it is further decomposed into a time-specific shock (ν_t), affecting all the firms equally in a given period t, a time-invariant and firm-specific component (η_i), and an idiosyncratic productivity shock (ϵ_{it}).

In this framework, excess employee turnover enters the production function through the total factor productivity. It is obviously not a standard input, such as labor, capital or

[4] The optimal labor turnover rate is defined as the one maximizing labor productivity. They use a discrete time measure of turnover.

[5] See also Siebert et al. [2006] for a similar analysis.

[6] A precise definition of how we compute excess employee turnover will be given later in the discussion.

materials; however it is likely to have a role in determining the firm's output: the potential channels are several and already highlighted in the previous Section. They include: decreased efficiency due to loss of firm-specific human capital (in case of a separation) or costly learning process (in case of a hire); increased efficiency if an underperforming worker leaves the firm or if an overperforming worker enters the firm; increased efficiency if excess employee turnover is seen as a valuable resource in terms of knowledge spillover or decreased efficiency if it is seen by remaining workers as a sign of weakness of the firm in retaining workers.

In practice, the production function that we try to estimate is obtained by dividing both side of (1) by L_{it}, by using (2) and (3) and by taking logs:

$$y_{it} - l_{it} = (\alpha_l - 1)l_{it} + \alpha_k k_{it} + \alpha_m m_{it} + \theta EET_{it} + \nu_t + \eta_i + \epsilon_{it} + u_{it} \tag{4}$$

where: y is the natural logarithm of output produced and l, k and m are respectively the natural logarithms of labor, capital and materials. Equation (4) can be rewritten as:

$$y_{it} - l_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \theta EET_{it} + \nu_t + \eta_i + \epsilon_{it} + u_{it} \tag{5}$$

where: $\beta_l = \alpha_l - 1$ and $\beta_{k,m} = \alpha_{k,m}$.

On the basis of the assumptions on the (composite) error term that we are willing to make, we obtain different estimates of θ. Since our goal is to find the *causal* effect of excess employee turnover on firm productivity, we now discuss which assumptions on the error term and hence which identification strategy is the most suitable for our purpose.

To begin, let us assume that there is not measurement error in the regressors, that is $u_{it} = 0 \; \forall i, t$. Moreover, let us assume that each regressor in (5) is *strictly exogenous* with respect to ϵ_{it} and ν_t, that is such that $E[\epsilon_{it}\boldsymbol{W_{is}}] = E[\nu_t \boldsymbol{W_{is}}] = \mathbf{0}; \forall \; t, s$, where $\boldsymbol{W_{is}}$ collects all the regressors in (5).

If also η_i is uncorrelated with each regressors in (5), an OLS regression on (5) consistently identifies θ and the other parameters. However, there are reasons to believe that η_i is indeed correlated with (at least some of) the regressors in (5). Consider the following example: assuming that η_i is uncorrelated with excess employee turnover means that we are excluding that managerial ability (inside η_i, since unobservable and very likely not varying over time - at least over our short panel) has an impact on productivity *and* on excess employee turnover. Indeed it is possible to conceive situations in which the managerial ability does have an impact on productivity (better managers reach better productivity results) *and* on excess employee turnover (better managers may are abler than poorer ones in choosing better employees and in retaining them). If this is the case and if we do not take it into account, we tend to overestimate the negative impact of employee turnover on firm productivity.[7] Hence, since η_i is most likely correlated with excess employee turnover (and may also inputs), a simple OLS regression on (5) does not identify the causal effect of interest.

Exploiting the panel nature of our data, we are able to get rid of η_i by considering a within-group transformation of (5):

$$\widetilde{y_{it} - l_{it}} = \beta_l \widetilde{l_{it}} + \beta_k \widetilde{k_{it}} + \beta_m \widetilde{m_{it}} + \theta \widetilde{EET}_{it} + \widetilde{\nu_t} + \widetilde{\epsilon_{it}} \tag{6}$$

where the tilde operator indicates the within-group transformation: $\widetilde{x_{it}} = x_{it} - \frac{1}{T}\sum_{t=1}^{T} x_{it}$. As long as we are willing to maintain the assumption of strict exogeneity of regressors with respect to ν_t and ϵ_{it}, an OLS regression on (6)[8] identifies the causal effect of interest.

However, regressors in (5) are most likely not strictly exogenous with respect to ν_t and ϵ_{it}.

It seem sensible to assume that past and contemporaneous economy-wide shocks, through changes in the input and output markets' general conditions, affect the inputs' choices and may also the excess employee turnover level. This is not a substantial limitation, since the time-specific error term ν_t can be easily removed by applying the following transformation to (5):

$$(y_{it} - l_{it})^* = \beta_l l_{it}^* + \beta_k k_{it}^* + \beta_m m_{it}^* + \theta EET_{it}^* + \eta_i^* + \epsilon_{it}^*$$

where the star operator applied to a generic variable x_{it} gives: $x_{it}^* = x_{it} - \frac{1}{N}\sum_{i=1}^{N} x_{it}$. The same goal can be reached by including year dummies in the regressions, a strategy that we follow.

Claiming that regressors in (5) are strictly exogenous with respect to the idiosyncratic productivity shock ϵ_{it} is contrived.[9] This assumption would imply, for example, that managers do not adjust the level of inputs used after a production shock happens. This behavior is consistent with a situation in which the manager can observe past and contemporaneous shocks *and* does not react to them; or with another one in which the manager does not observe neither past nor contemporaneous shocks *tout court*. In practice, both seem to be very unlikely. In particular, it seems sensible to assume that input variables are endogenous with respect to the idiosyncratic productivity shock, i.e. assuming that $E[\epsilon_{it} I_{jis}] \neq 0, \ \forall \ t \leq s$ and $E[\epsilon_{it} I_{jis}] = 0, \ \forall \ t > s$ $(j = l, k, m)$. Intuitively, in a given period t, managers know the sign and the magnitude of productivity shocks that have hit their firms in the past (at

[7] Notice that it is possible to make similar arguments with respect to culture, degree of internationalization and many other factors, which are unobservables and time-invariant (and hence inside η_i).

[8] This procedure is knows as fixed-effect or within-group regression.

[9] By now we assume that ϵ_{it} follows a white noise process; ν_t's stochastic process is not restricted since we do remove it through year dummies.

period $t-1$ and before) and in the present (at period t) and *consequently* adjust the level of inputs used in the production process at t.

Furthermore, job-search theory[10] has highlighted that excess employee turnover is higher for low-productivity (and consequently low-wage) firms, and correspondingly lower for high-productivity (and consequently high-wage) ones.[11] Hence, it may happen that not only excess employee turnover does have an impact on firm performance (as both FSHC theory and matching theory suggest), but also that excess worker turnover itself is influenced by firm performance, as on-the-job search models suggest. If this is the case, excess employee turnover is correlated with the contemporaneous and lagged idiosyncratic error term, causing it to be endogenous.

These arguments on the endogenous nature of regressors with respect to ϵ_{it} (and to a lesser extent ν_t - which can always be removed through year dummies) invalidate the consistency of the fixed-effect estimator.

In view of these considerations, we can identify the causal effect of interest by following the procedure proposed in Arellano and Bond [1991].[12] In the first place, in order to remove the unobserved firm-specific effect η_i, we consider the first-differenced version of (5)[13]:

$$\Delta(y-l)_{it} = \beta_l \Delta l_{it} + \beta_k \Delta k_{it} + \beta_m \Delta m_{it} + \theta \Delta EET_{it} + \Delta\epsilon_{it} \tag{7}$$

In the second place, in order to purge estimates from endogeneity caused by the correlation between regressors and the idiosyncratic productivity shock, we instrument first-differenced inputs and first-differenced excess employee turnover with suitable lags of their *levels*.[14] In particular, given our set of assumptions, a GMM estimator based on the following moment conditions, is able to consistently estimates our parameters:

[10]We cite, among others, Burdett and Mortensen [1998].

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

[12]We will refer to the estimator proposed by Arellano and Bond [1991] as DIFF-GMM or Arellano/Bond estimator.

[13]For the moment we maintain the assumptions of no measurement error and white noise process in ϵ_{it}. Moreover, we include year dummies in order to remove the potentially dangerous time-specific shock ν_t.

[14]Notice that, over and above exogeneity of the instruments, their relevance is needed. Essentially, this amounts to require that inputs and excess employee turnover follow an autoregressive process whose coefficient lies strictly inside the unit circle.

$$E\left[\begin{bmatrix} inputs_{i1} \\ ... \\ inputs_{i\,t-2} \\ EET_{i1} \\ ... \\ EET_{i\,t-2} \end{bmatrix} \Delta\epsilon_{it}\right] = 0 \quad t = 3, ..., T \tag{8}$$

At this stage, we relax the assumptions that there is not measurement error and that the idiosyncratic shock follows a white noise process.

For what concern the measurement error, we allow it to follow a white noise process, i.e. $u_{it} \sim$ WN.

On the other hand, up to now we have maintained the hypothesis that the idiosyncratic productivity shock follows a white noise process. This is not an innocuous assumption since the validity of the moment conditions in (8) crucially depends on the stochastic process followed by ϵ_{it}. Moreover, assuming that ϵ_{it} is a white noise is assuming that the idiosyncratic productivity shock is not autocorrelated over time, which seems too restrictive.[15] There are reasons to believe that its stochastic structure is more articulated. In particular, it seems plausible that it is influenced by its own previous values. Hence, in order to allow for more flexibility in the structure of the stochastic process of the productivity shock, we let it follow an AR(1) process:

$$\epsilon_{it} = \rho\epsilon_{it-j} + v_{it} \tag{9}$$

where v_{it} is a white noise shock.

In order to proceed, first note that since ϵ_{it} is assumed to follow an AR(1) process, no lags of the (endogenous) regressors are valid instruments, since ϵ_{it} is correlated (though degressively) with all past shocks. The problem is easily solved by pseudo-differencing (5). Consider (5) with ϵ_{it} entering through its expression $\rho\epsilon_{it-1} + v_{it}$. Lagging (5) by one period, multiplying both sides by ρ, and isolating $\rho\epsilon_{it-1}$, we get

$$\begin{aligned}\rho\epsilon_{it-1} = \rho(y_{it-1} - l_{it-1}) - \rho\beta_l l_{it-1} - \rho\beta_k k_{it-1} - \rho\beta_m m_{it-1} - \rho\theta EET_{it-1} + \\ -\rho\nu_{t-1} - \rho\eta_i - \rho u_{it-1}\end{aligned} \tag{10}$$

Now that we have an expression for $\rho\epsilon_{it-1}$, we can substitute (10) inside (5), so that we get:

$$\begin{aligned}y_{it} - l_{it} = \rho(y_{it-1} - l_{it-1}) + \beta_l l_{it} - \rho\beta_l l_{it-1} + \beta_k k_{it} - \rho\beta_k k_{it-1} + \beta_m m_{it} + \\ -\rho\beta_m m_{it-1} + \theta EET_{it} - \rho\theta EET_{it-1} + \nu_t^* + \eta_i^* + w_{it}\end{aligned} \tag{11}$$

[15] Technically, a with noise process χ_{it} is such that $E[\chi_{it}] = 0$, $Var[\chi_{it}] = \sigma^2$ and $E[\chi_{it}\chi_{is}] = 0$, $\forall s \neq t$.

where:

$$\nu_t^* = \nu_t - \rho\nu_{t-1}$$

$$\eta_i^* = \eta_i - \rho\eta_i$$

$$w_{it} = v_{it} + u_{it} - \rho u_{it-1}$$

Equation (11), can be written as:

$$\begin{aligned} y_{it} - l_{it} = \pi_1(y_{it-1} - l_{it-1}) + \pi_2 l_{it} + \pi_3 l_{it-1} + \pi_4 k_{it} + \pi_5 k_{it-1} + \pi_6 m_{it} + \\ + \pi_7 m_{it-1} + \pi_8 EET_{it} + \pi_9 EET_{it-1} + \nu_t^* + \eta_i^* + w_{it} \end{aligned} \tag{12}$$

where: $-\pi_1\pi_2 = \pi_3$, $-\pi_1\pi_4 = \pi_5$, $-\pi_1\pi_6 = \pi_7$, $-\pi_1\pi_8 = \pi_9$ are four testable non linear restrictions imposed by the model. Equation (12) is the result obtained by pseudo-differencing (5); it is easy to see that the idiosyncratic error term of (12) is just the combination of a white noise process (v_{it}) - the innovation in the idiosyncratic productivity shock - and the component $u_{it} - \rho u_{it-1}$ - related to the measurement error term.

In order to remove the (composite) time-specific and fixed-effect terms, year dummies has to be included and first-differences has to be taken in (12). Moment conditions for DIFF-GMM estimator can than be constructed considering that lags (of levels) $t-3$ and earlier are used as instruments for endogenous regressors[16].

Unfortunately, as [Arellano and Bover, 1995] explains, the Arellano-Bond estimator has some weaknesses, the most relevant of which is the weak instrument problem. In particular, the lagged instruments (which are in levels) become weak as the their own autoregressive process becomes stronger (approaching a random walk). In the case of production function estimation this is often the case, i.e. output and inputs are often highly persistent.

To solve this problem, Arellano and Bover [1995] and Blundell and Bond [1998] have proposed a system GMM estimator, usually called SYSTEM-GMM or Arellano-Bover/Blundell-Bond estimator, in which, in addition to the level instruments for the differenced equation used in the DIFF-GMM estimator, lagged differences are used as instruments for the level equation. In general, this estimator seems to perform better than the Arellano-Bond estimator, as shown in Blundell and Bond [2000].[17]

[16] Notice that, over and above the (first) lag of 'old' regressors (inputs and excess employee turnover), the pseudo-differencing procedure has actually added one new regressor to our production function: $(y_{it-1} - l_{it-1})$, which is by construction endogenous.

[17] For this additional set of instruments to satisfy the exogeneity condition, a mild assumption has to be fulfilled: the degree of correlation between the regressors and η_i should be constant over time.

4 The Data: VWH-AIDA

The dataset used in the paper is the result of the merger of two different data sources: the Veneto Workers History (VWH) and the Analisi Informatizzata delle Aziende Italiane (AIDA).

The VWH dataset has been constructed by a team leaded by Giuseppe Tattara at the University of Venice on the ground of the administrative data of the Italian Social Security System (INPS).[18] It collects labor market histories and earning records for the period 1975-2001 of each single individual employed for at least one day in the private sector[19] in Veneto, an administrative region in Italy with a population of around 5 million people (about 8% of the country's total).

During the seventies and eighties Veneto has experienced an industrialization process which made it one of the richest, most dynamic and most export-oriented regions in Italy. The vast majority of Veneto firms are small or medium-sized and operate in the manufacturing industry. Among the industries in which Veneto firms specialize we mention: chemistry, metal-mechanics, electronics, food products, wood and furniture, leather and footwear, textiles and clothing (Benetton, Sisley, Geox, Diesel, Replay are Venetian brands) and goldsmithing. Typical of Veneto is the organization of the territory into industrial districts. For example, the province of Venice hosts the large metallurgical and chemical district in Marghera and Mestre and also the glass handicraft district in Murano; the province of Belluno, where Luxottica (the world's largest manufacturer of eyeglasses) has production plants, hosts the eyewear district.

Essentially, VWH is made up of three parts: a *worker archive*, collecting personal information of the worker[20] (gender, age and birth place); a *job archive*, which contains information on the job held by the worker in the firm[21] (number of days worked during the year, total earnings during the year, contract type and qualification); a *firm archive*, containing information about the firm (name, location, establishment date, cessation date - if applicable - and industry[22]).

The AIDA dataset is provided 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.[23]

[18] See Tattara and Valentini [2007] and Tattara and Valentini [2010] for an accurate description of the dataset.

[19] Self-employed, farm workers and workers receiving no salary have been left out of the dataset.

[20] Each worker in the dataset is identified through an id number.

[21] Each firm in the dataset is identified through an id number: the firm's national tax number (*codice fiscale*).

[22] Industry is classified by ATECO 91 at five-digit level.

[23] Among the variables included in the AIDA dataset we mention: revenues, added value, profit, book

Firm's national tax number has been used to match job-year observations in the VWH with the firm information in AIDA.[24] The result is a longitudinal matched employer-employee dataset[25] covering the period 1995-2001 collecting job histories and earning records of all individuals working as employees (with the exception of farm workers and workers receiving no salary) in all (non-financial) incorporated Veneto firms operating in the private sector with revenues greater than 500,000 euros, for which we have balance sheet information.

As already discussed in Section 3, the inputs of the production function that we are going to estimate are (log of) labor, capital and materials. 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; capital input is the physical capital stock computed by a Perpetual Inventory Method with constant depreciation rate (0.08)[26]; and the amount of materials is measured by the 'raw, consumable materials' item in the balance sheet. Materials are deflated using two-digit producer price index. The dependent variable is (log of) revenues per full-time adjusted days worked. Revenues are also deflated using two-digit producer price index.

In order to obtain a measure of excess employee turnover we consider the definitions of jobs and workers flows in Davis et al. [1996]:

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

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

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

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

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

Discrete time data and therefore discrete time versions of employee turnover measures are the norm in the literature. In practice, the researcher can only observe stocks of employment at discrete points in time, for example on the first of January and on the 31st of December

value of capital, total wage bill, total number of employees and firm's national tax number (used as identifier for the firms).

[24] The merge of VWH and AIDA dataset has been conceived and conducted by David Card, Francesco Devicienti and Agata Maida, which accurately describe the merging procedure in Card et al. [2014].

[25] We will refer to it as VWH-AIDA.

[26] The benchmark at the first year is given by the book value of the 'tangible fixed assets' item in the balance sheet; investments are computed as the difference between the tangible fixed assets values as reported in two contiguous balance sheets.

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 at 31st of December but not on the first of January of the given year; similarly, separations are identified by looking at workers employed in the given firm on the first of January but not on the 31st of December of the given year. In this case, any employment relationship that begins after the first of January and terminates before 31st of December of the same given year, does not enter the count of hires and separations, even if it represents for the firm one hire and one separation in that year. Hence, employee turnover indexes computed using discrete time definitions are undercounted (unless all the employment relationships last for more than one calendar year - a pretty unlikely event). Since the VWH-AIDA dataset allows us to observe a daily history of each job held by a worker in a given firm, we are able to consider a *continuous* time version of the excess employee turnover (and of the other employee turnover measures - hires, separations and employee turnover). In particular, employee turnover measures are calculated on the basis of two variables present in the original version of the VWH dataset; one indicating the date of the hire and the other one indicating the date of the separation (if applicable) for each job. Essentially, if the hiring date is equal to or after the first of January of the given year, than it is a hire. If the separation date is prior or equal to the 31st of December of the given year, than it is a separation. Furthermore, notice that having a continuous time version of the data allows us to *construct* a discrete time version of them (while the reverse is obviously unfeasible). In order to show how much the two sets of turnover measures change when discrete time - instead of continuous time - definitions (and data) are used and in order to present results that are comparable with the previous literature[27], we also compute the employee turnover measures using the discrete time definitions. Following Davis and Haltiwanger [1992], in order to express employee turnover measures in rates, we divide them by the average level of employment, defined as the sum of the number of employees on the first of January and on the 31st of December of a given year divided by two.

Finally, some workforce characteristics' variables - among which: females, migrants, young workers proportions - have been constructed by weighting workers on a monthly basis. For example, in the construction of the variable measuring the proportion 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.

The sample used in the estimation procedures is the result of some further cleaning with respect to the complete VWH-AIDA dataset. In particular, we restrict our analysis to manufacturing firms, which account for about 65% of the original sample. We consider only

[27]The vast majority of empirical works assessing the impact of turnover on productivity uses discrete time measures of worker turnover. One exception is [Siebert et al., 2006].

firms established at least one calendar year before we observe them and firms which are still alive at least one calendar year after we observe them.[28] As a further precaution, we restrict the sample to firms which are classified as 'active', thus excluding closing firms. Firms with non-positive book values of physical capital, materials and revenues are excluded from the sample; the same is done for firms with (on average - over the observation period) less than five employees[29]. This is done in order to clean the dataset from systematic 'window dressing' procedures usually carried out by very small firms. Furthermore, we remove firms for which the number of employees (monthly weighted) and the book value of physical capital, materials and revenues increase or decrease over years at implausibly high rates. In particular, we apply a standard trimming procedure according to which firms with logarithmic first-difference of such figures above 1 and below -0.5 are removed from the sample. Then, we remove firm-year observations for which excess employee turnover rate[30] is (strictly) greater than 1. This has been done in order to purge the sample from disturbing outliers; even if few firms (about 1%) have such implausibly high values of excess worker turnover, still estimates are largely affected by them in terms of precision. Finally, in order to apply the estimation strategy described in Section 3, we have to restrict our attention to firms for which we have at least fours *consecutive* years of observations.

The final dataset used for estimation is the firm-level 'collapsed' version of the matched employer-employee one; it consists of 15,194 firm-year observations for 2,619 firms.

Table 1 shows the number of consecutive observations: for about 18% of the firms we have 4 consecutive observations; for 17% of them we have 5 consecutive observations; for 29%, 6 and for 34%, 7 consecutive observations.

Table 2 shows the distribution of firm-year observations by Ateco two-digit industry. Ferrous products (excluding machinery), machinery products and furniture, together with food and beverage, textile and clothing industry collect most of the firm-year observations.

Table 3 presents summary statistics of the sample.

On average, firms have about 61 employees and obtain 11,568,960 euros per year from the sale of goods and services produced. However, for 50% of the companies, employees are less than 33 and revenues are less than 4,995,000 euros. Each day worked (by each worker) brings on average about 665 euros of revenues, but for 50% of the firms this figure is less than 501 euros. The average firm is about 15.7 years old and gets 20 euros of net profit out

[28]We always know the establishment date of the firms, so that we are able to identify those firms settled less than one year before we observe them (and consequently to eliminate them from the sample). On the other hand, for the last year of observation (2001) we are not able to identify which firms have closed in the following year (and consequently we cannot eliminate them from the sample).

[29]This measure of employment is monthly weighted; this is allowed by the continuous time nature of our data.

[30]Technically, the continuous time version of excess employee turnover rate.

of 1,000 euros of sales.

In the typical firm, 28% of the workers are female, 6% are migrant, 38% are under 30 years old 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 (23%); 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 6.76 years and earn about 129 euros per day.

Average net job creation rate is 0.032; hiring and separation rates are on average respectively 0.220 and 0.188, so that mean turnover rate is 0.408; and average excess turnover rate is 0.315.

The average firm hires 12 workers and separates from 10 workers, thus experiencing an employee turnover of 22 workers (12 hires + 10 separations); the average net job creation is positive and equal to 2.[31] Therefore, the average firm could have accommodated the job creation by simply hiring 2 workers and by firing no one. Instead, it decided to hire 12 workers and, at the same time, to fire 10 workers. It might as well have hired 25 employees and fired 23. Hence, in principle, all the configurations of hires and separations such that their difference is 2 would be fine. Ultimately, our research question has to do with this: is it better to reach a given employment level through high or low *excess* employee turnover?

As previously said, we also computed turnover measures using the discrete time version definitions (and data). As expected, these figures are significantly lower than their continuous counterparts: average hiring rate, separation rate, employee turnover rates are respectively 0.159, 0.128 and 0.287 instead of 0.220, 0.188 and 0.408 for their continuous counterpart. Excess employee turnover rate is now on average equal to 0.193, whereas for the continuous time version this figure is 0.315. Hence, average excess employee turnover is about 39% lower when considering discrete instead of continuous time version, suggesting that employment relations started and ended within a year are common.

5 Results

In this section we present results from simple OLS and FE estimation of (5) and SYSTEM-GMM estimation of (12).

In view of the discussion in Section (3), SYSTEM-GMM is the only estimation method able to identify the causal effect of interest, so that we rely on it when investigating causal

[31] More precisely: the average hires are 11.601; the average separations are 10.071; the average worker turnover is 21.673; the average net job creation is 1.530. We consider integer numbers in order to make the discussion about the 'average firm' realistic.

relationships. On the other hand, we still present results from simple OLS and FE on (5) in order to explore the potential bias of these two estimation methods.

In all the estimations we include year dummies in order to remove the potentially dangerous time-specific effect.

OLS and FE estimations are robust to heteroskedasticity, since robust standard errors are computed; the same applies to SYSTEM-GMM estimation, since we use the robust two-step version of it. However, Arellano and Bond [1991] have found out that the two-step variance-covariance matrix is seriously downward biased; in order to solve this problem, Windmeijer [2005] has constructed a finite sample correction, called Windmeijer's Correction (WC), which we apply.

Let us recall that SYSTEM-GMM estimates are obtained considering inputs and excess employee turnover as endogenous; whereas the lagged dependent variable is, by construction, endogenous. Moreover, for (12) in first-differences we use as instruments for endogenous variables their lags $t-3$ and earlier in levels; while, for (12) in levels, we use as instruments for the endogenous regressors the lag $t-2$ of their first-difference.

For what concerns SYSTEM-GMM, we proceed as follows: we first estimate the unrestricted version of (12) and then, when the common factor restrictions imposed by the model are not rejected by the data, we also estimate the restricted version of it, where the structural parameters (ρ, β_l, β_k, β_m and θ) are recovered through a minimum distance estimator. If the common factor restrictions imposed by the model are rejected by the data, we will consider (12) as an unrestricted autoregressive-distributed lag model. In this case, we simply report the long-run effects.

SYSTEM-GMM estimation is performed using the user-written STATA program `xtabond2`, developed by Roodman [2009]. While minimum distance estimation is performed using the user-written STATA program `md_ar1`, developed by Söderbom in 2009.

Results from the estimation of the basic model are shown in Table 4. The second column of the table reports OLS results, while the third one is for FE results for the equation (5). The fourth column reports SYSTEM-GMM estimates for (12): the upper panel shows the estimation results for the unrestricted model, while the bottom panel reports the structural parameters estimates from the restricted model, obtained through minimum distance estimation; Comfac shows the p-value associated to the test for the joint validity of the common factor restrictions imposed by the model in (12); on the right hand side of the table some GMM diagnostics are presented. They include the robust Hansen-J test statistic, which tests for the validity of the overidentifying restrictions imposed by the model; some diff-in-Hansen test statistics, which test the validity of specific subsets of instruments; and the p-value associated to the Arellano-Bond tests for autocorrelation in the first-differenced error term (up to the third order).

According to OLS estimates the impact of excess employee turnover on firm productivity is negative (-0.029) and significantly different from zero at any conventional level (p-value 0.001). One standard deviation increase in excess employee turnover rate (0.219) would cause a decrease in revenues per day worked by about 0.63%. However, as largely discussed in Section 3, OLS estimator is most likely not able to identify the causal effect of interest, principally because excess employee turnover rate is most likely not correlated with unobserved fixed-effects (example of managerial ability) and with the productivity shock (reverse causality coming from on-the-job search).

When controlling for unobserved fixed heterogeneity (such as managerial ability), the coefficient on excess employee turnover changes its sign, becoming positive (0.007), and loses its significance (p-value 0.203). The negative bias of OLS casts light on the negative correlation between the unobserved fixed-effect and excess employee turnover. It seems, then, that managerial ability is negatively correlated with excess employee turnover (i.e. that better managers systematically reach a lower degree of excess employee turnover). However, if, on the one hand, fixed effect estimation is able to deal with unobserved fixed heterogeneity, on the other hand, it does not deal with the simultaneity issue implied by on-the-job search theory (i.e. with the correlation between excess employee turnover and the idiosyncratic productivity shock).

When taking into account the simultaneity issue, over and above the firm-specific fixed-effects, we are able to fully investigate the causal effect of interest. This is done through SYSTEM-GMM estimation. Since the common factor restrictions imposed by the model in (12) cannot be rejected at any conventional significance level - the p-value associated to Comfac is 0.679 -, we can investigate the causal impact of interest by looking at the minimum distance estimator of the structural parameter θ; it is positive (0.014), but not significantly different from zero at any conventional level, the associated p-value being 0.773. Hence, when also dealing with the simultaneity issue, though the point estimate of the causal effect remains positive, is it by far more likely to be zero (p-value 0.773 of SYSTEM-GMM *versus* 0.203 of FE).

It is worth recalling that also production function inputs are likely to be correlated with the fixed-effect and with the idiosyncratic productivity shock. Hence, over and above the endogeneity of excess employee turnover, also the one of inputs has to be taken into account. Both in itself and in view of our purpose: the identification of the impact of excess employee turnover on firm productivity. Indeed, endogeneity of one regressor (not necessarily the one of our direct interest), not only causes inconsistency in its estimation, but also in the estimation of the other parameters of the model (and hence also the one of our direct interest). This is a further motivation for relying on SYSTEM-GMM estimates, instead of on OLS or FE ones, since they do appropriately deal with endogeneity of inputs.

The SYSTEM-GMM estimate of β_l is -0.846, so that α_l (i.e. the elasticity of labor input) is estimated to be equal to 0.154; a 10% increase in labor days worked would then increase revenues by about 1,54%; since β_m is estimated to be 0.748, a 10% increase in the materials usage would increase revenues by about 7.48%. Both the estimates of labor and materials elasticities are significantly different from zero at any conventional level (p-value 0.000). The capital elasticity (β_k) is estimated to be 0.064, so that a 10% increase in physical capital increases revenues by about 0.64%; the estimate is significantly different from zero at 10% level (p-value 0.062). The autoregressive parameter of the productivity shock is estimated to be 0.763 (p-value 0.000), showing that the idiosyncratic productivity shock is highly persistent over time.

GMM diagnostics show that our instruments are overall valid (p-value of Hansen-J test 0.487); the validity of subsets of instruments is not rejected at any conventional significance level (p-values range among 0.259 and 0.590). The Arellano-Bond tests for first- and second-order autocorrelation between first-differenced residuals strongly reject the null hypothesis of no autocorrelation (which is coherent with our model); the same test for third-order autocorrelation does not reject the null at any conventional significance level (p-value 0.277), which again is coherent with our model.

Several scenarios are consistent with our finding, i.e. the fact that the estimated effect of excess employee turnover on firm productivity is not significantly different from zero in the basic equation (12). It may be that, differently from other results in the empirical literature, which find a negative - most of the time - or a positive - less frequently - impact of employee turnover (*not* excess employee turnover) on firm productivity, we simply find that on average excess employee turnover has no significant impact on it, so that a zero level of excess employee turnover would be essentially the same compared to having a huge amount of it, in terms of the effect on firm productivity of labor. It may also be the case that the impact of interest is indeed non-linear; more precisely, one could expect it to have an inverted-U shape, so that excess employee turnover would be beneficial up to some point before becoming harmful. It may also be that the effect of interest is very diversified among firms across several dimensions, though being linear. In particular, we think that the relevant dimensions are four. The degree of intensity of capital usage in the firm, as shown by the capital to labor ratio; belonging or not to the high-tech industry, which, at least to some extent, is related to the intensity of capital; the volatility of demand and the age of the firm.

Table 5 presents results for the non-linear version of the basic model, i.e. with squared excess employee turnover added as a regressor.[32] OLS estimates associated with excess employee turnover and its square are respectively -0.044 (with p-value 0.106) and 0.019 (with p-value 0.557). Already the, tough biased, OLS estimates shows that the presence of non-linearities in the impact of interest is not confirmed by our data. If, on the one hand, the negative coefficient on the linear term is preserved, though with a little more reservations (higher p-value) with respect to the basic model, on the other hand, the squared term is not significantly different from zero at any conventional level. The same situation, in the sense of the preservation of the result associated to the linear term (with respect to the basic model) and non significance of the square term applies to the FE. The estimate associated to the linear term is 0.009 (p-value 0.504), while the one associated to the squared term is -0.003, with p-value 0.853. For what concerns SYSTEM-GMM, since the five common factor restrictions imposed by the model are overall accepted (p-value 0.544), we look at the minimum distance estimates of the structural parameters. Coefficient θ_1 and θ_2 in Table 5 represent the structural parameters respectively associated to excess employee turnover and its square; θ_1 is estimated to be negative (-0.020) but not significantly different from zero (p-value 0.856), while θ_2 is estimated to be positive (0.032) but again not significantly different from zero (p-value 0.795). Hence, our results strongly reject the hypothesis that the impact of excess employee turnover on productivity is non-linear.[33]

It seems plausible that the impact of excess employee turnover on firm productivity is very diversified across firms. One can argue, for instance, that it is even beneficial for the food and beverage industry and harmful for the aerospace industry. With this respect, it is worth highlighting that at the heart of the effect of excess labor turnover on firm performance acts a trade-off, for which the ultimate question for the firm is: is it better to try with a new worker, in the hope he does better than what my employee is doing by now or to stay with him, in the fear of loosing his firm-specific knowledge? As long as firm-specific knowledge amounts to package snacks, than opening to new workers cannot hurt that much. On the other hand, when firm-specific skills are precious and scarce from the point of view of the employer, than quitting workers, even if not the best ones, can really hurt the firm, at least in the short period or anyway until (and if) a new employee catches up with old employee's productivity. This points the finger to two dimensions over which the impact of interest can be explored: the degree of capital intensity and belonging or not to the high-tech industry.

Table 6 shows OLS, FE and SYSTEM-GMM results for an 'augmented' version of (5) -

[32]In the SYSTEM-GMM estimation of (12) also its lag is included.

[33]What said before with respect to the estimates of the other structural parameters and SYSTEM-GMM diagnostic applies sufficiently well also here, so that we will not again go through that, in order to keep the focus on our primary object of interest. For any information on this we remind the reader to the results tables. Notice that the same applies to the next results shown.

and (12) -, where we allow for a difference in the impact of excess employee turnover on firm productivity across the degree of capital intensity. The degree of capital intensity for each firm in each year is computed as the capital to labor ratio; the average (over time) value for each firm is calculated. Firms are then classified 'low capital intensive' ('high capital intensive') if their (average) capital to labor ratio is below (above) the median. Finally, these dummies are interacted with the excess employee turnover rate and inserted in (5) and in (12).[34] OLS estimates for the effect of excess employee turnover on firm productivity are still negative for both low and high capital intensity firms (respectively -0.012 and -0.046); however, the coefficient associated with the low capital intensive firms loses significance (p-value 0.264), while the other is statistically different from zero at 1% level (p-value 0.000). According to the (more robust) fixed effect estimates these coefficients change sign - becoming positive - and lose significance (p-values 0.324 and 0.408, respectively). Things substantially change when considering the (fully) robust SYSTEM-GMM estimates. Since the five common factor restrictions are accepted by the data (p-value of Comfac 0.451), we refer to the structural parameter estimates. The impact of excess employee turnover on firm productivity is estimated to be positive (0.108) and statistically different from zero at 10% level (p-value 0.062) for low capital intensive firms; and negative (-0.089) and statistically different from zero at (almost) 10% level (p-value 0.104) for high capital intensive firms. This result seems to confirm, though not strongly, the feeling that the more is a firm capital intensive the more retaining firm-specific human capital (and hence reducing excess worker turnover) is important. However, we have to admit that, splitting the firms according to capital intensity into fours groups[35] - instead of two -, results for the SYSTEM-GMM (actually, the minimum distance estimators of the structural parameters) get less significant: though preserving their signs (positive for the low and medium-low capital intensive firms and negative for the medium-high and high capital intensive ones), their significance levels lower (p-value from 0.128 for medium-high up to 0.849 for high capital intensive firms). Complete results are reported in Table 7. This casts doubts on the validity of the result that the effect of excess worker turnover on firm productivity is positive for low capital intensive firms and negative for high capital intensive firms.

Table 8 and Table 9 show results for the case in which we allow for differences in the impact of interest between high-tech and low-tech industries. In particular, in the Table 8, we report results obtained after splitting the sample into two categories: low-tech and high-tech firms. The definition of high-tech industry is quite broad and covers 24.36% of

[34] As for the non-linear case, their lags are also included in equation (12).

[35] That is: low (first quartile), medium-low (second-quartile), medium-high (third-quartile), high (fourth quartile).

the observations in our sample. In Table 9, we further split the high-tech firms into two categories: medium high-tech and high high-tech; the definition of high high-tech industry is quite restrictive and only covers 6.75% of the observations. Medium high-tech firms are those which are high-tech but not high high-tech: this category includes 24.36% - 6.75% = 17.61% of the observations in our sample.[36] When the first - broader - definition of high-tech industry is used to split the sample (Table 8), OLS estimates show that the impact of excess employee turnover on productivity is negative for both low- and high- tech firms, though stronger on the high-tech ones (-0.019 and -0.065, respectively). These estimates are statistically different from zero at 5% and 1% levels, respectively. With FE estimation these effects become positive (0.008 and 0.004, for low- and high-tech firms respectively), but lose significance (p-values 0.207 and 0.705). SYSTEM-GMM estimates provide again different results. Since the five common factor restrictions imposed by the model are overall accepted (p-value associated to Comfac 0.345), we report the minimum distance estimates of the structural parameters. The impact of excess employee turnover for low-tech firms is estimated to be positive (0.055) but not significantly different from zero at any conventional level (p-value 0.286); while the same impact for high-tech firms is estimated to be negative (-0.051) but again not significantly different from zero at any conventional level (p-value 0.518). When we split the sample into the three categories (low-tech, medium high-tech and high high-tech - Table 9), and hence we allow the impact of excess employee turnover to differ across these dimensions, we find very similar results with respect to the previous case. In particular, minimum distance estimates (from the restricted version of (12)) still reports a positive, though not significant (p-value 0.443), impact of excess employee turnover on firm productivity for low-tech firms, and a negative (-0.099 and -0.075), though not significant (p-values 0.259 and 0.311), impact for medium and high high-tech firms, respectively. Hence, though the sign of the estimated coefficients seem to indicate that excess employee turnover is beneficial for low-tech firm and harmful for high-tech ones, as it seems sensible to believe, the high p-values associated with them do not allow us to conclude so.

We believe that there are still two relevant dimensions across which the impact of excess employee turnover on firm productivity should be examined: volatility of demand and age of the firm. In particular, we argue that firms facing high volatility of demand benefit from excess worker turnover (more than firms with low-volatility of demand do). The reason being that high excess worker turnover means high levels of hires and separations during the year and hence high flexibility of the workforce. Or, put in another way, since firms facing highly volatile demand need to be flexible in terms of the number of employees (relatively few employees in periods of low demand and relatively many in periods of high demand),

[36]For more details on how this indicators are defined see the notes below the relevant tables.

excess worker turnover is beneficial for firm productivity. We also argue that young firms benefit from excess worker turnover. In the early life of a firm the 'optimal' job-matches still have to be reached. And excess employee turnover is the only way in which it could be done. On the other hand, we argue that the effect on mature firms is more controversial. It may be that mature, but not old, firms are damaged by excess worker turnover, because of loss of firm-specific human capital (and good job-matches); while old firms benefit from it (at least to a small extent) in that it brings some 'fresh air' in the firm.

Table 10 reports results for OLS, FE and SYSTEM-GMM estimation of a version of (5) - and, for SYSTEM-GMM of (12) - in which the impact of excess worker turnover is allowed to vary across degree of volatility of demand. In particular, we compute volatility of demand for each firm in each year as the percentage deviation of revenues from their mean. We consider the mean (over time) volatility of demand. Firms are then classified to have 'high volatility of demand' ('low volatility of demand') if their mean volatility of demand is below (above) the median. As usual, these dummies are interacted with the excess employee turnover rate and inserted in (5) and in (12).[37] According to the OLS estimates the effect of excess employee turnover on firm productivity is negative for both high- and low-volatile firms. However, if, on the one hand, the effect for low-volatile firms is strongly significant, the one for high-volatile firms is not statistically different from zero (p-value 0.239). Fixed effect estimation provides positive coefficients; the one associated with low-volatile firms is statistically different at 5% level, while the one associated with high-volatile firms is non significant at all (p-value 0.949). More interestingly, SYSTEM-GMM estimates, through the restricted model minimum distance estimates (p-value of Comfac 0.236), tell us that the effect of excess employee turnover on firm productivity for high-volatile firms is positive and three times larger than the one associated to low-volatile firms (0.064 and 0.025, respectively). However, we cannot safely rely on this results, since the p-values associated to the estimated coefficients are high, 0.377 for high-volatile firms and 0.682 for low-volatile ones.

Table 11 shows OLS, FE and SYSTEM-GMM results for a model that allows for different impacts of excess employee turnover on productivity across age of the firm. We split the sample into three groups: young firms, mature firms and old firms. Young firms are the ones whose average age in our observation window is lower or equal to 5 years; mature firms are the ones for which the same figure is over 5 years and below 20 years; old firms are defined as the ones whose average age is equal to or over 20 years. Following the usual procedure, we interact the dummies for young, mature and old firms with excess employee turnover rate and insert these interaction variables in (5) and (12). OLS results predict a positive (but not significant - p-value 0.025) impact of excess employee turnover on firm productivity for young firms, while

[37] As usual, their lags are also included in equation (12).

a negative effect for mature and old firms (-0.014 and -0.099, respectively). While the effect for mature firms is not significant (p-value 0.142) the one for old firms is highly significant (p-value 0.000). When controlling for unobserved firm-specific characteristics, OLS results changes: while the effect on young firms is quite similar (0.024, with p-value 0.202), the predicted effect for mature firms changes sign, becoming positive (but non significant - p-value 0.245), and the predicted effect on old firms, though remaining negative, completely lose significance (p-value 0.799). When dealing with SYSTEM-GMM, since the six common factor restrictions imposed by the model are accepted (p-value of Comfac is 0.943), again we consider the minimum distance estimates of the structural parameters. All the effects are predicted to be positive and highly non-significant. The coefficients are 0.054, 0.013 and 0.027 with associated p-values 0.606, 0.810 and 0.670 for young, mature and old firms, respectively. Hence, also with respect to age the casual effect of excess employee turnover on firm productivity is predicted to be null.

As a robustness check, and especially for comparative purposes, we perform the same set of estimations using the discrete time measure of excess worker turnover rate instead of the continuous time one. In Table 12, we present the usual set of results for the basic model. The results are very similar to the ones for the continuous case. We also performed the other set of estimations (i.e. for the non linear case, for high- *versus* low-capital intensive firms, for high- *versus* low-tech firms, for high- *versus* low-volatility of demand firms, for young, mature and old firms) and we find that the main results are preserved. Results are available from the author upon request.

In Section 3 we have largely discussed about the identification of the causal effect of interest. And we have explained why OLS and FE estimations are not reliable. On the other hand, we have shown how SYSTEM-GMM is able to fully deal with the endogeneity problem, which, if not taken into account, prevents us from the identification of the causal effect. In this section we have presented results for the basic model, where excess employee turnover rate enters the production function as an observable part of the total factor productivity. SYSTEM-GMM estimates have shown that the causal impact of it on average product of labor is null. At this point, we have argued that there were three possible scenarios coherent with this situation; that the causal impact is indeed null, that it is non-linear, that it is different across several dimensions. We then have checked for non-linearities and for heterogeneity across degree of capital intensity, belonging to high-tech *versus* non belonging to high-tech industry, degree of volatility of demand and age of the firm. In all these cases, robust SYSTEM-GMM estimates predict that the impact of excess worker turnover rate on firm productivity is not significantly different from zero. Hence we must conclude that it is indeed, *non significantly different from zero.* The interpretations of this robust results can be twofold. If, on the one hand, we are willing to believe to the two theories on the impact of excess worker turnover on firm productivity (namely FSHC and job-matching theory), we read the results in terms of a practically equal weight of the firm-specific effect as compared to the job-matching effect. So that what we do actually observe is a null effect. On the other hand, if we are not willing to attach great importance to the theories, we just take notice of the result as it is.

What is important, in our opinion, is that, since OLS (and to a lesser extent FE) estimation does not appropriately deal with endogeneity issues, we cannot safely rely on this estimates to interpret a causal effect. For example, if we had relied on simple OLS, we would have concluded that excess employee turnover is dangerous, whereas we have discovered that it is indeed innocuous.

6 Conclusions

This paper aims at investigating the causal impact of excess employee turnover on the firm productivity of labor. Excess employee turnover is defined as that part of worker turnover (hires plus separations) over and above the worker turnover which is needed to accommodate for job creation (or, alternatively, job destruction). Ultimately, our research interest resides in this basic question: whether it is beneficial or not for the firm productivity to change the composition of the workforce; and to what extent.

Throughout the analysis, we have paid particular attention to the identification of the causal effect of interest; this has led us to carefully take care of endogeneity issues, deriving from both unobserved fixed-effects and simultaneity problems. Unobserved fixed components and on-the-job search effect, which predicts that, since workers prefer to work for better firms (which pay better wages), worse firms are characterized by higher levels of employee turnover, have been carefully accounted for in the SYSTEM-GMM estimation. Moreover, attention has been devoted to the endogeneous nature of the production function inputs. All this makes our SYSTEM-GMM estimates fully endogeneity-robust and, beacuse of that, more reliable than the other empirical works in the literature, which only present pooled OLS or RE estimates, as Harris et al. [2006] or, at most, FE estimates, as Siebert et al. [2006].

The main finding is that excess employee turnover has no significant effect on firm productivity. This is an atypical results in the literature, which seems to find both positive and negative, but not null, effects.

By presenting OLS and FE estimates, over and above SYSTEM-GMM ones, we show that not fully taking into account endogeneity (i.e. simply considering OLS, and, to a lesser extent, FE) leads to wrong conclusions. Indeed, OLS estimates of the causal effect prove to be strongly downward biased, mostly because of the negative correlation between excess employee turnover and unobserved fixed-effects (i.e. managerial ability). On the other hand, FE estimates, taking into account the unobserved fixed heterogeneity, provides more appropriate results, i.e. more similar to fully robust SYTEM-GMM results. However, FE effect estimation is not able to deal with the simultaneity issue from on-the-job search theory. In particular, if we do not take into account this problem, we end up underestimating the causal effect. However, we have to admit that FE estimates provides quite similar predictions of the causal effect of interest with respect to our SYSTEM-GMM benchmark. This casts light on the minor importance of the simultaneity issue coming from on-the-job search theory. Still, we believe that SYSTEM-GMM estimation is overall better than FE in that it is able to deal with correlation between inputs and productivity shock and with measurement error, which are confirmed by the data.[38]

Moreover we deeply explore the impact of excess worker turnover on firm productivity by allowing for non-linearities and for different effects across several relevant dimensions, such as degree of capital intensity, degree of volatility of demand, belonging to the high-tech industry or not and age of the firm. SYSTEM-GMM estimations still predict that the effect of interest is indeed null.

This leads us to conclude that the our primary finding, i.e. that the excess employee turnover has no impact on firm productivity, is not the result of some kind of misspecification (i.e. linear instead of non-linear) or not-accounted-for heterogeneity (i.e. different impact across some relevant dimensions), but is valid as it is.

[38]We have performed SYSTEM-GMM estimates in which the inputs are treated as exogenous. And GMM diagnostics strongly reject this hypothesis. In the same vein we have performed SYSTEM-GMM estimations where inputs are treated as endogenous but productivity shock is treated as a simple white noise (instead of an AR(1)). Again GMM diagnostics strongly reject the validity of this configuration. Lastly, we have performed SYSTEM-GMM estimations identical to the one presented in the paper except for the presence of white noise measurement error (i.e. with lag $t-2$ as instruments for the differenced equation, and $t-1$ for the level one). Again, GMM diagnostics strongly reject the validity of no measurement error assumption.

Table 1: Number of consecutive observations

Number of consecutive observations	**Firms**	**Observations**
4	479	1,916
5	460	2,300
6	782	4,692
7	898	6,286
Total	2,619	15,194

Source: VWH-AIDA dataset

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

Sector of economic activity	**Percentage**
Food and beverage	5.51
Textile	4.75
Clothing	4.70
Leather and leather goods	7.24
Wood and wood products (excluding furniture)	4.05
Paper and paper product	2.03
Printing and publishing	2.18
Coke and petroleum products	0.32
Chemical products	3.86
Rubber and plastics	5.32
Non-ferrous production	7.90
Ferrous production	2.21
Ferrous products (excluding machinery)	15.90
Machinery products	14.18
Office machinery and computers	0.04
Electrical machinery	1.86
Radio, TV and TLC equipment	0.53
Medical equipment and measurement instruments	2.01
Motor vehicles	1.08
Other transportation equipment	0.80
Furniture and other manufacturing industries	13.35
Recycling	0.18
Total	100

Source: VWH-AIDA dataset

Table 3: Summary statistics

Variable	**Notes**	**Mean/ Percentage**	**Std. Dev.**	**1st Q.**	**Median**	**3rd Q.**
Revenues	1,000's euros (2000 euros prices)	11,568.96	28,005.65	2,728	4,995	11,018
log Revenues		8.650	1.010	7.883	8.489	9.278
Revenues per day worked	FTE adjusted - 1,000's euros (2000 euros prices)	0.665	0.645	0.352	0.501	0.754
log Revenues per day worked		-0.629	0.613	-1.045	-0.691	-0.283
Days worked	FTE adjusted	18,195.40	46,225.00	5,686.00	9,836.50	18,638.00
log Days worked		9.278	0.902	8.646	9.194	9.833
Capital	Tangible fixed assets (PIM) - 1,000's euros	1,785.785	4,998.422	300.00	715.76	1,651.824
log Capital		6.556	1.316	5.704	6.573	7.410
Materials	1,000's euros (2000 euros prices)	6,064.134	15,758.400	1,141.920	2,311.993	5,484.362
log Materials		7.856	1.204	7.040	7.746	8.610
Number of employees	Monthly weighted	61.244	157.342	19.167	33.083	63.000
Firm's age	Years	15.712	7.634	9	16	23
Profit margin	Profit over Revenues	0.020	0.525	0.0008	0.007	0.027
Net job creation		1.530	12.756	-1	1	3
Net job creation rate		0.032	0.139	-0.035	0.026	0.095
Abs(Net job creation rate)		0.094	0.108	0.030	0.069	0.128
Hires	Continuous time	11.601	23.527	3	6	13
Separations	Continuous time	10.071	20.515	3	6	11
Employee turnover	Continuous time	21.673	42.261	6	12	24
Excess employee turnover	Continuous time	17.192	34.511	4	10	20
Hiring rate	Continuous time	0.220	0.154	0.109	0.192	0.303
Separation rate	Continuous time	0.188	0.133	0.100	0.167	0.255
Employee turnover rate	Continuous time	0.408	0.251	0.222	0.364	0.545
Excess employee turnover rate	Continuous time	0.315	0.219	0.154	0.279	0.444
Hires	Discrete time	8.324	17.648	2	5	9
Separations	Discrete time	6.794	15.046	2	4	8
Employee turnover	Discrete time	15.118	30.215	5	9	17
Excess employee turnover	Discrete time	10.637	21.961	2	6	12
Hiring rate	Discrete time	0.159	0.116	0.080	0.140	0.216
Separation rate	Discrete time	0.128	0.101	0.067	0.112	0.170
Employee turnover rate	Discrete time	0.287	0.168	0.171	0.263	0.373
Excess employee turnover rate	Discrete time	0.193	0.138	0.095	0.177	0.273
Female workers proportion	Monthly weighted	0.284	0.229	0.105	0.203	0.428
Migrant workers proportion	Monthly weighted	0.060	0.078	0	0.036	0.084
Young workers proportion	Under 30 - Monthly weighted	0.378	0.162	0.261	0.366	0.482

Table 3: Summary statistics (continued)

Variable	**Notes**	**Mean/ Percentage**	**Std. Dev.**	**1st Q.**	**Median**	**3rd Q.**
Part-time workers proportion	Monthly weighted	0.042	0.060	0	0.023	0.061
Temporary workers proportion	Monthly weighted	0.037	0.054	0	0.016	0.055
Blue-collar workers proportion	Monthly weighted	0.703	0.159	0.631	0.730	0.811
White-collar workers proportion	Monthly weighted	0.237	0.150	0.135	0.206	0.296
Manager proportion	Monthly weighted	0.012	0.027	0	0	0.013
Apprentice proportion	Monthly weighted	0.040	0.059	0	0.014	0.059
Average workers' age	Monthly weighted	34.854	3.664	32.327	34.816	37.415
Average workers' tenure	Years	6.763	3.094	4.417	6.318	8.697
Average workers' gross wage	In 2003 euros prices	129.393	35.336	110.312	125.124	142.833
						Number of firm-year observations 15,194
						Number of firms 2,619

Source: VWH-AIDA dataset

Table 4: Estimation results - Basic model; Continuous time excess worker turnover rate; Estimation methods: OLS, FE, SYSTEM-GMM

Production Function Estimates *Dependent variable:* $y_{it} - l_{it}$					**SYSTEM-GMM diagnostic**	
Variable	**OLS**	**FE**	**SYSTEM-GMM**			
			Unrestricted model			
$y_{it-1} - l_{it-1}$	-	-	0.748 (0.000)		Number of instruments	76
l_{it}	-0.670 (0.000)	-0.702 (0.000)	-0.844 (0.000)		Hansen-J test	60.71 (0.487) [61]
l_{it-1}	-	-	0.617 (0.000)		Diff-in-Hansen test 1	29.11 (0.259) [25]
k_{it}	0.061 (0.000)	0.013 (0.001)	0.052 (0.215)		Diff-in-Hansen test 2	6.70 (0.350) [6]
k_{it-1}	-	-	-0.035 (0.385)		Diff-in-Hansen test 3	14.12 (0.590) [16]
m_{it}	0.587 (0.000)	0.598 (0.000)	0.675 (0.000)		Diff-in-Hansen test 4	47.22 (0.505) [48]
m_{it-1}	-	-	-0.476 (0.000)		ART(1)	(0.000)
EET_{it}	-0.029 (0.001)	0.007 (0.203)	0.045 (0.409)		ART(2)	(0.000)
EET_{it-1}	-	-	-0.023 (0.685)		ART(3)	(0.277)
			Restricted model			
			Structural parameters:			
			β_l	-0.846 (0.000)		
			β_k	0.064 (0.062)		
			β_m	0.748 (0.000)		
			θ	0.014 (0.773)		
			ρ	0.763 (0.000)		
			Comfac	(0.679)		
					Number of firm-year observations	15,194
					Number of firms	2,619

Source: VWH-AIDA dataset

Year dummies are included in OLS, FE and SYSTEM-GMM estimates; robust standard error are used for OLS and FE, while two-step robust and WC corrected standard errors are used for SYSTEM-GMM; p-values in parenthesis; degrees of freedom in square brackets; Hansen J-test tests the validity of the overidentifying restrictions (robust to heteroskedasticity); Diff-in-Hansen test 1 tests the validity of the (first-differenced) instruments for the equation in levels; Diff-in-Hansen test 2 tests the validity of the instruments for the lagged dependent variable (in the first-differenced and level equation); Diff-in-Hansen test 3 tests the validity of the instruments for the excess worker turnover rate (in the first-differenced and level equation); Diff-in-Hansen test 4 tests the validity of the instruments for the inputs (in the first-differenced and level equation); ART(1), ART(2) and ART(3) items show the p-value associated with the Arellano/Bond test for (respectively) first, second and third order autocorrelation in the first-differenced residuals; Comfac tests the joint validity of the common factor restrictions imposed by the model in (12) *- it is distributed as a* χ^2 *with degrees of freedom equal to the number of common factor restrictions imposed.*

Table 5: Estimation results - Non-linear model (square of excess worker turnover rate); Continuous time excess worker turnover rate; Estimation methods: OLS, FE, SYSTEM-GMM

Production Function Estimates *Dependent variable:* $y_{it} - l_{it}$					**SYSTEM-GMM diagnostic**	
Variable	**OLS**	**FE**	**SYSTEM-GMM**			
			Unrestricted model			
$y_{it-1} - l_{it-1}$	-	-	0.738 (0.000)		Number of instruments	90
l_{it}	-0.669 (0.000)	-0.702 (0.000)	-0.861 (0.000)		Hansen-J test	68.32 (0.633) [73]
l_{it-1}	-	-	0.625 (0.000)		Diff-in-Hansen test 1	35.12 (0.322) [32]
k_{it}	0.061 (0.000)	0.013 (0.001)	0.055 (0.185)		Diff-in-Hansen test 2	6.51 (0.164) [4]
k_{it-1}	-	-	-0.039 (0.331)		Diff-in-Hansen test 3	21.44 (0.922) [32]
m_{it}	0.587 (0.000)	0.598 (0.000)	0.647 (0.000)		Diff-in-Hansen test 4	46.28 (0.544) [48]
m_{it-1}	-	-	-0.443 (0.000)		ART(1)	(0.000)
EET_{it}	-0.044 (0.106)	0.009 (0.504)	0.133 (0.432)		ART(2)	(0.000)
EET_{it-1}	-	-	-0.060 (0.745)		ART(3)	(0.269)
EET^2_{it}	0.019 (0.557)	-0.003 (0.853)	-0.112 (0.571)			
EET^2_{it-1}	-	-	-0.060 (0.745)			
			Restricted model			
			Structural parameters:			
			β_l	-0.847 (0.000)		
			β_k	0.063 (0.055)		
			β_m	0.737 (0.000)		
			θ_1	-0.020 (0.856)		
			θ_2	0.032 (0.795)		
			ρ	0.765 (0.000)		
			Comfac	(0.544)		
					Number of firm-year observations	15,194
					Number of firms	2,619

Source: VWH-AIDA dataset

Parameters θ_1 and θ_2 represent the structural coefficients respectively associated to excess employee turnover and its square; Diff-in-Hansen test 3 tests the validity of the instruments for the excess worker turnover rate and its square (in the first-differenced and level equation); for the rest see notes on Table 4.

Table 6: Estimation results - High- vs low-capital intensive firms (1); Continuous time excess worker turnover rate; Estimation methods: OLS, FE, SYSTEM-GMM

Production Function Estimates *Dependent variable:* $y_{it} - l_{it}$					SYSTEM-GMM diagnostic	
Variable	**OLS**	**FE**	**SYSTEM-GMM**			
			Unrestricted model			
$y_{it-1} - l_{it-1}$	-	-	0.723 (0.000)		Number of instruments	90
l_{it}	-0.673 (0.000)	-0.702 (0.000)	-0.853 (0.000)		Hansen-J test	61.68 (0.825) [73]
l_{it-1}	-	-	0.595 (0.000)		Diff-in-Hansen test 1	27.94 (0.672) [32]
k_{it}	0.065 (0.000)	0.013 (0.001)	0.048 (0.208)		Diff-in-Hansen test 2	5.09 (0.278) [4]
k_{it-1}	-	-	-0.022 (0.544)		Diff-in-Hansen test 3	20.03 (0.951) [32]
m_{it}	0.587 (0.000)	0.598 (0.000)	0.658 (0.000)		Diff-in-Hansen test 4	38.36 (0.839) [48]
m_{it-1}	-	-	-0.438 (0.000)		ART(1)	(0.000)
$EET_{it} * LCI_{it}$	-0.012 (0.264)	0.007 (0.324)	0.170 (0.010)		ART(2)	(0.000)
$EET_{it-1} * LCI_{it-1}$	-	-	-0.084 (0.292)		ART(3)	(0.327)
$EET_{it} * HCI_{it}$	-0.046 (0.000)	0.006 (0.408)	-0.043 (0.471)			
$EET_{it-1} * HCI_{it-1}$	-	-	0.040 (0.538)			
			Restricted model			
			Structural parameters:			
			β_l	-0.856 (0.000)		
			β_k	0.074 (0.015)		
			β_m	0.744 (0.000)		
			θ_1	0.108 (0.062)		
			θ_2	-0.089 (0.104)		
			ρ	0.755 (0.000)		
			Comfac	(0.451)		
					Number of firm-year observations	15,194
					Number of firms	2,619

Source: VWH-AIDA dataset

Low (high) capital intensity is a dummy variable taking the value 1 if the mean value (over years) of capital (physical assets - computed according to the Permanent Inventory Method) over labor (monthly weighted number of employees) is below (over) the median; θ_1 *and* θ_2 *represent the structural coefficients respectively associated to excess employee turnover for low capital intensity firms and excess employee turnover for high capital intensity firms; Diff-in-Hansen test 3 tests the validity of the instruments for the excess worker turnover for low and high capital intensity firms (in the first-differenced and level equation); for the rest see notes on Table 4.*

Table 7: Estimation results - High- vs low-capital intensive firms (2); Continuous time excess worker turnover rate; Estimation methods: OLS, FE, SYSTEM-GMM

Production Function Estimates

Dependent variable: $y_{it} - l_{it}$

Variable	**OLS**	**FE**	**SYSTEM-GMM**	
			Unrestricted model	
$y_{it-1} - l_{it-1}$	-	-	0.726 (0.000)	
l_{it}	-0.676 (0.000)	-0.702 (0.000)	-0.776 (0.000)	
l_{it-1}	-	-	0.521 (0.000)	
k_{it}	0.070 (0.000)	0.013 (0.001)	0.026 (0.461)	
k_{it-1}	-	-	-0.0004 (0.988)	
m_{it}	0.586 (0.000)	0.598 (0.000)	0.622 (0.000)	
m_{it-1}	-	-	-0.4025 (0.000)	
$EET_{it} * LLCI_{it}$	0.045 (0.004)	0.012 (0.275)	0.111 (0.150)	
$EET_{it-1} * LLCI_{it-1}$	-	-	-0.084 (0.387)	
$EET_{it} * LCI_{it}$	-0.054 (0.000)	0.003 (0.783)	0.158 (0.080)	
$EET_{it-1} * LCI_{it-1}$	-	-	-0.073 (0.484)	
$EET_{it} * HCI_{it}$	-0.074 (0.000)	-0.009 (0.367)	-0.112 (0.162)	
$EET_{it-1} * HCI_{it-1}$	-	-	-0.007 (0.931)	
$EET_{it} * HHCI_{it}$	-0.034 (0.015)	0.019 (0.058)	0.024 (0.688)	
$EET_{it-1} * HHCI_{it-1}$	-	-	-0.0004 (0.995)	
			Restricted model	
			Structural parameters:	
			β_l	-0.811 (0.000)
			β_k	0.063 (0.021)
			β_m	0.681 (0.000)
			θ_1	0.093 (0.189)
			θ_2	0.077 (0.323)
			θ_3	-0.104 (0.128)
			θ_4	-0.011 (0.849)
			ρ	0.837 (0.000)
			Comfac	(0.207)

SYSTEM-GMM diagnostic

Number of instruments	118
Hansen-J test	90.75 (0.659) [97]
Diff-in-Hansen test 1	56.82 (0.111) [45]
Diff-in-Hansen test 2	0.22 (0.636) [1]
Diff-in-Hansen test 3	55.83 (0.727) [63]
Diff-in-Hansen test 4	46.07 (0.552) [48]
ART(1)	(0.000)
ART(2)	(0.000)
ART(3)	(0.347)

Number of firm-year observations 15,194
Number of firms 2,619

Source: VWH-AIDA dataset

Very low (medium-low) (medium-high) (high) capital intensity is a dummy variable taking the value 1 if the mean value (over years) of capital (physical assets - computed according to the Permanent Inventory Method) over labor (monthly weighted number of employees) is in the first (second) (third) (fourth) quartile; θ_1, θ_2, θ_3 and θ_4 represent the structural coefficients respectively associated to excess employee turnover for low, medium-low, medium-high and high capital intensity firms; Diff-in-Hansen test 3 tests the validity of the instruments for the excess worker turnover for low, medium-low, medium-high and high capital intensity firms (in the first-differenced and level equation); for the rest see notes on Table 4.

Table 8: Estimation results - High- vs low-tech firms; Continuous time excess worker turnover rate; Estimation methods: OLS, FE, SYSTEM-GMM

Production Function Estimates *Dependent variable:* $y_{it} - l_{it}$					SYSTEM-GMM diagnostic	
Variable	**OLS**	**FE**	**SYSTEM-GMM**			
			Unrestricted model			
$y_{it-1} - l_{it-1}$	-	-	0.696 (0.000)		Number of instruments	90
l_{it}	-0.669 (0.000)	-0.702 (0.000)	-0.722 (0.000)		Hansen-J test	81.99 (0.221) [73]
l_{it-1}	-	-	0.461 (0.001)		Diff-in-Hansen test 1	38.68 (0.193) [32]
k_{it}	0.060 (0.000)	0.013 (0.001)	0.002 (0.964)		Diff-in-Hansen test 2	9.10 (0.059) [4]
k_{it-1}	-	-	0.009 (0.815)		Diff-in-Hansen test 3	33.68 (0.386) [32]
m_{it}	0.587 (0.000)	0.598 (0.000)	0.657 (0.000)		Diff-in-Hansen test 4	53.45 (0.273) [48]
m_{it-1}	-	-	-0.417 (0.000)		ART(1)	(0.000)
$EET_{it} * LT_{it}$	-0.019 (0.046)	0.008 (0.207)	0.080 (0.147)		ART(2)	(0.000)
$EET_{it-1} * LT_{it-1}$	-	-	-0.050 (0.454)		ART(3)	(0.285)
$EET_{it} * HT_{it}$	-0.065 (0.000)	0.004 (0.705)	-0.069 (0.420)			
$EET_{it-1} * HT_{it-1}$	-	-	-0.057 (0.490)			
			Restricted model			
			Structural parameters:			
			β_l	-0.793 (0.000)		
			β_k	0.034 (0.264)		
			β_m	0.718 (0.000)		
			θ_1	0.055 (0.286)		
			θ_2	-0.051 (0.518)		
			ρ	0.790 (0.000)		
			Comfac	(0.345)		
					Number of firm-year observations	15,194
					Number of firms	2,619

Source: VWH-AIDA dataset

Low-tech (high-tech) is a dummy variable taking the value 1 if the firm belongs to the low-tech (high-tech) industry; high-tech industry includes: chemical products, machinery products, office machinery and computers, electrical machinery, radio, TV and TLC equipment, medical equipment and measurement instruments, motor vehicles, other transportation equipment; θ_1 *and* θ_2 *represent the structural coefficients respectively associated to excess employee turnover for low-tech and high-tech firms; Diff-in-Hansen test 3 tests the validity of the instruments for the excess worker turnover for low- high-tech firms (in the first-differenced and level equation); for the rest see notes on Table 4.*

Table 9: Estimation results - High- vs medium- vs low-tech firms; Continuous time excess worker turnover rate; Estimation methods: OLS, FE, SYSTEM-GMM

			Production Function Estimates		**SYSTEM-GMM diagnostic**	
			Dependent variable: $y_{it} - l_{it}$			
Variable	**OLS**	**FE**	**SYSTEM-GMM**			
			Unrestricted model			
$y_{it-1} - l_{it-1}$	-	-	0.698 (0.000)		Number of instruments	104
l_{it}	-0.669 (0.000)	-0.702 (0.000)	-0.721 (0.000)		Hansen-J test	97.63 (0.165) [85]
l_{it-1}	-	-	0.471 (0.000)		Diff-in-Hansen test 1	49.60 (0.099) [38]
k_{it}	0.060 (0.000)	0.013 (0.001)	0.015 (0.717)		Diff-in-Hansen test 2	1.64 (0.650) [3]
k_{it-1}	-	-	-0.005 (0.899)		Diff-in-Hansen test 3	52.08 (0.283) [47]
m_{it}	0.587 (0.000)	0.599 (0.000)	0.636 (0.000)		Diff-in-Hansen test 4	58.01 (0.153) [48]
m_{it-1}	-	-	-0.403 (0.000)		ART(1)	(0.000)
$EET_{it} * LT_{it}$	-0.019 (0.044)	0.008 (0.207)	0.066 (0.222)		ART(2)	(0.000)
$EET_{it-1} * LT_{it-1}$	-	-	-0.026 (0.685)		ART(3)	(0.258)
$EET_{it} * MT_{it}$	-0.069 (0.000)	0.013 (0.247)	-0.095 (0.306)			
$EET_{it-1} * MT_{it-1}$	-	-	-0.051 (0.596)			
$EET_{it} * HT_{it}$	-0.057 (0.000)	-0.016 (0.386)	-0.062 (0.433)			
$EET_{it-1} * HT_{it-1}$	-	-	0.050 (0.568)			
			Restricted model			
			Structural parameters:			
			β_l	-0.777 (0.000)		
			β_k	0.045 (0.145)		
			β_m	0.692 (0.000)		
			θ_1	0.040 (0.443)		
			θ_2	-0.099 (0.259)		
			θ_3	-0.075 (0.311)		
			ρ	0.800 (0.000)		
			Comfac	(0.354)		

Number of firm-year observations 15,194

Number of firms 2,619

Source: VWH-AIDA dataset

Low-tech (medium-tech) (high-tech) is a dummy variable taking the value 1 if the firms belongs to the low-tech (medium-tech) (high-tech) industry; high-tech industry collects firms operating in pharmaceutical industry, office machinery and computers industry, radio, TV and TLC equipment, medical equipment and measurement instruments, electrical machinery, construction of aircraft and spacecraft, manufacture of basic chemicals, manufacture of pesticides and other chemical products for agriculture,manufacture of other chemical products, manufacture of synthetic and artificial fibers; medium-tech industry collects all the high-tech industry as defined in Table 8 with the exception of industries that here are defined as high-tech; θ_1*,* θ_2 *and* θ_3 *represent the structural coefficients respectively associated to excess employee turnover for low-tech, medium-tech and high-tech firms; Diff-in-Hansen test 3 tests the validity of the instruments for the excess worker turnover for low-tech, medium-tech and high-tech firms (in the first-differenced and level equation); for the rest see notes on Table 4.*

Table 10: Estimation results - High- vs low-volatile firms; Continuous time excess worker turnover rate; Estimation methods: OLS, FE, SYSTEM-GMM

Production Function Estimates *Dependent variable:* $y_{it} - l_{it}$					**SYSTEM-GMM diagnostic**	
Variable	**OLS**	**FE**	**SYSTEM-GMM**			
			Unrestricted model			
$y_{it-1} - l_{it-1}$	-	-	0.718 (0.000)		Number of instruments	90
l_{it}	-0.669 (0.000)	-0.702 (0.000)	-0.642 (0.000)		Hansen-J test	76.48 (0.368) [73]
l_{it-1}	-	-	0.368 (0.007)		Diff-in-Hansen test 1	41.19 (0.128) [32]
k_{it}	0.061 (0.000)	0.012 (0.001)	0.054 (0.214)		Diff-in-Hansen test 2	8.35 (0.079) [4]
k_{it-1}	-	-	-0.034 (0.412)		Diff-in-Hansen test 3	22.51 (0.893) [32]
m_{it}	0.586 (0.000)	0.599 (0.000)	0.604 (0.000)		Diff-in-Hansen test 4	62.68 (0.076) [48]
m_{it-1}	-	-	-0.354 (0.000)		ART(1)	(0.000)
$EET_{it} * LV_{it}$	-0.052 (0.000)	0.014 (0.028)	0.027 (0.680)		ART(2)	(0.001)
$EET_{it-1} * LV_{it-1}$	-	-	0.047 (0.484)		ART(3)	(0.500)
$EET_{it} * HV_{it}$	-0.012 (0.239)	0.001 (0.949)	0.105 (0.184)			
$EET_{it-1} * HV_{it-1}$	-	-	-0.169 (0.032)			
			Restricted model			
			Structural parameters:			
			β_l	-0.694 (0.000)		
			β_k	0.073 (0.030)		
			β_m	0.631 (0.000)		
			θ_1	0.025 (0.682)		
			θ_2	0.064 (0.377)		
			ρ	0.890 (0.000)		
			Comfac	(0.236)		
					Number of firm-year observations 15,194	
					Number of firms 2,619	

Source: VWH-AIDA dataset

Low- (high-) volatility is a dummy variable taking the value 1 if the mean value (over years) of volatility of demand is below (over) the median; θ_1 and θ_2 represent the structural coefficients respectively associated to excess employee turnover for low-volatile firms and excess employee turnover for high-volatile firms; Diff-in-Hansen test 3 tests the validity of the instruments for the excess worker turnover for low- and high-volatile firms (in the first-differenced and level equation); for the rest see notes on Table 4.

Table 11: Estimation results - Young vs mature vs old firms; Continuous time excess worker turnover rate; Estimation methods: OLS, FE, SYSTEM-GMM

Production Function Estimates

Dependent variable: $y_{it} - l_{it}$

Variable	**OLS**	**FE**	**SYSTEM-GMM**	
			Unrestricted model	
$y_{it-1} - l_{it-1}$	-	-	0.764 (0.000)	
l_{it}	-0.667 (0.000)	-0.702 (0.000)	-0.857 (0.000)	
l_{it-1}	-	-	0.658 (0.000)	
k_{it}	0.063 (0.000)	0.013 (0.001)	0.076 (0.058)	
k_{it-1}	-	-	-0.057 (0.138)	
m_{it}	0.586 (0.000)	0.598 (0.000)	0.667 (0.000)	
m_{it-1}	-	-	-0.490 (0.000)	
$EET_{it} * Y_{it}$	0.025 (0.206)	0.024 (0.202)	0.091 (0.436)	
$EET_{it-1} * Y_{it-1}$	-	-	-0.078 (0.478)	
$EET_{it} * M_{it}$	-0.014 (0.142)	0.008 (0.245)	-0.034 (0.554)	
$EET_{it} * M_{it-1}$	-	-	-0.011 (0.850)	
$EET_{it} * O_{it}$	-0.099 (0.000)	-0.002 (0.799)	0.046 (0.506)	
$EET_{it} * O_{it-1}$	-	-	-0.025 (0.767)	
			Restricted model	
			Structural parameters:	
			β_l	-0.826 (0.000)
			β_k	0.083 (0.012)
			β_m	0.714 (0.000)
			θ_1	0.054 (0.606)
			θ_2	0.013 (0.810)
			θ_3	0.027 (0.670)
			ρ	0.783 (0.000)
			Comfac	(0.943)

SYSTEM-GMM diagnostic

Number of instruments	104
Hansen-J test	81.82 (0.578) [85]
Diff-in-Hansen test 1	46.99 (0.150) [38]
Diff-in-Hansen test 2	2.47 (0.481) [3]
Diff-in-Hansen test 3	42.02 (0.679) [47]
Diff-in-Hansen test 4	49.12 (0.428) [48]
ART(1)	(0.000)
ART(2)	(0.000)
ART(3)	(0.240)

Number of firm-year observations 15,194

Number of firms 2,619

Source: VWH-AIDA dataset

Young (mature) (old) is a dummy variable taking the value 1 if the mean value (over our observation window) of age of the firm is below or equal to 5 years (between 5 and 20 years) (equal to or more than 20 years); θ_1, θ_2 and θ_3 represent the structural coefficients respectively associated to excess employee turnover for young, mature, old firms; Diff-in-Hansen test 3 tests the validity of the instruments for the excess worker turnover for young, mature and old firms (in the first-differenced and level equation); for the rest see notes on Table 4.

Table 12: Estimation results - Basic model; Discrete time excess worker turnover rate; Estimation methods: OLS, FE, SYSTEM-GMM

Production Function Estimates *Dependent variable:* $y_{it} - l_{it}$					**SYSTEM-GMM diagnostic**	
Variable	**OLS**	**FE**	**SYSTEM-GMM**			
			Unrestricted model			
$y_{it-1} - l_{it-1}$	-	-	0.745 (0.000)		Number of instruments	76
l_{it}	-0.669 (0.000)	-0.702 (0.000)	-0.795 (0.000)		Hansen-J test	57.11 (0.618) [61]
l_{it-1}	-	-	0.593 (0.000)		Diff-in-Hansen test 1	31.68 (0.168) [25]
k_{it}	0.061 (0.000)	0.012 (0.001)	0.047 (0.270)		Diff-in-Hansen test 2	5.80 (0.446) [6]
k_{it-1}	-	-	-0.036 (0.370)		Diff-in-Hansen test 3	10.67 (0.830) [16]
m_{it}	0.587 (0.000)	0.598 (0.000)	0.684 (0.000)		Diff-in-Hansen test 4	44.78 (0.606) [48]
m_{it-1}	-	-	-0.493 (0.000)		ART(1)	(0.000)
EET_{it}	-0.032 (0.032)	0.016 (0.033)	0.071 (0.446)		ART(2)	(0.000)
EET_{it-1}	-	-	0.002 (0.984)		ART(3)	(0.252)
			Restricted model			
			Structural parameters:			
			β_l	-0.763 (0.000)		
			β_k	0.043 (0.205)		
			β_m	0.718 (0.000)		
			θ_1	0.045 (0.606)		
			ρ	0.745 (0.000)		
			Comfac	(0.931)		
						Number of firm-year observations 15,194
						Number of firms 2,619

Source: VWH-AIDA dataset
See notes on Table 4.

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