The Effect of Learning by Hiring on Productivity*

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Abstract

This work studies the phenomenon of inter-firm labor mobility as potential channel of knowledge transfer. Using data from the Danish employer-employee register, covering the period 1995-2005, it investigates how the knowledge embedded into recruited workers, coming from other firms, contributes to the process of knowledge diffusion and boosts the firms' productivity. Specifically, estimating both parametric (Cobb-Douglas) and semi-parametric production functions (Olley and Pakes, 1996; Levinsohn and Petrin, 2003), the impact of recruited technicians and highly educated workers on total factor productivity at the firm level is found to be significantly positive. A matching analysis, which allows for continuous treatment effect evaluation (Hirano and Imbens, 2004) in a panel data setting (Eichler and Lechner, 2002) corroborates this finding.

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1 Introduction

Knowledge can be defined as the fundamental resource employed in all valuable human activities. Its identification as economic good has requested a long time and enduring efforts (Antonelli, 1995). A group of models belonging to the so-called New Growth Theory represents the attempt to understand and describe the role of knowledge in driving productivity and thereby fostering economic growth. Specifically, several macroeconomists (Romer 1990, Grossman and Helpman 1991, Aghion and Howitt 1992, among the pioneers) have identified knowledge spillovers as the main driver of sustained economic growth.

A potential channel of knowledge transfer is the inter-firm labor mobility. Most of valuable knowledge, characterized by a tacit and complex nature, is embedded in highly educated or skilled workers. Thus, moving from one firm to another, such individuals carry this knowledge and apply it to new contexts. The acquired knowledge hardly can be transmitted in a different way since it tends to be stably localized within firms. Given the stickiness in routines and procedures, its transfer cannot be effectively prevented by patents or other forms of Intellectual Property Rights, which can only protect forms of codified or at least articulate knowledge (Petit and Tolwinski 1996, Gilson 1998). This process of knowledge transmission via inter-firm labor mobility is known as learning by hiring.

In literature very little evidence exists about the effect of such process on firm's performance. Previous works found a positive impact of specific categories of recruited workers on the firms' patenting activity. However, the distribution of patenting firms is strongly concentrated and the fruits of knowledge transfers may or may not be related to the patenting activity. Instead, they surely may affect the production process. Thus, an opportune strategy to test the effects of learning by hiring is productivity as a broader measure of firms' performance. This variable allows to take into account a huge number of firms and therefore to work on a quite representative sample of the production and service sectors.

This paper opens to the modeling of the learning by hiring and investigates how the composition of newly recruited workers, coming from other enterprises, affects the productivity in the arrival firm. Specifically, the analysis is focused on the role of who experienced a wage increase after moving (from the donor firm) and was characterized by a tertiary (Bachelor, Master or Post-Graduate Degree) or vocational/technical education. The higher wage offered to the newly employed may represent a signal of precise willingness in her enrolment shown by the firm. That can be interpreted as a necessary condition for the identification of the incoming knowledge carriers, which do not simply replace retired or fired workers. The sufficiency is instead fulfilled by the above mentioned employees' educational attainments. However, the plausibility of a given knowledge transfer do not inform also on the nature of its receipt. That may depend on two relevant features: proximity and intensity. The first refers to the technological distance between the donor and recipient firm.[1] It is the distance in a metric space generated by vectors, which elements are firms' characteristics. Instead, the intensity is a concave function of the number of incoming workers from a given firm.

In the empirical analysis both parametric (Cobb-Douglas) and semi-parametric production functions (Olley and Pakes, 1996; Levinsohn and Petrin, 2003) are estimated. Measures of Total Factor Productivity (TFP henceforth) are successively obtained as residuals and then regressed on the two variables representing the knowledge inflows. The effects are positive and significant for both categories of knowledge carrier. The relevant contribution of the learning by hiring to firms' productivity is also confirmed by implementing a matching analysis. Specifically, allowing for continuous treatment effect evaluation (Hirano and Imbens, 2004) in a panel data setting (Eichler and Lech-

[1] Jaffe (1986); Adams (1990); Inkmann and Pohlmeier (1995); Cincera (2005).

ner, 2002), the treatment effects show a consistently positive impact on firms' performance. Overall the results are consistent with New Growth theoretical models, which place a strong emphasis on knowledge diffusion, and may partially explain the rapid increase in the productivity observed in Denmark during the last decades. In particular, they suggest improvements in modeling the process of knowledge transmission at micro level, stimulating further analysis on the additional effects associated with the inter-firm labor mobility.

The structure of the paper is as follows: section 2 briefly reviews the relevant economic literature, section 3 describes the data set, section 4 provides details on the empirical strategy, section 5 illustrates our results, section 6 shows the sensitivity analysis, and section 7 concludes.

2 Literature background

The process known as learning by hiring refers to the valuable knowledge transferred by inter-firm labor mobility. It is defined as the acquisition of knowledge from other firms through the hiring of experts (Song, Almeida and Wu, 2003). In accordance with this definition, benefits of learning by hiring may not be confused with either the usual high labor productivity characterizing the newly employed experts, or potential externalities associated with scale effects. In such context, it is worth emphasizing that inflows of knowledge, carried by some categories of workers, are typically forms of developed but not codified knowledge. As a consequence, what carried by qualified mobile workers cannot spill over freely. Hence, the impact of learning by hiring can be precisely quantified only if a donor and a recipient firm are identified. This clearly implies that in absence of a matched employer-employee register is not possible to estimate the contribution of this knowledge transfer to any kind of firm's performance indicator. However, even after the availability of the cited registers, the use of labor mobility as an inter-firm learning mechanism has not received particular attention.

Although their study is not conducted at firm level, Almeida and Kogut (1999) find that the mobility of engineers holding major patents affects the intra- and inter-regional pattern of patent citations, which is considered as a proxy of knowledge flow. Mapping the US semiconductor plant clusters through the use of county level establishment and employee data, they illustrate how mobile engineers partially explain innovations occurred among regional clusters.

A step forward is moved by Rosenkopf and Almeida (2003). Tracking both inter-firm mobility of engineers and patent citations for the second wave of entrants in the US semiconductor industry, their analysis concludes that the effectiveness of labor mobility in terms of knowledge flows increases with technological distance between firms. These findings are confirmed and even reinforced by Song, Almeida and Wu (2003). In this work they investigate the conditions under which labour mobility is more likely to facilitate knowledge transfers. Results seem to support the hypotheses that learning by hiring is more effective (in terms of contribution to patent production) in case (i) the recipient firm is less path dependent;[2] (ii) the mobile engineers carry knowledge distant from that characterizing the recipient firm; (iii) the knowledge carriers work in noncore technological areas in the arrival firm. Thus, inter-firm labour mobility may mitigate the difficulties of learning from firms characterized by research in distant technological areas and increase the possibility to benefit from external knowledge.

A different perspective is instead investigated by Kim and Marschke (2005). Using in a sample of US firms, they analyze how the risk of a key employee's departure reduces the firm's R&D expenditure and/or increase its patenting propensity. Their findings are consistent with the statement that firms use patenting to minimize the negative

[2]The path dependence is measured as number of self-cited patents. Self-citing occurs when a patent filed by a firm cites another patent from the same firm (Song, Almeida and Wu, 2003).

effect associated with the departure of an engineer or scientist. Furthermore, that may help explaining what determines different propensity to patent among firms.

A crucial study for the main purpose of this paper is Kaiser, Kongsted and Rnde (2008). They constructed a dataset in which patent applications by Danish firms to EPO are matched to the employer-employee register. Their research question is how labor mobility affects innovation in Danish firms, and more in detail how the composition and past patenting experience of labor inflows influence the firm-level patenting activity. They split the firm's work force into "R&D workers" and "non-R&D workers". Whereas the former class is composed of employees with Bachelor's or Master's degree in natural in technical fields , the latter one identify individuals with the same level of education but in humanities. The results of their analysis support the idea that mobile R&D workers contribute more to the firm's patenting activity than immobile R&D employees. This effect is stronger in case the R&D worker has been previously hired by a patenting firm. However, they find weak evidence that R&D employees carry a larger amount of knowledge than employees with other qualifications.

Although Kaiser, Kongsted and Rnde (2008) assess more formally the quantitative effects of labor mobility on innovations, their paper does not differ from the other mentioned studies for the variable indicating the firm's performance. This common feature is the focus on the patenting activity that is a proxy for innovation efforts. Therefore, they constrain the amount of knowledge transferred to patent applications or grants. These may represent a measure of codified, rather than tacit or less articulated, knowledge created by a firm: fruits of knowledge transfers can or cannot be related to patenting activities. Moreover, since the patenting activity is particularly concentrated among firms (this holds even strongly in Denmark) the number of firms observed in the sample may not be representative of the production activities in which a relevant part of valuable knowledge sticks.

3 Data

3.1 Data Sources

The dataset used in the empirical analysis were constructed by merging information from three different main sources. The first data source is the "Integrated Database for Labor Market Research" (IDA henceforth) provided by Denmark Statistics. IDA is a longitudinal employer-employee register containing valuable information (age, demographic characteristics, education, labor market experience, tenure and earnings) on each individual employed in the recorded population of Danish firms during the period 1980-2005. Apart from deaths and permanent migration, there is no attrition in the dataset. The labor market status of each person is recorded at the 30th of November each year. The retrieved information has been aggregated at firm level and consequentially merged to variables like enterprises' location (County), size and related industry.[3]

The second data source refers to firms' business accounts (REGNSKAB henceforth) and has been also provided and compiled by Denmark Statistics. It covers the construction industry from 1994, manufacturing from 1995, wholesale trade from 1998 and the remaining part of the service industry from 1999 onwards. Data in REGNSKAB are aggregations of yearly financial items that are crucial for the estimation of the production function. In particular, it is possible to retrieve information on sales, intermediate goods or materials, fixed assets, and profits. Although statistics in REGNSKAB have been gathered in several ways, part of them refers to selected firms for direct surveying: all firms with more than 50 employees or profits higher than a given threshold. The other firms are recorded in accordance with a stratified sample strategy. The surveyed firms can choose whether submit their annual accounts and other specifications or fill

[3]In our empirical analysis we exclude from the analysis the following sectors: i) agriculture, fishing and quarrying; ii) electricity, gas and water supply and iii) public services.

out a questionnaire. In order to facilitate responding, questions are formulated in the same way as required in the Danish annual accounts legislation.

Finally, further information is gathered from a third dataset on patent applications and grants ascribed to Danish firms at the European Patent Office (henceforth EPO) in the period 1978-2003. The access to such data has been made possible thank to the Centre for Economic and Business Research (CEBR).[4] A total of 12,109 patent applications have been recorded. Being available the unique assigned identifier, 2,822 Danish non-person patent applicants, 1,152 Danish private (non-firm) applicants and 591 foreign (co-) applicants have been identified.[5] That allows computing measures of technological proximity (partially or totally) based on patent applications.

3.2 Variables

This section describes the variables used in the empirical analysis. Since the purpose of this paper is to provide evidence concerning the impact of learning by hiring on firms' productivity, the attention is devoted almost completely to the explanation of the measures indicating inter-firm knowledge transfers via labor mobility.

Combining the needed information from the three data sources previously described, the final dataset allows for the mapping of all mobile workers aged 18 to 60. For the identification of the knowledge carriers a set of necessary and sufficient conditions is imposed. Whereas the sufficiency is provided by the attainment of either a tertiary (at least Bachelor's degree) or a vocational/technical education, the necessary conditions are the following: i) the mobile worker has to experience a real wage increase after moving; ii) the real[6] annual wage of the current job should be higher than the average

[4] An independent research centre affiliated with the Copenhagen Business School (CBS).

[5] More details concerning the construction and composition of the dataset can be found in Kaiser and Schneider (2005).

[6] The annual wage is deflated using the price deflator for the year 2000.

of real wages of the last three or two years; iii) the incomers' wage should be greater than the average wage in the recipient firm; iv) the sending firm is not downscaling the labor force[7]; v) the eventual period of unemployment preceding the start of the new job should be less than 3 months. The necessary conditions can be interpreted as a signal of precise and intentional recruitment strategy implemented by the recipient firm. In fact, it is here assumed that every recipient firm, being aware of the expected benefit deriving from the knowledge embodied into some educated and skilled workers, is willing to pay an opportune wage premium. To rule out the possibility that the recipient firms are benefiting from a variation in the composition of the labour force, we select only those firms whose annual variation of the shares of highly skilled workers and technicians over the total number of employees is less than 1 per cent.

Knowledge carriers are divided into two categories: technicians (*tech*) and highly educated employees (*hs*). That reflects which educational qualification is fulfilled between the two alternative sub-conditions for the sufficiency. For both categories three measures of inter-firm knowledge transfers have been defined.

The first measure is simply constructed as the sum of all incoming workers "j" fulfilling all the previous necessary conditions from the donor firm d to the recipient r .

$$tot - hs_r = \sum_{d=1}^{D} \sum_{j=1}^{J} hs_{djr}$$

$$tot - tech_r = \sum_{d=1}^{D} \sum_{j=1}^{J} ts_{djr}$$

Though quite similar to the first measure, the second one weights the number of

[7]The yearly variation in the total labour force should be less than 1 per cent.

incoming workers from the same donor firm using a concave function. The concavity is ensured by the inverse of the total of qualified workers (highly educated employees and technicians), respectively H_d and T_d:

$$tot-hs-concave_r = \sum_{d=1}^{D}\left(\sum_{j=1}^{J} hs_{djr}\right)^{1/H_d}$$

$$ts-tech-concave_r = \sum_{d=1}^{D}\left(\sum_{j=1}^{J} ts_{djr}\right)^{1/T_d}$$

It obviously implies that $tot{-}hs{-}concave_r$ or $tot{-}tech{-}concave_r$ increase less than proportionally with respect to the total number of qualified workers leaving a given donor firm and employed in the same recipient firm. The first and second measure coincide just in case single workers move towards a given arrival firm. This means that the concave version adjust for the intensity of each inter-firm knowledge inflow: two workers with similar qualification from the same firm may transfer together less than the double amount of knowledge that a single one could transfer. Hence, a large amount of knowledge embodied in procedures or production processes is brought by the first mover in both categories. The second measure attributes more public good features to the knowledge inflow, even though it is still characterized by partial-excludability[8] and low degree of appropriability.

The third and most complete measure introduces a further element represented by the proximity index ψ:

$$tot-hs-prox_r = \sum_{d=1}^{D}\psi(d,r)\left(\sum_{j=1}^{J} hs_{djr}\right)^{1/H_d}$$

[8]Non-excludability means that once a good has been produced, it is not possible to prevent other people from gaining access to it (more realistically, it is costly for the provider to exclude unauthorized users)

$$ts - tech - prox_r = \sum_{d=1}^{D} \psi(d,r) \left(\sum_{j=1}^{J} ts_{djr} \right)^{1/T_d}$$

That allows to correct the intensity of inter-firm labor mobility for the technological distance between the donor and recipient firm (Jaffe 1986, Adams 1990, Inkmann and Pohlmeier 1995, Cincera 2005). The assumption behind this index is that the technology developed by a firm can affect the productivity of other firms, even though no transactions of intermediate or capital goods occur. Thus, the level of exploitability associated with the labor mobility could depend on the degree of similarity in the technological knowledge characterizing the two firms. In order to measure the distance between firms' technological capabilities, a technological space needs to be defined. In the present work, the generator vector f is composed of elements reflecting the following firms' characteristics: shares of highly educated workers and technicians, stock of patent applications in different technological areas, and related industry.[9] The technological distance is here computed using the uncentered correlation suggested by Jaffe (1986):

$$\psi_{dr} = \frac{f_d f_r'}{\left[\left(f_d f_d' \right) \left(f_r f_r' \right) \right]^{1/2}}$$

If the donor and recipient firm coincide perfectly in the generated technological space, then $\psi = 1$. Conversely, If they do not overlap at all, the weight takes on the value 0.

[9]The technological areas are in particular: chemicals, consumer goods, machinery, process engineering amd other

Besides the three described measures, the variables used in the empirical analysis are: firm's valued added, materials capital stock, labor force, dummies for counties[10], industries and years. Using the price deflator for the year 2000, the monetary values have been converted in real terms.

3.3 Descriptive statistics

Once depicted data composition and defined variables, the exposition continues showing some descriptive statistics related to the variables used in the empirical analysis. Table 1 reports their number of observations, median, mean values and standard deviations for the whole sample and by size. This is classified into three categories (size1, size2 and size3), which are referred respectively to firms with less than 50, between 50 and 99 and more than 100 employees. A huge number of observations is recorder over time and more than 95% is represented only by the category size1.

This percentage is quite consistent with the Danish industrial structure (private sector), which is largely dominated by small sized enterprises.[11] Although not all industries have been recorded from the first years of the sample period, percentages reported among industries reflects partially aggregate data for the same time span. Whereas observations for construction and manufacturing industry are over-represented, the opposite is shown by those for financial and business sector. However, that is entirely explained by the unbalanced structure: construction and manufacturing have been the only industries recorded in the first years, whilst financial and business only in the last ones.

Looking at values of accounting (reported in thousands of DKK) and workforce

[10]The counties are: Kobenhavns, Freriksborg, Roskilde, Vestsjaellands, Storstroms, Bornholms, Fyns, Sonderjyllands, Ribe, Vejle, Ringkobing, Arhus, Viborg, Nordjyllands

[11]"Considering both how few enterprises have more than 100 employees and the general structure of Danish enterprises, in a Danish context it seems reasonable to distinguish between SME and large enterprises using a limit of 100 employees. Enterprises employing between 50 and 99 workers correspond to some 3%" (European Industrial Relations Observatory - EIRO, 1998).

variables, a considerable distance between median and mean values can be easily recognized. That points out a certain degree of skewness (and polarization) among firms in the sample, confirmed also by the notable dimension of standard deviations. It is worth outlining that, taking the mean values of accounting variables per worker, differences among size decrease considerably: except for size3, capital and value added flow around a given amount. Descriptive statistics change sensibly among the three definitions of inter-firm labor mobility. Count measures present the highest mean values, but reduce drastically the size of standard errors for the largest firms. Instead measures including the proximity index show the lowest mean values. Both in absolute and per worker terms, the three measures increase their dimension with respect to the firms' size. However, distances in weighted measures are attenuated when computed per worker, particularly for highly educated carriers.

4 Empirical Strategy

4.1 Productivity estimation

Firm level productivity is obtained from a Cobb-Douglas production function containing real value added (Y), labor (L), capital (K) and a number of other controls affecting productivity, such as year, size and regional dummies (Z). Since the proportion of input factors and input prices may differ across different industries, we estimate the production function for each 2-digit sector separately. Therefore, our reported results use the following specification:

$$ln(Y_{it}) = cons + \mathrm{a}ln(L_{it}) + \mathrm{b}ln(K_{it}) + \mathrm{c}(Z_{it}) + u_{it} \quad (1)$$

and where the error term u_{it} consists of an unobserved time-invariant firm effect,

ν_i, and of an idiosyncratic component, ε_{it}. Before discussing in more detail the nature of our empirical estimation, it is necessary to describe the construction of the variables derived from either the firm business accounts or the register data. The value added has been calculated using the suggested formulas provided by Statistics Denmark. We use the measure of the capital stock reported every year in the REGNSKAB. Value added and capital are all adjusted using GDP deflators with base year 2000 drawn from the World Bank Development Indicators. The most straightforward approach to estimating equation (1) is to simply run OLS on the panel with standard errors clustered by firm. Since we have panel data, an alternative is to estimate the production function using the within estimator to remove the bias related to the omission of the firm fixed effect. However, if capital, employment and output are chosen simultaneously or if there are measurement errors in the explanatory variables (particularly in the measure of capital), the within estimator will be inconsistent (Griliches and Hausman 1986). For this reason we compare the within estimator to two alternative semi-parametric approaches: the Olley and Pakes (1996) and the Levinshon and Petrin (2003a) estimators. The Olley and Pakes (1996) estimator allows not only to correct for simultaneity but also for selection bias resulting from the relationship between productivity shocks and the probability of exit from the market. Specifically, let's assume that the error term, u_{it}, is split up into two shocks:

$$u_{it} = \Omega_{it} + \eta_{it} \tag{2}$$

where Ω_{it} is the productivity shock that is observed by the firm but not by the econometrician and η_{it} is an unexpected productivity shock that is unobserved by both the firm and the econometrician.[12] The assumption on Ω_{it} implies that inputs are correlated with realization of productivity shocks (simultaneity issue). In addition

[12] Ω_{it} is assumed to follow a first-order Markov process.

if profitability is positively related to K_{it}, then a firm with a higher capital stock will expect larger future profitability at current productivity levels and thus lower profitability realizations will cause the exit of small firms from the market (Yasar et al. 2008). The Olley and Pakes (1996) (OP, henceforth) approach assumes that incumbent firms decide at the beginning of each period whether to continue participating in the market and then choose level of investment and inputs employed. Hence, applying the OP method first involves modelling the firm's decision to invest in further capital, I_{it} as

$$I_{it} = I(\Omega_{it}, K_{it}) \tag{3}$$

This investment decision equation implies that firms experiencing a large positive productivity shock in the current period t will invest more in the next period t+1. Provided that I_{it} is strictly positive, we can write the inverse function for the unobserved shock, Ω_{it} as

$$\Omega_{it} = I^{-1}(I_{it}, K_{it}) = h(I_{it}, K_{it}) \tag{4}$$

This function can be used to control for the simultaneity problem. Substituting (2) and (4) into (1) yields

$$ln(Y_{it}) = \mathrm{a}ln(L_{it}) + \mathrm{c}ln(Z_{it}) + \phi(ln(I_{it}), ln(K_{it})) + \eta_{it} \tag{5}$$

where $\phi(ln(I_{it}), ln(K_{it})) = cons + \mathrm{d}ln(K_{it}) + h(I_{it}, K_{it})$ and ϕ is approximated by a second-order polynomial series in capital and investment. The identification of d requires the estimate of survival probabilities, which will then allow us to control for selection bias. Specifically, firm i will decide to continue producing or exit the market if its productivity is greater or less than a given threshold subject which depends on its current and past capital stock, K_{it}. Following Yasar et al. (2008), the survival probability has been estimated by fitting a probit model on I_{it} and K_{it}, as well as on their squares and cross products. Let's call the predicted probabilities from this model $\hat{P}_{it}$. In the third step, the following equation has been estimated by nonlinear least squares:

$$\begin{aligned} ln(Y_{it}) &= \mathbf{a}ln(L_{it}) + \\ &\quad \mathrm{c}(Z_{it}) + \mathrm{b}ln(K_{it}) + g(\hat{\phi}_{t-1} - b_{t-1}ln(K_{i,t-1}), \hat{P}_{it}) + \eta_{it} \end{aligned} \tag{6}$$

where the unknown function g(.) is approximated by a second-order polynomial in $(\hat{\phi}_{t-1} - d_{t-1}ln(K_{i,t-1}))$ and $\hat{P}_{it}$. One major drawback of the OP estimator is that investment proxy may not smoothly respond to productivity shock, because of adjustment costs, violating the consistency assumption. Moreover the investment proxy is only valid for plants reporting nonzero investment, inducing potential truncation bias. To overcome these limits, Levinsohn and Petrin (2003) (LP, henceforth) suggested to use intermediates instead of investment in the estimation of firm productivity. On one hand, if it is less costly to adjust the intermediate input, it may respond more fully to the entire productivity term than investment. On the other hand, since many intermediates are almost always non-zero, this circumvents the data-truncation problem generated by zero-investment spells. The LP model is more complex to program than the OP procedure. However, it is available a user friendly Stata program called *levpet* , which runs LP estimations. Using the estimates of the production coefficients, we define the log of measured TFP of firm i at time t for each industry j, denoted by TFP_{ijt}, as

$$TFP_{ijt} = ln(Y_{it}) - ln(L_{it}) - ln(K_{it}) \tag{7}$$

We then analyze the relationship between total factor productivity values and alternative measures of learning by hiring through the estimation of an equation of the following form:

$$ln(TFP_{ijt}) = \alpha + \alpha_1 ln(TFP_{ijt-1}) + \beta_1 ln(tot - hs) + \beta_2 ln(tot - tech) + \gamma_t + \gamma_r + \gamma_j + \xi_i t$$

where β_1 measures the knowledge spillover effect of hiring high skilled workers, $tot - hs$, while β_2 represents the effect of hiring technicians, $tot - tech$. γ_t, γ_r and γ_j are time, regional and industry controls.

4.2 Treatment effects based on the generalized propensity score

In this section we describe an alternative econometric methodology to evaluate the effect of learning by hiring on productivity. Following the treatment evaluation literature, we compare, for a given year, the total factor productivity of firms exposed to learning by hiring with "matched" firms which are less exposed or not exposed at all. This approach interprets the number of newly hired employees (highly educated or technicians) as the treatment and evaluates the effect of such treatment on total factor productivity. To recover the average treatment effect on the treated, the matching method tries to mimic ex post an experiment by choosing a comparison group from among the non-treated such that the selected group is as similar as possible to the treatment group in terms of their observable characteristics. Under the conditional independence assumption (CIA or uncounfoundedness assumption, thereafter), all the outcome-relevant differences between treated and non-treated individuals are captured in their observable attributes, the only remaining difference between the two groups being their treatment status. Given the longitudinal nature of our dataset, we decide to combine matching with Difference in Difference method to generalize and make less restrictive the CIA assumption (Heckman et al., 1997).[13] The idea behind is that, even if the CIA does not hold, it may be reasonable to assume that the evaluation bias is constant over time (or at least it is the same for one date before the treatment and one date after it). As a consequence, we decide to evaluate the effect of the treatment on the change in log of total factor productivity, $\Delta log(TFP_{ijt}) = log(TFP_{ijt}) - log(TFP_{ij,t-1})$.

Let us consider a population of N firms and suppose that each i-th firm can take part in a certain treatment D_{it} in a given year t (in our case, hiring a highly educated worker or a technician). As above mentioned, ΔTFP_{ijt} is the outcome variable, D_{it} is the treatment and $X_{i,t-1}$ the vector of pre-treatment characteristics. As Hirano and Imbens (2004) suggest, we define a set of potential treatment values, and $\Delta TFP_{ijt}(d)_{d \in D}$, where D is a continuous set of potential treatment values, and ΔTFP_{ijt} is a random

[13] Identification in this case requires that, conditional on the propensity score, the change in the non treatment outcome is independent of treatment assignment. This generalized version of the CIA assumption is known in the literature as the conditional Bias Stability Assumption (BSA). The main advantage of using this identifying assumption is that BSA requires less restrictions for ATT identification than under the CIA. The main drawback is shared with the traditional Diff-in-Diff estimator, and it consists in the choice of the time periods (before and after treatment) and of the observable characteristics (X): neither economic theory nor econometric tests guide this choice, and the results heavily depend on it.

variable that maps a particular potential treatment, d, to a potential outcome. Refer to $\Delta TFP_{ijt}(d)_{d\in D}$ as the unit-level dose-response function. We are interested in the average dose-response function, $\mu(t) = E[\Delta TFP_{ijt}]$. We assume that $\Delta TFP_{ijt}(d)_{d\in D}$, D_{it}, and X_i are defined on a common probability space; that D_{it} is continuously distributed with respect to a Lebesgue measure on D, and that $\Delta TFP_{ijt} = \Delta TFP_{ijt}(D_{it})$. To simplify the notation, we will drop the i and t subscripts in the sequel. The propensity function is defined as the conditional density of the actual treatment given the observed covariates: $r(d, x) = f_{D|X}(d|x)$; then the generalized propensity score (GPS, thereafter) is $R = r(D, X)$. The GPS has a balancing property similar to that of the standard propensity score; that is, within strata with the same value of $r(d, x)$, the probability that D=d does not depend on the value of X:

$$X \perp I(D = d)|r(d, x) \tag{8}$$

where I(.) is the indicator function. Hirano and Imbens (2004) show that, in combination with a suitable CIA assumption, such balancing property implies that assignment to treatment is unconfounded, given the GPS. Assuming that assignment to the treatment is weakly unconfounded, given pretreatment variables X, then

$$\beta(d, r) = E\Delta TFP(d)|r(d, X) = r = E(\Delta TFP|D = d, R = r) \tag{9}$$

and

$$\mu(d) = E[\beta d, r(d, X)] \tag{10}$$

The implementation of the GPS method consists of three steps (Bia and Mattei, 2008). In the first step, the score $\hat{R}$ is estimated, assuming that the treatment (or its transformation) has a normal distribution conditional on the covariates:

$$g(D)|X \approx N[h(\gamma, X), \sigma^2] \tag{11}$$

where g(D) is a suitable transformation of the treatment variable and $h(\gamma, X)$ is a function of covariates with linear and higher-order terms, which depends on a vector of parameters, γ. [14] In the simple normal model, the parameters γ and σ^2 are estimated by maximum likelihood.[15]

In the second step, the conditional expectation of the outcome, ΔTFP, given D and R, is modelled as a flexible function of its two arguments. We use polynomial approximations of order three:

$$E(\Delta TFP|D, R) = \alpha_0 + \alpha_1 D + \alpha_2 D^2 + \alpha_3 D^3 + \alpha_4 R + \alpha_5 R^2 + \alpha_6 R^3 + \alpha_7 DT \tag{12}$$

Thus, we estimate these parameters by ordinary least squares. As Hirano and Imbens (2004) emphasize, there is no direct meaning to the estimated coefficients in the selected model, except for testing w whether the covariates introduce any bias (no coefficient is statistically different from zero). Given the parametric model we use

[14]The choice of the higher-order terms to include is only determined by the need to obtain an estimate of the GPS that satisfies the balancing property.

[15]The estimated GPS equals $\frac{1}{\sqrt{2\pi\hat{\sigma}^2}} exp(-\frac{1}{2\hat{\sigma}^2}(g(D) - h(\hat{\gamma}, X))$.

for the GPS and the regression function one can demonstrate root-N consistency and asymptotic normality for the estimator. Asymptotic standard errors can be calculated using expansion based on the estimating equation (Hirano and Imbens, 2004). We use, however, bootstrapping methods to generate standard errors and confidence intervals. The last step consists of averaging the estimated regression function over the score function evaluated at the desired level of treatment (Bia and Mattei, 2008). Specifically, in order to obtain an estimate of the entire dose-response function, we estimate the average potential outcome for each level of the treatment we are interested in as

$$E\Delta T\hat{F}P(d) = \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}d, \hat{d}(d, X_i) = \frac{1}{N}\sum_{i=1}^{N}\varphi^{-1}[\hat{\psi}d, \hat{d}(d, X_i); \hat{\alpha}](13)$$

where $\hat{\alpha}$ is the vector of the estimated parameters at the second stage.

5 Results

This section illustrates and discusses results obtained by the implemented empirical analysis. Firstly, the attention is devoted to the estimation of the TFP level and how such estimate is associated with learning by hiring measures. Secondly, the analysis moves to the investigation of potential causal effect of learning by hiring on firms' productivity. As outlined in section 4.1, three different approaches (FE, OP and LP) have been followed in order to estimate productivity at firm level. Specifically, this is obtained by regressing the log of value added variable on capital stock, labor force and several dummy variables (time periods, firms' geographical location and size) in each two-digit sector separately. As the OP approach requires positive investment values to estimate the production function coefficients, it has been possible to estimate different production technologies at one-digit industry codes only. The two-digit sector specific elasticities for capital and labor stock estimated using the FE and the LP approaches are reported in Table 2. Table 3 include the results from the OP approach. Whereas the OP and LP estimations lead to similar results, the labor (capital) coefficients are underestimated (overestimated) with FE. Once estimated production function parameters, the TFP is therefore computed like a residual. The log of TFP is then regressed (by using OLS) on its lag and alternative measures of learning by hiring. In these regressions, residuals are clustered at firm level. The introduction of the lagged variable is reputed a necessary solution to deal with potential biases caused by any further firm specific or transitory effect (not completely removed by controls in the previous estimation). Although the TFP lag is clearly an endogenous variable and hence estimates of its parameter may be biased, that should not affect the consistent estimation of the coefficients associated with learning by hiring measures. In fact, the correlation between such measures and TFP lag is very low (no collinearity problems can incur) and in a linear setting the bias of an estimate does not affect other estimates. Measures of learning by hiring show significant and positive coefficients. These seem to be quite stable among definitions and specifications. Looking at Table 4, it can be easily observed that coefficients related to both the categories of knowledge carriers are similar, and the elasticities vary between 0.01 (the count measure) and 0.03 (the proximity measure). TFP estimates coming from LP method may be the most precise ones. In fact, even though the OP semi-parametric approach deals with the typical FE estimation problems due to simultaneity and endogeneity (as well as the LP method), it generates a data-truncation problem caused by zero-investment spells. Implementing the OP estimation method, the number of observations is less than one third with respect to the LP one. Estimations by industry reveal that measures of learning by hiring have a significant and positive impact on TFP in almost the two-digits sectors. These seem to be quite stable among definitions and specifications. Looking at the results reported in Tables 5-10, it can be easily observed that coefficients related to both categories of knowledge carriers are similar, and the elasticities vary between 0.01 and 0.03.

The discussed regression analysis sheds light on the plausibility of the positive impact of knowledge transfer via inter-firm labor mobility. Contributions of capital and labor stock and any other variable included in the estimation of production function must not affect TFP values. Furthermore, since potential unobserved factors are captured by the TFP lag variable, the contribution of learning by hiring measures to TFP may be correctly identified. Therefore, it is somehow hard to state that an increase in the TFP leads to recruit more workers with given characteristics instead of the opposite causation direction. However, this interpretation is still possible to be claimed.

In order to investigate the potential causal effect of learning by hiring on firms' productivity, a matching analysis has been conducted. Specifically, the focus is here on the estimation of the dose-response function and treatment effect behavior. The time span selected for the matching analysis is the period 2000-2004. This choice is based on the fact that before 1999 not all industries are included in the final dataset and data recorded in this year are used as pre-determined characteristics for the evaluation of the treatment effect in the year 2000. The outcome variable is taken in growth rates (rather than in levels) in order to correct for time invariant unobserved characteristics. Taking the difference in logarithm of firms' total factor productivity, we combine the matching strategy with DID approach, relaxing de facto the conditional independence assumption. The matching variables include the lag of total factor productivity, capital, number of employees, the shares of high skilled workers and technicians, average age of employees. All these characteristics have been measure the year before treatment occurs. We also add a full set of industry and regional dummies to control for common aggregated demand and supply shocks. In matching estimations, the treatment variable has a normal distribution conditional on the covariates and the balancing property is satisfied: selected covariates do not introduce any bias. Table 10 and 11 show a positive impact of learning by hiring measures of both high skilled workers and technicians. Focusing on the inter-firm mobility of highly skilled workers, the effect on TFP growth increases with respect to its intensity. On the other hand, the effect of newly recruited technicians decreases its intensity according to all the proposed measures. Overall the treatment effects are more precisely estimated when using the count and the proximity definitions rather than the concave one. Table 13 and 14 show a positive impact of learning by hiring measures on TFP growth also one year after.

6 To be added

7 Conclusions

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Table 1: Descriptive statistics

	Total			Size1			Size2			Size3		
Accounting Variables:	**Median**	**Mean**	**Sd**	**Median**	**Mean**	**Sd**	**Median**	**Mean**	**Sd**	**Median**	**Mean**	**Sd**
Value added	1506	6718.00	78422.27	1441	3161.65	11197.09	31055.83	39303.02	86691.02	94697.68	214030.50	613193.90
Materials	2164.76	17029.10	262278.80	2059.02	8093.46	60985.91	52998.44	107439.3	419312.8	172895.8	527813.30	2040933
Capital	2272.00	21656.78	585564.10	2156	9635.97	282841.8	53263.5	126536.1	944463.5	191437	728620.6	4165061.0
Workforce Variables:												
Number of employees	3	11.63	108.40	3	5.59	7.44	66	68.89	14.04	181	361.92	839.73
Newly hired workers (high skilled)	0	0.94	309.54	0	0.01	0.18	0	0.40	2.04	0	66.58	2613.52
Newly hired workers (technicians)	0	0.80	177.28	0	0.02	0.26	0	0.71	3.22	0	55.51	1496.31
Newly hired workers (high skilled), concave measure	0	0.05	1.39	0	0.01	0.25	0	0.36	1.76	0	2.28	11.18
Newly hired workers (technicians), concave measure	0	0.08	1.21	0	0.03	0.37	0	0.64	2.37	0	3.30	8.79
Newly hired workers (high skilled), proximity measure	0	0.01	0.40	0	0.01	0.13	0	0.10	0.89	0	0.61	2.98
Newly hired workers (technicians), proximity measure	0	0.02	0.49	0	0.01	0.19	0	0.28	1.18	0	0.99	3.54
Sectors:												
Manufacturing	0	0.19	0.38	0	0.18	0.38	0	0.43	0.49	0	0.52	0.49
Construction	0	0.20	0.40	0	0.20	0.40	0	0.10	0.30	0	0.07	0.24
Wholesale trade	0	0.38	0.49	0	0.39	0.49	0	0.25	0.43	0	0.20	0.40
Transport	0	0.06	0.24	0	0.07	0.25	0	0.06	0.24	0	0.06	0.23
Financial	0	0.17	0.36	0	0.16	0.37	0	0.15	0.35	0	0.16	0.36
Years:												
1995	0	0.05	0.21	0	0.05	0.21	0	0.05	0.21	0	0.05	0.21
1996	0	0.04	0.21	0	0.04	0.21	0	0.04	0.21	0	0.05	0.21
1997	0	0.05	0.21	0	0.05	0.21	0	0.04	0.21	0	0.04	0.21
1998	0	0.06	0.23	0	0.06	0.23	0	0.05	0.21	0	0.05	0.21
1999	0	0.10	0.29	0	0.10	0.29	0	0.06	0.24	0	0.06	0.24
2000	0	0.10	0.29	0	0.10	0.29	0	0.06	0.24	0	0.06	0.24
2001	0	0.10	0.27	0	0.10	0.27	0	0.06	0.24	0	0.06	0.24
2002	0	0.13	0.33	0	0.13	0.33	0	0.16	0.37	0	0.16	0.37
2003	0	0.12	0.31	0	0.12	0.31	0	0.16	0.37	0	0.16	0.37
2004	0	0.13	0.33	0	0.13	0.33	0	0.14	0.35	0	0.15	0.37
2005	0	0.13	0.33	0	0.13	0.33	0	0.16	0.36	0	0.15	0.36
Observations		682064			661181			11320			9563	

Notes: Size1: Employees ≤ 49; Size2: $49 \leq$ Employees ≤ 99; Size3: $100 \leq$ Employees ≤ 149; Size4: Employees ≥ 150.

Table 2: Main elasticities from Fixed Effects and Levinhson and Petrin estimations of the production function.

Food, beverages and tobacco			*Sale and repair of motor vehicles*		
	FE	**LP**		**FE**	**LP**
Log(K_it)	0.45***	0.29***	Log(K_it)	0.47***	0.41***
Capital	(0.00)	(0.00)	Capital	(0.00)	(0.00)
Log(L_it)	0.18***	0.26***	Log(L_it)	0.17***	0.33***
Labor	(0.00)	(0.00)	Labor	(0.00)	(0.00)
Observations	14866	14957	Observations	31150	31256
Textiles			*Wholesale trade*		
	FE	**LP**		**FE**	**LP**
Log(K_it)	0.49***	0.44***	Log(K_it)	0.57***	0.41***
Capital	(0.00)	(0.00)	Capital	(0.00)	(0.00)
Log(L_it)	0.30***	0.48***	Log(L_it)	0.21***	0.33***
Labor	(0.00)	(0.00)	Labor	(0.00)	(0.00)
Observations	7411	7413	Observations	75588	31256
Wood products			*Retail trade*		
	FE	**LP**		**FE**	**LP**
Log(K_it)	0.48***	0.45***	Log(K_it)	0.47***	0.55***
Capital	(0.00)	(0.00)	Capital	(0.00)	(0.00)
Log(L_it)	0.26***	0.33***	Log(L_it)	0.16***	0.39***
Labor	(0.00)	(0.00)	Labor	(0.00)	(0.00)
Observations	23033	23057	Observations	114233	75703
Chemicals			*Hotels and restaurants*		
	FE	**LP**		**FE**	**LP**
Log(K_it)	0.52***	0.35***	Log(K_it)	0.35***	0.44***
Capital	(0.00)	(0.00)	Capital	(0.00)	(0.00)
Log(L_it)	0.26***	0.50***	Log(L_it)	0.15***	0.21***
Labor	(0.00)	(0.00)	Labor	(0.00)	(0.00)
Observations	8296	8296	Observations	38052	114598
Other non-metallic mineral products			*Transport*		
	FE	**LP**		**FE**	**LP**
Log(K_it)	0.48***	0.51***	Log(K_it)	0.43***	0.32***
Capital	(0.00)	(0.00)	Capital	(0.00)	(0.00)
Log(L_it)	0.26***	0.28***	Log(L_it)	0.22***	0.12***
Labor	(0.00)	(0.00)	Labor	(0.00)	(0.00)
Observations	4333	4359	Observations	42375	38362
Basic metals			*Post and telecommunications*		
	FE	**LP**		**FE**	**LP**
Log(K_it)	0.50***	0.48***	Log(K_it)	0.35***	0.36***
Capital	(0.00)	(0.00)	Capital	(0.00)	(0.00)
Log(L_it)	0.26***	0.34***	Log(L_it)	0.22***	0.41***
Labor	(0.00)	(0.00)	Labor	(0.00)	(0.00)
Observations	56603	56695	Observations	1388	43304
Furniture			*Financial intermediation*		
	FE	**LP**		**FE**	**LP**
Log(K_it)	0.52***	0.30***	Log(K_it)	0.48***	0.48***
Capital	(0.00)	(0.00)	Capital	(0.00)	(0.00)
Log(L_it)	0.26***	0.49***	Log(L_it)	0.16***	0.34***
Labor	(0.00)	(0.00)	Labor	(0.00)	(0.00)
Observations	10709	10716	Observations	23785	23776
Construction			*Business activities*		
	FE	**LP**		**FE**	**LP**
Log(K_it)	0.43***	0.36***	Log(K_it)	0.43***	0.35***
Capital	(0.00)	(0.00)	Capital	(0.00)	(0.00)
Log(L_it)	0.28***	0.37***	Log(L_it)	0.23***	0.49***
Labor	(0.00)	(0.00)	Labor	(0.00)	(0.00)
Observations	137971	138346	Observations	85023	85158

Notes: The dependent variable in all estimations is log value added at the firm level. All regressions include dummies for years, sizes and counties. Estimated standard errors are shown in parentheses. Significance levels: ***1%, **5%, *10%. FE: Fixed Effects. LP: Levinhson and Petrin.

Table 3: Main elasticities from Olley and Peakes estimation of the production function.

	Manufacturing	**Construction**	**Ws and retail trade**	**Transport**	**Financial and business activies**
Log(K_it)	0.37***	0.39***	0.42***	0.18***	0.17***
Capital	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log(L_it)	0.45***	0.49***	0.40***	0.54***	0.54***
Labor	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	50587	57490	94134	56302	99718

Notes: The dependent variable in all estimations is log value added at the firm level. All regressions include dummies for years, sizes and counties. Estimated standard errors are shown in parentheses. Significance levels: ***1%, **5%, *10%.

Table 4: Estimated learning by hiring effects, main results.

	Model1	**Model2**	**Model3**	**Model4**	**Model5**	**Model6**	**Model7**	**Model8**	**Model9**
Log(tot-hs)	0.01***			0.01***			0.006***		
	(0.00)			(0.00)			(0.00)		
Log(tot-tech)	0.01***			0.01***			0.01***		
	(0.00)			(0.00)			(0.00)		
Log(tot-hs-concave)		0.01***			0.01***			0.01***	
		(0.00)			(0.00)			(0.00)	
Log(tot-tech-concave)		0.02***			0.01***			0.01***	
		(0.00)			(0.00)			(0.00)	
Log(tot-hs-prox)			0.02***			0.01***			0.01***
			(0.00)			(0.00)			(0.00)
Log(tot-tech-prox)			0.02***			0.02***			0.02***
			(0.00)			(0.00)			(0.00)
Observations	499731	499731	499731	166667	166668	166669	499931	499931	499931

Notes: The dependent variable is: i) in Model1, Model2 and Model3 is TFP estimated from the FE estimation; ii) in Model4, Model5 and Model6 is TFP estimated from the Olley and Peakes estimation; iii) in Model7, Model8 and Model9 is TFP estimated from the Levinhson and Petrin estimation. All regressions include dummies for years, industries and counties. Estimated standard errors are shown in parentheses. Significance levels: ***1%, **5%, *10%.

Table 5: Estimated learning by hiring effects by industry. Count measure.

Food, beverages and tobacco			*Sale and repair of motor vehicles*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs)	0.01***	0.02***	Log(tot-hs)	0.02**	0.02**
	(0.00)	(0.00)		(0.01)	(0.01)
Log(tot-tech)	0.02***	0.02***	Log(tot-tech)	0.01**	0.01*
	(0.00)	(0.00)		(0.01)	(0.01)
Observations	11521	11522	Observations	22797	22798
Textiles			*Wholesale trade*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs)	–0.00	–0.01	Log(tot-hs)	0.01***	–0.00
	(0.01)	(0.01)		(0.00)	(0.00)
Log(tot-tech)	0.01*	0.00	Log(tot-tech)	0.02***	0.00*
	(0.00)	(0.00)		(0.00)	(0.00)
Observations	5702	5702	Observations	56144	56153
Wood products			*Retail trade*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs)	0.01**	0.01**	Log(tot-hs)	0.02***	0.02***
	(0.00)	(0.00)		(0.00)	(0.00)
Log(tot-tech)	0.01***	0.01***	Log(tot-tech)	0.02***	0.01***
	(0.00)	(0.00)		(0.00)	(0.00)
Observations	18222	18224	Observations	83720	83720
Chemicals			*Hotels and restaurants*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs)	0.00	0.00	Log(tot-hs)	0.02***	0.02***
	(0.01)	(0.01)		(0.00)	(0.00)
Log(tot-tech)	0.01*	0.01	Log(tot-tech)	0.02***	0.03***
	(0.00)	(0.00)		(0.01)	(0.01)
Observations	6691	6691	Observations	23421	23429
Other non-metallic mineral products			*Transport*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs)	0.00	0.00	Log(tot-hs)	0.01	0.00
	(0.01)	(0.01)		(0.01)	(0.01)
Log(tot-tech)	0.02***	0.02***	Log(tot-tech)	0.02***	0.02***
	(0.00)	(0.00)		(0.00)	(0.00)
Observations	3415	3415	Observations	30403	30426
Basic metals			*Post and telecommunications*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs)	0.01**	0.00	Log(tot-hs)	0.03*	0.02
	(0.00)	(0.00)		(0.01)	(0.01)
Log(tot-tech)	0.01***	0.01***	Log(tot-tech)	0.01	0.02
	(0.00)	(0.00)		(0.01)	(0.01)
Observations	45286	45294	Observations	748	748
Furniture			*Financial intermediation*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs)	0.01*	0.01***	Log(tot-hs)	0.02*	0.01
	(0.00)	(0.00)		(0.01)	(0.01)
Log(tot-tech)	0.01***	0.01***	Log(tot-tech)	0.03***	0.02***
	(0.00)	(0.00)		(0.01)	(0.01)
Observations	8378	8378	Observations	15833	15845
Construction			*Business activities*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs)	0.02***	0.02***	Log(tot-hs)	0.02***	0.00
	(0.00)	(0.00)		(0.00)	(0.00)
Log(tot-tech)	0.02***	0.02***	Log(tot-tech)	0.03***	0.01***
	(0.00)	(0.00)		(0.00)	(0.00)
Observations	105349	105358	Observations	85023	57447

Notes: The dependent variable is TFP estimated from either the FE or the Levinhson and Petrin estimation. All regressions include the first lag of TFP and dummies for years, sizes and counties. Estimated standard errors are shown in parentheses. Significance levels: ***1%, **5%, *10%.

Table 6: Estimated learning by hiring effects by industry. Count measure.

	Manufacturing	**Construction**	**Ws and retail trade**	**Transport**	**Financial and business activies**
Log(tot-hs)	0.01***	0.01*	0.00*	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log(tot-tech)	0.01***	0.01***	0.01***	0.02***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	99718	105349	186795	31235	73314

Notes: The dependent variable is TFP estimated from Olley and Peakes estimation. All regressions include the first lag of TFP and dummies for years, sizes and counties. Estimated standard errors are shown in parentheses. Significance levels: ***1%, **5%, *10%.

Table 7: Estimated learning by hiring effects by industry. Concave measure.

Food, beverages and tobacco			*Sale and repair of motor vehicles*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs-concave)	0.02***	0.02***	Log(tot-hs-concave)	0.02**	0.02*
	(0.00)	(0.00)		(0.01)	(0.01)
Log(tot-tech-concave)	0.02***	0.02***	Log(tot-tech-concave)	0.01*	0.01*
	(0.00)	(0.00)		(0.01)	(0.01)
Observations	11521	11522	Observations	22797	22798
Textiles			*Wholesale trade*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs-concave)	0.00	–0.01	Log(tot-hs-concave)	0.02***	–0.00
	(0.01)	(0.01)		(0.00)	(0.00)
Log(tot-tech-concave)	0.01*	0.00	Log(tot-tech-concave)	0.02***	0.00*
	(0.00)	(0.00)		(0.00)	(0.00)
Observations	5702	5702	Observations	56144	56153
Wood products			*Retail trade*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs-concave)	0.01***	0.01**	Log(tot-hs-concave)	0.02***	0.02***
	(0.00)	(0.00)		(0.00)	(0.00)
Log(tot-tech-concave)	0.01***	0.01***	Log(tot-tech-concave)	0.02***	0.02***
	(0.00)	(0.00)		(0.00)	(0.00)
Observations	18222	18224	Observations	83720	83720
Chemicals			*Hotels and restaurants*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs-concave)	0.00	0.00	Log(tot-hs-concave)	0.02***	0.02***
	(0.01)	(0.01)		(0.00)	(0.00)
Log(tot-tech-concave)	0.01*	0.01	Log(tot-tech-concave)	0.03***	0.03***
	(0.00)	(0.00)		(0.01)	(0.01)
Observations	6691	6691	Observations	23421	23429
Other non-metallic mineral products			*Transport*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs-concave)	0.00	0.00	Log(tot-hs-concave)	0.01	0.00
	(0.01)	(0.01)		(0.01)	(0.01)
Log(tot-tech-concave)	0.02***	0.02***	Log(tot-tech-concave)	0.02***	0.02***
	(0.00)	(0.00)		(0.00)	(0.00)
Observations	3415	3415	Observations	30403	30426
Basic metals			*Post and telecommunications*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs-concave)	0.01**	0.01*	Log(tot-hs-concave)	0.03*	0.02
	(0.00)	(0.00)		(0.01)	(0.01)
Log(tot-tech-concave)	0.01***	0.01***	Log(tot-tech-concave)	0.02	0.02
	(0.00)	(0.00)		(0.01)	(0.01)
Observations	45286	45294	Observations	748	748
Furniture			*Financial intermediation*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs-concave)	0.01**	0.01***	Log(tot-hs-concave)	0.02*	0.01
	(0.00)	(0.00)		(0.01)	(0.01)
Log(tot-tech-concave)	0.01***	0.02***	Log(tot-tech-concave)	0.03***	0.02**
	(0.00)	(0.00)		(0.01)	(0.01)
Observations	8378	8378	Observations	15845	15846
Construction			*Business activities*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs-concave)	0.02***	0.03***	Log(tot-hs-concave)	0.02***	0.01*
	(0.01)	(0.01)		(0.00)	(0.00)
Log(tot-tech-concave)	0.02***	0.02***	Log(tot-tech-concave)	0.03***	0.02***
	(0.00)	(0.00)		(0.00)	(0.00)
Observations	105349	105358	Observations	57446	57447

Notes: The dependent variable is TFP estimated from either the FE or the Levinhson and Petrin estimation. All regressions include the first lag of TFP and dummies for years, sizes and counties. Estimated standard errors are shown in parentheses. Significance levels: ***1%, **5%, *10%.

Table 8: Estimated learning by hiring effects by industry. Concave measure.

	Manufacturing	**Construction**	**Ws and retail trade**	**Transport**	**Financial and business activies**
Log(tot-hs-concave)	0.01***	0.01*	0.00*	0.01	0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log(tot-tech-concave)	0.01***	0.01***	0.01***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	99718	105349	186795	31235	73314

Notes: The dependent variable is TFP estimated from Olley and Peakes estimation. All regressions include the first lag of TFP and dummies for years, sizes and counties. Estimated standard errors are shown in parentheses. Significance levels: ***1%, **5%, *10%.

Table 9: Estimated learning by hiring effects by industry. Proximity measure.

Food, beverages and tobacco			*Sale and repair of motor vehicles*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs-prox)	0.02***	0.02***	Log(tot-hs-prox)	0.03*	0.02*
	(0.00)	(0.00)		(0.01)	(0.01)
Log(tot-tech-prox)	0.02***	0.02***	Log(tot-tech-prox)	0.02*	0.02*
	(0.00)	(0.00)		(0.01)	(0.01)
Observations	11521	11522	Observations	22797	22798
Textiles			*Wholesale trade*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs-prox)	–0.01	–0.01	Log(tot-hs-prox)	0.02***	–0.01
	(0.02)	(0.01)		(0.00)	(0.00)
Log(tot-tech-prox)	0.01	0.00	Log(tot-tech-prox)	0.02***	0.00
	(0.01)	(0.01)		(0.00)	(0.00)
Observations	5702	5702	Observations	56144	56153
Wood products			*Retail trade*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs-prox)	0.00	0.00	Log(tot-hs-prox)	0.03***	0.03***
	(0.01)	(0.01)		(0.00)	(0.00)
Log(tot-tech-prox)	0.02***	0.02***	Log(tot-tech-prox)	0.01	0.01
	(0.00)	(0.00)		(0.01)	(0.01)
Observations	18222	18224	Observations	83720	83720
Chemicals			*Hotels and restaurants*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs-prox)	0.01	0.00	Log(tot-hs-prox)	0.02**	0.02**
	(0.01)	(0.01)		(0.01)	(0.01)
Log(tot-tech-prox)	0.01**	0.01**	Log(tot-tech-prox)	0.03*	0.03*
	(0.00)	(0.00)		(0.01)	(0.01)
Observations	6691	6691	Observations	23421	23429
Other non-metallic mineral products			*Transport*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs-prox)	0.01	0.01	Log(tot-hs-prox)	–0.02	–0.03
	(0.01)	(0.01)		(0.02)	(0.02)
Log(tot-tech-prox)	0.02***	0.02***	Log(tot-tech-prox)	0.03***	0.02***
	(0.00)	(0.00)		(0.01)	(0.01)
Observations	3415	3415	Observations	30403	30426
Basic metals			*Post and telecommunications*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs-prox)	0.02***	0.01***	Log(tot-hs-prox)	0.01	0.01
	(0.00)	(0.00)		(0.01)	(0.02)
Log(tot-tech-prox)	0.01***	0.01***	Log(tot-tech-prox)	0.05***	0.05***
	(0.00)	(0.00)		(0.01)	(0.01)
Observations	45286	45294	Observations	748	748
Furniture			*Financial intermediation*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs-prox)	0.03**	0.03***	Log(tot-hs-prox)	0.01**	–0.00
	(0.01)	(0.01)		(0.00)	(0.02)
Log(tot-tech-prox)	0.01	0.01*	Log(tot-tech-prox)	0.04***	0.02**
	(0.00)	(0.00)		(0.01)	(0.01)
Observations	8378	8378	Observations	15845	15846
Construction			*Business activities*		
	FE	**LP**		**FE**	**LP**
Log(tot-hs-prox)	0.02**	0.02***	Log(tot-hs-prox)	0.03***	0.01*
	(0.01)	(0.01)		(0.00)	(0.00)
Log(tot-tech-prox)	0.03***	0.03***	Log(tot-tech-prox)	0.03***	0.02***
	(0.00)	(0.00)		(0.00)	(0.00)
Observations	105349	105358	Observations	57446	57447

Notes: The dependent variable is TFP estimated from either the FE or the Levinhson and Petrin estimation. All regressions include the first lag of TFP and dummies for years, sizes and counties. Estimated standard errors are shown in parentheses. Significance levels: ***1%, **5%, *10%.

Table 10: Estimated learning by hiring effects by industry. Proximity measure.

	Manufacturing	Construction	Ws and retail trade	Transport	Financial and business activies
Log(tot-hs-prox)	0.01***	0.01	0.01	-0.00	0.01**
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Log(tot-tech-prox)	0.01***	0.01***	0.01*	0.03***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	99718	105349	186795	31235	73314

Notes: The dependent variable is TFP estimated from Olley and Peakes estimation. All regressions include the first lag of TFP and dummies for years, sizes and counties. Estimated standard errors are shown in parentheses. Significance levels: ***1%, **5%, *10%.

Table 11: Estimated treatment effects of newly hired high skilled workers on the first difference of the log of TFP in the same year.

Treatment (tot-hs)					
	2001	2002	2003	2004	2005
Treatment effect for delta=1	0.05**	0.02*	0.01	0.06***	0.01
	(0.02)	*(0.01)*	*(0.01)*	*(0.01)*	*(0.02)*
Treatment effect for delta=2	0.10	0.06**	0.03	0.10**	0.01
	(0.06)	*(0.03)*	*(0.02)*	*(0.04)*	*(0.03)*
Treatment effect for delta=3	0.20**	0.15**	0.09**	0.13	0.04
	(0.09)	*(0.04)*	*(0.03)*	*(0.06)*	*(0.05)*
Treatment (tot-hs-concave)					
	2001	2002	2003	2004	2005
Treatment effect for delta=0.5	0.01	0.01	0.04	0.01	0.06***
	(0.02)	*(0.01)*	*(0.03)*	*(0.01)*	*(0.01)*
Treatment effect for delta=1.5	0.03	0.03	0.07*	0.02	0.09
	(0.06)	*(0.03)*	*(0.04)*	*(0.03)*	*(0.04)*
Treatment effect for delta=2.5	0.09	0.12**	0.10	0.06	0.10
	(0.10)	*(0.06)*	*(0.06)*	*(0.05)*	*(0.07)*
Treatment (tot-hs-proxy)					
	2001	2002	2003	2004	2005
Treatment effect for delta=0.5	0.03	0.05***	0.01	0.00	0.08**
	(0.02)	*(0.01)*	*(0.02)*	*(0.01)*	*(0.01)*
Treatment effect for delta=1.5	0.20**	0.12***	0.04	0.05	0.16***
	(0.10)	*(0.04)*	*(0.03)*	*(0.05)*	(0.04)
Treatment effect for delta=2.5	0.33	0.17*	0.05	0.15	0.18**
	(0.27)	*(0.09)*	*(0.06)*	*(0.14)*	(0.09)

Notes: TFP estimated from estimation. Delta refers to the treatment level. Estimated standard errors are shown in parentheses. Significance levels: ***1%, **5%, *10%.

Table 12: Estimated treatment effects of newly hired technicians on the first difference of the log of TFP in the same year.

Treatment (tot-tech)					
	2001	2002	2003	2004	2005
Treatment effect for delta=1	0.05**	0.02*	0.00	0.03**	0.02
	(0.02)	*(0.01)*	(0.01)	*(0.01)*	*(0.02)*
Treatment effect for delta=2	0.05	0.05**	0.01	0.06**	0.03
	(0.04)	(0.02)	(0.03)	(0.03)	(0.03)
Treatment effect for delta=3	0.08	0.08***	0.06	0.08	0.04
	(0.05)	(0.03)	(0.04)	(0.05)	(0.05)
Treatment (tot-tech-concave)					
	2001	2002	2003	2004	2005
Treatment effect for delta=0.5	0.01	0.03**	0.01	0.02**	0.02
	(0.01)	*(0.01)*	*(0.02)*	*(0.01)*	*(0.02)*
Treatment effect for delta=1.5	0.03	0.09**	0.03	0.04	0.05
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)
Treatment effect for delta=2.5	0.03	0.11**	0.07*	0.04	0.05
	(0.05)	(0.04)	(0.04)	(0.05)	(0.13)
Treatment (tot-tech-proxy)					
	2001	2002	2003	2004	2005
Treatment effect for delta=0.5	0.04**	0.03	0.02**	0.01	0.1***
	(0.01)	*(0.02)*	*(0.01)*	*(0.01)*	*(0.01)*
Treatment effect for delta=1.5	0.03	0.06**	0.07*	0.05	0.23***
	(0.03)	(0.03)	(0.04)	(0.05)	(0.04)
Treatment effect for delta=2.5	0.03	0.07	0.13*	0.18	0.27***
	(0.11)	(0.06)	(0.07)	(0.13)	(0.10)

Notes: TFP estimated from Levinhson and Petrin estimation. Delta refers to the treatment level. Estimated standard errors are shown in parentheses. Significance levels: ***1%, **5%, *10%.

Table 13: Estimated treatment effects of newly hired high skilled workers on the first difference of the log of TFP the year after.

Treatment (tot-hs)				
	2001	2002	2003	2004
Treatment effect for delta=1	0.09***	0.02*	0.13***	0.01
	(0.03)	*(0.01)*	*(0.03)*	*(0.01)*
Treatment effect for delta=2	0.16***	0.00	0.15***	0.04**
	(0.05)	*(0.01)*	*(0.05)*	*(0.02)*
Treatment effect for delta=3	0.22**	0.00	0.24***	0.07
	(0.11)	*(0.01)*	*(0.08)*	*(0.04)*
Treatment (tot-hs-concave)				
	2001	2002	2003	2004
Treatment effect for delta=0.5	0.04**	0.01	0.01	0.04***
	(0.02)	*(0.01)*	*(0.01)*	*(0.01)*
Treatment effect for delta=1.5	0.10	0.06**	0.03	0.07***
	(0.06)	*(0.01)*	*(0.02)*	*(0.01)*
Treatment effect for delta=2.5	0.16**	0.03**	0.07	0.09***
	(0.08)	(0.01	(0.08)	(0.03)
Treatment (tot-hs-proxy)				
	2001	2002	2003	2004
Treatment effect for delta=0.5	0.02	0.06***	0.00	0.00
	(0.02)	*(0.01)*	*(0.01)*	*(0.01)*
Treatment effect for delta=1.5	0.08	0.15***	0.03	0.02*
	(0.05)	*(0.03)*	*(0.04)*	*(0.01)*
Treatment effect for delta=2.5	0.16*	0.17*	0.20	0.05
	(0.08)	*(0.09)*	*(0.18)*	*(0.09)*

Notes: TFP estimated from Levinhson and Petrin estimation. Delta refers to the treatment level. Estimated standard errors are shown in parentheses. Significance levels: ***1%, **5%, *10%.

Table 14: Estimated treatment effects of newly hired technicians on the first difference of the log of TFP the year after.

Treatment (tot-tech)				
	2001	2002	2003	2004
Treatment effect for delta=1	0.03	0.01	0.04**	0.01
	(0.02)	*(0.02)*	*(0.02)*	*(0.01)*
Treatment effect for delta=2	0.07	0.02	0.09**	0.00
	(0.04)	*(0.03)*	*(0.04)*	*(0.01)*
Treatment effect for delta=3	0.12**	0.04	0.23***	0.00
	(0.06)	*(0.03)*	*(0.06)*	*(0.01)*
Treatment (tot-tech-concave)				
	2001	2002	2003	2004
Treatment effect for delta=0.5	0.03**	0.01	0.01	0.00
	(0.01)	*(0.01)*	*(0.02)*	*(0.01)*
Treatment effect for delta=1.5	0.14***	0.03**	0.06***	0.01
	(0.03)	*(0.01)*	*(0.02)*	*(0.01)*
Treatment effect for delta=2.5	0.14***	0.05	0.15**	0.02
	(0.04)	*(0.04)*	*(0.07)*	*(0.04)*
Treatment (tot-tech-proxy)				
	2001	2002	2003	2004
Treatment effect for delta=0.5	0.06***	0.02*	0.01	0.01**
	(0.02)	*(0.01)*	*(0.01)*	*(0.00)*
Treatment effect for delta=1.5	0.10**	0.04**	0.04	0.03
	(0.03)	*(0.02)*	*(0.03)*	*(0.02)*
Treatment effect for delta=2.5	0.19**	0.04	0.22***	0.09
	(0.08)	*(0.07)*	*(0.08)*	*(0.08)*

Notes: TFP estimated from Levinhson and Petrin estimation. Delta refers to the treatment level. Estimated standard errors are shown in parentheses. Significance levels: ***1%, **5%, *10%.