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Abstract[2]

Knowledge is transferred between firms explicitly or tacitly. While non-embedded knowledge can be transferred explicitly through patent citations, embedded knowledge is essentially transferred tacitly through knowledgeable workers' movements. Given the higher prevalence of the latter, improved matching and allocation efficiency gains due to workers' displacement can exert relevant impact on a firm's performance and on economic growth. This paper explores knowledge spill overs across firms occurring due to displacement of workers who transit from better to less performing firms. Allegedly, workers who move from more successful firms carry with them some knowledge of the technology that induces improvements of performance in the recipient firms. Different measures of firms' performance are studied (proxies for firms' productivity such as average quality of labor workforce and estimated TFP per firm). Discrimination according to sector of sending and recipient firms (R&D intensive or not) and type of moving worker (scientific or not) is taken into consideration to differentiate results. Matched employer-employee administrative records of the Peruvian formal sector allow to control for several time varying observables and time invariant non-observables on both ends (firms and workers). Our preliminary findings suggest that spillovers exist, that is, recipient firms improve performance after receiving workers from better performing firms. This happens with more intensity for workers transiting across firms of more than 50 workers, with higher educational levels, with occupations related to sciences, technology and engineering and in firms operating in more R&D oriented sectors.

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1. Introduction

In his classic contribution to the growth literature, Solow (1957) denominates "technical change" as any shift in firms' output that is not attributable to inputs accumulation. More recently, the mainstream of the endogenous growth literature gravitates around Hicks neutral production functions where this change is usually induced by innovation[3]. While innovation (and hence technical change) can happen by creation within the firm, innovation can also happen by absorption of knowledge already available outside the firm. Existing knowledge outside the firm, in turn, can be transferred explicitly (non-embedded knowledge is transferred through patent citations) or tacitly (embedded knowledge is transferred through knowledgeable workers movements). This paper asks whether improvements in firms' performance can be related to technical transfers across firms occurring through moving workers carrying knowledge from their firms of origin, that is, whether firms' growth can be in part explained by knowledge spillovers.

While this question is not new[4] and quite recent research has been advanced for more developed countries (see Table 1), very little research has been conducted on this in Latin America,[5] and none in Peru. This paper intends to fill that gap and applies recent methodological advances to exploit the dimensionality of Peruvian national employer-employee administrative records in the identification of performance indicators and proxies for productivity differences between sending and receiving firms. By using populational datasets of payroll-related observables for workers and firms, this paper contributes to the understanding of the convergence process of Peruvian firms driven by technical transfer through knowledge spillovers originated by labor turnover.

The process of technology spillover due to interfirm mobility of workers requires at least three conditions. First, firms must be heterogeneous in their stock of knowledge or technology and this heterogeneity must translate into differenced productivity and performance across sender firms. Second, relevant knowledge from better performing firms must be transferrable to the moving workers and from these workers to the recipient firm. Third, knowledge absorbed by the receiving firms has to be transformed into economic gains (improved efficiency in the firms, improved salaries of the workers, etc.). While the role of firms' heterogeneity in economic literature of firms' growth is well established[6], as well as the theory of endogenous growth due to technological innovation[7], and, more recently, the theory of knowledge transfer[8], each of these elements still pose a challenge in the simultaneous empirical identification of spillovers and available data covering all three aspects at the same time is virtually inexistent.

In fact, existing empirical literature distinguishes two salient aspects on the analysis of interfirm technical transfers through worker turnover. First, attention is put into where the technical change occurs (the sender firm's profile). Second, attention is put into who transfers the technology (the moving worker's profile). Related to the first point, Stoyanov and Zubanov (2012) present a literature review showing evidence that hiring knowledge workers from R&D-intensive firms is linked to better performance by the hiring firms[9]. Indeed, initial empirical approaches to identify and estimate spillovers of this sort combine information on explicit and tacit transfers, that is, the identification used by early literature followed workers

[3] We understand as innovation to any effort conducing to new ways of production (this is called "process innovation", which according to international convention can be organizational, managerial, or technical) or to new generations or varieties of products (this is called "product innovation"), or both.

[4] Modelling of knowledge spillovers date back to seminal contributions to the endogenous growth literature: Romer (1990), Grossman and Helpman (1991). Moreover, the intuition of the spillover mechanism was already portrayed by Arrow (1962) who says that "no amount of legal protection can make a thoroughly appropriable commodity of something so intangible as information" and that "mobility of personnel among firms provides a way of spreading information". Acemoglu (2009) curates a number of models encompassing technical transfer through spillovers.

[5] See Poole (2013) for a study in Brazil, Castillo et al (2016) for a study in Argentina.

[6] Some of the most influential references are Jovanovic (1982), Hopenhayn (1992), Melitz (2005) and Luttmer (2007). See Kueng et al (2017) for a detailed discussion on different firm growth theories.

[7] See the two most influential versions of innovation-based growth theory: the one developed by Romer (1990) and the Schumpeterian version developed by Aghion and Howitt (1992) and Grossman and Helpman (1991). See Aghion and Howitt (1998) for a survey of Schumpeterian endogenous growth models.

[8] See for example Dasgupta (2012) for a model of knowledge diffusion where workers learn from their managers and knowledge diffusion across firms takes place through worker mobility.

[9] The review covers work by Rao and Drazin (2002); Kaiser, Kongsted, and Rønde (2008); and Maliranta, Mohnen, and Rouvinen (2009)

moving from one firm to another and observed whether after the worker's arrival, the hiring firms increased the number of citations of patents formerly granted to the sender firms[10]. Some of this work also focused exclusively on the movement of R&D workers, taking us to the second point. Related to that point, Almeida and Kogut (1999) show for the semiconductor industry, that ideas are spread through the mobility of key engineers. More recently, Parrotta and Pozzoli (2012) investigate how knowledge carriers—technicians and highly educated workers recruited from a donor firm—contribute to knowledge diffusion and enhanced productivity in the hiring (recipient) firm in Denmark. The role of the knowledge carrier is also emphasized by studies arguing in favor of positive externalities generated by the carrier movements after comparing the gains of the movement for the receiving firm vis a vis the gains of the movement for the hired worker. For example, Stoyanov and Zubanov (2014) find that firms do not fully compensate incoming workers for the firm productivity effects caused by the technical transfer, implying positive externalities to firms. On a related note, Møen (2005) sustains that potential externalities associated with labor mobility of technical staff are partially internalized in the labor market through wage adjustments (technical staff in R&D-intensive firms pay for the knowledge they accumulate on the job through lower wages in the beginning of their career and that they later earn a return on these implicit investments through higher wages), confirming the importance of spillovers even in the valuation of incumbent labor.

Most recent literature on the identification and estimation of technical transfer through interfirm labor mobility has been advanced for more developed countries exploiting high dimensional employer-employee administrative records to simultaneously identify this type of spillovers (see Table 1). This literature consistently finds a positive relation between firm productivity gains and hiring workers from technologically superior firms. In order to sort heterogeneous firms according to the level of technical superiority, this literature follows two approaches. The first one used by Stoyanov and Zubanov (2012, 2014) measures the productivity gap between the firm that sends the worker and the firm that hires her. The second one, by Serafinelli (2013) studies the impact of worker inflows from high-paying firms on receiving non-high-paying firms' productivity using the, by now, traditional AKM approach[11]. More recently, Stockinger and Wolf (2016) using a similar setup investigate whether the heterogeneity of sending and hiring establishments alone accounts for potential productivity effects of worker inflows, or whether workers' relative wage position in the sending establishment also plays a part and find that the inflows are positively selected (hires were paid above the average wage in the sending firm) and that after taking this into account the positive effect on the hiring firms' productivity disappears.

Is interfirm mobility a significant channel to transfer knowledge in Peru as well? Is technical superiority and firms' heterogeneity more evident in R&D intensive sectors? Is the spillover in these sectors more notorious? Are transiting workers with more R&D oriented occupations (engineers, for example) more likely to carry knowledge and generate impact on receiving firms? Is the technical superiority of the sender firm or the higher productivity of the moving worker responsible for improvements in the receiving firms? What are the policy implications of these dynamics? By exploiting Peruvian payroll administrative records - the monthly census of formal employers and employees that is collected through the national social security contributory system by the Peruvian tax authority - this paper reports preliminary results of an attempt to answer these questions, focusing exclusively on the formal sector. Given that major technical transfers are expected from more skilled workers, who usually work in the formal sector (and who can complement more suitably with productive factors of the formal firms who hire them), the study helps to unveil the effects of technical transmission in the most sensitive labor sector to this kind of effect, that is, the formal sector.

The rest of the paper is organized as follows: section 2 describes the data sources and provides the motivation for the study based on some stylized facts that suggest spillover may exist after turnover of workers with certain profiles across firms of specific characteristics. Section 3 explains the methodology used for the estimation of the productivity proxies, the productivity gaps and the specifications followed for

[10] See Singh and Agrawal (2011) for a review of literature related to patent citation, mobile inventors and knowledge flow.

[11] Abowd, Kramarz and Margolis (1999) proposed a methodology to decompose workers compensations (wages) into components related to observable employee characteristics, personal heterogeneity and firms' heterogeneity. The latter two estimated through high dimensional fixed effects. Abowd, Kramarz and Roux (2006) illustrate the applicability of the methodology in a study of simultaneous determination of worker mobility and wage rates.

the estimation of the spillover effect due to labor turnover. Section 4 reports the results of several specifications after accounting for different sources of potential heterogeneity. Section 5 concludes.

2. Data and stylized facts

The main source of information used for this study is the Peruvian payroll administrative records from 2012 to 2016. The electronic payroll is collected by the national revenue authority through two platforms: the labor information records (T-Registro) and the monthly payroll (PLAME). In both cases, firms provide the information online as part of their regular monthly declarations to the revenue authority. T-Registro stores information about employers, employees, retired pensioners, outsourcers, trainees, etc. while PLAME stores the social security information and the income data of workers (salaries and number of hours and days worked per month).

This unbalanced exhaustive panel of the population of formal firms and workers is updated on a monthly basis and allows for a comprehensive assessment of the employer-employee histories. During the period under study, 356,068 different firms registered information for 6'981,549 different workers. 26'241,389 job to job transitions happened, 3'951,374 increases in firms' productivity and 75'462,146 wage rises were registered (1'951,619 after job to job movements). An average of 3.2 million workers and 211 thousand firms are recorded each year in the dataset.

The individual level data covers all individuals aged between 17 and 70 (99.6% of the observations) and include gender, age, years of education, salary, hours worked, occupation, type of contract (permanent, temporary). The firm level data covers all private firms that contribute to social security and include region and economic sector (up to 5-digit CIIU). By aggregation of information of workers, firm measures about number of workers, payroll expenditure, total hours worked, average shifts, average salary, as well as proxies of productivity, measures can also be computed (see section 3). It is Important to note that CIIU and occupational codes allow us to classify firms belonging to sectors more oriented to conducting R&D and science, technology, engineering and mathematics (STEM) workers.

Additional sources of information include the annual official minimum wage drawn from the Ministry of Labor, monthly national consumer prices indices reported by the Central Bank, international codification data for STEM careers as defined by the United States Labor Bureau and international codification data for technological industries according to the OECD classification of manufacturing industries into categories based on R&D intensities. Appendix 1 provides a detailed definition of sector categories, R&D intense sectors, occupational categories and STEM occupations.

Table 2 reports a summary of the main statistics of the dataset. The Table reports an increase in the number of firms from 150 thousand to 210 thousand between 2011 and 2016. For the same period, formal workers increased from 2.3 million to 3.1 million in the country. Firms entered the market at a rate of about 20% per year and exited at a rate of 14% per year, although the net entry of firms per year has been decreasing. Similarly, workers joined the market at rates close to 30% per year, 16% of workers moved from one firm to another, while about one fourth of workers separated from the formal labor market on average each year. Given the prevalence of the informal economy in the country[12], observed exit rates from the formal sector are not striking. It is worth noting that 60% of the formal firms have 3 or less workers and only 2% have 100 or more. Among these workers, one third are female and two thirds are between 25 and 50 years old. Two of every 10 firms operate in the secondary sector (7 in the tertiary sector) and of these, about 4 operate in R&D intensive sectors. Sector workers participation is consistent with the firm's sectoral distribution for the secondary sector. The primary sector concentrates a higher share of the labor force than it does in the distribution of firms and the opposite happens in the tertiary sector. Formal workers educational attainment is bimodal with about 90% of the labor force equally distributed between secondary and tertiary education. Occupational categories show a high concentration of elemental occupations. Administrative and technical occupations concentrate another important share of the labor force. About 6% of the labor force work in R&D intensive industries and 8% have STEM occupations. The average monthly

[12] About 72% of workers and 56% of firms are informal (INEI, 2017)

salary of a formal worker fluctuated between USD526 and USD690 in the period under study for 32 hours of work per week on average.

An analysis of transitioning workers shows that about 50% of them remain in the same sector when changing jobs (Table 3). The sector with major yearly retention of workers is agriculture, forestry and fishery (64%), followed by the financing industry (57%) while mining, construction and manufacturing are sectors with the highest exit rates (they retain 46% or less of the workers observed in the same sector as the previous year). The financial sector attracts most of the intersectoral movements. Figure 1 provides a richer view of these facts by synthetizing populational transitions of workers (some hundreds of thousands) moving across sectors, occupational ranks and different productivity firms. In particular, Figure 1A shows that inter and intra sectoral mobility is high among formal workers in Peru. This is a point that will be taken into consideration in the empirical identification of spillovers as special attention will be put into firms operating in the manufacturing and R&D intensive sectors. Transition of workers happens within and between occupations as well. Figure 1B accounts for this fact. As STEM occupations will be of special interest, accounting for the fact of high intensity of occupations' updates after worker's displacements is also of importance. In summary, preliminary evidence of worker's transitions reveals considerable activity within and between sectors and occupations.

Are these transitions related to dynamics in firms as well? Figure 2 showcases the catching up of firms receiving workers from better performing firms (and its reciprocal flows for those receiving workers from worse performing firms). The Figures show three groups differentiated by the productivity[13] of the sender firm. Figure 2A shows for instance that firms hiring workers coming dominantly from less productive firms remain in their productivity group whereas Figure 3A shows that firms hiring workers coming dominantly from more productive firms move upwards to the next productivity group, or remain in their same group. Very generally, and before controlling for any confounding factor, these figures suggest that there is at least an unconditional positive correlation between the performance tier of the firm of origin of a moving worker and the future performance of the firms that hire this worker. In parallel, Table 4 shows that workers climbing up the career ladder, are those moving from the group of less productive to the group of more productive firms and vice versa (workers moving from more to less productive are usually moving from managerial or technical to operators or more basic occupations), partially reflecting that some determinants related to moving workers condition the relative performance of the hiring firms.

Further, and in the same spirit of Stoyanov and Zubanov (2012), if moving workers enable spillovers by spreading knowledge from one firm to another, one would expect a more concentrated productivity distribution in industries with higher rates of worker turnover from more to less productive firms. Figure 3 plots the relationship between productivity variance and the 2011-2016 average turnover rate from top 40 percent to bottom 40 percent of firms (crosses), and from top quartile to bottom quartile (dots). As expected, there is a strong negative correlation between worker turnover and productivity dispersion: − 0.61 for the top to bottom 40 percent and − 0.67 for the top to bottom quartile. That this correlation becomes stronger as we increase the productivity difference between sending and receiving firms suggests that spillovers depend on the magnitude of this difference. In fact, Stoyanov and Zubanov (2012) find that the productivity difference between the sending and receiving firms (the productivity gap) to be a convenient measure of the receiving firms' exposure to spillovers from hiring. The empirical strategy of this paper exploits this fact.

3. Methodology

As explained previously, our data covers the whole population of formal workers and firms of the private sector operating in Peru between 2011 and 2016. Data records are collected on a monthly basis and this allows the identification of employer and employees dynamics at several frequencies. For the purposes of our estimations we roll monthly estimations of annual transitions[14]. Workers with multiple jobs

[13] The definition of productivity used in this section is the approximate TFP deduced by applying sector output elasticities as described in the next section and in Appendix 2.

[14] As in the mainstream literature of applied studies on labor and firm dynamics, we base our estimations on annual transitions as to abstract from the effects of seasonality and at the same time to be able to capture cyclical movements rather than volatile short period adjustments.

are counted once for their principal activity[15] and followed during all the months in which they show up in throughout the dataset. Similarly, incumbent firms in 2011, as well as all entrant firms since, are followed during all periods in which they keep operating formally until 2016.

For most of the analysis conducted in this paper, we follow the empirical strategy of Stoyanov and Zubanov (2012). As such, productivity gains are analyzed using a productivity gap measure constructed as follows:

$$gap_{j,t} = \frac{\sum_{i=1}^{H_{j,t}} (A^s_{i,t-1} - A^r_{i,t-1})}{H_{j,t}} * \frac{H_{j,t}}{N_{j,t}} \qquad (1)$$

Where $A^s_{i,t-1}$ and $A^r_{i,t-1}$ are normalized productivities of the receiving and sending firms in year t − 1 (one year before hiring), $H_{j,t}$ is the number of new workers and $N_{j,t}$ is the total number of workers[16]. While studies following this approach usually contain firms' information about value added, materials and energy input, profit, fixed assets stock and investments, a major limitation of our dataset is the lack of variables related to production, value added or sales. Two different firm productivity proxies are used: (i) the approximate TFP deduced by applying sector output elasticities (see Appendix 2) and, (ii) the average level of the quality of the labor factor (percentage of highly educated workers and in highly paid occupations). Positive and negative versions of the gap are also computed discriminating the cases in which the recipient firm has a lower measure of productivity than the sender (negative gap) from those in which the recipient firm has a higher measure of productivity (positive gap)[17].

$$A^r_{j,t+1} = \sum_{k=0}^{L-1} \alpha_k A^r_{j,t+1} + \beta \overline{\widetilde{gap}}_{j,t} + X_j \gamma_j + \overline{Y}^1_{j,t} \gamma_2 + \overline{Y}^2_{j,t} \gamma_3 + \overline{\varepsilon}_{j,t+1} \qquad (2)$$

Where $A^r_{j,t+1}$ is the sector-normalized productivity of the receiving firm one year after hiring, X_j is a vector of receiving firm's fixed effects, $Y^1_{j,t}$ is the vector of incumbent workers' characteristics[18], and $Y^2_{j,t}$ is the vector of new workers' characteristics[19], both averaged at the receiving firm level.

Further, and as to analyze possible heterogeneity in the contribution of gaps according to the sector of origin of the worker displacements a slight variation of equation (2) is estimated:

$$A^r_{j,t+1} = \sum_{k=0}^{L-1} \alpha_k A^r_{j,t-k} + \beta_{\neq} \overline{\widetilde{gap}}^{\neq}_{j,t} + \beta_{=} \overline{\widetilde{gap}}^{=}_{j,t} + X_j \gamma_j + \overline{Y}^1_{j,t} \gamma_2 + \overline{Y}^2_{j,t} \gamma_3 + \overline{\varepsilon}_{j,t+1} \qquad (3)$$

Where $\overline{\widetilde{gap}}^{=}_{j,t} = \sum_{i=1}^{N_{j,t}} I^{=}_{i,t} \left(A^s_{i,t-1} - A^r_{j,t-1}\right) / N_{j,t}$; $\overline{\widetilde{gap}}^{\neq}_{j,t} = \sum_{i=1}^{N_{j,t}} \left(1 - I^{=}_{i,t}\right) \left(A^s_{i,t-1} - A^r_{j,t-1}\right) / N_{j,t}$ and $I^{=}_{i,t}$ is an indicator variable which takes the value of one if worker *i* moved from one firm to another in year *t* within the *same* two-digit industry, and zero otherwise. That is, $\overline{\widetilde{gap}}^{=}_{j,t}$ and $\overline{\widetilde{gap}}^{\neq}_{j,t}$ are productivity gaps for workers moving within and between industries, respectively, weighed by their respective shares in the receiving firms' workforce.

[15] The principal activity of a worker is defined each month as the job to which the worker dedicates most of her working hours that month. In the case of multiple jobs with the same number of hours worked per month, the principal activity is defined as the one that provides the major share of her monthly income, taking as monthly income to the summation of incomes coming from all formal sources declared in the administrative records that month. In the case of multiple jobs with the same number of hours and salaries, the principal activity for the month is defined as the one to which the worker dedicates more days of work that month.

[16] In order to prevent false identification of moving workers in merge and acquisition scenarios, firms are filtered if two simultaneous conditions are fulfilled: (i) if having more than 50 workers in period t-1, the firm reports that more of 50% of its workforce was newly hired in that period; and (ii) if the firm also reports that more than 50% of its workers are new hires in period t.

[17] The formula for the positive and negative gaps are: $Positive\ gap_{j,t} = \frac{\sum_{i=1}^{H_{j,t}} D_{i,t} (A^s_{i,t-1} - A^r_{i,t-1})}{H_{j,t}} * \frac{H_{j,t}}{N_{j,t}}$ and $Negative\ gap_{j,t} = \frac{\sum_{i=1}^{H_{j,t}} (1 - D_{i,t}) (A^s_{i,t-1} - A^r_{i,t-1})}{H_{j,t}} * \frac{H_{j,t}}{N_{j,t}}$ where $D_{i,t}$ is an indicator variable equal to one if $\left(A^s_{i,t-1} - A^r_{i,t-1}\right) > 0$ and zero otherwise.

[18] Educational attainment, age, experience, occupational category, gender, type of contract.

[19] Same as before.

Likewise, possible heterogeneity in the contribution of gaps according to the educational level of the displaced workers is assessed through a similar variation:

$$A_{j,t+1}^{r} = \sum_{k=0}^{L-1} \alpha_k A_{j,t-k}^{r} + \beta_{high} \widetilde{\overline{gap}}_{j,t}^{high} + \beta_{college} \widetilde{\overline{gap}}_{j,t}^{college} + \beta_{univ} \widetilde{\overline{gap}}_{j,t}^{univ} + X_j \gamma_j + \overline{Y}_{j,t}^{1} \gamma_2 + \overline{Y}_{j,t}^{2} \gamma_3 + \overline{\varepsilon}_{j,t+1} \quad (4)$$

Where $\widetilde{\overline{gap}}_{j,t}^{l} = \sum_{i=1}^{N_{j,t}} I_{i,t}^{l} \left(A_{i,t-1}^{s} - A_{j,t-1}^{r} \right) / N_{j,t}$; l is education level, l = {high school, college, university} and $I_{i,t}^{l}$ is an indicator variable which takes the value of one if worker i with education level l was hired by firm j in period t. That is, $\widetilde{\overline{gap}}_{j,t}^{l}$ is the average productivity gap for education group l weighed by its share in total work-force.

4. Results

Tables 5 to 8 report the results after estimating different specifications for a balanced panel subsample for manufacturing firms[20]: (i) the base specification as explained by Equation (2) is reported in Table 5; (ii) Table 6 reports estimations that discriminate when productivity positive (negative) gap is calculated only when a worker is hired from a more (less) productive firm, (iii) results discriminating productivity gaps when hiring from same and different sectors, as portrayed by Equation 3, are reported in Table 7, and (iv) heterogeneous spillover effects due to differenced educational attainment of new employees, as specified by Equation 4, are reported in Table 8. Tables 6, 7 and 8 also report results for two additional scenarios: when estimations consider differentiated weights according to the share of STEM workers in the receiving firms and when estimations are conducted exclusively for those receiving firms operating in allegedly more R&D intensive sectors.

Results of the benchmark specification are reported in Table 5 and reveal a significant and positive link between the receiving firm's productivity and the gap. For instance, the coefficient 0.246 in column 1 (the specification with no additional controls) using the relative TFP proxy implies that a hypothetical firm hiring 10 percent of its workers from 10 percent more productive firms experiences a 0.1×0.1×0.246 = 0.25 percent productivity gain in the year after hiring. Reported result by Stoyanov and Zubanov (2012) for Denmark is 0.2. Panel B shows the results for the estimation using the human capital proxy of productivity. Estimates hovering around 0.2 are found in Table 5B. Table 5 also shows non-significant results for the sample including small sized firms. In all specifications, spillovers are more significant in larger firms, where technology transfer can have a more disruptive effect on receivers, and where the likelihood of displacement of specialized workers is higher. It is interesting to note that controlling for workers characteristics does not exert a major alteration in the estimation of the contribution of the gap (columns 2 to 4). Constraining the exercise to firms with productivities above the average sector productivity (column 5) or to firms that experience productivity growth (column 6) does exert positive changes in the results that become more apparent in the next specifications, where heterogeneity in the direction of the gap or in the nature of the transitions are taken into account. Overall results using the alternative definition of productivity (proxied by human capital) depict similar patterns.

The gap can adopt three sorts of values. If the sender firm is less, equal or more productive than the receiver, the productivity gap will be negative, zero or positive respectively. Table 6 presents results differentiating the effect of positive (β_p) and negative (β_n) productivity gaps. The Table also reports results for positive hiring scenarios in order not to confound a situation of zero gap due to no hiring (where $H_{j,t}$ equals zero) with a situation of zero gap due to positive hiring with equal productivities of sender and receiving firms. A number of interesting results emerge. First, and foremost, in all specifications shown in the Table, the positive productivity gap is positive and significant while the negative gap is non-significant. This is one of the most important findings as it confirms the spillover hypothesis: hiring workers moving

[20] In order to prevent confounding effects due to age or experience of entrant firms, or due to displacement induced by firms about to exit, analysis is conducted for firms of the manufacturing sector that appear uninterruptedly in all months of the period under study. For this version of the paper, we focus on recipient firms on the manufacturing sector (sender firms can operate at any sector) to have a better reading of the differentiated effects of STEM workers and in firms operating in R&D more oriented sectors.

from more productive firms exert a positive impact on the productivity of recipient firms while hiring workers coming from less productive firms have neutral effects on productivity. Second, compared to the results shown in Table 5, in which the whole sample (including small firms) yielded non-significant results, Table 6 shows significant results for the positive gap in the whole sample, in the sample constrained to small firms and in the sample constrained to firms with more than 50 workers. The effect of the positive gap on small firms is about one third of that observed in bigger firms. Third, when looking only at firms that reported positive hiring the effect persists and accounts for similar magnitudes. Table 6 shows two additional sets of results, those obtained after weighting the observations by the percentage of STEM workers in the recipient firm and those obtained after constraining the sample to R&D sectors. If the results are actually driven by spillovers and not just because employers-employee sorting or because better hires come after productivity improvements of the recipients, one should observe increased effects of the gaps for firms with a higher mass of specialized workers (who can carry more specialized tacit knowledge and thus exert higher impact on the productivity of the recipients), or for firms operating in sectors prone to engaging in R&D activities. Estimates jump from 0.3 to 0.6 in the case of the STEM adjusted specification and increase to 0.45 in the case of the R&D sectors. Results for the alternative definition of productivity go in a similar direction but seem to be more sensitive to the differentiation of the direction of the gap. Indeed, estimates more than duplicate from 0.2 to 0.5 in big firms with or without positive hiring, and go up to 0.6 in the STEM specification. Interesting to note is the fact that under this definition of productivity, small firms benefit from workers movement only in the firms with high participation of STEM workers.

Beyond the differentiated effect of positive and negative gaps, there are at least two other potential sources of heterogenous impact. Table 7 evaluates if knowledge transfer by new hires can overcome technology borders between industries, in which case, the coefficients $\beta_{\neq}$ and $\beta_{=}$ should be equal. In other words, Table 7 explores if the technical barriers imposed by inter sectoral displacements[21] reduce the likelihood of technical transmission through workers mobility. Evidence reported in Table 7 shows that in Peru, that is not the case. In fact, the dominant transfers come from other industries. It is important to note that the sample used for all estimations corresponds to receiving firms operating in the manufacturing sector. The inter sectoral movement is measured then as displacements between two-digit ISIC manufacturing sectors. Results using the TFP proxy only show a dominant effect of the same industry displacements for the sample of growing firms operating in R&D sectors, suggesting that only among firms with a higher likelihood to conduct R&D, new hires coming from the same industry are more impactful than those bringing experience from other sectors. In spite of this, when positive and negative gaps are considered in this setup, the positive productivity gap is significant only for the share of hires coming from the same sector, and the effect increases for the STEM and the R&D samples.

Finally, if more educated workers can absorb and convey knowledge better, then we would expect that higher educated workers will transfer more knowledge and hence will cover a larger share of the productivity gap between their old and new employers ($\beta_{high} < \beta_{coll} < \beta_{univ}$). This progressivity is clearly observed when using the human capital definition in Table 8. For example, when looking at growing firms in the estimation using STEM weights, the coefficient of the gap for hires with completed university degrees is 2.3, while the corresponding figure for hires with college education is 2 and 1.4 for hires with high school. For the proxied TFP definition, and without discriminating between positive and negative gaps, Table 8 shows that workers with high school education and workers with university education are the ones responsible for most of the spillover effects in the majority of the specifications. After negative and positive gaps are distinguished, it becomes apparent that the contribution of high school workers is more on the negative side, while the contribution of the university graduates is positive, significant and higher. The specification with STEM weights dilutes the significance of the negative impact of high school transitions. In R&D sectors, high school workers contribute significantly when coming from both, more and less productive sender firms (positive and negative gaps are significant), although the positive gap effect is dominant. The net effect however is not as high or significant as that observed for hires with university degrees.

[21] Displacements across manufacturing subsectors (across two digit ISIC industries) are considered.

5. Conclusions

Is technical transfer observed through workers mobility in the Peruvian labor market? Is it more intense for specific types of workers or different for firms operating in more R&D oriented sectors? This paper answers these questions exploiting administrative records covering all private firms that contribute to social security. Processing information of 356,068 different firms, 6'981,549 different workers, 26'241,389 job to job transitions happened, 3'951,374 increases in firms' productivity and 75'462,146 wage rises (1'951,619 after job to job movements), the study finds that a hypothetical firm hiring 10 percent of its workers from 10 percent more productive firms experiences a 0.25 percent productivity gain in the year after hiring (0.13 for small and 0.32 for large firms after discriminating between positive and negative gaps). For larger firms, the analysis shows that the positive gap effect on the recipient firm's productivity doubles after pondering by the percentage of STEM workers in the recipient firms (results go from 0.3 to 0.6), while for smaller firms it remains almost unchanged (0.14 on average). Results also show that when looking only at receiving firms operating in more R&D oriented sectors, the effect of the gap increases (from 0.3 to 0.48) for larger firms, and becomes non-significant for smaller ones. Heterogeneity analysis on whether these effects are different when distinguishing the contribution of hiring workers with different educational levels shows that university graduates are responsible for most of the impact, especially after weighting for STEM workers participation or when focusing on firms operating in R&D oriented sectors.

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Table 1. Studies of technical transfer through labor mobility using employer-employee datasets

Authors and year of publication	Studied country and spell	Sample	Dependent variable	Impact
Abowd et al (2007)	France 1976-1996	1,800	Firm's value added	none
Balsvik (2011)	Norway	2.1 MM workers and 56,5 M firms	Firm's total factor productivity	27%-28%
Braunerhjelm et al (2017)	Sweden 1987-2008	1.1MM firms	Firm's knowledge production (Cobb-Douglas production function of physical capital and human capital)	68%
Maliranta et al (2009)	Finland 1995-2000	1339 firms and 200 M workers	Firm's average productivity (average of value added per person)	Hiring R&D workers from other firms has a positive effect on productivity, when they are hired to non-R&D occupations. On the other hand, no statistically significant effects can be found when workers are hired to R&D occupations, irrespective of the source of these flows.
Parrotta and Pozzoli (2012)	Denmark 1995-2005	682 M firms	Firm's value added	1% - 2%
Poole (2013)				
Serafinelli (2013)	Veneto, Italy 1992-2001	17 M firms	Firm's production (natural logarithm of real value of total firm production).	10%
Stockinger and Wolf (2016)	Germany 2002-2007	1,791 manufacturing establishments	Firm's value added	Inflow from better performers does not exert impact but hiring from non better performer firms improves performance of recipients
Stoyanov and Zubanov (2012)	Denmark 1995-2007	60,000 manufacturing firms	Firm's value added (natural logarithm of value added per worker normalized by the applicable industry-year average)	0.35% per year

Source: Authors' compilation based on cited references.

Table 2. Summary statistics of the Peruvian Payroll Administrative Records

A. Firms Statistics

	2011	2012	2013	2014	2015	2016
Number of firms in January	149,816	165,844	175,330	186,557	194,019	204,502
Number of firms in December	157,675	177,321	186,780	194,541	205,043	210,882
Number of new firms (not observed before the year)	-	40,995	34,383	32,687	35,332	33,681
Number of exiting firms (not observed after the year)	21,354	24,907	24,921	24,831	27,850	-
% of firms with less than 4 workers	58.7	58.8	59.5	60.0	60.7	61.0
% of firms with 4 to 5 workers	13.0	13.1	12.8	12.8	12.5	12.5
% of firms with 6 to 10 workers	12.5	12.5	12.3	12.1	12.0	11.7
% of firms with 11 to 20 workers	7.6	7.6	7.5	7.4	7.3	7.3
% of firms with 21 to 30workers	2.1	2.1	2.1	2.0	2.0	1.9
% of firms with 31 to 50workers	2.0	2.0	1.9	1.9	1.9	1.9
% of firms with 51 to 100 workers	1.8	1.7	1.7	1.7	1.6	1.6
% of firms with more than 100 workers	2.1	2.0	1.9	1.9	1.9	1.8
% of firms with more than 1000 workers	0.2	0.2	0.2	0.2	0.2	0.2
% of workers in Primary sector	4.2	4.2	4.0	3.8	3.6	3.6
% of workers in Secondary sector	24.3	23.9	23.3	22.9	22.6	22.8
% of workers in Tertiary sector	71.4	71.9	72.7	73.3	73.7	73.6
% of firms in R&D intense sectors	4.3	4.2	4.1	4.1	4.1	3.9

B. Workers Statistics

	2011	2012	2013	2014	2015	2016
Number of workers in January	2'329,867	2'527,352	2'691,077	2'828,365	2'907,112	2'980,346
Number of workers in December	2'564,229	2'823,281	2'894,989	2'975,084	3'100,596	3'153,163
Number of new workers (not observed before the year)		813,538	742,482	763,382	812,633	780,659
Number of workers changing firms		436,379	452,991	447,790	467,855	488,199
Number of exiting workers (not observed after the year)	556,392	667,980	683,297	687,125	728,152	-
% of female workers	31.3	32.2	31.3	33.2	33.9	34.6
% of workers younger than 25	20.4	18.0	18.4	17.5	17.2	17.1
% of workers between 26 and 35 years	36.1	26.5	34.2	33.6	33.0	32.4
% of workers between 36 and 50 years	31.0	20.7	31.3	31.4	31.9	32.2
% of workers older than 51	12.5	34.7	16.0	17.6	17.8	18.3
% of workers with less than primary education	2.8	1.9	1.5	1.6	1.4	1.4
% of workers with primary education	5.2	4.6	4.1	4.1	4.2	4.1
% of workers with secondary education	47.3	47.0	47.3	46.2	45.8	46.2
% of workers with tertiary education	44.8	46.5	47.1	48.1	48.6	48.3
% of workers with elemental occupation	25.5	24.6	24.7	24.3	24.2	24.1
% of workers with administrative occupation	20.5	20.3	20.6	21.1	21.2	21.4
% of workers with technical occupation	13.0	13.1	13.3	13.6	13.7	13.7
% of workers with professional occupation	11.7	11.8	11.6	11.7	11.8	11.9
% of workers with managerial occupation	4	5	5	5	5	5
% of workers with craft and trade occupation	9	9	9	8	8	8
% of workers in Primary sector	14	13	12	12	13	13
% of workers in Secondary sector	28	28	27	25	25	24
% of workers in Tertiary sector	58	59	61	62	62	63
% of workers in R&D intense sectors	6	6	6	6	5	5
% of STEM workers	8	8	8	8	8	8
% of STEM workers in manufacturing	6	6	6	6	6	6
% of STEM workers in R&D intense sectors	16	17	16	16	15	16
Average monthly salary (in nominal PEN)	1,719	1,757	1,821	1,806	1,791	1,804
Average monthly salary (in nominal USD)	637	690	651	603	526	552
Average hours worked per week	31	32	32	32	32	32

Source: Authors' computations based on administrative records and supplementary sources as indicated in Section 2.
Notes: Information corresponds to December of the reported year unless otherwise specified. See Appendix 1 for a definition of sector categories, R&D intense sectors, occupational categories and STEM occupations.

Table 3. Average annual intersectoral transition of workers who register a transition to a different firm

Sector T-1 \ Sector T	Agriculture, Forestry, Fishery	Mining	Manufacturing	Construction hotels	Commerce, restaurants,	Financial institutions, insurance, real estate	Other services	Total T-1	Sectoral distribution of transiting workers
Agriculture, Forestry, Fishery	64	1	19	2	5	6	4	150,457	7
Mining	2	44	5	10	5	24	10	66,595	3
Manufacturing	11	1	44	3	15	16	9	280,611	14
Construction	2	6	6	46	5	26	10	139,698	7
Commerce, restaurants, hotels	2	1	10	2	51	21	13	378,964	19
Financial institutions, insurance, real estate	1	3	8	6	13	57	13	598,963	31
Other services	2	2	7	4	14	22	50	329,649	17
Total	151,503	68,679	270,411	138,908	373,001	599,027	343,408	1'944,937	100

Source: Authors' computations based on administrative records.
Notes: Information corresponds to December of the reported year unless otherwise specified. See Appendix 1 for a definition of sector categories occupations.

Table 4. Average annual transition of different type of workers across firms of different productivity

	State T State T-1	Managers	Professionals and Technicians	Administrative Support	Plant worker	Basic occupation
		Less productive firms				
Less productive firms	Managers	18	10	6	3	3
	Professionals and Technicians	1	25	5	2	3
	Administrative Support	1	7	19	3	7
	Plant worker	0	2	2	24	6
	Basic occupation	0	3	4	5	28
Average productive firms	Managers	4	3	2	1	1
	Professionals and Technicians	1	6	2	1	2
	Administrative Support	0	3	4	1	2
	Plant worker	0	1	1	5	3
	Basic occupation	0	1	1	2	5
More productive firms	Managers	4	3	1	0	1
	Professionals and Technicians	1	4	1	1	1
	Administrative Support	0	2	4	1	2
	Plant worker	0	2	1	4	2
	Basic occupation	0	2	1	2	4
	Total (# of workers who move across firms)	10,155	77,208	49,262	62,377	87,216
		Average productive firms				
Less productive firms	Managers	11	15	9	3	4
	Professionals and Technicians	1	27	15	5	5
	Administrative Support	1	11	25	7	7
	Plant worker	0	5	5	34	12
	Basic occupation	0	6	9	15	19
Average productive firms	Managers	23	17	12	5	8
	Professionals and Technicians	2	38	15	8	8
	Administrative Support	1	15	39	8	9
	Plant worker	0	7	7	43	21
	Basic occupation	1	6	6	22	46
More productive firms	Managers	15	11	7	2	3
	Professionals and Technicians	2	22	9	5	5
	Administrative Support	2	11	22	6	6
	Plant worker	0	9	8	26	9
	Basic occupation	1	9	9	14	18
	Total (# of workers who move across firms)	28,100	284,370	274,434	368,316	355,403
		More productive firms				
Less productive firms	Managers	7	5	3	1	1
	Professionals and Technicians	0	5	2	2	1
	Administrative Support	0	3	6	2	1
	Plant worker	0	1	1	4	1
	Basic occupation	0	2	2	3	2
Average productive firms	Managers	10	6	4	1	2
	Professionals and Technicians	1	10	4	2	2
	Administrative Support	1	4	7	2	2
	Plant worker	0	2	1	6	2
	Basic occupation	0	2	2	2	3
More productive firms	Managers	29	13	7	2	3
	Professionals and Technicians	3	31	7	4	4
	Administrative Support	2	11	23	3	4
	Plant worker	1	7	4	23	4
	Basic occupation	2	9	7	7	13
	Total (# of workers who move across firms)	19,553	111,839	79,456	81,293	51,636

Source: Authors' computations based on administrative records.
Notes: Information corresponds to December of the reported year unless otherwise specified. See Appendix 1 for a definition of occupational categories.

Table 5. Receiving firm's productivity and the gap

A. Relative TFP definition

	All firms						Firms with more than 5 workers						Firms with more than 50 workers					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Productivity gap (β)	-0.078	-0.078	-0.078	-0.071	-0.134	-0.066	-0.015	-0.015	-0.017	-0.005	-0.056	-0.116	0.246**	0.246**	0.231**	0.252***	0.346***	0.310***
	(0.092)	(0.092)	(0.092)	(0.090)	(0.114)	(0.118)	(0.109)	(0.109)	(0.110)	(0.108)	(0.127)	(0.184)	(0.098)	(0.098)	(0.096)	(0.097)	(0.083)	(0.116)
Current productivity (α_0)	0.686***	0.686***	0.685***	0.684***	0.656***	0.522***	0.647***	0.647***	0.640***	0.638***	0.602***	0.417***	0.757***	0.757***	0.725***	0.726***	0.666***	0.488***
	(0.047)	(0.047)	(0.047)	(0.047)	(0.056)	(0.077)	(0.061)	(0.061)	(0.061)	(0.061)	(0.071)	(0.088)	(0.043)	(0.043)	(0.043)	(0.043)	(0.038)	(0.059)
Lag productivity (α_1)	0.159***	0.159***	0.159***	0.158***	0.150***	0.462***	0.245***	0.245***	0.242***	0.242***	0.246***	0.593***	0.194***	0.194***	0.186***	0.187***	0.254***	0.451***
	(0.047)	(0.047)	(0.047)	(0.046)	(0.051)	(0.097)	(0.055)	(0.055)	(0.054)	(0.054)	(0.059)	(0.116)	(0.045)	(0.045)	(0.043)	(0.043)	(0.032)	(0.063)
Lag productivity (α_2)	0.048*	0.048*	0.048*	0.046	0.038	0.014	0.013	0.013	0.011	0.010	-0.001	-0.022	0.004	0.004	0.004	0.004	0.001	-0.001
	(0.028)	(0.028)	(0.028)	(0.028)	(0.031)	(0.029)	(0.021)	(0.021)	(0.021)	(0.021)	(0.025)	(0.029)	(0.008)	(0.008)	(0.007)	(0.007)	(0.004)	(0.003)
N	320,419	320,419	320,237	320,237	92,507	101,902	172,519	172,519	172,519	172,519	70,395	65,023	32,410	32,410	32,410	32,410	20,074	13,855
R^2	0.76	0.76	0.76	0.76	0.70	0.74	0.78	0.78	0.78	0.78	0.72	0.74	0.86	0.86	0.86	0.86	0.83	0.84

B. Human Capital definition

	All firms						Firms with more than 5 workers						Firms with more than 50 workers					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
	0.015	0.015	0.013	-0.009	-0.021	0.079**	0.050	0.050	0.042	0.028	-0.025	0.104**	0.202*	0.202*	0.186*	0.210**	0.718**	0.223*
Productivity gap (β)	(0.026)	(0.026)	(0.026)	(0.026)	(0.038)	(0.039)	(0.032)	(0.032)	(0.032)	(0.033)	(0.054)	(0.044)	(0.105)	(0.105)	(0.105)	(0.106)	(0.307)	(0.127)
	0.794***	0.794***	0.795***	0.794***	0.818***	0.799***	0.792***	0.792***	0.795***	0.793***	0.809***	0.832***	0.810***	0.810***	0.814***	0.819***	0.586***	0.904***
Current productivity (α_0)	(0.007)	(0.007)	(0.007)	(0.007)	(0.011)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.017)	(0.013)	(0.025)	(0.025)	(0.025)	(0.025)	(0.120)	(0.048)
	0.082***	0.082***	0.081***	0.080***	0.075***	0.070***	0.080***	0.080***	0.079***	0.078***	0.069***	0.039***	0.123***	0.123***	0.122***	0.122***	0.268***	0.029
Lag productivity (α_1)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.010)	(0.008)	(0.008)	(0.008)	(0.008)	(0.011)	(0.012)	(0.029)	(0.029)	(0.029)	(0.029)	(0.074)	(0.040)
	0.047***	0.047***	0.047***	0.047***	0.038***	0.055***	0.055***	0.055***	0.055***	0.055***	0.040***	0.055***	0.026	0.026	0.030*	0.029*	0.073*	0.030
Lag productivity (α_2)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.009)	(0.007)	(0.017)	(0.017)	(0.018)	(0.018)	(0.042)	(0.021)
N	304,241	304,241	304,241	304,241	131,451	179,307	171,527	171,527	171,527	171,527	48,873	91,550	32,499	32,499	32,499	32,499	2,361	15,590
R^2	0.81	0.81	0.81	0.81	0.66	0.81	0.78	0.78	0.78	0.78	0.52	0.78	0.85	0.85	0.85	0.85	0.73	0.85

Notes: All specifications include industry-year fixed effects. Specification (1) does not control for any other covariate besides those reported in the table; Specification (2) controls for characteristics of firms in addition to covariates included in Specification (1); Specification (3) controls for average characteristics of incumbent workers in addition to covariates included in Specification (2); Specification (4) controls for average characteristics of new workers in addition to covariates included in Specification (3). In addition to Specification (4), Specification (5) considers only a sample of receiving firms with productivity levels above the average productivity observed on its economic sector. In addition to Specification (4), Specification (6) considers only receiving firms that evidence annual growth.
Robust standard errors in parentheses are clustered at the firm level. The time period covered is 2011-2016.
*** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level

Table 6: Receiving firm's productivity and the gap calculated separately for more and less productive sending firms

A. Relative TFP definition

	Unweighted for all types of firms					Weighted by % of STEM workers in recipient firm					For recipient firms in R&D sectors				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Positive productivity gap (βp)	0.155***	0.132***	0.320**	0.052	0.315**	0.188**	0.158*	0.613***	0.092	0.606***	0.119	0.105	0.480*	0.199*	0.445*
	(0.032)	(0.031)	(0.131)	(0.032)	(0.132)	(0.087)	(0.081)	(0.212)	(0.076)	(0.214)	(0.117)	(0.120)	(0.253)	(0.120)	(0.240)
Negative productivity gap (βn)	-0.258*	-0.267*	0.208	-0.131	0.209	-0.988	-1.130	0.172	-0.976	0.188	-0.033	-0.043	0.252**	-0.126	0.219*
	(0.145)	(0.150)	(0.144)	(0.118)	(0.146)	(0.750)	(0.839)	(0.142)	(0.812)	(0.143)	(0.078)	(0.080)	(0.121)	(0.101)	(0.121)
		Small firms (N <=49)	Large firms (N>=50)	Positive hiring (N <=49)	(N>=50)		Small firms (N <=49)	Large firms (N>=50)	Positive hiring (N <=49)	(N>=50)		Small firms (N <=49)	Large firms (N>=50)	Positive hiring (N <=49)	(N>=50)
N	320,145	287,735	32,410	61,629	31,689	38,403	25,627	12,776	12,410	12,494	95,701	65,837	29,864	28,253	29,277
R^2	0.76	0.75	0.86	0.79	0.86	0.63	0.59	0.88	0.72	0.88	0.817	0.800	0.866	0.674	0.868

B. Human Capital definition

	Unweighted for all types of firms					Weighted by % of STEM workers in recipient firm					For recipient firms in R&D sectors				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Positive productivity gap (βp)	-0.015	-0.022	0.521***	0.048	0.520***	0.257**	0.234*	0.663***	0.162	0.654***	0.003	-0.006	0.405	0.067	0.397
	(0.049)	(0.050)	(0.174)	(0.054)	(0.176)	(0.113)	(0.122)	(0.213)	(0.115)	(0.213)	(0.065)	(0.064)	(0.260)	(0.069)	(0.258)
Negative productivity gap (βn)	0.002	-0.003	0.138	-0.078*	0.128	-0.857	-0.963	0.135	-0.748	0.145	0.030	0.016	0.354***	-0.066	0.348***
	(0.033)	(0.033)	(0.143)	(0.040)	(0.146)	(0.588)	(0.633)	(0.163)	(0.538)	(0.165)	(0.047)	(0.048)	(0.104)	(0.056)	(0.106)
		Small firms (N <=49)	Large firms (N>=50)	Positive hiring (N <=49)	(N>=50)		Small firms (N <=49)	Large firms (N>=50)	Positive hiring (N <=49)	(N>=50)		Small firms (N <=49)	Large firms (N>=50)	Positive hiring (N <=49)	(N>=50)
N	304,241	271,742	32,499	60,852	31,774	40,666	33,982	6,684	10,900	6,574	110,896	95,853	15,043	25,989	14,791
R^2	0.81	0.80	0.85	0.71	0.85	0.74	0.73	0.89	0.77	0.89	0.81	0.79	0.87	0.69	0.87

Notes: All specifications include industry-year fixed effects, characteristics of receiving firm (X), and firm-average characteristics of new and incumbent workers (Y1 and Y2) as additional controls. A sample of firms with less than or equal to 49 workers are considered in Specification (2). Likewise, Specification (3) considers firms with more than or equal to 50 workers. Specification (4) and (5) replicate Specification (2) and (3), respectively, on the sample of receiving firms that hire new workers,
Robust standard errors in parentheses are clustered at the firm level. The time period covered is 2011-2016.
*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level

Table 7: Receiving firm's productivity and the gap calculated for same and different industries (firms with more than 50 workers)

A. Relative TFP definition

	Unweighted for all types of firms						Weighted by % of STEM workers in recipient firm						For recipient firms in R&D sectors					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Productivity gap, same industry (β)	0.046		0.013		-0.105		0.257		0.222		0.445		0.285		0.207		0.791**	
	(0.518)		(0.203)		(0.401)		(0.252)		(0.248)		(0.360)		(0.261)		(0.299)		(0.376)	
Productivity gap, different industry (β)	0.280***		0.368***		0.338***		0.320***		0.360***		0.442***		0.426***		0.472***		0.521***	
	(0.077)		(0.085)		(0.116)		(0.106)		(0.114)		(0.149)		(0.099)		(0.100)		(0.158)	
Positive productivity gap, same industry (βp)		-0.084		-0.348		-0.007		0.275		0.232		0.671		0.403		0.503		0.816
		(0.259)		(0.370)		(0.334)		(0.491)		(0.643)		(0.700)		(0.382)		(0.491)		(0.536)
Positive productivity gap, different industry (βp)		0.334**		0.408***		0.514***		0.473***		0.500***		0.612***		0.510***		0.556***		0.660***
		(0.133)		(0.145)		(0.174)		(0.175)		(0.182)		(0.213)		(0.166)		(0.163)		(0.216)
Negative productivity gap, same industry (βn)		0.129		0.062		-0.709		0.280		0.229		0.092		0.078		-0.041		0.345
		(0.654)		(0.257)		(0.850)		(0.268)		(0.238)		(0.521)		(0.319)		(0.336)		(0.547)
Negative productivity gap, different industry (βn)		0.220***		0.295***		0.036		0.145		0.165		0.176		0.254**		0.283***		0.128
		(0.085)		(0.086)		(0.154)		(0.113)		(0.116)		(0.142)		(0.103)		(0.105)		(0.165)
N	32,410	32,410	20,074	20,074	13,855	13,855	29,778	29,778	19,245	19,245	12,776	12,776	14,994	14,994	11,603	11,603	6,684	6,684
R^2	0.86	0.86	0.83	0.83	0.84	0.84	0.87	0.86	0.84	0.84	0.88	0.88	0.88	0.88	0.86	0.86	0.89	0.89

Notes: All specifications include industry-year fixed effects, characteristics of receiving firm (X), and firm-average characteristics of new and incumbent workers (Y1 and Y2) as additional controls. Specifications (3) and (4) consider only a sample of receiving firms with productivity levels above the average productivity observed on its economic sector. Specifications (5) and (6) consider only receiving firms that evidence annual growth. Robust standard errors in parentheses are clustered at the firm level. The time period covered is 2011-2016. Firms are considered to be in the same industry if they have the same 2-digit CIIU industry code.
*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level

B. Human Capital definition

	Unweighted for all types of firms						Weighted by % of STEM workers in recipient firm						For recipient firms in R&D sectors					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Productivity gap, same industry (β)	-0.260		0.413		0.102		-0.456		0.508		0.159		-0.112		-0.556		-0.218	
	(0.215)		(0.595)		(0.202)		(0.357)		(0.712)		(0.402)		(0.285)		(0.752)		(0.463)	
Productivity gap, different industry (β)	0.344**		0.736***		0.285*		0.410***		1.429***		0.284		0.449***		0.677***		0.217	
	(0.135)		(0.254)		(0.161)		(0.120)		(0.330)		(0.223)		(0.118)		(0.217)		(0.200)	
Positive productivity gap, same industry (βp)		0.529**		0.627		0.413*		0.483		2.673		0.627		0.201		-18.874***		0.068
		(0.206)		(2.622)		(0.227)		(0.414)		(2.671)		(0.451)		(0.455)		(3.029)		(0.505)
Positive productivity gap, different industry (βp)		0.527**		0.884		0.363		0.488*		4.063		0.496		0.434		1.674		0.402
		(0.206)		(1.564)		(0.226)		(0.283)		(2.734)		(0.304)		(0.291)		(1.613)		(0.277)
Negative productivity gap, same industry (βn)		-0.739**		-0.335		0.148		-0.691		-0.592		0.621		-0.062		0.039		0.354
		(0.375)		(0.584)		(0.582)		(0.490)		(0.624)		(0.992)		(0.397)		(0.462)		(1.151)
Negative productivity gap, different industry (βn)		0.267		-0.229		0.334*		0.365***		0.855**		0.163		0.433***		0.448		0.179
		(0.174)		(0.447)		(0.181)		(0.115)		(0.342)		(0.241)		(0.114)		(0.283)		(0.231)
N	32,499	32,499	2,361	2,361	15,590	15,590	29,864	29,864	2,228	2,228	14,165	14,165	15,043	15,043	1,135	1,135	6,987	6,987
R^2	0.85	0.85	0.73	0.70	0.85	0.85	0.87	0.87	0.73	0.70	0.86	0.86	0.87	0.87	0.83	0.83	0.88	0.88

Notes: All specifications include industry-year fixed effects, characteristics of receiving firm (X), and firm-average characteristics of new and incumbent workers (Y1 and Y2) as additional controls. Specifications (3) and (4) consider only a sample of receiving firms with productivity levels above the average productivity observed on its economic sector. Specifications (5) and (6) consider only receiving firms that evidence annual growth. Robust standard errors in parentheses are clustered at the firm level. The time period covered is 2011-2016. Firms are considered to be in the same industry if they have the same 2-digit CIIU industry code.
*** Significant at the 1 percent level,** Significant at the 5 percent level,* Significant at the 10 percent level

Table 8: Receiving firm's productivity and the gap by new workers' education level (firms with more than 50 workers)

A. Relative TFP definition

	Unweighted for all types of firms						Weighted by % of STEM workers in recipient firm						For recipient firms in R&D sectors					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Productivity gap, high school (β)	0.290**		0.424***		0.459**		0.549**		0.664**		0.746**		0.560***		0.685***		0.910***	
	(0.134)		(0.162)		(0.200)		(0.275)		(0.330)		(0.313)		(0.191)		(0.212)		(0.298)	
Productivity gap, college (β)	0.009		0.034		-0.011		-0.041		-0.145		0.115		0.221		0.172		0.386	
	(0.221)		(0.241)		(0.231)		(0.480)		(0.554)		(0.220)		(0.288)		(0.317)		(0.259)	
Productivity gap, university (β)	0.374**		0.470***		0.412*		0.239		0.300		0.443*		0.380**		0.395**		0.370	
	(0.153)		(0.140)		(0.214)		(0.227)		(0.225)		(0.231)		(0.184)		(0.180)		(0.236)	
Positive productivity gap, high school (βp)		0.064		0.172		0.278		0.299		0.371		0.470		0.613**		0.743***		0.883**
		(0.166)		(0.211)		(0.199)		(0.319)		(0.370)		(0.405)		(0.271)		(0.284)		(0.373)
Positive productivity gap, college (βp)		0.015		0.003		0.036		0.221		0.158		0.242		0.176		0.204		0.495
		(0.163)		(0.187)		(0.247)		(0.264)		(0.264)		(0.322)		(0.242)		(0.256)		(0.341)
Positive productivity gap, university (βp)		0.789***		0.802***		0.972***		0.701***		0.708***		0.847***		0.598***		0.587***		0.593**
		(0.176)		(0.177)		(0.233)		(0.238)		(0.243)		(0.259)		(0.190)		(0.190)		(0.255)
Negative productivity gap, high school (βn)		0.365**		0.459***		0.239		0.507*		0.569**		0.496*		0.408**		0.483**		0.344
		(0.167)		(0.148)		(0.253)		(0.267)		(0.287)		(0.258)		(0.189)		(0.198)		(0.254)
Negative productivity gap, college (βn)		-0.039		0.052		0.308		-0.097		-0.179		0.356		0.255		0.223		0.420
		(0.315)		(0.328)		(0.289)		(0.595)		(0.645)		(0.218)		(0.368)		(0.395)		(0.293)
Negative productivity gap, university (βn)		-0.147		0.004		-1.255***		-0.511		-0.407		-0.881**		-0.385		-0.346		-0.694*
		(0.233)		(0.238)		(0.430)		(0.325)		(0.332)		(0.356)		(0.338)		(0.337)		(0.394)
N	32,410	32,410	20,074	20,074	9,415	13,855	29,778	29,778	19,245	19,245	8,978	12,776	14,994	14,994	11,603	11,603	5,464	6,684
R^2	0.86	0.86	0.83	0.83	0.81	0.84	0.87	0.87	0.84	0.84	0.87	0.88	0.88	0.88	0.86	0.86	0.87	0.89

Notes: All specifications include industry-year fixed effects, characteristics of receiving firm (X), and firm-average characteristics of new and incumbent workers (Y1 and Y2) as additional controls. Specifications (3) and (4) consider only a sample of receiving firms with productivity levels above the average productivity observed on its economic sector. Specifications (5) and (6) consider only a sample of receiving firms that evidence annual growth. Robust standard errors in parentheses are clustered at the firm level.The time period covered is 2011-2016. *** Significant at the 1 percent level,** Significant at the 5 percent level,* Significant at the 10 percent level

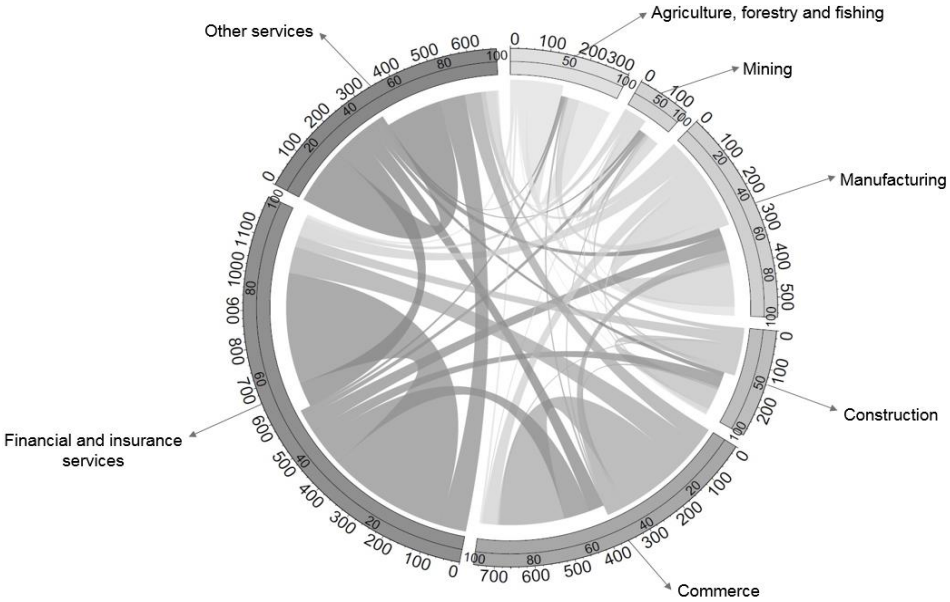
B. Human Capital definition

Productivity: Human Capital	**Unweighted for all types of firms**						**Weighted by % of STEM workers in recipient firm**						**For recipient firms in R&D sectors**					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Productivity gap, high school (β)	0.152		0.331		0.957		0.398**		1.715**		1.406*		0.366**		0.676		0.485	
	(0.163)		(0.459)		(0.638)		(0.165)		(0.749)		(0.841)		(0.155)		(0.829)		(0.938)	
Productivity gap, college (β)	0.386*		1.230**		1.709**		-0.030		1.470**		2.074**		0.242		0.085		0.096	
	(0.200)		(0.593)		(0.855)		(0.351)		(0.563)		(0.853)		(0.246)		(0.651)		(1.213)	
Productivity gap, university (β)	0.401		1.994***		1.574		0.438		2.612***		2.303**		0.659**		2.517**		3.682**	
	(0.259)		(0.754)		(0.987)		(0.381)		(0.834)		(1.108)		(0.274)		(1.107)		(1.491)	
Positive productivity gap, high school (βp)		0.718***		2.716		0.561**		0.772**		4.064*		0.600*		0.533		3.533**		0.262
		(0.233)		(1.659)		(0.261)		(0.349)		(2.061)		(0.340)		(0.377)		(1.654)		(0.293)
Positive productivity gap, college (βp)		-0.167		2.966		-0.182		0.019		6.450*		0.244		0.082		4.102		0.227
		(0.336)		(2.573)		(0.315)		(0.519)		(3.377)		(0.532)		(0.483)		(4.443)		(0.473)
Positive productivity gap, university (βp)		0.393		3.671		0.151		0.489		3.323		0.514		0.598		2.420		0.782*
		(0.468)		(2.537)		(0.482)		(0.580)		(4.594)		(0.611)		(0.516)		(4.544)		(0.470)
Negative productivity gap, high school (βn)		-0.070		-0.988***		0.006		0.275		0.088		-0.134		0.306*		-0.141		-0.045
		(0.219)		(0.191)		(0.240)		(0.207)		(0.518)		(0.315)		(0.164)		(0.744)		(0.305)
Negative productivity gap, college (βn)		0.759***		1.181**		0.781**		0.092		0.794		0.766		0.360		-0.002		0.377
		(0.279)		(0.474)		(0.360)		(0.416)		(0.563)		(0.588)		(0.320)		(0.677)		(0.452)
Negative productivity gap, university (βn)		0.688***		1.064***		0.468		0.517		1.065***		-0.245		0.685**		1.131**		0.521
		(0.266)		(0.356)		(0.558)		(0.412)		(0.384)		(0.566)		(0.294)		(0.458)		(0.739)
N	32,499	32,499	2,361	2,361	1,176	15,590	29,864	29,864	2,228	2,228	1,121	14,165	15,043	15,043	1,135	1,135	543	6,987
R^2	0.85	0.85	0.73	0.72	0.72	0.85	0.87	0.87	0.73	0.70	0.77	0.86	0.87	0.87	0.83	0.83	0.85	0.88

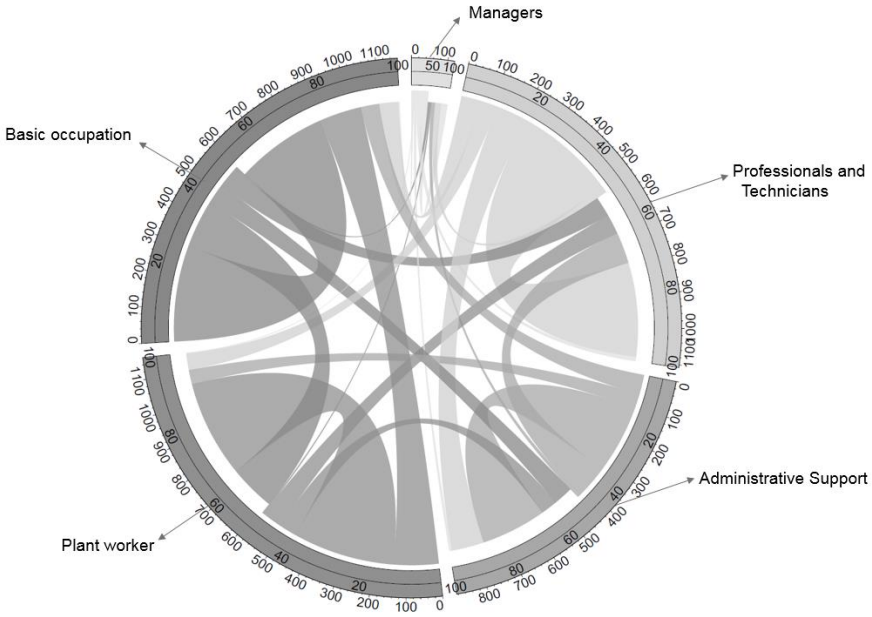
Notes: All specifications include industry-year fixed effects, characteristics of receiving firm (X), and firm-average characteristics of new and incumbent workers (Y1 and Y2) as additional controls. Specifications (3) and (4) consider only a sample of receiving firms with productivity levels above the average productivity observed on its economic sector. Specifications (5) and (6) consider only a sample of receiving firms that evidence annual growth. Robust standard errors in parentheses are clustered at the firm level. The time period covered is 2011-2016. *** Significant at the 1 percent level,** Significant at the 5 percent level,* Significant at the 10 percent level

Figure 1. Workers' transitions across firms

A. By economic sector of the firm



B. By worker's occupation



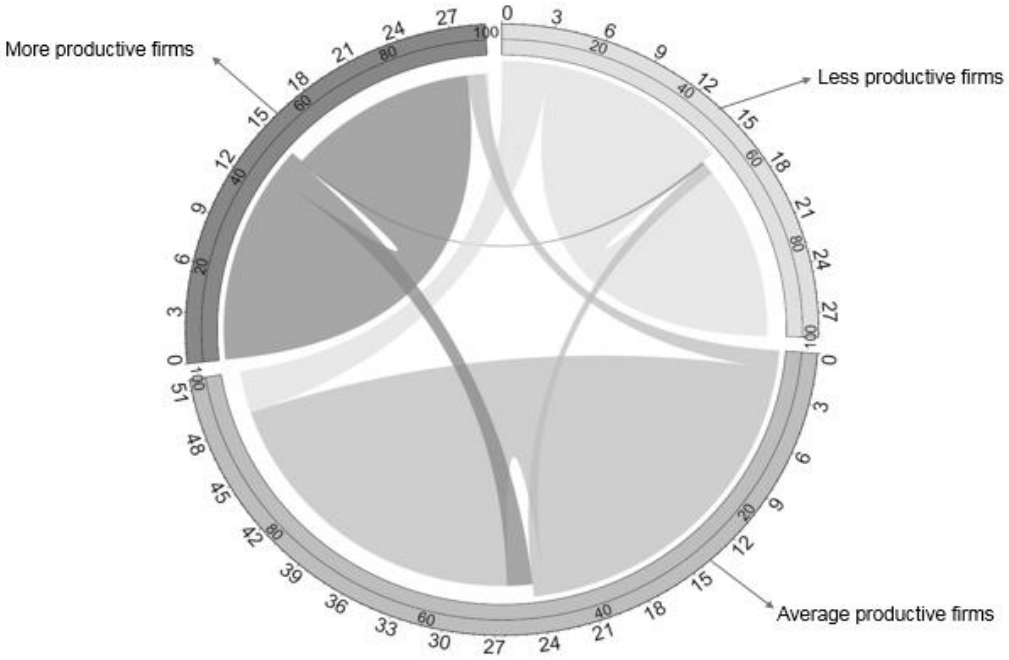
Source: Authors' computations based on administrative records.

Notes: Figures report workers transitions according to the firms' economic sector or according to the workers' occupations at origin and destination. The figures depict about 2 million yearly job to job transitions observed at December of each of the years under analysis (notice that the figure depicts simultaneously points of origin and destination and therefore for each transition there are two points identified in the circle). Each line represents the mass of workers who have changed jobs and are flowing from one sector/occupation to another. The sector/occupation of origin of the transition is determined by the extreme of the line closer to the outer circle. The outer circle shows the aggregate number of job to job transitions (in thousands) registered per sector/occupation during the last month of the five years under study.

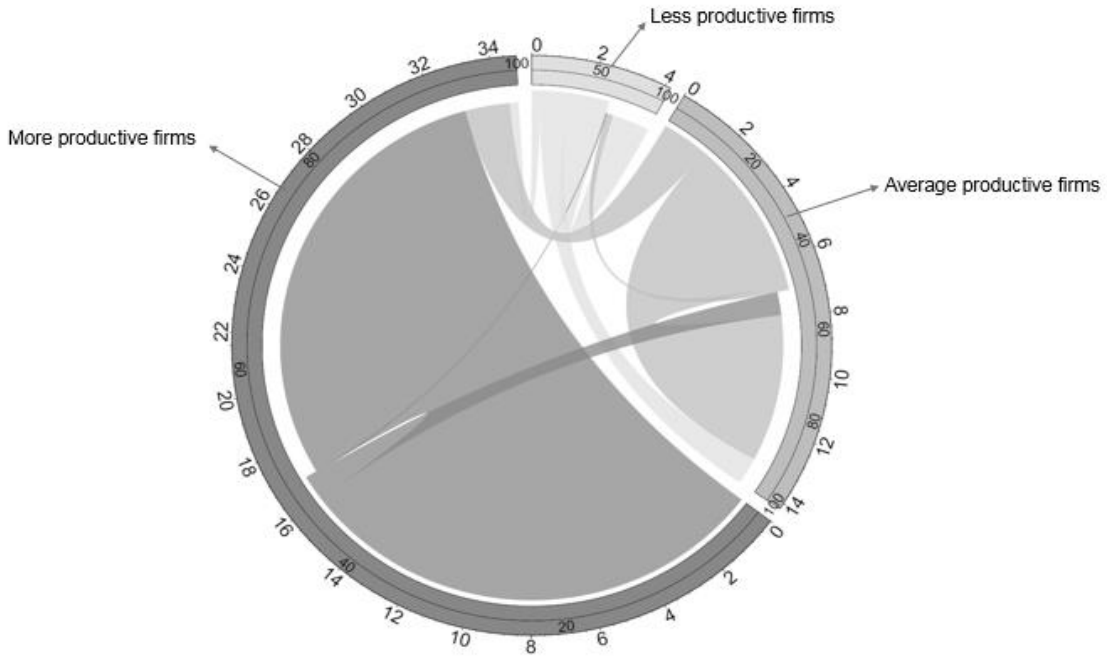
Figure 2. Firms' transitions

A. Hiring from less productive firms

B. Hiring from equally productive firms



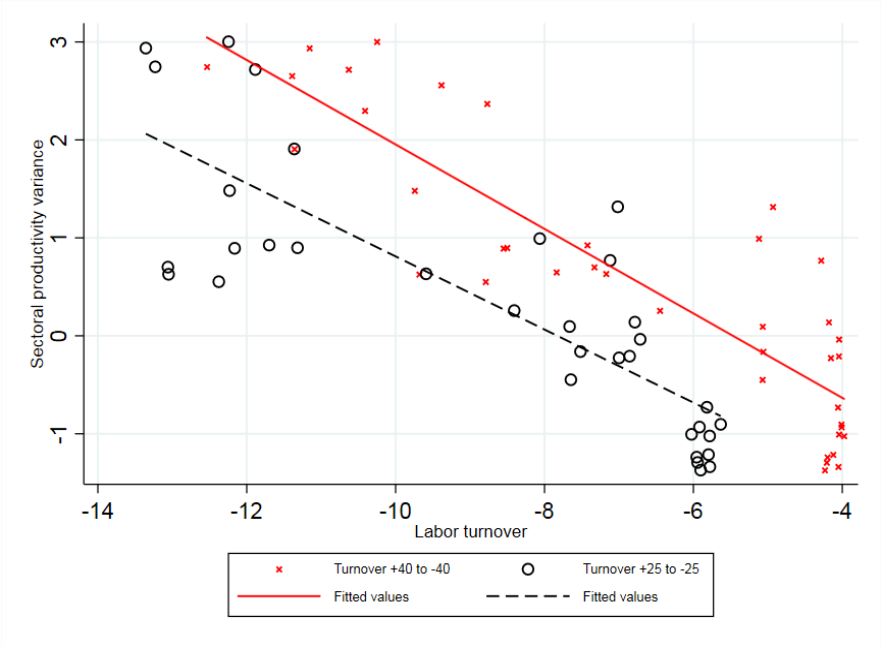
C. Hiring from equally productive firms



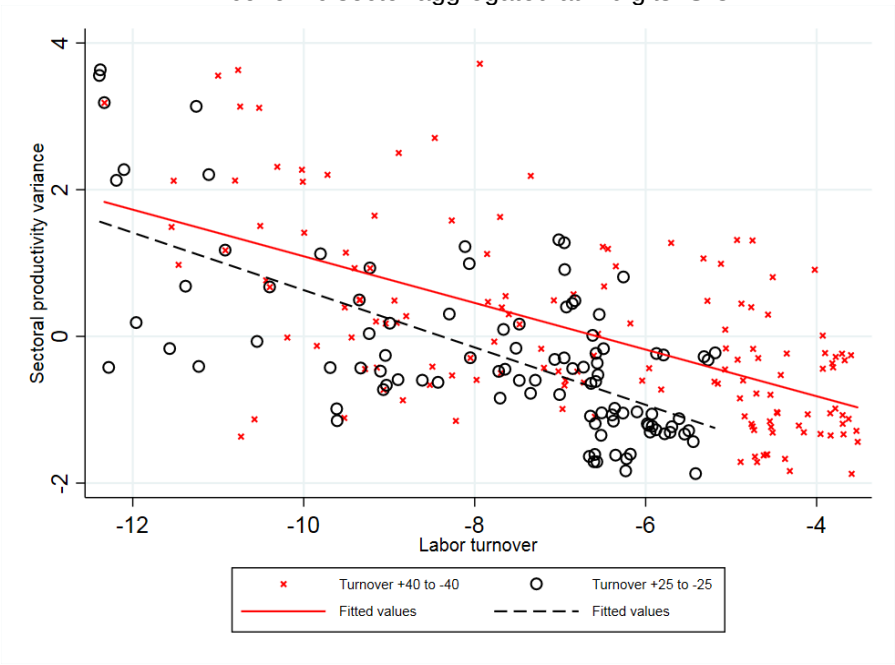
Source: Authors' computations based on administrative records.
Notes: Figures report firms' transitions according to the firms' productivity group. The firms' productivity groups are computed each December sorting firms according to approximate TFPs, deduced by applying sector output elasticities as described in the Section 2 and in Appendix 2. Firms are identified twice, at the first December they show up in the dataset and in the last one. In all Decembers between the first one and the last one in which the firm shows up (including also the first and last points), annual transitions of incoming workers are tracked. All of these workers' transitions are aggregated and sorted according to the productivity group of the sender firm. The receiving firm is considered in one of the three groups (hiring from more/equal/less productive firm) according to the dominant productivity group from which the workers hired by the receiving firm are coming the most. Each line represents the mass of firms that are flowing from one productivity group to another, given that its hires are dominantly coming from either less/equally or more productive firms. The productivity group of origin of the receiving firm is determined by the extreme of the line closer to the outer circle. The outer circle shows the aggregate number of annual firms' transitions (in thousands) registered during the last month of the five years under study.

Figure 3. Labor turnover and Variance of productivity proxies

Economic sector aggregated at 1 digit ISIC



Economic sector aggregated at 2 digits ISIC



Appendix 1

Definition of Variables

Industry categories

- Same industry: Encompasses workers whose sending and receiving firms have equal 2-digit CIIU industry code.

- Different industry: Encompasses workers whose sending and receiving firms have different 2-digit CIIU industry code.

Educational categories

- High school: Includes workers who have completed secondary education and who have not obtained any higher degree.

- College: Includes workers that completed non-university higher education and who have not obtained any further degree. Comprises workers who have concluded colleges and/or technical schools.

- University: Includes workers that completed university higher education at the bachelor level, and who have not obtained any further degree. Excludes workers that obtained postgraduate degrees.

Occupational categories

- Managers: As defined by ISCO 08, “managers plan, direct, coordinate and evaluate the overall activities of enterprises and/or the organizational units within them”.

- Professionals: “increase the existing stock of knowledge; apply scientific or artistic concepts and theories; teach about the foregoing in a systematic manner”.

- Technicians and Associate Professionals: “perform technical and related tasks connected with research and the application of scientific or artistic concepts and operational methods, and/or business regulations”.

- Craft and related Trades Workers: “apply specific technical and practical knowledge and skill to construct and maintain buildings; form metal; erect metal structures; set machine tool or make, fit, maintain and repair machinery, equipment or tools; carry out printing work; and produce or process foodstuffs; textiles and wooden, metal and other articles, including handicraft goods”.

- Administrative Support Workers: “record, organize, store, compute and retrieve information. They also perform a number of clerical duties in connection with money-handling operations”.

- Elementary Occupations: “involve the performance of simple and routine tasks which may require the use of hand-held tools and considerable physical effort”.

- Science, Technology, Engineering and Mathematics (STEM): As defined by the United States Bureau of Labor Statistics, “includes professional and technical support occupations in the fields of computer science and mathematics, engineering, and life and physical sciences”.

Appendix 2

Proxy of productivity using sectoral output elasticities

Following conventional practice, output elasticities of labor and capital can be expressed as expenditure shares after solving the unconstrained producer optimization problem with a Cobb-Douglas production function:

$$Max\ \pi = pY - wL - rK \text{ , where } Y = AK^{\alpha}L^{\beta}$$

$$\frac{\partial Y}{\partial L} = \frac{w}{p} = \beta AK^{\alpha}L^{\beta-1}\ ;\ \frac{\partial Y}{\partial K} = \frac{r}{p} = \alpha AK^{\alpha-1}L^{\beta}$$

$$\frac{wL}{pY} = \beta;\ \frac{rK}{pY} = \alpha$$

In addition, by comparing the output of each firm to the aggregate output of its corresponding industry, an expression for the TFP of a specific firm relative to the aggregate TFP of its corresponding industry can be derived as:

$$\frac{Y_i}{Y} = \frac{A_i}{A}\frac{K_i^{\alpha}}{K^{\alpha}}\frac{L_i^{\beta}}{L^{\beta}}$$

$$\frac{A_i}{A} = \frac{Y_i}{Y}\left(\frac{K}{K_i}\right)^{\alpha}\left(\frac{L}{L_i}\right)^{\beta}$$

From industry data, we have α and β for 9 industries[22] (see Céspedes et al 2016). Given that $\beta = wL/pY$ and assuming the same production function for each firm i then we can estimate $Y_i = (wL)_i/p\beta$ and summing up for each firm, we obtain Y and Y/Yi (notice that even β and p differ across industries, their effect is neutral on the ratio of interest within a same industry). Given that L/L_i is known, the missing term is K/K_i which can be estimated using the fact that $\alpha = \frac{rK}{pY} = \frac{r_iK_i}{pY_i}$. Hence $\frac{K_i}{K} = \frac{rY_i}{r_iY}$, which is computable under some assumption for r/r_i [23]

[22] Agriculture, Fishing, Mining, Construction, Manufacturing, Commerce, Public Utilities, Finance and Insurance Services, Other Services.

[23] We assume that all firms within a sector face similar relative input prices ($r_i/w_i = r/w$), hence $r/r_i = w/w_i$, where w_i is the average cost of a unit of labor in firm i and w is the average cost of a unit of labor in the industry