Educational Diversity and Knowledge Transfers via Inter-Firm Labor Mobility

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Abstract

This article contributes to the literature on knowledge transfer via labor mobility by providing new evidence regarding the role of educational diversity in knowledge transfer. In tracing worker flows between firms in Denmark over the period 1995-2005, we find that knowledge carried by workers who have been previously exposed to educationally diverse workforces significantly increases the productivity of hiring firms. Several extensions of our baseline specification support this finding and show that insignificant effects are associated with the prior exposure of newly hired employees to either demographic or culturally diverse workplaces.

JEL Classification: J24, J60, L20.

Keywords: Educational diversity, knowledge transfer, inter-firm labor mobility, firm productivity.

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1 Introduction

Worker flows are closely connected to firm outcomes, reflecting the contributions to firm productivity of both incoming workers human capital and the knowledge that they carry over from previous workplaces. Therefore, inter-firm worker movement provides insight into how inter-firm knowledge transfer typically occurs. However, although economists have long discussed and relied on the notion of inter-firm transmission of knowledge as a means to explain growth (Romer 1990; Grossman and Helpman 1991), they have devoted less attention to the mechanisms governing these knowledge spillovers. Up until now, no study has, for example, investigated how knowledge transfers are linked via labor mobility to the previous exposure of mobile workers to educationally heterogeneous workforces.

When workers move from one firm (the sending or departure firm) to another (the receiving or arrival firm), they carry with them knowledge that they have obtained both from their work and from their interactions with co-workers at their previous workplaces. Thus, through inter-firm labor mobility, an enterprise may gain access to the knowledge pool to which incoming workers have been exposed in past work environments. This knowledge pool arises partly from learning-by-using or learning-by-doing activities. It also arises from the interpersonal exchanges between co-workers.

Since Marshall (1890), the firm environment has been viewed as a main locus in which social interactions favor the sharing and transfer of knowledge (Moretti, 2004). The likelihood and frequency of social interactions in workplaces induces employees to share what they know and use what they learn in addressing both simple and complex problems. Although the magnitude of such knowledge transfer is highly context specific and is strongly related to the heterogeneity of the actors involved, co-worker interactions rarely occur without some form of knowledge sharing and exchange.

Researchers have recently examined the contribution of labor heterogeneity to firm productivity by considering the direct relationship between these variables without evaluating the possible influence of the workforce composition of the departure firm. Among other studies at the firm level (e.g., Leonard and Levine, 2006; Iranzo et al., 2008), Parrotta et al. (2014a) investigate the existence and magnitude of this direct relationship. The study findings provide descriptive evidence of the positive relationship between educational diversity and firm productivity. This evidence is consistent with the theoretical predictions of Lazear (1999), who argues that labor diversity in terms of educational background is productivity enhancing if one worker's information set is relevant to and does not overlap with another's. However, the same study finds that ethnic and demographic heterogeneity generally does not positively correlate with productivity, suggesting that the negative effects of the communication and integration costs associated with a more demographically and culturally diverse workforce counteract the positive effects of diversity that arise from enhanced creativity and knowledge spillover (Lazear, 1999; Glaeser et al., 2000; and Alesina and La Ferrara, 2005).

Based on the findings of Parrotta et al. (2014a), we expect to observe that, with all other things being equal, a more heterogeneous departure firm's educational pool results in a more likely knowledge transfer from the departure firm to the arrival firm to occur through labor mobility. Thus, interactions with co-workers who have heterogeneous knowledge due to their different educational backgrounds may create the opportunity for new combinations of knowledge and skill complementarities and may promote learning opportunities that can eventually be transferred to firms through labor mobility. This finding would provide evidence that workers in more heterogeneous workplaces can access a valuable part of a firm's knowledge pool and carry it with them when they change employers.[1]

Labor flows between firm pairs are a conventional proxy for knowledge transfers. Earlier studies have traced the movement of specific categories of workers, such as engineers, scientists and technical personnel, and have focused on labor mobility as producing knowledge transfer from foreign-owned (Balsvik, 2011; Poole, 2012), R&D-intensive (Moen, 2005), patenting (Kim and Marschke, 2005) or more productive (Stoyanov and Zubanov, 2012) firms, all of which enjoy clear competitive advantage. Nevertheless, Parrotta and Pozzoli (2012) provide evidence that labor mobility is a potential channel for knowledge spillover within a broader set of firms in both the manufacturing and the service sector, introducing a deeper and more generalized process of learning-by-hiring into the economy. As a result, the advanced knowledge embedded in specific categories of firms seems to reflect only part of the phenomenon of inter-firm knowledge transfer. This gives us reason to view workers as the actual carriers of knowledge, who induce productivity improvements across firms.

Although Parrotta and Pozzoli (2012) provide critical details regarding the general knowledge transmission mechanism, they do not explore how differences in co-worker profiles in previous workplaces may encourage knowledge transmission. To examine the latter is our main goal in this paper. Specifically, we investigate whether and to what extent past workforce diversity in education affects arrival firm productivity. In addition, we test whether diversity of ethnicity and the demographics of departure firms play a role in the knowledge transfer mechanism.

It is worth underlining that the effect of knowledge transfer originating from the exposure to educationally diverse workforce may not be confused with any unobservable preference characteristic of movers, like 'ability to work with different people' or 'attitudes towards exerting effort', because in our estimation strategy we take into account (i) the level of educational diversity of the arrival firm, and (ii) the contribution of labor input to firm productivity. Moreover, a battery of tests provides evidence that knowledge carried by who

[1] This knowledge transfer is also a key factor in starting a new business. Indeed, Marino et al. (2012) find that educational diversity promotes entrepreneurial behavior (transitions from employment to self-employment) among employees.

have been previously exposed to educationally diverse workforces significantly increases the productivity of hiring firms independently of the mobile workers' characteristics, which could eventually be correlated with the unobservable preferences above mentioned.

Furthermore, we also provide evidence that the knowledge transfer in object occurs independently of whether the departure firm is innovative, belongs to a R&D intense industry, exports, is (at least partly) foreign owned, presents a share of tertiary educated workers above the industrial median, or is more productive than the arrival firm.

In treating the average departure firm's educational diversity as a production input that is selected by the firm, we follow Ackerberg et al. (2006). The main advantage of this approach is that it allows us to overcome potential issues of endogeneity and collinearity by allowing firms to observe productivity shocks before hiring knowledge carriers. Addressing potential endogeneity problems in this fashion is of fundamental importance for the empirical analysis, which otherwise might suffer from severe bias related to the key parameters of interest.

Our findings suggest that knowledge transfers are productivity enhancing when they originate from educationally diversified departure firm workforces. On average, a one-standard-deviation increase in such knowledge transmission increases arrival firm productivity by approximately 1 percent. A larger effect is estimated when we consider only hires with managerial competencies, tertiary education and a longer tenure within their departure firms. Larger effects are also estimated for employees who receive a wage increase after moving and for employees who do not switch jobs for family reasons. By contrast, unsurprisingly, no significant effects are associated with the ethnic and demographic diversity of previous workplaces.

The structure of the remainder of this paper is as follows. Section 2 briefly describes the data and provides information on the main variables of interest, as well as the descriptive statistics. Section 3 explains in detail the empirical strategy that we have implemented. Section 4 explains the results of our empirical analysis, and section 5 offers concluding remarks.

2 Data

2.1 Data sources

We use two different Danish register data sets that can be linked to each other thanks to their common firm identifiers. Both data sources are administered by Statistics Denmark, and together, they provide data for the time period 1995-2005.

The master data set is the "Integrated Database for Labor Market Research" (henceforth IDA) database, a longitudinal employer-employee register that contains valuable information (regarding age, demographic characteristics, education, labor market experience, earnings, place of work and residence) for each individual employed in the recorded population of Danish firms during the period 1980-2005. Apart from deaths and permanent migration, IDA does not present any further attrition in its records. The listed labor market status of each individual is as of the end of November of each year. In our final data set, we include individuals (i) who are 18 to 60 years old, (ii) who have stable occupations (i.e., students, trainees and part-time employees are disregarded), (iii) who have positive labor income and (iv) who belong to neither the top nor the bottom percentile of the earning distribution. In addition, transitions that may have resulted from mergers or acquisitions, i.e., transitions in which more than half of an enterprise's workforce moves to the same arrival firm, are excluded from the final data set.

The retrieved information is then aggregated at the firm level to obtain data regarding firm size, workforce composition (i.e., average firm tenure and the shares of managers, middle managers, males, highly skilled workers, technicians, and employees who belong to each age distribution quintile), labor diversity,[2] partial/total foreign ownership and whether the firm includes more than one establishment (plant).

The second data source provides information about the firms' business accounts (henceforth REGNSKAB).[3] This source covers the construction and manufacturing industries from 1995 onward, wholesale trade from 1998 onward and the remaining part of the service industry from 1999 onward. From REGNSKAB, the following accounting items are retrieved to estimate the production function: value added,[4] materials (intermediate goods), capital (fixed assets) and related industry.[5] All of the companies in the final sample that was used in the empirical analysis have at least 10 employees and are not in the public sector. Furthermore, all of the firms with imputed accounting variables are excluded from the analysis.

The key features of the sources used to construct our final data set are that they provide extensive data regarding employees and firms and that it is possible to match the records from the two sources. Both features make the data set especially suitable for our purposes, as they enable us to examine moving workers for each year, along with their departure and arrival firms.

[2] The next subsection provides a detailed description of how labor diversity is calculated.

[3] Firm-level statistics have been gathered in several ways. All firms with more than 50 employees or profits above a given threshold have been surveyed directly. Other firms are recorded based on a stratified sample strategy. The surveyed firms can choose whether to submit their annual accounts and other specifications or whether to fill out a questionnaire. To facilitate responses, questions are formulated as they are formulated in the Danish annual accounts legislation.

[4] Computed as the difference between total sales and the costs of intermediate goods.

[5] The following sectors are excluded from the empirical analysis: i) agriculture, fishing and quarrying; ii) electricity, gas and water supply and iii) public services.

2.2 Variables

This section mainly describes our measures of inter-firm knowledge transfer via worker mobility, where knowledge arises from labor diversity. First, we identify mobile workers and their associated departure and arrival firms.

Second, for each labor inflow, i.e., inflow involving the same departure and arrival firms, we compute the educational diversity to which the given set of workers has been exposed during the previous year. As in Parrotta et al. (2014b), we sum the Herfindahl indices calculated for each workplace belonging to the same firm, weighted by the number of individuals employed at each workplace, as follows:

$$diversity_{it} = \sum_{w=1}^{W} \frac{N_w}{N_i} \left(1 - \sum_{s=1}^{S} p_{swt}^2\right), \quad (1)$$

where $diversity_{it}$ is the educational diversity of a generic firm i at time t, W is the total number of workplaces belonging to firm i, S is the total number of educational categories,[6] N_w and N_i are respectively the total number of employees of workplace w in firm i.[7] Thus, the ratio between the last two variables corresponds to the weighting function, while p_{swt} is the proportion of employees falling into each category s at time t in each workplace. Following Marino et al. (2012), we compute departure firm workforce diversity excluding mobile workers and their characteristics. In calculating arrival/receiving firm workforce diversity, by contrast, we include the inflow of newly hired employees.

Finally, we calculate, a measure of inter-firm knowledge transfers, kt. This variable is constructed as a simple average of the educational diversity associated with all departure firms, D (d refers to a single departure firm from which at least one worker moves to arrival firm) i at time t:

$$kt_{it} = \frac{\sum_{d=1}^{D} diversity_{dt-1}}{D} .$$

To complement the analysis of the role of educational diversity, we also calculate a measure of inter-firm knowledge transfer, looking at both ethnic and demographic diversity. More details about how sending firm diversity is measured in terms of these two dimensions are provided in Appendix 1.

[6]Educational categories are the eight highest levels of education achieved by the employees in our sample: primary education, secondary education (general high school, business high school, vocational education) and tertiary education (engineering, humanities, natural sciences, and social sciences) (Parrotta et al., 2014a; and Marino et al., 2012).

[7]By calculating diversity as in (1), we assume that educational diversity between and within workplaces contribute to the index in the same way. We indirectly test the impact of this assumption on the estimation of the knowledge transfers effect by excluding multi-establishment departure firms from the analysis, as described in the sub-section 4.2.

2.3 Descriptive statistics

Because the main hypothesis of this paper is that educational mobility is a channel for knowledge transmission between firm pairs, we devote particular attention in our final data set to documenting worker flows.

As reported in Table 1, the final sample consists of 104,699 observations involving approximately 11,000 firms over the sample period 1995-2005. Unsurprisingly, approximately 70 percent of the observations involve firms with fewer than 50 employees, as the Danish industrial structure is dominated by small firms.[8] Compared with larger firms, small companies are more likely to be single-plant operations and not surprisingly to have substantially lower levels of value added, materials and capital stock.[9] Moreover, whereas small firms are characterized by large shares of blue-collar and relatively younger employees, companies with more than 50 employees tend to have employees with longer tenures and larger proportions of middle managers in their workforces. Given the relatively low level of foreign capital penetration in the Danish economy,[10] large differences in the shares of foreign ownership for small and large firms are not observed. In addition, no substantial differences are recorded in inflows of new workers and in the shares of women, foreigners and workers in different educational categories. Interestingly, large firms show consistently higher values for labor diversity than do small firms, and large firms seem to recruit employees from firms with more heterogeneous workforces. This finding may be consistent with the assumption that larger firms typically focus more than small firms do on knowledge management practices and may be more aware of the benefits of labor poaching than are small companies.

Table 2 provides information on the characteristics of mobile workers. These workers represent approximately 13 percent of the overall workforce and generally are younger and have shorter tenures and less work experience than immobile workers. We generally observe that movers coming from departure firms with above-average labor diversity are slightly more likely to be women, to hold managerial positions and to be better educated.

Finally, Table 3 shows that the majority of job changes (as a share of labor force) occur within the service industry, particularly transport (27 percent) and financial and business services (16 percent). The largest degree of job mobility is visible within industries and is directed toward mid-sized and large firms.

[8] According to the OECD (2005), the population of Danish firms mainly consists of small and medium-sized companies. Firms with fewer than 50 employees account for 97 percent of firms and represent 42 percent of employment in manufacturing and services.

[9] Accounting values are reported in thousands of real DKK. Monetary Values, retrieved from the World Bank database, are deflated using the GDP deflator with 2000 as the base year.

[10] In 2008, less than 1 percent of all private firms in Denmark were foreign-owned (Økonomi- og Erhvervsministeriet, 2011). Indeed, Danish firms invest more abroad than foreign firms do in Denmark. This pattern is consistent with the observation that Danish firms are very active in offshoring labor-intensive manufacturing to low-cost countries, whereas Denmark does not attract substantial investments from foreign manufacturing firms (Carlsen and Melgaard Jensen, 2008).

3 Estimation strategy

One of the major issues discussed in the literature concerning firm production functions is the simultaneity (endogeneity) affecting the estimation of parameters on input variables. In fact, there could be factors (shocks) influencing production that are unobserved by the econometrician but observed by the firm. Hence, firms may respond to positive (negative) productivity shocks by expanding (reducing) their output, which requires a higher quantity and/or quality of production inputs. A number of estimation approaches have been developed to address the simultaneity issue, such as those advocated by Olley and Pakes (1996) (OP henceforth) and Levinsohn and Petrin (2003) (LP henceforth). These approaches have been extensively used and propose the identification of a proxy variable (investments for the former and materials for the latter) that being a strictly increasing function of the time-varying productivity shocks may allow for the consistent estimation of the input parameters. However, Ackerberg, Caves and Frazen (2006) (ACF henceforth) show that OP and LP can suffer from potential collinearity problems and thus propose a more proper estimation approach. In line with ACF, Wooldridge (2009) suggests an estimation approach that also deals with the simultaneity issue but following more closely the LP rationale.

For our empirical analysis we implement the structural techniques suggested by ACF, being the latter the most recognized way to properly cope with the simultaneity in identifying the input coefficients. More specifically, we estimate firm productivity by using a Cobb-Douglas production function that contains real value added, Y, labor, L, capital, C; and a set of additional variable inputs. These additional inputs are our measure of knowledge transfer, kt, and a vector for workforce composition, X, for both arrival and departure firms. The latter in particular includes the arrival firm average tenure and share of foreigners, managers, middle managers, males, workers with either tertiary or secondary education and differently aged workers belonging to the employees' age distribution quintile. The same vector also include the departure firms' average shares of: foreigners, managers, middle managers, males, workers with either tertiary or secondary education and differently aged workers belonging to the employees' age distribution quintiles.[11]

The log-linear production function is specified as follows:

$$lnY_{it} = cons + \alpha lnL_{it} + \beta lnC_{it} + \gamma kt_{it} + \delta(X_{it}) + u_{it} \tag{2}$$

The error term u_{it} consists of a time-varying firm specific effect v_{it}, unobserved by econometricians, and an idiosyncratic component ε_{it}. Following Ackerberg et al. (2006), we assume that

[11] We also specify other control variables for partial/total foreign ownership, whether a firm includes multiple establishments, year, industry classification and region because such variables can potentially affect productivity.

$$E\left(\varepsilon_{it} \mid l_{it}, c_{it}, kt_{it}, X_{it}, m_{it}, l_{it-1}, c_{it-1},, kt_{it-1}, X_{it-1}, m_{it-1}, ..., l_{i1}, c_{i1}, kt_{i1}, X_{i1}, m_{i1}\right) = 0, \tag{3}$$

with $t = 1, 2, ..., T$, and where m refers to our proxy variable (materials) and lower-case letters to log-variables. As past values of ε_{it} are not included in the conditioning set, it means that we allow for serial dependence in the pure shock term. However, we need to restrict the dynamics in the productivity process:

$$E\left(v_{it} \mid v_{it-1}, v_{it-2}, ..., v_{i1}\right) = E\left(v_{it} \mid v_{it-1}\right) \equiv f\left(v_{it-1}\right), \tag{4}$$

with $t = 1, 2, ..., T$, and for given functions $f(\cdot)$. As in ACF's approach, we assume material input to be chosen after labor input. In addition, we assume that our indeces and the other additional variable inputs, X , are set before or at the same time as material input is chosen. As a result, material demand will not only be a function of capital and productivity, but also of l, kt and X:

$$m_{it} = f(c_{it}, v_{it}, l_{it}, kt_{it}, X_{it}) \tag{5}$$

and assuming that the material demand function is strictly increasing in productivity shock v_{it}, we get

$$v_{it} = f^{-1}(c_{it}, m_{it}, , l_{it}, kt_{it}, X_{it}). \tag{6}$$

The key advantage of this approach is that it allows our key variable kt_{it} , to have dynamic implications or to depend on unobserved input price shocks that may not be serially correlated. Plugging the inverse material demand into the production function, we obtain the first-stage equation, which here serves only to separate v_{it} from ε_{it},

$$y_{it} = cons + \alpha l_{it} + \beta c_{it} + \gamma kt_{it} + \delta X_{it} + f^{-1}(c_{it}, m_{it}, l_{it}, kt_{it}, X_{it}) + \varepsilon_{it}. \tag{7}$$

The function $f^{-1}(\cdot)$ is proxied with a polynomial in materials, capital, labor, kt_{it} and X_{it}. Thus, the estimated output, net of the idiosyncratic component, is used to identify the parameters of the inputs in the second stage. Recalling that v_{it} is a first-order Markov process, we define a_{it} as an innovation that can be correlated with current values of the proxy variable m_{it} and inputs l_{it}, kt_{it} and X_{it}:

$$a_{it} = v_{it} - g\left(v_{it-1}\right), \tag{8}$$

where a_{it} is mean independent of all information known at $t-1$ and $g(\cdot,\cdot)$ is proxied also with a low-degree polynomial in dependent variables. Given our timing assumption, we suggest using the moments:

$$E\left[a_{it}\middle| \begin{array}{c} c_{it} \\ l_{it-1} \\ kt_{it-1} \\ X_{it-1} \end{array}\right] = 0 \tag{9}$$

to identify coefficients on c, l, kt, and X.

4 Results

4.1 Main results

Our main findings are reported in Table 4. The first column contains the OLS estimates. The second column shows the results obtained by estimating equation (1) with the algorithm suggested by Olley Pakes (OP henceforth), which allows for the control of sample selection issues and deals with firm exit. The third column includes the estimates from the Wooldridge's approach (2012) and all the other columns show parameters from our preferred method, i.e. the ACF approach, given that the latter seems to be one of the best way to properly sort out simultaneity in identifying the input coefficients. The first 4 columns do not include the additional variable inputs, X, in addition to our measure of inter-firm knowledge transfer, kt; they are instead added in columns 6 to investigate whether our parameter of interest changes in terms of its sign, size or significance level.[12] Column 5 adds to the basic specification the arrival firm educational diversity.

The first two rows in Table 4 report the labor and capital elasticities, which differ slightly across the methods and specifications used. Specifically, the labor (capital) elasticity tends to be lower (higher), when standard OLS is used than when the OP, Wooldridge and ACF methods are used (column 2,3 and 4). Therefore, as in other studies (Ackerberg et al. 2006; Konings and Vanormelingen 2009; Parrotta et al. 2014a, Parrotta and Pozzoli, 2012), a lower (higher) labor (capital) contribution is estimated when endogeneity

[12] However, all specifications include standard control variables: a foreign-ownership dummy, a multi-establishment dummy and a set of 3-digit industry, year and county dummies.

and similtaneity issues in estimating the production function are controlled for. Furthermore, comparing the estimated elasticities across OP, Wooldridge and ACF methods, we find that, even though the OP and Wooldridge estimates of the labor (capital) coefficients are sligthly smaller (larger) than their ACF counterparts, all these input elasticities are farily comparable. For the sake of brevity, we therefore proceed by discussing the results obtained with ACF approach only. With respect to the other input variables, the proportion of employees with tertiary and secondary education and the share of foreign and male workers are all statistically significant and carry a positive sign (column 6). The results also show that productivity is increasing in educational diversity of the arrival firm (column 5) and in the proportion of longer-tenured workers (column 6).

Our variable of interest, the measure of knowledge transfer along the educational dimension, enters the production function with a positive sign, i.e., the average educational diversity of the departure firms positively affects receiving firm productivity. Taking the sixth column, which includes all controls and therefore contains our more reliable estimates, we find that a one-standard-deviation increase in the knowledge transfer index leads to a productivity enhancement of approximately 0.68 (0.189×0.036) percent. To facilitate the interpretation of our variable of interest, we have also computed our knowledge transfer index, restricted to cases of single, double and triple movements for each pair of departure-arrival firms. The regression results for this empirical exercise are reported in the Table 5 and show that a hypothetical firm that hires one worker from another firm, whose educational diversity is one standard deviation higher than the average level, experiences a 0.51 (0.189×0.027) percent productivity gain. An hypothetical firm hiring two (three) workers from the same departure firm, whose educational diversity is one standard deviation higher than the average level, experiences a 0.88 (0.92) percent productivity gain. These results may suggest that knowledge transfers increase less than proportionally with respect to the total number of movers leaving a given departure firm, confirming a result on knowledge transfer mechanisms shown in Parrotta and Pozzoli (2012).

Our findings support the hypothesis that mobile workers who come from firms characterized by high educational diversity and therefore have had contact with co-workers with different educational backgrounds transfer valuable knowledge to the arrival firm and thus positively affect its performance. Hence, in moving from one firm to another, workers are able to carry more valuable knowledge with them if they have been exposed to greater educational diversity at the workplace level. Interestingly, we find similar results with respect to diversity within arrival firms: diversity of educational background within an arrival firm's labor force significantly enhances firm productivity (see also Parrotta et al., 2014a). These results, taken together, are consistent with the hypothesis that interactions with co-workers with heterogeneous education, skills, perspectives and attitudes toward problem-solving facilitates new combinations of knowledge and skill complementarities, promoting a balanced skill-mix across different competencies within firms.

The importance of knowledge transfer via labor mobility and that of departure firms' educational diversity seems particularly heightened in manufacturing, wholesale and retail trade, and financial and business services, as reported in Table 6. Thus, it appears that spillover from more educationally diverse workforces is a general phenomenon that induces larger productivity gains in both service and manufacturing industries. Although the contribution of such knowledge transfers does not vary substantially across industries, we find that firms benefit more in terms of the acquired knowledge from intra-industry worker flows than from inter-industry ones, as the estimated coefficient of our knowledge transfer measure for within-industry labor mobility flows is larger than the estimated coefficient for between-industry flows. This result provides some support for the assumption that knowledge transfers can more easily yield productivity gains when they originate with co-workers who are employed in similar environments and core businesses. Hence, as in Stoyanov and Zubanov (2012), we find that the knowledge introduced into firms by newly hired workers is mostly industry specific.

Table 7 shows estimates on our variable of interest according to the arrival firm size and location. It appears that the spillover related to the average departure firm's educational heterogeneity remains significant and increases with the size of the arrival firm's workforce. The estimates for single-establishment companies are very similar to our main findings, likely because such firms represent the majority of the enterprises in the sample. In the last column of Table 7, we exclude all firms located in Copenhagen and the surrounding area because large cities usually have a more diverse supply of workers and a larger percentage of highly productive firms.[13] The results obtained using this exclusion do not qualitatively differ from those reported in Table 4.

4.2 Robustness checks

In this section, we estimate various extensions of our baseline specification by using alternative conditions in calculating our knowledge transfer index. In this way, we determine whether and how such refinements influence the estimates.

We begin by testing the robustness of our results with respect to the exclusion of certain types of departure firms to investigate whether the knowledge generated by new hires is mainly related to specific characteristics of the departure firms (such as their human capital, productivity and division of labor), other than the educational diversity of their workforces. More specifically, in using our knowledge transfer measure, we do not qualify newly hired workers as knowledge carriers from firms that belong to R&D-intensive industries, that have at least one patent application at the European Patent Office,[14] that export goods or services,

[13]The only real agglomeration area in Denmark is Copenhagen and its environs.

[14]More details concerning the composition of the data set, including all patent applications sent to the European Patent Office by Danish firms, can be found in Kaiser, et al. (2012).

that have foreign shareholders, that have a share of tertiary education workers above the industrial median during the year before the hire, or that have a total factor productivity[15] larger than the one of the arrival company.[16] All these refinements together with the estimates separately by the sending firms' size and by whether the sending firm is mono-establishment are reported in Table 8. In these checks coefficients on our variable of interest are fairly similar to the main results. Only excluding exporting firms significantly reduces the effect of our knowledge transfer measure. Moreover, the same effect seems to be increasing in the size of departure firms and to be smaller for mono-establishment sending companies. These findings might in part reflect the fact that bigger firms typically have workforces characterized by greater educational heterogeneity and at the same time pay higher wages because they are able to attract more able workers. These results however allow us to safely dismiss the idea that the new hires might benefit the arrival firms only when they originate from highly productive, innovative and internationalized firms, or from employers which pay more (tipically larger companies) or from firms with a large endowment of human capital thanks to a highly educated workforce. Hence, knowledge transfer through interaction with educationally diverse co-workers is a broad phenomenon that involves the entire production system rather than specific categories of enterprises.

The previous literature in this field (Song et al. 2003; Kaiser et al. 2012, Parrotta and Pozzoli 2012, Stoyanov and Zubanov 2012) has shown that worker characteristics (i.e., education, occupation and certain unobserved traits like for example motivation) are notably related to their ability to transfer knowledge to new contexts and apply it there. Based on Table 9, we can evaluate whether new workers' education, unobserved ability, nationality, occupation and tenure within their departure firms affect the magnitude of the knowledge transfer effects. For each group, we separately compute our knowledge transfer measure, imposing no knowledge transfers for the other group. Starting with occupation, we divide new hires into two categories, managers and non-managers. For both occupational categories, we find a significant, positive contribution of spillover from past co-workers' educational diversity to the productivity levels of the arrival firms. Our results, however, suggest that the knowledge transfer that occurs through manager mobility is much greater than the knowledge transfer associated with non-managers. Stronger effects are also found when we restrict knowledge transfer to workers who are native hires or workers with either tertiary education or with a tenure of at least three years at the departure firms. By dividing new hires according to whether their fixed effects estimated from a wage equation[17] are above/below the median of overall fixed effects distribution

[15] Total factor productivity is estimated separately by 2-digit industry by using ACF.

[16] We impose that incoming workers from such departure firms do not transfer any knowledge and assign to them a value of zero in the calculation of the knowledge transfer variable, *kt*.

[17] We measure the unobserved ability of each mover, independent of observed time-variant worker characteristics and any firm-specific effects, as the the time-invariant worker effect estimated from wage equation à la Abowd, Kramarz and Margolis (1999). In our panel data there is enough mobility of workers across firms, to decompose annual labor income into a component due to time-variant observable individual characteristics (such as, for example, work experience, tenure, education, marital status, the number of children), a pure time-invariant worker effect, a pure firm effect and a statistical residual. Another requirement for identifying individual fixed effects is that there are enough groups of connected workers (Abowd et al. 1999) and firms. In our

of the sending firms, we find that the knowledge spillover effect is slightly smaller when we focus on those movers with below median fixed effects compared to the effect obtained by considering movers with above average ability. Furthermore, by restricting the analysis to knowledge carriers who have received at least a 5 percent wage increase after being hired by the arrival firm (a signal of the employer's willingness to recruit the individual), we find an even stronger effect on our variable of interest. These findings are consistent with the assumption that more able workers or workers with more education or longer job tenure usually have better employer transferability because of their superior cognitive skills or their greater amount of time spent accumulating knowledge through interactions with co-workers. However the fact that our coefficient of interest remains positive and statistically significant even when we focus on knowledge carriers with low education or with a blue-collar occupation or below median ability allows us to dismiss the surmise that the effect estimated on our knowledge spillovers variable is merely due to the movers' productivity, ability or human capital. Finally, we exclude among knowledge carriers those individuals who change employers but not their place of residence. This change may reduce the influence of non-random movements on the estimation of the knowledge transfers effect, as individuals who change their place of residence in connection to a job switch are either those workers who move for family reasons or those who move to seek out an employer with a brighter future. The coefficient of the average departure firm's educational diversity is still positive and even greater in this case than in the main analysis.

In summary, the productivity gains associated with hiring from firms with higher degrees of educational diversity are magnified when the newly hired workers are more educated, belong to a higher occupation group, had a longer tenure at their departure firms, experience a wage increase after moving and do not change their place of residence in connection to a job chance. Therefore, it can be argued that these worker categories are viewed as more attractive by potential arrival firms. However, all workers seem able to transfer some degree of valuable knowledge, which suggests that knowledge that is acquired through exposure to educationally diverse workplaces and that is transferred through job-changing is not necessarily associated with specific types of labor inflow.

The final important robustness checks are reported in Table 10. As workers may interact not only with their colleagues but also with other individuals living or working in the geographic area in which departure firms are located, we alternatively compute our measure of knowledge transfers by averaging the departure firms' diversity calculated at the commuting area level.[18] Measuring diversity at this level of geographical aggregation[19] surely helps us to understand whether knowledge transfer originates from interactions not only

data-set only 0.43 % of the observations are disconnected.

[18]Using the algorithm suggested in Andersen et al. (2000), we have identified approximately 100 commuting areas.

[19]The commuting area diversity is calculated excluding among knowledge carriers all individuals who are employed at the sending firms.

with co-workers but also with other people (e.g., friends). It is noteworthy that in this test, we do not include mobility flows in which both the departure company and the arrival company are located in the same commuting area. If we did, it would be more difficult to capture any geographically specific effects, given that both the arrival and the departure firms could gain from the same geographical educational heterogeneity. Using our chosen approach, we find that the coefficient of our measure of knowledge transfer is positive but insignificant, as reported in the first column of Table 10. This finding provides evidence that knowledge transfers that are profitable from the firm viewpoint mainly originate from co-worker interactions. In the third column of Table 10, we calculate two alternative indices of knowledge transfers and include them both in the production function (1). The first measure is based on a Herfindhal index for the type of tertiary education (this index now has only 4 categories: engineering, natural sciences, social sciences and humanities), while the second is the standard deviation of the years of education of the sending firms' workers. This allows us to disentangle the knowledge transfer effects associated with the level of education from those related to the type of tertiary education. We find that both indices have a positive and statistically significant, with a larger effect associated with the measure of knowledge spillovers based on Herfindhal index for the type of tertiary education. These results are consistent with the idea that workers are more likely to work most closely with and to learn most from other workers of the same educational level but with a different field of study.

In the last two columns of Table 10, we test whether the exposure of mobile workers to ethnic or demographic diversity enhances the productivity of arrival firms. The coefficients that we estimate for these spillover measures are positive but insignificant. This finding might be a function of communication barriers due to differences in language, values, age, and gender, which may somehow have hindered co-worker interactions and, therefore, knowledge exchange between colleagues. Hence, according to our analysis, educational heterogeneity is the main source of valuable knowledge transmission among co-workers.

5 Conclusions

This article investigates the effect on firm productivity of hiring workers from educationally diverse enterprises. In particular, we evaluate how arrival firm productivity is affected by the average educational diversity of departure firms when there is inter-firm labor mobility. From such a perspective, workers who have been previously exposed to educationally heterogeneous co-workers are viewed as potential knowledge carriers.

To assess these learning effects, we estimate firm productivity using the algorithm suggested by Ackerberg et al. (2006), which allows us to address the endogeneity and collinearity issues that typically arise when structural estimation methods are used with production functions.

We find that hiring workers who have had contact and relationships with co-workers with different educational backgrounds is beneficial to arrival firm productivity because such interactions encourage the transfer of complementary knowledge, enriching the arrival firm's knowledge pool. Furthermore, the average departure firm's ethnic and demographic diversity seems not to induce productivity gains for arrival firms. Thus, our findings support the hypothesis that the exposure of poached employees to past co-workers with different educational backgrounds promotes learning opportunities in arrival firms. These learning effects seem to be mainly driven by differences in fields of study at the level of tertiary education rather than in educational levels.

The benefits that originate from departure firms' educational diversity are particularly policy relevant because they are distributed throughout the entire economy rather than being concentrated in innovative or highly productive firms; the learning phenomenon that we describe is general rather than being particular to specific categories of firms (i.e., larger, more innovative, or more export oriented firms) or movers (i.e., workers with higher education or long tenure).

The evidence that the average sending firm's educational diversity contributes to arrival firm productivity has important implications for both private and public management policy. In choosing their hiring criteria, firms should devote more attention to the educational composition of the labor force from which they recruit their workers. In addition, public institutions might implement policies that are intended to ease inter-firm labor mobility (e.g., by reducing rigidity in the labor market) and that favor education in different fields of study (e.g., by boosting investment in education).

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Table 1: Descriptive statistics of firm characteristics, main sample and by size

Variables	Definition	Total		Small size firms		Middle and big size firms	
IDA Variables:		**Mean**	**Sd**	**Mean**	**Sd**	**Mean**	**Sd**
edu knowledge transfer index	average educational diversity of all departure firms	0.466	0.189	0.447	0.205	0.512	0.129
ethnic knowledge transfer index	average ethnic diversity of all departure firms	0.255	0.212	0.236	0.226	0.303	0.166
demo knowledge transfer index	average demographic diversity of all departure firms	0.679	0.254	0.656	0.279	0.735	0.162
inflow of new workers	number of workers moving from departure to arrival firms	1.320	3.704	1.241	1.811	1.517	6.301
share of men	men as a proportion of all employees	0.687	0.246	0.691	0.256	0.678	0.221
share of foreigners	non-Danish emloyees as a proportion of all employees	0.052	0.093	0.049	0.096	0.059	0.085
age15-32	employees aged 15-32 as a proportion of all employees	0.318	0.217	0.337	0.225	0.268	0.188
age33-41	employees aged 33-41 as a proportion of all employees	0.286	0.132	0.276	0.140	0.309	0.105
age42-50	employees aged 42-50 as a proportion of all employees	0.213	0.114	0.205	0.120	0.233	0.092
age51-65	employees aged 51-65 as a proportion of all employees	0.252	0.150	0.218	0.172	0.206	0.162
primary education	employees with compulsory education as a proportion of all employees	0.272	0.128	0.272	0.324	0.298	0.333
secondary education	employees with a secondary/ post-secondary education as a proportion of all employees	0.612	0.177	0.610	0.188	0.616	0.146
tertiary education	employees with a tertiary education as a proportion of all employees	0.039	0.092	0.035	0.090	0.051	0.095
tenure	average tenure	4.179	1.880	4.066	1.911	4.461	1.769
share of managers	managers as a proportion of all employees	0.037	0.052	0.038	0.056	0.036	0.039
share of middle managers	middle managers as a proportion of all employees	0.149	0.200	0.132	0.194	0.193	0.208
bluecoll	blue collars as a proportion of all employees	0.762	0.242	0.773	0.244	0.727	0.231
edu diversity arrival firm	diversity index based on employees' education (9 categories)	0.585	0.130	0.567	0.133	0.629	0.111
ethnic diversity arrival firm	diversity index based on employees' language (40 categories)	0.191	0.284	0.115	0.235	0.380	0.307
demo diversity arrival firm	diversity index based on employees' demographic characteristics (10 categories)	0.869	0.094	0.854	0.098	0.904	0.075
Accounting Variables:							
value added	(1000 kr.)	31183.570	190248.800	8693.019	22840.600	87262.870	347477.000
materials	(1000 kr.)	82812.540	640034.800	24088.120	118713.800	229239.500	1168730.000
capital	(1000 kr.)	98976.920	1310085.000	24833.630	594240.500	283850.300	2251144.000
foreign ownership	1, if the firm is foreign owned	0.004	0.063	0.004	0.061	0.005	0.068
multi	1, if the firm is multi-establishment	0.144	0.351	0.037	0.188	0.411	0.492
N		104,699		74,729		29,970	

Notes: All Employer-Employee (IDA) and Accounting (REGNSKAB) variables are expressed as time averages from 1995 to 2005. The industrial sectors included in the empirical analysis are the following: food, beverages and tobacco (4.05 %); textiles (2 %), wood products (6.19 %), chemicals (3.95 %), other non-metallic mineral products (1.94 %), basic metals (18.95 %), furniture (3.46 %), construction (15.07 %), sale and repair of motor vehicles (3.64 %), wholesale trade (14.67 %), retail trade (6.06 %), hotels and restaurants (2.08 %), transport (6.12 %), post and telecommunications (0.40 %), financial intermediation (1.17 %) and business activities (10.25 %). Small size firms: Employees ≤ 49; Middle and big size firms: Employees ≥ 50.

Table 2: Descriptive statistics of workers' characteristics

Variables	**All workers**		**Movers**		**Movers from firms with above avg edu diversity**	
	Mean	*S.d.*	*Mean*	*S.d.*	*Mean*	*S.d.*
log(wage_lag)	12.302	0.614	12.232	0.667	12.285	0.658
age	38.232	10.995	35.357	9.732	35.504	9.464
tenure	5.159	4.839	2.813	2.981	2.848	3.025
labor market experience	15.675	9.762	13.455	8.755	13.352	8.746
manager	0.029	0.169	0.028	0.166	0.033	0.178
middle manager	0.239	0.427	0.246	0.431	0.313	0.464
blue collar	0.731	0.443	0.725	0.446	0.654	0.476
skill0 (1, if with primary education)	0.378	0.485	0.316	0.465	0.312	0.463
skill1 (1, if with secondary and post-secondary education)	0.572	0.495	0.620	0.485	0.598	0.490
skill2 (1, if with tertiary education)	0.050	0.217	0.063	0.244	0.091	0.288
female	0.337	0.473	0.302	0.459	0.343	0.475
foreigner	0.049	0.216	0.045	0.208	0.047	0.212
Obs	5,291,642		705,292		273,751	

Table 3: Labor mobility by year and arrival firm industry and size

	Total number of movers	**Movers' share of the labor worforce**
manufacturing	272,704	0.100
construction	93,649	0.168
whole sale and retail trade	167,031	0.147
transport	89,937	0.266
financial and business service	81,087	0.159
within industry mobility	391,828	0.074
between industry mobility	313,464	0.059
arrival firm with less than 50 employees	130,151	0.025
arrival firm with more than 50 employees	575,141	0.108

Table 4: Knowledge transfer effects on firm productivity, main results

	(1) OLS	(2) OP	(3) Wooldridge	(4) ACF	(5) ACF	(6) ACF
log(L)	0.658***	0.680***	0.673***	0.715***	0.713***	0.745***
	(0.009)	(0.005)	(0.009)	(0.020)	(0.018)	(0.010)
log(C)	0.351***	0.273***	0.281***	0.306***	0.303***	0.259***
	(0.006)	(0.013)	(0.015)	(0.012)	(0.012)	(0.011)
edu knowledge transfer index	0.091***	0.107***	0.087***	0.082***	0.081***	0.036***
	(0.007)	(0.008)	(0.009)	(0.008)	(0.006)	(0.007)
edu diversity arrival firm					0.136**	0.083**
					(0.041)	(0.043)
share of middle managers						0.321***
						(0.031)
share of managers						0.360***
						(0.049)
tenure						0.238***
						(0.027)
secondary education						0.138***
						(0.018)
tertiary education						0.163***
						(0.042)
age15-32						0.077
						(0.083)
age33-41						-0.000
						(0.056)
age42-50						-0.210**
						(0.098)
share of men						0.393***
						(0.079)
share of foreigners						0.300**
						(0.103)
N	104,098	68,190	36,868	46,292	46,292	46,292
R2	0.834	0.823	0.712	0.814	0.823	0.883

Notes: The dependent variable is the log of value added. All regressions include foreign-owned, multi-establishment, 2-digit industry, year, and county dummies. Column 5 adds to the controls the arrival firm's educational diversity. Column 6 also includes: the arrival firm average tenure and share of foreigners, managers, middle managers, males, workers with either tertiary or secondary education and differently aged workers belonging to the employees' age distribution quintile; the departure firms' average shares of foreigners, managers, middle managers, males, workers with either tertiary or secondary education and differently aged workers belonging to the employees' age distribution quintiles. Standard errors are computed by using a block bootstrap procedure with 300 replications and are robust against heteroskedasticity and intra-group correlation. Significance levels: ***1%, **5%, *10%.

Table 5: Knowledge transfer effects on firm productivity, results by number of knowledge carriers from a sending firm

	No more than one mover from the same sending firm	No more than two movers from the same sending firm	No more than three movers from the same sending firm
log(L)	0.729***	0.747***	0.746***
	(0.010)	(0.011)	(0.011)
log(C)	0.267***	0.255***	0.256***
	(0.010)	(0.010)	(0.010)
edu knowledge transfer index	0.027***	0.047***	0.049***
	(0.008)	(0.010)	(0.010)
N	46,292	46,292	46,292
R2	0.892	0.892	0.892

Notes: The dependent variable is the log of value added. All regressions include the full set of control variables (both arrival and departure firms' characteristics). Standard errors are computed using a block bootstrap procedure with 300 replications and are robust against heteroskedasticity and intra-group correlation. Significance levels: ***1%, **5%, *10%.

Table 6: Estimates by arrival firm's industry

	Manufacturing	Construction	Whole sale and retail trade	Transport	Financial and business service	Within industry labor mobility	Between industry labor mobility
log(L)	0.672***	0.811***	0.742***	0.723***	0.741***	0.730***	0.770***
	(0.017)	(0.023)	(0.025)	(0.044)	(0.052)	(0.017)	(0.011)
log(C)	0.337***	0.246***	0.275***	0.299***	0.289***	0.262***	0.240***
	(0.020)	(0.042)	(0.029)	(0.078)	(0.031)	(0.017)	(0.021)
edu knowledge transfer index	0.041***	0.028	0.041**	0.006	0.062*	0.034**	0.024***
	(0.014)	(0.018)	(0.020)	(0.108)	(0.032)	(0.014)	(0.011)
N	18,272	8,430	13,398	2,811	3,364	46,292	46,292
R2	0.916	0.885	0.860	0.853	0.833	0.851	0.890

Notes: The dependent variable is the log of value added. All regressions include the full set of control variables (both arrival and departure firms' characteristics). Standard errors are computed using a block bootstrap procedure with 300 replications and are robust against heteroskedasticity and intra-group correlation. Significance levels: ***1%, **5%, *10%.

Table 7: Estimates by arrival firm characteristics

	Receiving firms with less than 50 employees	Receiving firms with between 50 and 100 employees	Receiving firms with more than 100 employees	Receiving firms are mono-establishment enterprises	*Copenhagen* is excluded
log(L)	0.776***	0.762***	0.729***	0.747***	0.738***
	(0.092)	(0.095)	(0.027)	(0.009)	(0.010)
log(C)	0.266***	0.287***	0.283***	0.256***	0.268***
	(0.009)	(0.050)	(0.044)	(0.012)	(0.011)
edu knowledge transfer index	0.035***	0.040**	0.062***	0.033***	0.027***
	(0.007)	(0.018)	(0.020)	(0.007)	(0.006)
N	26,010	6,650	8,342	35,341	46,292
R2	0.680	0.328	0.749	0.833	0.888

Notes: The dependent variable is the log of value added. All regressions include the full set of control variables (both arrival and departure firms' characteristics). Standard errors are computed using a block bootstrap procedure with 300 replications and are robust against heteroskedasticity and intra-group correlation. Significance levels: ***1%, **5%, *10%.

Table 8: Estimates by departure firm characteristics

	Departure firm is not in R&D intense industries	Departure firm is a non-patenting enterprise	Departure firm is a non-exporting enterprise	Departure firm is not foreign-owned	Departure firm's total factor productivity lower than the one of the receiving firm
log(L)	0.732***	0.732***	0.779***	0.730***	0.730***
	(0.011)	(0.009)	(0.020)	(0.008)	(0.007)
log(C)	0.265***	0.260***	0.240***	0.269***	0.268***
	(0.015)	(0.013)	(0.019)	(0.009)	(0.002)
edu knowledge transfer index	0.032***	0.036***	0.022**	0.035***	0.024**
	(0.012)	(0.013)	(0.011)	(0.005)	(0.010)
N	46,292	46,292	46,292	46,292	46,292
R2	0.903	0.906	0.891	0.951	0.852
	Departure firm with a share of tertiary education workers below industrial median	Departure firm is not a multi-establishment enterprise	Departure firm with less than 50 employees	Departure firm with between 50 and 100 employees	Departure firm with more than 100 employees
log(L)	0.745***	0.714***	0.721***	0.733***	0.740***
	(0.011)	(0.026)	(0.016)	(0.012)	(0.014)
log(C)	0.258***	0.272***	0.274***	0.267***	0.262***
	(0.011)	(0.031)	(0.019)	(0.012)	(0.014)
edu knowledge transfer index	0.029***	0.031**	0.027	0.039***	0.040***
	(0.008)	(0.014)	(0.185)	(0.008)	(0.009)
N	46,292	46,292	46,292	46,292	46,292
R2	0.879	0.877	0.899	0.901	0.897

Notes: The dependent variable is the log of value added. All regressions include the full set of control variables (both arrival and departure firms' characteristics). Standard errors are computed using a block bootstrap procedure with 300 replications and are robust against heteroskedasticity and intra-group correlation. Significance levels: ***1%, **5%, *10%.

Table 9: Estimates by newly hired workers' characteristics

	Only blue collars, as movers	Only managers, as movers	Only workers with tertiary education, as movers	Only workers with primary or secondary education, as movers	Only workers with unobserved ability below median of the sending firm's workers distribution
log(L)	0.750***	0.755***	0.742***	0.742***	0.740***
	(0.011)	(0.052)	(0.010)	(0.010)	(0.008)
log(C)	0.256***	0.251***	0.260***	0.260***	0.273***
	(0.012)	(0.072)	(0.011)	(0.011)	(0.006)
edu knowledge transfer index	0.018**	0.093***	0.052***	0.037***	0.023**
	(0.007)	(0.013)	(0.007)	(0.007)	(0.011)
N	46,292	46,292	46,292	46,292	46,292
R2	0.912	0.824	0.903	0.903	0.903
	Only workers with unobserved ability above median of the sending firm's workers distribution	Only native workers, as movers	Only workers with at least 3 years of tenure in the departure firm, as movers	Only workers with at least 5% wage increase, as movers	Only workers without a change in the commuting distance, as movers
log(L)	0.756***	0.734***	0.715***	0.726***	0.728***
	(0.008)	(0.011)	(0.010)	(0.011)	(0.015)
log(C)	0.263***	0.269***	0.274***	0.270***	0.269***
	(0.006)	(0.011)	(0.012)	(0.014)	(0.017)
edu knowledge transfer index	0.042***	0.041***	0.039***	0.059***	0.054***
	(0.012)	(0.007)	(0.008)	(0.008)	(0.009)
N	46,292	46,292	46,292	46,292	46,292
R2	0.903	0.897	0.913	0.911	0.905

Notes: The dependent variable is the log of value added. All regressions include the full set of control variables (both arrival and departure firms' characteristics). Standard errors are computed using a block bootstrap procedure with 300 replications and are robust against heteroskedasticity and intra-group correlation. Significance levels: ***1%, **5%, *10%.

Table 10: Estimates by alternative definitions of knowledge transfer

	Commuting area diversity	Edu knowledge transfer indexes based on level and type of education	Ethnic diversity	Demographic diversity
log(L)	0.729***	0.745***	0.738***	0.734***
	(0.016)	(0.010)	(0.010)	(0.010)
log(C)	0.278***	0.259***	0.268***	0.267***
	(0.022)	(0.011)	(0.011)	(0.009)
sending firms average sd of the years of education		-0.059		
		(0.036)		
edu knowledge transfer index, type of tertiary education		0.091***		
		(0.027)		
edu knowledge transfer index, commuting area average	0.024			
	(0.033)			
ethnic knowledge transfer index			0.010	
			(0.006)	
demo knowledge transfer index				0.025
				(0.015)
N	46,292	46,292	46,292	46,292
R2	0.885	0.882	0.886	0.876

Notes: The dependent variable is the log of value added. All regressions include the full set of control variables (both arrival and departure firms' characteristics). Standard errors are computed using a block bootstrap procedure with 300 replications and are robust against heteroskedasticity and intra-group correlation. Significance levels: ***1%, **5%, *10%.

Appendix 1: Ethnic and demographic diversity

In the robustness check of section 4.2, we calculate two separate knowledge spillover indices based on the cultural and the demographic diversity of the sending firms.

Cultural diversity is represented by the languages foreign employees speak.[1] It has been argued in the previous literature that linguistic distance serves as a good proxy for cultural distance (Guiso et al., 2009; Adsera and Pytlikova, 2011). Therefore, we have grouped employees together by the languages spoken in their countries of origin. This linguistic classification is more detailed than the grouping by nationality. We group countries (using the major official language spoken by the majority) at the third linguistic tree level, e.g., Germanic West vs. Germanic North vs. Romance languages. The information on languages is drawn from the encyclopedia of languages entitled *Ethnologue: Languages of the World*.[2]

[1] Second-generation immigrants are not treated as foreigners.

[2] We use the following linguistic groups: Germanic West (Antigua Barbuda, Aruba, Australia, Austria, Bahamas, Barbados, Belgium, Belize, Bermuda, Botswana, Brunei, Cameroon, Canada, Cook Islands, Dominica, Eritrea, Gambia, Germany, Ghana, Grenada, Guyana, Haiti, Ireland, Jamaica, Liberia, Liechtenstein, Luxemburg, Mauritius, Namibia, Netherlands, Netherlands Antilles, New Zealand, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and Grenadines, Seychelles, Sierra Leone, Solomon Islands, South Africa, St. Helena, Suriname, Switzerland, Trinidad and Tobago, Uganda, United Kingdom, United States, Zambia, Zimbabwe), Germanic Nord (Denmark, Iceland, Norway, Sweden), Slavic West (Czech Republic, Poland, Slovakia), Slavic South (Bosnia and Herzegovina, Croatia, Serbia, Slovenia), Slavic East (Belarus, Georgia, Mongolia, Russian Federation, Ukraine), Baltic East (Latvia, Lithuania), Finno-Permic (Finland, Estonia), Ugric (Hungary), Romance (Andorra, Angola, Argentina, Benin, Bolivia, Brazil, Burkina Faso, Cape Verde, Chile, Columbia, Costa Rica, Cote D'Ivoire, Cuba, Djibouti, Dominican Republic, Ecuador, El Salvador, Equatorial Guinea, France, French Guina, Gabon, Guadeloupe, Guatemala, Guinea, Guinea Bissau, Holy See, Honduras, Italy, Macau, Martinique, Mexico, Moldova, Mozambique, Nicaragua, Panama, Peru, Portugal, Puerto Rico, Reunion, Romania, San Marino, Sao Tome, Senegal, Spain, Uruguay, Venezuela), Attic (Cyprus, Greece), Turkic South (Azerbaijan, Turkey, Turkmenistan), Turkic West (Kazakhstan, Kyrgystan), Turkic East (Uzbekistan), Gheg (Albania, Kosovo, Republic of Macedonia, Montenegro), Semitic Central (Algeria, Bahrain, Comoros, Chad, Egypt, Irak, Israel, Jordan, Kuwait, Lebanon, Lybian Arab Jamahiria, Malta, Mauritiania, Morocco, Oman, Qatar, Saudi Arabia, Sudan, Syrian Arab Republic, Tunisia, Yemen, United Arabs Emirates), Indo-Aryan (Bangladesh, Fiji, India, Maldives, Nepal, Pakistan, Sri Lanka), Mon-Khmer East (Cambodia), Semitic South (Ethiopia), Malayo-Polynesian West (Indonesia, Philippines), Malayo-Polynesian Central East (Kiribati, Marshall Islands, Nauru, Samoa, Tonga), Iranian (Afghanistan, Iran, Tajikistan), Betai (Laos, Thailand), Malayic (Malasya), Cushitic East (Somalia), Viet-Muong (Vietnam), Volta-Congo (Burundi, Congo, Kenya, Lesotho, Malawi, Nigeria, Rwanda, Swaziland, Tanzania, Togo), Barito (Madagascar), Mande West (Mali), Lolo-Burmese (Burma), Chadic West (Niger), Guarani (Paraguay), Himalayish (Buthan), Armenian (Armenia), Sino Tibetan (China, Hong Kong, Singapore, Taiwan), Japonic (Japan, Republic of Korea, Korea D.P.R.O.).

It is important to note that for ethnic diversity, the shares of foreign workers of different nationalities/linguistic groups in each workplace have been calculated as follows:

$$p_{swt} = \frac{foreigners_{swt}}{foreigners_{wt}}.$$

The demographic index is built from the intersection of gender and age quintiles. To measure diversity at the firm level for each of these two dimensions, we use the Herfindhal index as in (1).