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 robustness checks 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.

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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. (2011) investigate the existence and magnitude of this direct relationship. The study findings provide robust, detailed evidence of the positive effects of educational diversity on firm productivity. This evidence is consistent with the theoretical predictions of Lazear (1999), who argues that labor diversity 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 affect 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. (2011), 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.

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

[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.

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

In addition to the "Ethnologue: Language of the World" database, which can be downloaded from the Internet, 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.

2.2 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. (2010), 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:

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

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

[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.

[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,

the total number of employees of workplace w in firm i. 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.[7] More details about how sending firm diversity is measured in terms of these dimensions are provided in Parrotta et al. (2010).

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 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 differences are

humanities, natural sciences, and social sciences) (Parrotta et al. 2011; Marino et al., 2012).

[7] Ethnic diversity is computed using the main language spoken in the employees' country of origin, in accordance with the third linguistic family tree level in the Ethnologue data. Demographic diversity is computed by combining gender and five age dichotomous indicators associated with the quintiles of the overall age distribution.

[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).

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 occur within the service industry, particularly transport (27 percent) and financial and business services (16 percent), and that the total number of mobile workers increased over the years until it reached its maximum value in 2002. The largest degree of job mobility is visible within industries and is directed toward mid-sized and large firms.

3 Estimation strategy

Following the literature on the identification of the production function, we implement the structural techniques suggested by Ackerberg et al. (2006). More specifically, in our analysis, productivity is estimated 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. Examples of the latter include average firm tenure and the shares of workers with either tertiary or secondary education.[11]

The log-linear production function is specified as follows:

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

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

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

[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.

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:

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

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:

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

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

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

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} ,

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

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}:

$$a_{it} = v_{it} - g(v_{it-1}) \ ,$$

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:

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

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 other columns show parameters from the ACF approach, which allows us to properly sort out simultaneity in identifying the input coefficients. Columns 1 and 2 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 4 and 5 to investigate whether our parameter of interest changes in terms of its sign, size or significance level.[12]

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 elasticity is 0.75, whereas the capital elasticity fluctuates around 0.26 in the most complete specification (column 4). As in other studies (Ackerberg et al. 2006; Konings and Vanormelingen 2009; Parrotta et al. 2011, Parrotta and Pozzoli, 2012), a slightly lower (higher) labor (capital) contribution is estimated when OLS is used than when the ACF algorithm is used. 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. The results also show that productivity is increasing in the proportion of longer-tenured workers.

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 fourth 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 movements for each pair of departure-arrival firms. The regression results for this empirical ex-

[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.

ercise are reported in the last column of Table 4 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.

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., 2011). 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 5. 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 6 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 6, 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

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

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 other than the educational diversity of their workforces. More specifically, in using our knowledge transfer measure, we exclude newly hired workers from firms that belong to R&D-intensive industries, that have at least one patent application at the European Patent Office,[14] or that export goods or have foreign shareholders during the year before the hire. All these refinements, reported in Table 7, generate estimated coefficients for our variable of interest that are fairly similar to the main results. Only excluding non-exporting firms reduces the effect of our knowledge transfer measure. Moreover, the same effect seems to be increasing in the size of departure firms. This finding might reflect the fact that larger firms typically have workforces characterized by greater educational heterogeneity. These results allow us to safely dismiss the idea that the new hires might benefit the arrival firms only when they originate from highly productive firms, i.e., innovative and internationalized firms. 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 and occupation) are notably related to their ability to transfer knowledge to new contexts and apply it there. Based on Table 8, we can evaluate whether new workers' education, nationality, occupation and tenure within their departure firms affect the magnitude of the knowledge transfer effects. Starting with occupation, we divide new hires into two categories, managers and non-managers. For each group, we separately compute our knowledge transfer measure. 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 and workers with either tertiary education or a tenure of at least

[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).

three years at the departure firms. These findings are consistent with the assumption that 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. 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. Finally, we exclude those individuals who change employers to work closer to their place of residence. This change may reduce the influence of family-specific effects on an individual's job acceptance decision. As expected, the coefficient of the average departure firm's educational diversity is also 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 jobs for family reasons. 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 9. 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.[15] Measuring diversity at this level of geographical aggregation[16] surely helps us to understand whether knowledge transfer originates from interactions not only 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 9. This finding provides evidence that knowledge transfers that are profitable from the firm viewpoint mainly originate from co-worker interactions.

In the last two columns of Table 9, 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

[15]Using the algorithm suggested in Andersen et al. (2000), we have identified approximately 100 commuting areas.
[16]The commuting area diversity is calculated excluding all individuals who are employed at the sending firms.

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 and skill complementarities in arrival firms. 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 tertiary education and 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		104699		74729		29970	

Notes: All IDA and Accounting 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 ave 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	5291642		705292		273751	

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

	Total number of movers	**Movers' share of the labor worforce**
1996	32943	0.086
1997	31663	0.083
1998	35575	0.092
1999	70080	0.155
2000	84487	0.143
2001	79113	0.133
2002	104962	0.167
2003	82955	0.133
2004	89487	0.142
2005	94027	0.148
manufacturing	272704	0.100
construction	93649	0.168
whole sale and retail trade	167031	0.147
transport	89937	0.266
financial and business service	81087	0.159
within industry mobility	391828	0.074
between industry mobility	313464	0.059
arrival firm with less than 50 employees	130151	0.025
arrival firm with more than 50 employees	575141	0.108

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

	(1) OLS	(2) ACF	(3) ACF	(4) ACF	(5) ACF
log(L)	0.658***	0.715***	0.713***	0.745***	0.729***
	(0.009)	(0.020)	(0.018)	(0.010)	(0.010)
log(C)	0.351***	0.306***	0.303***	0.259***	0.267***
	(0.006)	(0.012)	(0.012)	(0.011)	(0.010)
edu knowledge transfer index	0.091***	0.082***	0.081***	0.036***	0.027***
	(0.007)	(0.008)	(0.006)	(0.007)	(0.008)
edu diversity arrival firm			0.136**	0.083**	0.085**
			(0.041)	(0.043)	(0.043)
share of middle managers				0.321***	0.324***
				(0.031)	(0.029)
share of managers				0.360***	0.381***
				(0.049)	(0.049)
tenure				0.238***	0.210***
				(0.027)	(0.026)
secondary education				0.138***	0.134***
				(0.018)	(0.016)
tertiary education				0.163***	0.099**
				(0.042)	(0.038)
share of men				0.393***	0.439***
				(0.079)	(0.082)
share of foreigners				0.300**	0.370**
				(0.103)	(0.117)
N	104699	46292	46292	46292	36209
R2	0.834	0.814	0.823	0.883	0.892

Notes: The dependent variable is the log of value added. All regressions include whether the firm is foreign-owned, a multi-establishment dummy, a full set of 3-digit industry, year and county dummies. Columns 4 and 5 include the arrival firm share of differently aged workers belonging to the employees age distribution quintiles. They 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. 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 5: 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	18272	8130	13098	2411	3564	46292	45852
R2	0.916	0.885	0.860	0.853	0.833	0.851	0.890

Notes: All regressions include both arrival and departure firms' characteristics, year and 3-digit industry dummies. 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 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-establishments firms*	*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	26010	6650	8342	35341	46292
R2	0.680	0.328	0.749	0.833	0.888

Notes: The dependent variable is the log of value added. All regressions include both arrival and departure firms' characteristics, year and 3-digit industry dummies. 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 departure firm characteristics

	Departure firm is not in R&D industries	*Departure firm is a non patenting firm*	*Departure firm is a non exporting firm*	*Departure firm is not foreign-owned*
log(L)	0.732***	0.732***	0.779***	0.730***
	(0.011)	(0.009)	(0.020)	(0.008)
log(C)	0.265***	0.260***	0.240***	0.269***
	(0.015)	(0.013)	(0.019)	(0.009)
edu knowledge transfer index	0.032***	0.036***	0.022**	0.035***
	(0.012)	(0.013)	(0.011)	(0.005)
N	46292	46292	46292	46292
R2	0.903	0.906	0.891	0.951

	Departure firm with less than 50 employees	*Departure firm with between 50 and 100 employees*	*Departure firm with more than 100 employees*
log(L)	0.721***	0.733***	0.740***
	(0.016)	(0.012)	(0.014)
log(C)	0.274***	0.267***	0.262***
	(0.019)	(0.012)	(0.014)
edu knowledge transfer index	0.027*	0.039***	0.040***
	(0.014)	(0.008)	(0.009)
N	46292	46292	46292
R2	0.899	0.901	0.897

Notes: The dependent variable is the log of value added. All regressions include both arrival and departure firms' characteristics, year and 3-digit industry dummies. 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 newly hired workers' characteristics

	Only blue collars, as movers	*Only managers, as movers*	*Only movers with tertiary education, as movers*	*Only movers with primary or secondary education, as movers*
log(L)	0.750***	0.755***	0.742***	0.742***
	(0.011)	(0.052)	(0.010)	(0.010)
log(K)	0.256***	0.251***	0.260***	0.260***
	(0.012)	(0.072)	(0.011)	(0.011)
edu knowledge transfer index	0.018**	0.093***	0.052***	0.037***
	(0.007)	(0.013)	(0.007)	(0.007)
N	46292	46292	46292	46292
R2	0.912	0.824	0.903	0.903
	Only natives, as movers	*Only movers with at least 3 years of tenure in the departure firm, as movers*	*Only movers with at least 5% wage increase, as movers*	*Only movers without a change in the commuting distance, as movers*
log(L)	0.734***	0.715***	0.726***	0.728***
	(0.011)	(0.010)	(0.011)	(0.015)
log(C)	0.269***	0.274***	0.270***	0.269***
	(0.011)	(0.012)	(0.014)	(0.017)
edu knowledge transfer index	0.041***	0.039***	0.059***	0.054***
	(0.007)	(0.008)	(0.008)	(0.009)
N	46292	46292	46292	46292
R2	0.897	0.913	0.911	0.905

Notes: All regressions include both arrival and departure firms' characteristics, year and 3-digit industry dummies. 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 alternative definitions of knowledge transfer

	Commuting area diversity	*Ethnic diversity*	*Demographic diversity*
log(L)	0.729***	0.738***	0.734***
	(0.016)	(0.010)	(0.010)
log(C)	0.278***	0.268***	0.267***
	(0.022)	(0.011)	(0.009)
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	46292	46292	46292
R2	0.885	0.886	0.876

Notes: The dependent variable is the log of value added. All regressions include both arrival and departure firms' characteristics, year and 3-digit industry dummies. 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%.