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Abstract

This paper investigates the impact of labour mobility on plant performance in Denmark. Our study shows that the effect of labour mobility can only be assessed when one accounts for the type of skills that flow into the plant, and the degree to which these match the existing skills at the plant level. As expected, we found that the inflow of skills that are related to skills in the plant impacts positively on plant productivity growth, while inflows of skills that are similar to the plant skills have a negative effect. We used a sophisticated indicator of revealed relatedness that measures the degree of skill relatedness between sectors on the basis of the intensity of labour flows between sectors. Intra-regional mobility of skilled labour had a negative effect on plant performance, but the impacts of intra- and inter-regional mobility depended on the type of skills that flow into the plant.

Keywords: labour mobility, revealed relatedness, plant performance, geographical proximity, related labour flows, Denmark

JEL classifications: J61, 018, R11

1. Introduction

Increasing attention is devoted to the meaning and significance of technological relatedness for innovation and economic growth. With technological relatedness, we mean that economic entities like firms or industries have a higher scope for interactive learning when there is some degree but not too much cognitive proximity between firms and industries (Nooteboom, 2000). This basic idea has been used to explain a range of economic phenomena, like the development of new technology systems (Carlsson and Stankiewicz, 1991), the economic success of mergers and acquisitions (Ahuja and Katila, 2001) and the performance of research collaboration networks (Gilsing *et al.*, 2007; Leten *et al.*, 2007). There is also increasing awareness that relatedness between industries is a crucial factor to explain regional phenomena, like regional economic growth (Frenken *et al.*, 2007), the spatial clustering of industries (Boschma and Wenting, 2007) and the process of diversification at the national (Hidalgo *et al.*, 2007) and the regional level (Neffke *et al.*, 2011; Boschma et al., 2012).

In this paper, we incorporate this idea of industry relatedness into labour mobility studies. Labour mobility is often regarded as a key mechanism through which knowledge diffuses across firms within regions (Angel, 1991; Almeida and Kogut, 1999; Pinch and Henry, 1999; Malmberg and Power, 2005; Iammarino and McCann, 2006; Rodriguez-Pose and Vilalta-Bufi, 2005). However, scholars have also pointed out that labour mobility may obstruct human capital formation at the regional level, because of labour poaching. Quantitative studies have indeed shown that intra-regional labour mobility is not *per se* a good thing (e.g. McCann and Simonen, 2005; Eriksson, 2011). In that context, Boschma *et al.* (2009) have claimed that the effect of labour mobility on firm performance can only be assessed when one accounts for the types of skills that are transferred when people change jobs, and the degree to which these match the existing skills in the firm. They showed in a study on Sweden that the inflow of new skills should not be identical, but related to the existing skills in a plant (i.e. new employees recruited from related industries) to impact positively on plant performance.

The main objective of the paper is to test these ideas empirically in the case of Denmark. We employ the so-called IDA-database that provides detailed information on individuals and plants for the whole Danish economy, and we will analyse close to 52,000 high-skilled job moves into almost 17,000 Danish plants in the period 1999-2003. We hypothesize that new employees that bring in work experience from the same industry will not really contribute to plant performance, because these do not add something new to the existing skills in the plant. The same applies to the inflow of new skills that are unrelated to the skills of the plant. In that case, the plant cannot easily absorb these, and we expect the plant is unlikely to learn and benefit from it. By contrast, we expect that new employees recruited from industries related to the activity of the plant to have a positive effect on plant performance, because they offer real learning opportunities. Contrary to previous studies, we make use of an advanced revealed industry relatedness indicator developed by Neffke and Henning (2012) to identify and measure related labour inflows. The main advantage of this relatedness indicator is that it is based on the actual mobility of non-managerial skilled workers across industries, rather than being defined on the basis of pre-fixed standard industry NACE codes. Our findings show indeed that the impact of mobility of related skills is positive while the effect of inflows of similar skills is negative on plant performance, as expected, with the exception of plants in the Copenhagen region. Moreover, we estimated the effects of geographical proximity on the relationship between labour mobility and plant performance. As expected, we find evidence that the effects of labour mobility on productivity growth of plants depend on whether new employees are recruited from within the same region, or from other regions.

The paper consists of four sections. First, we discuss the main literature on the relationship between labour mobility, relatedness and plant performance. Based on that discussion, we present our hypotheses. After that, we present the data and explain which variables have been constructed, and which methodology has been used. Then, we present the main empirical findings. Finally, we draw some conclusions and provide suggestions for future research.

2. Labour mobility, relatedness and plant performance

Labour mobility is often regarded as a mechanism that enhances the competitiveness of firms and regions (e.g. Lawson, 1999; Hudson, 2005; Rodriguez-Pose and Vilalta-Bufi, 2005; Dahl and Sorenson, 2011). Because individuals embody tacit knowledge they have acquired at work, job mobility is regarded to facilitate the dissemination of this type of knowledge (e.g. Almeida and Kogut, 1999; Pinch and Henry, 1999; Cooper, 2001; Power and Lundmark, 2004). In this literature, the benefits of labour mobility are often assumed to exceed the downsides, such as labour poaching (Kim and Marschke, 2005; Combes and Duranton, 2006).

What is implicit in this literature is that the effect of labour mobility is almost taken for granted, as if the new employees are integrated in the organization of the firm without any major frictions, and as if the new employees will contribute to internal learning processes and the well-being of the firm (Wenting, 2008; Boschma *et al.*, 2009). This implicit assumption needs to be revised. Studies have observed empirically that a high rate of labour mobility may have negative effects on firm's performance (e.g. McCann and Simonen, 2005; Faggian and McCann, 2006; Boschma *et al.*, 2009; Eriksson, 2011). Moreover, little attention has been drawn to the types of knowledge and skills that are transferred between firms through job-hopping. In innovation studies, it is well-known that firms require absorptive capacity to understand external knowledge and transform it into growth (Cohen and Levinthal, 1990). However, there is also increasing awareness that absorptive capacity may not be sufficient for learning to take place. What might be more important is whether external knowledge is close, but not quite similar to the knowledge base of the firm. In this context, Nooteboom (2000) made the claim that inter-firm learning requires some degree of cognitive proximity between firms, in order to enable effective communication, but not too much cognitive proximity, to avoid cognitive lock-in.

This idea has recently been applied to labour mobility studies. In a study on the effects of labour mobility on plant performance in Sweden, Boschma *et al.* (2009) concluded that the effect of labour mobility of plant performance can only be assessed when one accounts for the type of skills that flow into the plant, and the degree to which these new skills match the existing set of skills at the plant level. Based on the analysis of about 100,000 job moves, they found strong empirical evidence that inflows of skills that were related to the existing knowledge base of the plant had a positive effect on plant performance, while the inflow of new employees with skills that were already present in the plant had a negative impact. More precisely, their study showed that new employees with work experience in industries related to the sector of the plant contributed to plant productivity growth, in contrast to employees from the same sector and from unrelated sectors. Apparently, some degree of cognitive proximity between the new employee and the firm, but not too much of that, is required to ensure that labour flows will materialize in and contribute to the performance of firms.

The economic effect of labour mobility has also drawn attention from economic geographers. One reason is that the overwhelming majority of job moves occurs within a region (Power and Lundmark, 2004), implying that knowledge transfer via job mobility predominantly is a local process. Economic geographers have emphasized that labour mobility contributes significantly to new knowledge formation at the regional level. Since tacit knowledge follows people and their mobility patterns, this type of knowledge is considered to be spatially sticky and locally embedded (Gertler, 2003; Iammarino and McCann, 2006). Almeida and Kogut (1999) argue that inter-firm mobility of labour may be held responsible for knowledge spillovers in regions like Silicon Valley. In addition, labour mobility creates linkages between firms through social ties between former colleagues. These social relationships in turn facilitate knowledge flows between firms (Breschi and Lissoni, 2003). Since most of the job moves are intra-regional, these social networks are formed locally, and will enhance further knowledge accumulation at the regional level (Dahl and Pedersen, 2003). From this line of thought, it can be concluded that mobility of skilled labour plays an important role in understanding the economic benefits of agglomerations (Malmberg and Power, 2005).

Having said that, it remains uncertain whether new employees should come from the same region or from elsewhere to have the largest impact on firm performance. As noted above, economic geographers often claim that geographical proximity may be beneficial because it facilitates the understanding and implementation of new knowledge. In the literature, increasing attention is paid to the crucial role of extra-local linkages, since too much reliance on merely local knowledge may result in lock-in that may be harmful to the performance of firms and regions (e.g. Bresnahan *et al.*, 2001; Asheim and Isaksen, 2002). To our knowledge, this idea has not yet been applied to labour mobility. Following Boschma *et al.* (2009), we argue that the effects of labour mobility on firm performance can only be accounted for after differentiating between types of labour inflows, in this case depending on whether new employees are recruited from the same region or from other regions.

Boschma *et al.* (2009) found evidence that intra-regional labour mobility is not *per se* a good thing, as often assumed by the economic geography literature. Labour mobility crossing regional boundaries is not necessarily good or bad for firm performance either. Once again, that depends on the types of skills that flow into the firms, and to what extent these match the existing skill portfolio of firms. Their study on Sweden clearly showed that inflows of unrelated skills only contributed to plant performance when these are recruited from the same region. This was explained by the fact that the problem of communication inherent to hiring new employees with skills that are totally new to the plant is even more pronounced when these are recruited from other regions. Moreover, Boschma *et al.* (2009) found that labour mobility across regions only had a positive effect on productivity growth of plants when this concerned new employees with related skills.

3. Method

3.1 Data and Sampling

This paper applies these ideas on labour mobility to the case of Denmark. Denmark is an interesting case since earlier studies have shown that Denmark, together with the Anglo Saxon countries, has one of the most flexible labour markets; i.e. job durations are shorter and the job-to-job changes are higher, compared to the European average (Schettkat, 1997; Albæk and Sørensen, 1998; Bingley *et al.* 1999; Madsen, 2002; EUROFOUND, 2006). Other Nordic countries, e.g. Finland and Sweden, show a slightly different pattern since workers have longer tenure compared to Denmark (Madsen, 2002). Roughly 30 percent of employees are hires, which means that they work in a different plant compared to the previous year, and the percentage of separations between two consecutive years is approximately the same (Albæk and Sørensen, 1998; Bingley *et al.*, 1999). Even in times of recession the share of hires is considerable, i.e. around 25 percent (Albæk and Sørensen, 1998; Bingley *et al.*, 1999). It has been said that the Danish institutional setting of high social security in combination with low employee protection, called “flexicurity”, is an important factor in explaining these high mobility rates (Schettkatt, 1997; Bingley *et al.*, 1999; Madsen, 2002). However, the short job duration might also be explained by the Danish industry structure that is characterized by relatively small firms and a low retirement age (Andersen and Svarer, 2007).

For the empirical analysis, we rely on the Danish Integrated Database for Labour Market Research (IDA). IDA is a longitudinal and universal linked employer-employee dataset constructed from government registers and maintained by Statistics Denmark (DST). The database contains detailed information on *all* individuals and *all* plants in Denmark from 1980 onwards. The longitudinal character enables us to identify labour mobility flows by comparing employer-employee relationship in consecutive Novembers.[1] A change in this relationship would indicate a move. As a result, short-term employment relationships within a year, e.g. from December until August, cannot be identified.[2] From this database we selected a total of 16,709 plants active in manufacturing and services that over a five-year period, i.e. 1999-2003, experienced an inflow of highly skilled employees.

The identification of unique plants is an important issue whenever one wants to identify job movers. A plant is an abstract and complex entity that is subject to different type of changes, i.e. change in employee composition, mergers and acquisitions, separation, etc. In many of these cases, IDA maintains the same plant identity number. For those cases in which the plant identification number changes we need to identify which individuals follow this identity change and therefore *cannot* be regarded as job-movers.

Since we are interested in the effect of high-skilled labour mobility, we included only plants that experienced an inflow of highly skilled employees that have an established position on the labour market. We apply a conservative method for identifying skilled workers in which the new employee needs to fulfil the following criteria in order to be considered as skilled: (i) earns a yearly income that is equal or higher than the median wage in that particular year, (ii) is at least 25 years of age, (iii) has a contract of at least 20 hours a week, and (iv) is registered to have moved between plants. This last requirement implies that individuals without any registered work experience, or that experienced a long spell of unemployment, will not be included. To identify highly skilled job-movers, these job-movers had to (v) hold a university degree, or belong to the top 20 percent wage earners. The wage requirement was added because key individuals do not necessarily have an academic education.

In addition to the criteria on highly skilled job-movers, we also included plant criteria. First, we focused on plants in both manufacturing and services, i.e. two-digit NACE (rev 1.1) codes 15-37 and 60-74. In addition, the four-digit NACE industry codes of the plants are crucial for creating the different variety measures. Consequently, information on industry affiliation should be available for all plants in the sample. Second, in order to identify the effect of labour mobility on productivity growth of plants, financial data needs to be available at two points in time, i.e. in the year in which a highly skilled inflow is observed (t_0) and two years after (t_2). Because this data is only available at the firm level, we removed all the plants that changed firm identity (i.e. experienced a change in ownership) during these two time points. We also removed newly founded plants in already existing firms, because these plants are experiencing only an inflow of workers. Finally, the performance of start-ups and young firms are heavily influenced by their liabilities of newness (Stinchcombe, 1965). For this reason, we omitted all firms younger than five years.[3]

Table 1 presents an overview of the number of plants that fulfil the above-mentioned criteria during the period 1999-2003.[4] The number of plants that experience an inflow of at least one high skilled worker varies between 2,800 and 4,200 per year, leading to a total of 16,709

[1] Statistics Denmark provides only yearly observations. The employer-employee relationships are identified in November; therefore, we can only identify the employer-employee relationships that exist in November.
[2] See Timmermans (2010) for a more thorough description of IDA.
[3] In an earlier analysis, we included start-ups and young firms. After omitting the younger firms the results in our analysis improved significantly.
[4] We are limited to this period due to data restrictions. First, there is a break in the financial data between 1998 and 1999, which prevents us from including plants prior to 1999. Second, the data available for the analysis runs until 2005, because we use a lag of two years to calculate productivity growth the last year in which we observe an inflow of high skilled is 2003.

observations over the five-year period. It should be noted that many plants are excluded from the sample despite experiencing inflow of skilled workers, e.g. due to lack of accounting data. The yearly number of highly skilled job-movers in the sample varies between 8,600 and 12,000. Each plant welcomes three high skilled workers on average, although the inflow decreases over the five-year period. Both the number of plants and highly skilled job movers are based on yearly observations. As a result, some plants will appear more than once in the sample. In total there are 8,929 unique plants (i.e. the number of unique plant identification numbers in the five-year period), 4,199 plants (47.03 percent) experience a high-skilled inflow in more than one year, and 342 plants (3.83 percent) experience an inflow in all years.

Insert Table 1 around here

3.2 Dependent Variable: Productivity Growth

In a similar fashion as Boschma *et al.* (2009), the performance measure that serves as the dependent variable is labour productivity growth, which is calculated as the growth of value added per worker. The Danish accounting database reports this value added only on the firm level. 6,402 plants (38.31 percent) in the sample are part of a firm that consists of multiple plants. The value added of these plants will be determined by distributing the firm's value added among the plants according to the distribution of wages. Afterwards, the value added is divided by the full time equivalent of the employees in these plants. As a last step, the productivity per person in a specific plant is subtracted from the productivity per person in the same plant two years ahead in time to identify labour productivity growth.[5] Following Boschma *et al.* (2009), we use a two-year lag because we expect that the impact of labour mobility will materialize only after a few years.[6] We take log values of labour productivity in the two years to account for skewed distributions.

3.3 Independent Variables

The independent variables are all measured at the beginning of each two-year period. For the skilled inflow, we only included those employees that have been identified as highly skilled and did not work in the plant in the previous year. To create measures for the inflow of similar, related and unrelated industry experience, we identified the employment relationships of the job movers in the last five years. These measures will be calculated by linking the employees' most related industry experience to the industry in which the plant is active. During the period 1999-2003, we identified a total of 468 four-digit NACE industry codes in the entire Danish economy, out of which 205 categories are in manufacturing and 53 categories in services (the remaining 210 four-digit NACE industry codes are to be found in the primary sector, construction, wholesale, retail, and the public sector). This industry experience can vary from employees that have no previous work experience (e.g. a new entry into the labour market), to employees that are highly mobile and have had experience in a range of industries. When an employee gained experience in multiple industries during the last five years, the degree of relatedness is determined by the most related industry

[5] To test the robustness of this method we have conducted a separate analysis on one-plant firms only. Although the level of significance and coefficients change, the overall pattern holds on the impact of revealed relatedness on plant performance.

[6] On top of that, incorporating a one-year lag did not present strong level of significance while a three-year lag showed similar results.

experience. Thus, if a person has worked for two plants, one being related and the other unrelated, the experience of this individual is regarded as related. And when an employee worked in two plants out of which one can be affiliated with the same four-digit NACE industry code, the skills of this person were treated as similar.

For each of the three main skilled inflow measures (inflow of similar, related and unrelated skills), we also made a distinction on whether the inflow is intra- or inter-regional. To determine whether this experience is intra- or inter-regional, we identify local labour market regions within Denmark. When an employee acquired this experience within the same local labour market, the experience is intra-regional, otherwise the experience is inter-regional. To identify local labour markets, we followed the approach by Andersen (2002). She defined a local labour market as an area that is relatively closed based on commuting patterns of workers in 1995. She identified 35 labour market regions. However, labour market regions are not fixed regional units because commuting patterns vary between industries and over time. Since we are interested in manufacturing and services and look at a different period in time, we assigned the 276 municipalities[7] to a total of 22 local labour market regions. The labour market regions are shown in Figure 1.

Above, we explained there is a ranking based on the level of industry relatedness. For instance, when a person has work experience in a similar and a related industry, the industry experience will be regarded as similar. When including a geographical dimension, we decided that the level of industry relatedness outweighs the geographical dimension. That is, when a person has experience both in a related industry in the same region and similar industry experience in another region, then the industry experience will be regarded as similar and inter-regional. Our ranking will thus be as follows: intra-regional similarity, inter-regional similarity, intra-regional related variety, inter-regional related variety, intra-regional unrelated variety, and inter-regional unrelated variety.

We also constructed three measures that indicate the pure size of the skilled inflow. The first measure is total skilled inflow by taking the log of the number of skilled inflows (Total Skilled Inflow). Making a distinction on whether this flow is intra- or inter-regional creates the two other variables (Intra-regional Skilled Inflow and Inter-regional Skilled Inflow). As explained above, whether the inflow is intra- or inter-regional will depend on the flow of the most related industry. So, if a person has both similar skills from another region and unrelated skills from the same region, the skill flow is identified as inter-regional.

Insert Figure 1 around here

We have nine different measures for the inflow of skilled employees. These variables will be calculated by linking the employees' most related industry experience to the industry in which the plant is active. Our database IDA provides information only on the main output for each plant. Consequently, each plant has only one industry code.

For measuring the inflow of similar skills (Inflow Sim), we count the number of highly skilled workers that entered the plant and in the five years prior to entering this plant worked for a firm that was active in the same four-digit NACE industry class. We also make a

[7] This is the number of municipalities from before the Danish municipality and regional reforms of 2007 where the number was reduced to 98 municipalities.

distinction between intra-regional (Intra Inflow Sim) and inter-regional inflow of similar skills (Inter Inflow Sim). Log values of this measure were used to control for high intensities of inflows.

The degree of inflow of skilled employees with related industry experience (Inflow Relvar) is measured by taking the number of employees that worked for a plant that was active in a related industry. This requires determining the degree of relatedness between industries. Contrary to previous studies, this related industry experience is not measured by determining whether industry sub-classes share the same industry class, based on the standard industry classification (Frenken *et al.*, 2007; Boschma *et al.*, 2009). This approach will grasp much but not all the industry relatedness within an economy because industries may be related across different industry classes (Neffke and Henning, 2008). Instead, we use a measure of revealed relatedness of industry codes based on the mobility of skilled non-managerial labour developed by Neffke and Henning (2012). This approach takes the point of departure in the skills of the workers and in the degree these skills are transferable between different industries. Neffke and Henning (2012) argues that skilled non-managerial workers will search for a new job in industries in which their skills are valued. Not doing so might lead to the destruction of their human capital. Therefore, a high rate of mobility of highly skilled non-managerial workers between two industries would indicate a high valuation of their skills in both industries, less human capital destruction, and thus a high degree of (skill-) relatedness.

To identify which industry pairs are related, Neffke and Henning (2012) constructed a matrix based on 435 four-digit NACE industries in the Swedish economy, creating a total of 188,790 unique industry pairs. For each industry pair, the total number of highly skilled non-managerial job moves were identified during the period 2004-2007. Neffke and Henning (2012) argues that revealed relatedness cannot be measured only based on these raw labour flows, because there are other industry characteristics that determine these labour flows. The industry effects for which they control are (i) size of the industry, because the intensity of the labour flow is positively correlated with the size of the industry, and (ii) wage differentials between industries, because higher wages are an important incentive for changing jobs. In doing so, they constructed a revealed relatedness measure, which is based on the degree by which observed labour flows are in excess of predicted labour flows. This so-called revealed relatedness index is formulated as:

$$RSR_{ij} = \frac{F_{ij}^{obs}}{\hat{F}_{ij}} \tag{1}$$

where the denominator stands for the observed labour flow, and the numerator for the predicted labour flow.

A problem is that the information on some industry combinations is too limited to claim revealed relatedness. For this reason, Neffke and Henning (2012) quantified a confidence level that can be linked to the revealed relatedness estimates. To do so they treated the mobility flow as a choice of each moving highly skilled individual to either stay in the same industry or to move to any of the other 434 industries. The alternative expression they constructed is:

$$RSR_{ij} = \frac{P_{ij}^{obs}}{\hat{P}_{ij}} \tag{2}$$

where the denominator and numerator of Equation 1 are divided by emp_i, i.e. the number of employees in the industry of origin. Then, they calculated if the observed relative frequency, P_{ij}^{obs}, is significantly higher than the expected probability, $\hat{P}_{ij}$.

With a revealed relatedness index of more than one and a significance level of 10 percent, they identified 9,919 related industry pairs. Our analyses rely on the same industry pairs as identified by Neffke and Henning (2012) [8], with the exception of two alterations. First, even though the Swedish and the Danish four-digit NACE codes are similar, a small recoding was necessary, because some industry codes did not match, i.e. some industries were present in Sweden but not in Denmark, and vice versa. Second, two industries, i.e. the public sector and hotel and restaurants, were removed from being related to other two-digit NACE industries, because these two industries employ a wide range of people from many other industries. Due to the more general nature of their skills, we decided to recode these industries as not being related to manufacturing and services.[9] As a result of this transformation process, we identified a total of 7,750 directed and related industry pairs.

The skilled inflow measures that remain are those that are regarded as unrelated. The inflow of unrelated skills (Inflow Unrelvar) is the count of highly skilled job movers into the plant that did not work in a similar or related industry in the last five years. Also here a distinction has been made whether this inflow of unrelated industry experience is intra- or inter-regional.

3.4 Control Variables

We also controlled for other factors that explain labour productivity growth. First, productivity levels vary significantly across industries. To control for industry effects, we use industry fixed effects based on the two-digit NACE industry classification, creating a dummy variable with the value one when the plant is active in this industry. In total, we identify 34 two-digit NACE industries. Second, location fixed effects variables have been added to the model by means of dummy variables for each of the 22 local labour markets. As expected, the labour market region that includes Copenhagen (the Copenhagen Labour Market Area – from now on abbreviated with CLMA) is by far the most represented in the sample. In total 45.6 percent of all plants and 44.3 percent of all employees identified in the sample are located in this area, which covers the entire island of Sealand. In addition, 56.2 percent of all highly skilled job-movers are active in this local labour market. And third, we include year fixed effects variables, i.e. the year in which the high-skilled inflow is observed. The dummy variable gives the value one for the year in which the move is observed.

Productivity is also influenced by the size and the age of the plant. To control for these effects, we included two variables measuring the number of employees and the age of the plant. Because productivity growth can also be explained by a change in labour force and an increase in capital, we added two measures to control for this, i.e. growth in the number of employees and fixed assets between t_0 and t_2. Finally, to control for human capital, we also

[8] There are two reasons for using the Swedish industry pair matrix as an instrument for the revealed relatedness of Danish industries. First, if we would have used the revealed relatedness measure based on the high skilled job mobility in Denmark we would have run the risk of endogeneity as the method for determining the revealed relatedness is similar to the method of establishing the degree of related and unrelated skills that are present in a plant. In addition, the mobility patterns of skilled workers in Sweden will have no immediate impact on the performance of the Danish plants in our sample. Second, there would be no reason to assume that industry specific skills would vary between Sweden en Denmark with the only exceptions that some industries are not present in the Danish or Swedish economy.

[9] The analyses show that the level of significance improves when the recoded related industry pairs are used.

included a measure that indicates the share of employees with a bachelor degree or higher. Table 2 presents the descriptive statistics for these variables.

Insert Table 2 around here

Table 3 presents a correlation matrix for all the above-mentioned variables. This table indicates that there is significant correlation between some variables. Variables that have a very high correlation (e.g. between intra-regional inflow and the three more specified intra-regional inflow measures) have never been combined in any of the regressions. We also tested for multicollinearity problems by using a variance inflation factor (VIF), and the results indicate that there are no such problems.

Insert Table 3 around here

3.5 The Model

For the analyses, we use an ordinary least square regression model with fixed effects estimates. The fixed effects estimators in the model are year fixed effects, two-digit NACE industry fixed effects, and region fixed effects. These fixed effects estimators are introduced to capture parts of the unobserved heterogeneity associated with studies on labour productivity. The main objective of this paper is to test whether different types of labour flows affect plant performance, as found in Boschma *et al.* (2009). More in particular, we make use of a sophisticated revealed relatedness indicator to assess the effect of related and unrelated labour inflows on plant performance. As explained above, the model includes only plants that have experienced an inflow of highly educated or high-income earners. The model is specified as follows:

$$\Delta \ln(Y_i) = \beta_0 + \sum_{i=1}^{n} \beta_1 X_i + \sum_{i=1}^{n} \delta_2 A_i + \epsilon \qquad (3)$$

where $\Delta \ln(\mathbf{Y_i})$ is the difference in labour productivity (log) between the period t_0 and t_2, β_0 is the intercept, $\sum_{i=1}^{n} \beta_1 X_1$ represents the sum of the different inflow measures, and $\sum_{i=1}^{n} \delta_2 A_1$ indicates the sum of the remaining control variables. All models will be weighted by employment size. The motivation for doing so is the large share of small plants in the sample (50 percent of the firms in the sample has less than 25 employees). As the top 10 percent largest companies employ just over 50 percent of all employees in the sample, they only account for a small part of all employees. By including weights, the larger plants will receive a larger proportional share of the total explained variance.

Because of the particular geography of Denmark, we created two sub-samples: one including only those plants located in the Copenhagen Labour Market Area (CLMA), and another sample that includes the plants located in the rest of Denmark. The CLMA is by far the most urbanized area of Denmark, much larger than the urban area of Århus, which is the second largest city in Denmark. Furthermore, the CMLA has relatively more firms active in services compared to manufacturing, while manufacturing and service industries are equally divided in the rest of Denmark. In addition, Winther (2001) identified a clear difference in performance between firms that are located in the Greater Copenhagen region compared with firms in other parts of Denmark. Table 4 shows other significant differences between the CLMA and the rest of Denmark: plants in the CMLA experience a significantly higher labour productivity growth, higher intra-regional inflows of skilled labour, and a significant higher share of higher educated. The rest of Denmark has significantly larger and older plants, and has a higher level of inter-regional inflow of high-skilled labour.

Insert Table 4 around here

4. Empirical results

The model estimations are presented for the rest of Denmark in Table 5 (n=9,264) and for the CLMA in Table 6 (n=7,445). Overall, these models show that labour growth has a negative impact on labour productivity growth, while the growth of fixed assets and the age of the firm have a positive impact. The impact of size is different compared between the two geographical areas, i.e. positive in the CLMA and negative in the rest of Denmark. The consequence of using large sets of micro data is the large degree of unobserved heterogeneity, even when including multiple fixed effects variables. Adding multiple years into the model increases the noise even further. Nevertheless, in Table 5 all the models have a R^2 above 0.66, and in Table 6 all models have a R^2 above 0.61, indicating an overall strong model fit. The significance levels of the control variables remain the same when including skilled inflow variables.

In Table 5, Model A1 and Model A2 present the effects of the total inflow of skilled labour while Model B1 and Model B2 make a distinction on whether the inflow is from within or from outside the labour market region. Overall, the models show results that confirm our expectations on how similar, related and unrelated labour inflows affect labour productivity growth.[10]. First of all, the inflow of skilled labour on its own does not have a significant impact on labour productivity growth. This is in line with the argument of Boschma *et al.* (2009) that it is not labour mobility *per se* that has a positive impact but rather particular types of skills that are associated with this inflow. This is confirmed in Model A2. The findings show comparable patterns to the Swedish study. The inflow of high-skilled labour with related industry experience has a positive impact on labour productivity growth, the effect of the inflow of unrelated skills is positive but not as strong as related inflows, while inflow of employees with similar skills has a significant negative impact on labour productivity growth.

[10] The results show the overall impact of different types of labour flows over a five-year period. During this period Denmark underwent both a period of high growth and recession. The impact in individual years will, for this reason, differ. Because different industries and sizes of firms react differently to periods of growth and recession, the difference in impact will also be visible on these plant characteristics. Nevertheless, the overall picture shows a clear impact of similar, related and unrelated labour flows on the performance of these plants.

Insert Table 5 around here

Model B1 makes the distinction on whether the inflow is from within (intra) or outside (inter) the local labour market. We observe that the impact differs depending on whether the high-skilled labour comes from inside our outside the labour market region: intra-regional flows have a significant negative impact on labour productivity growth while skilled labour flows coming from outside the region have a positive impact. This result stands in contrast with the findings of Boschma et al. (2009), where inter-regional inflow of labour appeared to be negative. Nevertheless, the effect is not surprising, since the literature, next to regarding geographical proximity as beneficial, also hints upon the potential negative effect of intra-regional linkages due to spatial lock-in (Boschma, 2005). Our result is also supported by an empirical study on labour mobility in the Finnish high-tech industry where local labour flows had a negative impact on the innovative performance of firms (McCann and Simonen, 2005).

In Model B2, we made again a distinction whether these inter- and intra-regional flows concern similar, related or unrelated labour flows. There are some clear indications that it is crucial to make this distinction. While the inflow of skilled workers with industry experience similar to the plant had a negative impact, this negative impact only remains visible when it concerns similar inflows from within the local labour market region. Intra- and inter-regional unrelated inflows had no significant impact on labour productivity growth. The effect of the inflow of related skills is positive and significant for both intra-regional and inter-regional labour flows, but this impact is stronger for inflows from outside the local labour market. Accordingly, the negative effect of intra-regional labour flows is turned into a positive effect when it concerns inflows of related skills within the same region.

We observed earlier that there are significant differences between the CMLA and the rest of Denmark on many of our variables, like the fact that firms in the CMLA outperform firms in the rest of Denmark with regard to labour productivity growth. To check whether this impacts on our findings, we present the same analyses for the CMLA in Table 6. Overall, the estimations show different results for the CLMA, as compared to the rest of Denmark.

Model C1 presents the basic model including the impact of high-skilled labour mobility. There is no such impact on labour productivity growth, which is similar to the estimated impact in the rest of Denmark. However, when we divide the inflows in similar, related and unrelated skills, there are some noticeable differences. The inflows of similar skills has now a significant positive (instead of a negative) impact on labour productivity growth, while the inflow of employees with related skills has a negative (instead of a positive) effect, although the latter is only significant at the ten percent level. No differences can be observed between the CLMA and the rest of Denmark concerning the effect of unrelated labour flows: this effect remains positive and significant.

Insert Table 6 around here

In Model D1, we included the regional dimension. Similar as to the rest of Denmark, the inflow of inter-regional skilled labour has a positive impact on plant productivity growth. The inflow of skilled labour from within the same labour market region has no significant effect, while in the rest of Denmark it had a slight negative impact. When making a distinction on whether the inflow concerns similar, related or unrelated skills (model D2), we observe that the intra- and inter-regional inflow of similar skills has a positive impact. The effect of intra-regional related inflows is negative, while we found no effect for inter-regional related inflows.

In sum, the plants located in the CLMA react differently to the inflow of skilled labour. To investigate this further, we made an additional divide by separating the CLMA into five smaller geographical areas, a division that is based upon the former Danish counties (see Figure 2).[11] This interest is motivated by the fact that these geographical areas within the CMLA are still very different. These differences can be of the same magnitude as the difference between the CMA and other areas within Denmark, although firms and people in these areas could benefit from their proximity to the CMA. The geographical area around Copenhagen, CMA, remains dominant in terms of number of plants, employees, and skilled labour inflow but that is to be expected given the extreme high level of urbanization compared to the rest of Denmark.[12]

Insert Figure 2 around here

Given these strong regional differences within the CMLA, we made an additional analysis where we separated the CMA from the rest of the CMLA, which we will briefly report here (see Table 7). The coefficients and significance in the CMLA excluding the CMA follow the expected pattern (as for the rest of Denmark), i.e. related labour inflows has the biggest positive impact on labour productivity growth. This provides a first indication that the different findings on related labour flows in Table 6 are caused by those plants that are located in the CMA. A more thorough analysis of the CMA supports this and shows that: (i) similar inflows has a positive impact on labour productivity growth, (ii) unrelated inflows has no impact, and (iii) related inflows has a strong negative impact on labour productivity growth. With respect to intra-regional mobility, we found that related labour flows has a strong negative impact on labour productivity growth, while the inflow of similar and unrelated skills from the same labour market region has no significant effect. With respect to inter-regional mobility, similar flows have a relatively strong significant impact, related and unrelated inflows have no significant impact. In sum, the negative impact of related labour inflows in the Copenhagen area (CMA) is only manifested when these occur within the Copenhagen labour market area, while the positive impact of similar labour flows occurs especially when coming from outside the region.

[11] CLMA covers the area that up to January first 2007 (partially) covered seven counties, i.e. Copenhagen municipality, Frederiksberg municipality, Copenhagen County, Frederiksborg County, Roskilde County, West Sealand County, and the area of Storstrøm County that is located on the large island of Sealand (the other part are the islands of Lolland and Falster). Since the municipalities of Copenhagen and Frederiksberg are relatively small geographical areas located within the Copenhagen County, these three counties are merged together as one area. This area will be indicated as the Copenhagen Metropolitan Area (CMA).

[12] CMA harbours 3,424 plant (i.e. 20.49 percent of the total number of plants in the sample), 193,406 employees (i.e., 18.96 percent of the total number of employees in the sample) and 15,611 skilled labour inflows (i.e., 30,26 percent of the total number of skilled labour inflow of the sample).

Overall, our findings show that the effect of related labour inflows is positive and the effect of similar inflows is negative on plant performance, as expected, with the exception of the Copenhagen region. A possible explanation for the latter result is the more dominant role of service industries in the CMA, as compared to the rest of Denmark. This might indicate that related inflows are less important for service industries. However, this might also be a statistical artefact, because service industries are less narrowly, more broadly defined than manufacturing sectors. This may provide an explanation for why inflows of similar skills has a positive impact on plant performance in the Copenhagen region, because in reality, this type of labour mobility within service industries concern not strictly similar skills but may still consist of a wide range of related skills. Another possible explanation is the fact that plants within the same industry might be more specialized in the Copenhagen region. This means that within each industry, there is still a considerable degree of variety of skills available in the Copenhagen region. This might imply that the recruitment of new employees from other plants in the same industry in the Copenhagen region actually concerns the inflow of new related skills. This might explain the positive impact of inflows of similar skills in the Copenhagen region. Related to that is the fact that workers are more likely to be more productive when coming from more specialized firms within the same industry.[13]

5. Conclusions

This paper has made an attempt to contribute to the growing literature that assesses the impact of labour mobility on plant performance. Making use of unique Danish data, our study provides strong evidence that the effect of labour mobility can only be assessed when one accounts for the type of skills that flow into a plant, and the degree to which these new skills match the existing skills in the plant. To assess the degree of relatedness between new and existing skills, we used a sophisticated indicator of revealed industry relatedness developed by Neffke and Henning (2012) that determines the degree of skill relatedness between sectors on the basis of mobility of non-managerial skilled workers across sectors.

As expected, we found that the inflow of related skills impacts positively on plant performance, while inflows of skills that are similar to the existing skills in the plant have a negative effect on plant performance. These results are in line with findings found in Sweden (Boschma *et al.*, 2009). An interesting and remarkable outcome was that these effects were different for plants located in the most densely populated region of Copenhagen. Moreover, we found evidence that the effect of labour mobility on plant productivity growth depends on whether new employees are recruited from the same region or from other regions. Inter-regional skilled labour mobility had a positive effect on plant performance, which is an outcome that stands out from claims made earlier by economic geographers. However, our findings also clearly showed that the effect of intra- and inter-regional labour mobility depended on the type of skills that flow into the plant.

These findings call for further research. First of all, the particular outcomes found in the Copenhagen region require further research. Contrary to the rest of Denmark, we found a negative impact of (intra-regional) inflows of related skills, and a positive impact of mobility of similar skills on plant performance. We discussed a number of plausible explanations in the previous section, but these need to be taken up in future research. For instance, is the

[13] To investigate whether the difference is driven by the difference in industry structure, we separated the sample in service and manufacturing industries. Despite the fact that the coefficients of the analyses and the model fit changed the overall pattern remained the same.

inflow of related skills more relevant for manufacturing industries, and less relevant for service industries? Secondly, more in general, it would be interesting to see whether our findings can be replicated for particular sectors. Do these findings differ from one sector to another? And do these findings also differ from one stage of the industry life cycle to the next stage? One could hypothesize that in the early stages, new firms need labour from related industries, like new firms also tend to benefit from entrepreneurs that have acquired experience in related industries (Boschma and Wenting, 2007; Klepper, 2007). Thirdly, how do different geographical areas react on the impact of mobility of similar, related and unrelated skills? We already noticed a remarkable difference between the Copenhagen region and the rest of Denmark. There might be other types of regions (like old industrial regions, peripheral regions, et cetera) that might show different labour mobility patterns, and different effects on plant performance. And fourthly, this kind of labour mobility studies could contribute to the spatial externalities literature. Do regions with a high degree of related labour mobility enhance regional growth in general? And fifthly, there is a need to investigate the effect of mobility of related skills more in detail at the firm level. In our study, this issue has remained a black box. What happens exactly when new employees with related skills enter a plant? We believe that these and others questions would contribute to increase our (yet) little understanding of how labour mobility affects the economic performance of plants and regions, and to what extent relatedness is a crucial input to that.

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Figure 1. Labour Market Areas in Denmark based on Commuting Patterns, 1995-2003

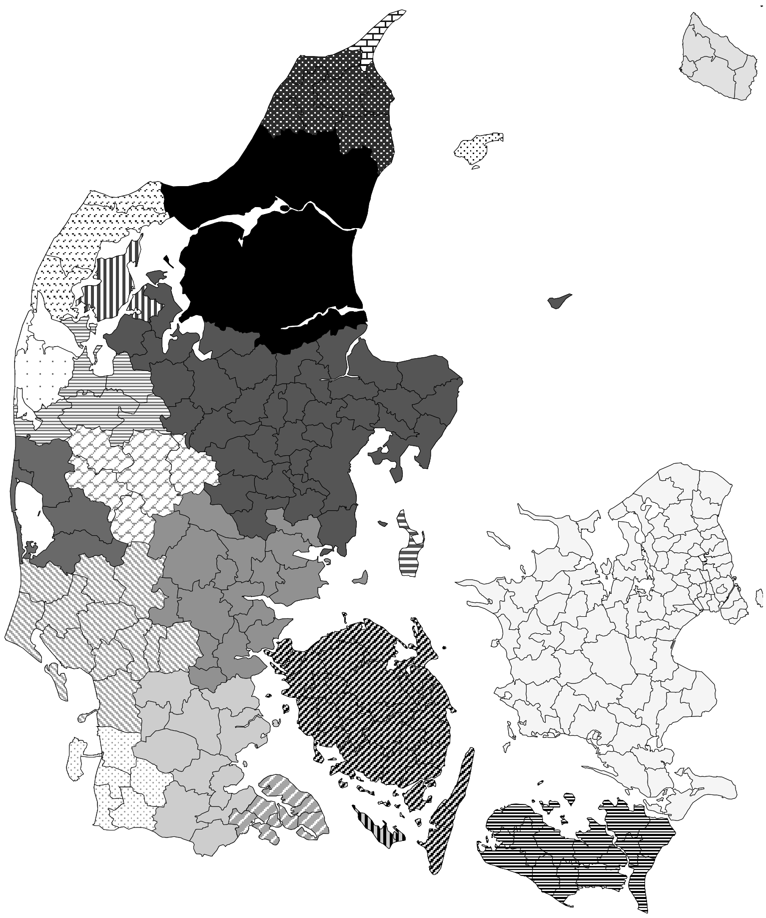

Table 1. High-Skilled Job Movers and Plants 1999-2003

Year	*Plants*	*Total employees*	*High skilled inflow*
1999	3,392	217,394	10,772
2000	4,229	233,010	12,146
2001	3,272	195,118	10,609
2002	3,039	189,929	9,414
2003	2,777	184,633	8,641
Total	16,709	1,020,084	51,582

Table 2. Variable description (n=16,709)

Variables		Mean	SD	Min	Max
Productivity Growth	Change in labour productivity t and t+2 (log)	0.26	1.87	-6.38	17.03
Growth of Labour	Change in employees between t and t+2 (log)	-0.08	0.46	-5.09	4.32
Growth of Fixed Assets	Change in fixed assets between t and t+2 (log)	-0.01	1.45	-14.84	16.85
Plant Size	Number of employees in the plant (log)	3.45	1.27	0.00	8.79
Firm Age	The age of the firm in the number of years (log)	2.77	0.66	1.61	4.71
High Education Ratio	Share of employees with at least a bachelor degree	0.17	0.23	0.00	1.00
Skilled Inflow	Total number of highly skilled inflows (log)*	1.11	0.60	0.69	5.51
Intra-regional Skilled Inflow	Total number of highly skilled inflows from within the same local labour market region (log) *	0.88	0.66	0.00	5.49
Inter-regional Skilled Inflow	Total number of highly skilled inflows from a different local labour market region (log) *	0.35	0.51	0.00	4.11
Inflow Sim	Number of highly skilled inflows with similar industry experience (log) *	0.46	0.61	0.00	5.15
Inflow Relvar	Number of highly skilled inflows with no similar but at least related industry experience (log) *	0.36	0.54	0.00	4.23
Inflow Unrelvar	Number of highly skilled inflows with solely unrelated industry experience (log) *	0.52	0.61	0.00	4.67
Intra Inflow Sim	Number of intra-regional highly skilled inflows with similar industry experience (log) *	0.36	0.56	0.00	5.15
Intra Inflow Relvar	Number of intra-regional highly skilled inflows with no similar but at least related industry experience (log) *	0.28	0.50	0.00	4.23
Intra Inflow Unrelvar	Number of intra-regional highly skilled inflows with solely unrelated industry experience (log) *	0.42	0.56	0.00	4.62
Inter Inflow Sim	Number of inter-regional highly skilled inflows with similar industry experience (log) *	0.13	0.35	0.00	3.91
Inter Inflow Relvar	Number of inter-regional highly skilled inflows with no similar but at least related industry experience (log) *	0.10	0.28	0.00	3.40
Inter Inflow Unrelvar	Number of inter-regional highly skilled inflows with solely unrelated industry experience (log) *	0.16	0.36	0.00	3.73

*Due to the high frequency of zero's we used the following log transformation log(x+1).

Table 3. Pearson Correlation Coefficients (n=16,709)

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Productivity Growth																	
2. Growth of Labour	**-0.10**																
3. Growth of Fixed Assets	**0.05**	**-0.03**															
4. Plant Size	**0.11**	-0.10	**0.01**														
5. Firm Age	**-0.06**	**-0.02**	-0.01	**0.25**													
6. High Education Ratio	**-0.06**	**0.04**	-0.01	-0.19	-0.08												
7. Skilled Inflow	**0.06**	**-0.04**	0.01	**0.56**	**0.13**	**0.14**											
8. Intra-regional Skilled	**0.06**	**-0.02**	0.01	**0.43**	**0.08**	**0.15**	**0.84**										
9. Inter-regional Skilled	0.01	**-0.03**	0.00	**0.35**	**0.11**	**0.02**	**0.48**	-0.01									
10. Inflow Sim	**0.11**	**-0.03**	0.00	**0.22**	**0.05**	**0.18**	**0.60**	**0.51**	**0.27**								
11. Inflow Relvar	-0.02	-0.01	0.00	**0.31**	**0.05**	**0.10**	**0.59**	**0.52**	**0.27**	**0.12**							
12. Inflow Unrelvar	0.00	-0.01	0.01	**0.49**	**0.14**	0.00	**0.65**	**0.55**	**0.35**	0.01	**0.20**						
13. Intra Inflow Sim	**0.11**	**-0.03**	0.01	**0.20**	**0.03**	**0.17**	**0.56**	**0.63**	0.01	**0.89**	**0.14**	**0.04**					
14. Intra Inflow Relvar	-0.01	-0.01	0.00	**0.26**	**0.03**	**0.11**	**0.56**	**0.61**	**0.05**	**0.15**	**0.90**	**0.21**	**0.19**				
15. Intra Inflow Unrelvar	0.01	-0.01	0.02	**0.43**	**0.13**	**0.03**	**0.62**	**0.67**	**0.10**	**0.05**	**0.22**	**0.90**	**0.10**	**0.25**			
16. Inter Inflow Sim	**0.05**	**-0.02**	-0.01	**0.13**	**0.06**	**0.08**	**0.32**	0.00	**0.63**	**0.52**	**0.05**	0.01	**0.11**	**0.02**	0.00		
17. Inter Inflow Relvar	-0.01	-0.01	0.00	**0.21**	**0.05**	**0.02**	**0.29**	**0.02**	**0.56**	**0.02**	**0.50**	**0.10**	-0.01	**0.11**	**0.05**	**0.11**	
18. Inter Inflow Unrelvar	**-0.02**	-0.01	0.01	**0.34**	**0.09**	**-0.04**	**0.38**	**0.06**	**0.69**	0.01	**0.11**	**0.57**	-0.01	**0.05**	**0.20**	**0.08**	**0.19**

Note: Correlation estimates indicates in bold are significant on the 5 percent level.

Table 4. T-test on the mean differences between firms located in the Copenhagen Labour Market Area (CLMA=1) and the rest of Denmark (CLMA=0).

Variable	CLMA =1	N^1=7,445	CLMA =0	N^0=9,264	p-value of two tailed t-test on mean difference
	Mean	*Std.err.*	*Mean*	*Std. err.*	
Productivity Growth	0.328	0.024	0.200	0.017	<0.000
Growth of Labour	-0.082	0,005	-0.078	0.005	0.556
Growth of Fixed Assets	0.008	0.019	-0.021	0.013	0.208
Plant Size	3.336	0.015	3.544	0.013	<0.000
Firm Age	2.754	0.008	2.791	0.007	<0.000
High Education Ratio	0.217	0.003	0.140	0.002	<0.000
Skilled Inflow	1.188	0.008	1.045	0.005	<0.000
Intra-regional Skilled Inflow	1.122	0.008	0.689	0.006	<0.000
Inter-regional Skilled Inflow	0.156	0.004	0.501	0.006	<0.000
Inflow Sim	0.512	0.008	0.417	0.006	<0.000
Inflow Relvar	0.425	0.007	0.311	0.006	<0.000
Inflow Unrelvar	0.566	0.008	0.497	0.006	<0.000
Intra Inflow Sim	0.474	0.007	0.265	0.005	<0.000
Intra Inflow Relvar	0.403	0.007	0.186	0.005	<0.000
Intra Inflow Unrelvar	0.531	0.007	0.322	0.005	<0.000
Inter Inflow Sim	0.062	0.003	0.182	0.004	<0.000
Inter Inflow Relvar	0.038	0.002	0.146	0.003	<0.000
Inter Inflow Unrelvar	0.069	0.003	0.228	0.004	<0.000

Note: all variables, with the exception of growth of labour and growth of fixed assets, are significantly different.

Figure 2. Copenhagen Labour Market Area divided in five smaller geographical entities (CMA is the geographical area furthest to the east).

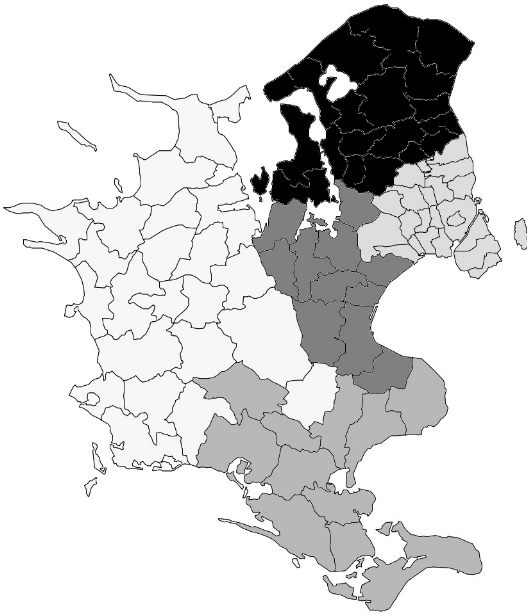

Table 5. Fixed effects regressions on the effects of labour mobility on productivity growth for all plants (excluding the plants in the CLMA) with inflow of skilled workers.

Productivity Growth	Model A1			Model A2			Model B1			Model B2		
	Coefficient		S.E.	*Coefficient*		S.E.	*Coefficient*		S.E.	*Coefficient*		S.E.
Intercept	-0.100		0.138	0.034		0.141	-0.078		0.140	0.015		0.143
Growth of Labour	-0.286	***	0.029	-0.291	***	0.029	-0.286	***	0.029	-0.295	***	0.029
Growth of Fixed Assets	0.135	***	0.014	0.136	***	0.014	0.136	***	0.014	0.137	***	0.014
Plant Size	-0.026		0.018	-0.053	***	0.018	-0.031	*	0.018	-0.050	***	0.018
Firm Age	0.158	***	0.022	0.162	***	0.021	0.156	***	0.022	0.157	***	0.022
High Education Ratio	0.007		0.155	-0.104		0.155	-0.040		0.156	-0.088		0.155
Total Skilled Inflow	-0.003		0.025									
Total Intra Skilled Inflow							-0.040	*	0.022			
Total Inter Skilled Inflow							0.054	**	0.023			
Inflow Sim				-0.053	**	0.021						
Inflow Relvar				0.090	***	0.025						
Inflow Unrelvar				0.049	**	0.024						
Intra Inflow Sim										-0.089	***	0.024
Intra Inflow Relvar										0.055	*	0.031
Intra Inflow Unrelvar										0.024		0.026
Inter Inflow Sim										0.026		0.031
Inter Inflow Relvar										0.106	***	0.034
Inter Inflow Unrelvar										0.024		0.028
Year Fixed Effects	yes			yes			yes			yes		
Industry Fixed Effects	yes			yes			yes			yes		
Region Fixed Effects	yes			yes			yes			yes		
Weighted by	employment size			employment size			employment size			employment size		
R2	0.662			0.663			0.662			0.663		
Adjusted R2	0.659			0.660			0.660			0.661		
N	9,264			9,264			9,264			9,264		

*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level

Table 6. Fixed effects regressions on the effects of labour mobility on productivity growth for all plants in the CLMA with inflow of skilled workers.

Productivity Growth	Model C1			Model C2			Model D1			Model D2		
	Coefficient		S.E.	*Coefficient*		S.E.	*Coefficient*		S.E.	*Coefficient*		S.E.
Intercept	-1.328	***	0.209	-1.170	***	0.220	-1.171	***	0.213	-1.079	***	0.221
Growth of Labour	-0.265	***	0.052	-0.267	***	0.053	-0.269	***	0.052	-0.260	***	0.053
Growth of Fixed Assets	0.132	***	0.023	0.128	***	0.023	0.130	***	0.023	0.126	***	0.023
Plant Size	0.350	***	0.038	0.313	***	0.038	0.334	***	0.038	0.304	***	0.037
Firm Age	0.163	***	0.044	0.158	***	0.044	0.144	***	0.044	0.140	***	0.044
High Education Ratio	-0.771	***	0.237	-0.850	***	0.235	-0.848	***	0.237	-0.944	***	0.234
Total Skilled Inflow	0.071		0.046									
Total Intra Skilled Inflow							0.011		0.046			
Total Inter Skilled Inflow							0.225	***	0.055			
Inflow Sim				0.120	***	0.038						
Inflow Relvar				-0.076	*	0.044						
Inflow Unrelvar				0.107	**	0.043						
Intra Inflow Sim										0.105	***	0.039
Intra Inflow Relvar										-0.097	**	0.045
Intra Inflow Unrelvar										0.064		0.046
Inter Inflow Sim										0.292	***	0.071
Inter Inflow Relvar										0.054		0.112
Inter Inflow Unrelvar										0.109		0.077
Year Fixed Effects	yes			yes			yes			yes		
Industry Fixed Effects	yes			yes			yes			yes		
Region Fixed Effects	yes			yes			yes			yes		
Weighted by	employment size			employment size			employment size			employment size		
R2	0.618			0.619			0.619			0.620		
Adjusted R2	0.616			0.617			0.617			0.618		
N	7,445			7,445			7,445			7,445		

*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level

Table 7. Fixed effects regressions on the effects of labour mobility on productivity growth for all plants in the CMA with inflow of skilled workers.

Productivity Growth	Model A1			Model A2			Model B1			Model B2		
	Coefficient		S.E.	*Coefficient*		S.E.	*Coefficient*		S.E.	*Coefficient*		S.E.
Intercept	-0.756	***	0.290	-0.829	***	0.304	-0.586	**	0.295	-0.749	**	0.305
Growth of Labour	-0.141	**	0.063	-0.129	**	0.064	-0.147	**	0.063	-0.118	*	0.064
Growth of Fixed Assets	0.113	***	0.028	0.111	***	0.279	0.109	***	0.028	0.11	***	0.028
Plant Size	0.175	***	0.057	0.183	***	0.055	0.166	***	0.057	0.18	***	0.055
Firm Age	0.339	***	0.064	0.352	***	0.064	0.321	***	0.064	0.339	***	0.064
High Education Ratio	-0.724	**	0.302	-0.757	**	0.298	-0.834	***	0.302	-0.88	***	0.298
Total Skilled Inflow	-0.015		0.064									
Total Intra Skilled Inflow							-0.106		0.067			
Total Inter Skilled Inflow							0.267	***	0.073			
Inflow Sim				0.137	***	0.051						
Inflow Relvar				-0.213	***	0.061						
Inflow Unrelvar				0.005		0.062						
Intra Inflow Sim										0.061		0.052
Intra Inflow Relvar										-0.221	***	0.063
Intra Inflow Unrelvar										-0.012		0.068
Inter Inflow Sim										0.542	***	0.092
Inter Inflow Relvar										-0.122		0.166
Inter Inflow Unrelvar										-0.121		0.109
Year Fixed Effects	yes			yes			yes			yes		
Industry Fixed Effects	yes			yes			yes			yes		
Region Fixed Effects	no[1]			no[1]			no[1]			no[1]		
Weighted by	employment size			employment size			employment size			employment size		
R2	0.587			0.588			0.588			0.592		
Adjusted R2	0.581			0.583			0.583			0.587		
N	3,424			3,424			3,424			3,424		

*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level

1: only one region included in the analysis