CESIS Electronic Working Paper Series

Paper No. 209

LABOR MOBILITY, KNOWLEDGE DIFFUSION AND REGIONAL GROWTH

Per Thulin

CESIS and the Division of Economics at KTH

December 2009

The Royal Institute of Technology
Centre of Excellence for Science and Innovation Studies (CESIS)
http://www.cesis.se

Labor Mobility, Knowledge Diffusion and Regional Growth[*]

Per Thulin

Abstract

This paper investigates the relationship between inter-firm labor mobility and regional productivity growth. Previous studies have shown that density is positively correlated with growth. I claim that it is not density in itself, but rather the attributes associated with it that drives economic growth. One such attribute is the increased possibility for labor mobility and knowledge diffusion that follows when firms and individuals locate in close proximity to each other. This hypothesis is tested using a matched employer-employee dataset where regional labor mobility is instrumented with density. The result shows that labor mobility increases regional growth rates.

Keywords: Labor mobility, regional growth, agglomeration economies
JEL classification: R11, R23, J62

[*] I would like to express my sincerest gratitude to Martin Andersson and Pontus Braunerhjelm for their support and constructive comments during the completion of this paper. Financial support from EU sixth framework program (MICRODYN project) is also gratefully acknowledged.

1. Introduction

The purpose of the paper is to empirically investigate the relationship between labor mobility and productivity growth at a regional level. A large literature suggests that labor mobility facilitates knowledge diffusion and increases labor market efficiency which in turn will have a positive impact on regional growth. I test this hypothesis using regression analysis based on a full-coverage, detailed matched employer-employee dataset for Swedish labor market regions. The result from the analysis supports the hypothesis.

Labor mobility can affect productivity in at least two ways. First, labor mobility facilitates knowledge diffusion by exposing the worker to a wider set of other workers, thereby increasing the potential for human interactions and knowledge flows. Knowledge flows from the new worker to the incumbent workforce, but also from the incumbent workforce to the new worker, leading to an overall increase in human capital in the region. Second, the quality of the match between a worker and a job is likely to improve as the worker move between different employers and tries different jobs. A better match between workers' skills and aptitudes and what is required by the job lead to a more efficient allocation of the workforce and higher overall productivity. Labor mobility can therefore be expected to have a positive impact on the level and growth rate of regional productivity regardless of which one of the two abovementioned mechanisms we refer to.

The econometric analysis is based on a matched employer-employee dataset covering all employed individuals, aged 16–64 years, in the private sector of the Swedish economy between 1997 and 2005. The impact of labor mobility on regional growth is estimated in two steps, where the first step is aimed at obtaining measures of labor mobility, controlling for heterogeneity along several dimensions. This step utilizes the micro structure of the dataset and implements probit analyses at the individual level, regressing intraregional labor mobility on individual and firm characteristics and a set of regional dummy variables. The estimated coefficients of the regional dummies are subsequently used as a measure of intraregional labor mobility.

The second step uses cross-section regression analysis to assess the impact of labor mobility on regional wage growth. The unit of observation is Swedish labor market regions (FA-regions), defined as areas in which people can live and work without having too long commuting times.[†] Regional wage growth is regressed on the intraregional labor mobility variable obtained in step one and a set of control variables, using density and density squared as instruments for labor mobility. Potential spatial autocorrelation is dealt with by including accessibility measures among the exogenous variables. The result from the analysis shows that labor mobility is statistically significant and positively related to productivity growth.

The rest of the paper is organized as follows. Section 2 provides a short summary of previous work on labor mobility, agglomeration economies and productivity while Section 3 presents the econometric design. The results from the analysis are reported in Section 4. Section 5 makes use of the panel structure of the dataset and estimates the relationship between labor mobility and productivity growth using fixed, region-specific effects as a robustness test of the cross-section estimations in Section 4. The paper ends with conclusions in Section 6.

2. Space and regional productivity – a short review

The importance of the spatial dimension for economic growth can be found in Lucas (1988), building on Romer's (1986) model of endogenous accumulation of knowledge. Romer assumes that firms' production capabilities not only depend on firm specific inputs,

[†] Sweden is divided into 72 FA-regions.

but also on the aggregate stock of knowledge in society. The basic premise for this approach is that knowledge constitutes a special type of good – nonrivalrous and only partially excludable. Based on this premise, Romer argues that firms' investments in new knowledge automatically spill over to the rest of the economy benefiting all other firms. This externality breaks the tight chains imposed by the neoclassical constant return property and the ensuing decreasing returns to capital accumulation that previously made perpetual growth unattainable in economic models.

While Romer treats knowledge as a disembodied production factor, i.e. like knowledge in a book, along with physical capital and labor, Lucas (1988) emphasizes the role of human capital and personal interactions for knowledge diffusion and growth. This view also gives the spatial dimension a center role in explaining economic growth. The potential for human interactions, and hence, the potential for knowledge diffusion, is larger in more dense environments where people live and work in close proximity to each other. Thus, if we want to understand why regions and countries have different economic growth rates we need to include the spatial dimension in the analysis.

I will base the ensuing discussion in this section on Figure 1, showing the interaction between the spatial dimension of economic activity, agglomeration economies and productivity. The taxonomy "learning, matching and sharing", characterizing the channels through which the spatial dimension is assumed to affect productivity, is borrowed from Duranton and Puga (2004).

FIGURE 1 HERE

The spatial distribution of economic activity has been shown in a number of empirical studies to affect productivity. The bulk of these studies have been carried out on either the regional or individual level, regressing productivity directly on various density measures. One of the most cited studies of this kind is Ciccone and Hall (1996) who find a positive correlation between density, measured as workers per acre of land, and labor productivity across U.S. states. Their results show that a doubling of employment density is associated with six percent higher productivity and that more than half of the variance in value-added per employee across U.S. states can be attributed to differences in density. In a follow-up study on European regions, Ciccone (2002) finds that a doubling of density is associated with about 4.5 percent higher productivity. Braunerhjelm and Borgman (2004) study the impact of industrial concentration on labor productivity growth in Swedish labor market regions over the period 1996-1999. They conclude that a doubling of average concentration, measured by the Ellison-Glaeser index, raises the growth of value added per employed by approximately 2–6 percent.

Other studies dig deeper and try to discern the mechanisms behind the observed positive relationship between density and productivity. Such approach is taken by Andersson and Thulin (2009) who use a matched employer-employee dataset to analyze the determinants of labor mobility within Swedish labor market regions. One conclusion from their study is that average labor mobility rates are higher in dense environments with a wider range of employers to choose from. They also find that labor mobility decreases with age and increases with educational attainment. Bleakley and Lin (2007) arrive at a somewhat different conclusion when studying regions in the U.S. They find that average labor mobility is lower in denser regions. When looking at the sub sample of younger individuals, though, labor mobility is higher in more densely populated areas. The authors argue that the observed mobility pattern is due to the impact density has on search costs. It takes less time and is therefore less costly to find new relevant jobs in denser areas with thicker labor markets and many employers within short time distances. Hence, workers are more likely to search for new jobs in denser regions and they do so early in their careers to maximize their work life income. Even though the two studies referred to reach somewhat different conclusions, they both emphasize the importance of the spatial distribution of economic activity for labor mobility, as indicated by the solid line in Figure 1. However, the causality can also go the other way. When workers move between different jobs and locations they also change the geographic distribution of economic activity, shown by the dotted line.

As workers move between different jobs, they carry with them knowledge that at least partially will benefit the receiving location and its close environments. This corresponds to the line connecting labor mobility and the "learning" box in Figure 1. Several studies confirm this view and show that knowledge flows tend to follow workers as they move between different locations (see e.g. Almeida and Kogut, 1999; Oettl and Agrawal, 2008 and Görg and Strobl, 2005). Almeida and Kogut (1999) is a well-known study that links mobility of engineers between firms to knowledge flows. They analyze the degree of knowledge localization, defined as the rate at which patents from the same regions cite each other, in the semiconductor industry across regions in the U.S. They find that inter-firm mobility of engineers within regions is a significant explanation for the degree of knowledge localization. Regions with high inter-firm mobility of engineers also have higher knowledge localization, all else equal.

Labor mobility also makes it more likely that the match between worker's skills and aptitudes and what is demanded by the jobs is of a high quality. The ensuing result is higher labor market efficiency as the labor force is allocated to the "right" jobs. This is shown by the line connecting labor mobility and the "matching" box in Figure 1. For instance, Topel and Ward (1992) show that the path to a stable employer-employee relation is characterized by frequent job switching and wage growth. They suggest that frequent job switching among young workers can be understood as a consequence of a search for a high match quality, and that a match need to be experienced to be evaluated, i.e. an experience good (Farber 1994).

Both the learning and matching effect can be expected to increase productivity within the region. However, the causality might also go in the other direction as productivity shocks are likely to induce labor mobility, as indicated by the dotted line. This has implications for studies where the focus is to empirically analyze the effects of labor mobility on productivity because labor mobility cannot be treated as an exogenous variable in this context. The final box, “sharing”, refers to benefits from common access to, for instance, large indivisible investments in e.g. infrastructure, made possible in larger and denser regions. These investments increase productivity for local firms by reducing different kinds of costs, such as transportation costs.

The literature discussed in this section suggests that the spatial dimension of economic activity affects local productivity and that labor mobility constitutes a mechanism through which this relationship works. This hypothesis is tested in the subsequent sections of the paper using regression analysis based on a matched employer-employee dataset for Swedish labor market regions.

3. Econometric framework

The data are provided by Statistics Sweden and constitute a unique matched employer-employee dataset spanning the period 1997–2005. The dataset comprises all firms, plants and employed individuals (16–64 years) in the private sector (NACE 15–74) of the Swedish economy, which makes it possible to follow individuals over time and between firms, plants and regions. Statistics Sweden has gone through great length to circumvent problems with registry-based statistics, which can be affected for jurisdictional reasons, to get stable identities for firms and plants. This enables me to identify true labor mobility without picking up labor mobility caused by firms changing their organizational identity numbers etc.

Labor mobility can be measured in many different ways and the choice of definition depends on the topic at focus. For instance, if our interest lies in studying the forces shaping the spatial distribution of economic activity, we might define labor mobility as interregional or international movements of workers. Spatial concentration would then occur should regional or national inflow of labor be greater than the outflow. The focal point in this paper is the relationship between labor mobility and productivity growth, emphasizing knowledge diffusion and matching as the prime means behind this relationship. The definition of labor mobility I will use is based on workers' intraregional movements between firms. Even though it is likely that both international and interregional mobility affect a region's productivity via the abovementioned mechanisms, it probably does so to a lesser extent than the movement of workers within regions since the latter type of mobility is a much more frequent phenomenon than the former, as can be seen in Table 1.

TABLE 1 HERE

Average intraregional labor mobility in Swedish labor market regions stand for between 42 and 90 percent of the regions' total labor mobility during the period 1997–2004 with an average across regions of 80 percent.

The purpose of the present paper is to investigate the impact of labor mobility on regional productivity growth. This raises a number of empirical issues that have to be addressed. First, autocorrelation between regions might introduce bias and/or inefficiency in the estimators. Second, as seen in Section 2, labor mobility is likely to be endogenous since productivity shocks can be expected to cause labor market dynamics which again will introduce bias in the estimators. Third, using labor mobility rates, defined as number of job switchers divided by overall employment, as regressors when explaining productivity growth is like using apples and pears. For instance, workers with different educational attainments are likely to affect productivity differently. We need to have a sharper measure of labor mobility that controls for regional heterogeneity in a variety of dimensions such as age- and industry structure, educational composition etc. The present section deals with these issues and presents the empirical model used to estimate the effect of labor mobility on regional growth.

3.1 Labor mobility measure

The first thing I will have to do is to get a measure of intraregional labor mobility. To achieve this, I will take advantage of the micro level structure of the dataset and estimate individuals' likelihood of changing jobs using a standard probit model,

$$\begin{aligned} &\Pr\left(Mob_{i,t}=1\,|\,\mathbf{x}_{i,t}\right)=\Phi\left(\mathbf{x}'_{i,t}\mathbf{\Gamma}\right), \\ &\mathbf{x}'_{i,t}\mathbf{\Gamma}=\alpha+\mathbf{r}'\boldsymbol{\beta}+\mathbf{z}'_{i,t}\boldsymbol{\gamma}+\varepsilon_{i,t} \end{aligned} \tag{1}$$

where $Mob_{i,t}$ takes on the value one if individual i has changed employer within the region between period t and $(t+1)$ and zero otherwise.[‡] Vector **r** consists of regional dummies and vector **z** of control variables included to capture regional heterogeneity. The estimated coefficients of the regional dummies in equation (1) are then used to form a new variable, Mob_r, which is subsequently implemented as a measure of intraregional labor mobility in the growth regressions.

[‡] The labor market Dorotea is excluded from the sample since the region lack intraregional labor mobility for highly educated throughout the period.

Turning to the variables in vector **z**, both age and age squared are included as regressors. This is motivated by the pattern of labor mobility observed in e.g. Andersson and Thulin (2009) and Topel and Ward (1992), who show that labor mobility decreases with age. Consequently, I assume that the probability of job switching is declining with age, possibly in a nonlinear fashion. Andersson and Thulin (2009) also find that labor mobility rates are higher for individuals with higher levels of education, which might be explained by better educated individuals having access to a wider range of employers. I control for this in the probit estimations by including six dummy variables indicating highest attained level of education. I also control for the length individuals have remained with the same employer by including a tenure variable. The longer the relationship between the employee and the employer, the more likely is it that the match is of high quality and hence, the less likely is the worker to search for a new job. Another reason for expecting a negative sign for this variable is the design of Swedish labor market regulations, where employment security increases with time spent with the same employer.

Furthermore, vector **z** includes the individual's wage. Being employed in a firm that ceteris paribus pays higher wages is likely to reduce the incentive to search for a new job so I expect this variable to have a negative coefficient. I also include a dummy variable taking on the value one for firms with declining employment between year ($t-1$) and t. Being employed in a firm that decreases its employment between year ($t-1$) and t can affect job switching in two ways. Either the worker loses its job between year t and ($t+1$) due to continued downsizing of the firm and is therefore forced to find a new job elsewhere or the worker chooses to look for a new job because the future within the firm looks less prosperous. Without distinguishing between these two alternatives the effect of declining employment at the firm level is likely to increase the average probability of job switching. I will also control for gender, time and industry where the individual works (2-digit NACE

Rev. 1), using dummy variables. Table 2 provides summary statistics for the variables, distributed on highly educated (at least three years of university education) and all individuals.

TABLE 2 HERE

3.2 Labor mobility and productivity growth

The impact of labor mobility on regional growth is estimated in a cross section fashion where the growth rate between 1998 and 2005 is regressed on the labor mobility measure obtained in the probit analysis and the initial values for a set of control variables.

There is an ongoing academic debate on which variable that is most appropriate to use as a dependent variable when trying to explain regional productivity growth (see for instance Glaeser et al., 1995 and Almeida, 2007). A number of empirical studies are based on the assumption that more productive regions attract more workers and consequently use employment growth as a proxy for long-run productivity growth (e.g. Glaeser et al., 1995). This approach is, however, based on the assumption of a national labor market, which in turn implies that wage growth is equalized across regions. However, as shown by Almeida (2007), there are a number of reasons why this assumption might fail. For instance, if migration costs are sufficiently high then labor will not move to equalize wage growth across regions. This, in turn, will break the proportionality between employment growth and long-run productivity growth. The unit of observation in this study is labor market regions and I will assume that wages are more locally determined.[§] Under this assumption, I argue that average regional wage growth constitutes a good proxy for regional productivity growth. A more formal

[§] According to the National Mediation Office (2009), approximately 90 percent of all employed individuals in Sweden are subject to some form of local wage setting.

motivation for using regional wage growth as a proxy for productivity growth is found in the Appendix.

The estimated coefficients for the regional dummies in (1) are used as a measure of labor mobility in the growth regression. This measure controls for regional heterogeneity in a variety of dimensions and is therefore a more appropriate measure of labor mobility than simple labor mobility ratios when studying the impact of labor mobility on productivity growth. Even though this measure of labor mobility is better in a regression context, I still need to address possible endogeneity problems.

Productivity shocks that affect regional growth are also likely to affect labor market dynamics in the region, which implies that labor mobility is correlated with the error term and hence that the estimators are biased. Consider for example the entry of a new firm in the ICT sector that introduces a productivity enhancing innovation to the ICT market. This implies that the average productivity level in the region where the firm is located jumps up. It will also increase the competitive pressure on incumbent ICT-firms, and potentially force some of them out of business. This, in turn, will lead to increased labor mobility as those formerly employed by the incumbent firms must search for new jobs.

I will use density, measured as numbers of workers per unit of land, and density squared as instruments for labor mobility to address potential endogeneity problems. As seen in Section 2, density has been shown to have a positive impact on regional productivity. However, it is not density in itself that affect productivity, but rather the attributes associated with it. One such attribute is the increased possibility for labor mobility that accompanies more dense environments with more employers within close proximity. Another is sharing of, for instance, a sophisticated infrastructure. Whereas labor mobility and its ensuing knowledge diffusion generate dynamic effects that promote growth, sharing can be expected to primarily affect the level of productivity. Hence, I argue that density is a valid instrument for labor mobility in the present study where the goal is to explain productivity growth rates, i.e. productivity changes normalized by its levels.

Even after controlling for possible endogeneity problems the model might still suffer from spatial autocorrelation. The unit of observation in the regression analysis is Swedish labor market regions, defined as areas in which people can live and work without having too long commuting times. This by itself reduces problems with spatial autocorrelation. However, I will implement the method described in Andersson and Gråsjö (2009) and include accessibility measures among the explanatory variables to further reduce possible problems with spatial correlation. More precisely, I will include regional access to other regions' highly educated workers, defined as

$$Access_r = \ln\left(\sum_i \frac{1}{t_{r,i}} Educ_i\right), \qquad i \neq r, \tag{2}$$

among the explanatory variables, where $Educ_i$ denotes the number of highly educated workers in region i and $t_{r,i}$ the travel time between region r and i. I allow for spatial dependence between regions within 180 minutes travel time of each other. Hence $Educ_i$ is equal to zero for all regions where $t_{r,i}$ is longer than 180 minutes.[**]

The model to estimate can then be written as

$$\Delta \ln\left(w_r\right) = \alpha + \beta Mob_r + \gamma Access_r + \mathbf{y}_r'\boldsymbol{\delta} + \varepsilon_r, \tag{3}$$

where $\Delta\ln(w_r)$ is the log difference in average wage between 1998 and 2005 in region r and $\mathbf{y}$ is a vector of control variables. The error term in (3) is assumed to exhibit the standard

[**] The labor market region Gotland do not have any neighbors when using this cut-off time and hence is excluded from the sample.

properties, i.e. independently and identically distributed across regions with zero mean and variance σ^2.

Vector **y** comprises exogenous variables capturing the region's industry structure, human capital level, average initial wage level etc. The industry structure is controlled for by including three variables defined as number of employed in high-tech manufacturing sector, low-skilled service sector and high-skilled service sector in relation to the region's total employment.[††] The level of human capital is measured as number of employed with at least three years of university education divided by overall employment in the region. Human capital has been shown in several empirical studies (see e.g. Barro, 1991, Mankiw et al., 1992 and Glaeser et al., 1995) to have a positive impact on productivity growth and, hence, I expect a positive sign for this variable in the regressions. The initial wage level is included to capture the theoretically motivated (Solow, 1956), and empirically documented (Barro, 1991), catch-up effect where poorer regions tend to grow faster than richer regions. Consequently, I expect a negative sign for this variable.

Vector **y** also includes two variables aimed at capturing the importance of entrepreneurship for economic growth. The role of the entrepreneur as a conduit for development and progress can at least be traced back to Schumpeter (1911). Several empirical studies have also corroborated this view of the entrepreneur and shown how economic growth, to a certain extent, is driven by entrepreneurial activities (e.g. Audretsch and Fritsch, 2002; Carree and Thurik, 2003; Braunerhjelm and Borgman, 2004; Acs and Armington, 2004).

[††] The classification is based on the OECD standard classification scheme. High-tech manufacturing comprises the following industries: Aerospace (NACE Rev 1.1; 35.3), Computers and office machinery (30), Electronics communication (32), Pharmaceuticals (24.4) and Scientific instruments (33). Low-tech manufacturing comprises all other manufacturing industries. High-skilled service sector includes Water transport (61), Air transport (62), Post and telecommunications (64), Financial intermediation (65–67), Real estate activities (70), Renting of machinery and equipment (71), Computer and related activities (72), Research and development (73) and Other business activities (74). The remaining service industries are classified as low-skilled.

Entrepreneurship can be defined in various ways, but is usually hard to measure empirically. Some studies use general measures of entrepreneurship, such as total number of self-employed or total number of start-ups, whereas other focus on knowledge-intensive entrepreneurship. These studies usually find that knowledge intensive entrepreneurial activity is particularly important for economic progress (see e.g. Audretsch et al., 2006). Following this discussion, I will base my entrepreneurship variables on self-employment in high-tech manufacturing industries and high-skilled service industries. More precisely, the first variable is defined as number of individuals that became self-employed in high-tech manufacturing sectors and high-skilled service sectors between 1997 and 1998, divided by overall employment 1998. This variable is referred to as new entrepreneurs. The second variable, referred to as all entrepreneurs, is defined as the stock of self-employed in high-tech manufacturing industries and high-skilled service industries 1998, divided by overall employment the same year. I expect that both these variables positively affect regional growth, but that the effect is larger for new entrepreneurs since evidence suggests that small and new firms have particularly high growth rates (Audretsch et al., 2006).

The final explanatory variable is a dummy variable taking on the value one for small regions, defined as labor market regions with less than 1,000 employed in 1998. Small regions are often very dependent on one or two large firms, which imply that firm-specific shocks could lead to dramatic labor force dynamics within the region, distorting the overall relationship with growth. The cut-off number is somewhat arbitrarily chosen, but the results are not particularly sensitive to other cut-off numbers such as 1,500 or 2,000 workers. Summary statistics and simple correlations for the variables are presented in Table 3 and 4.

TABLE 3 HERE

TABLE 4 HERE

4. Results

This section presents the results from the regression analysis. I will first show the results from the probit estimation where the regional dummies used in the growth regressions are estimated and then the results from the growth regressions.

4.1 Probability of job change

The regression results from the probit estimation are reported in Table 5. All variables except age squared for highly educated workers are significant at the 1-percent level. As expected, the probability of shifting jobs is decreasing with age. This result is in line with Topel and Ward (1992) who find that workers on average hold two thirds of their lifetime jobs during the first ten years in the labor market. The positive coefficient for age squared in column 1 indicates that the rate of job switching is decreasing with age when looking at all workers. By comparing column 1 and 2 we see that the effect age has on the probability of shifting jobs is much smaller for well educated workers as compared to the overall population.

Another result from Table 5 is that males are more likely to change jobs than females, as indicated by the positive sign for the male dummy. The difference between males and females is, however, smaller for those with a high education as compared to the overall sample. The tenure variable has the expected negative sign supporting the hypotheses that the probability of job switching is decreasing with the time spent with the employer. Furthermore, the dummy variable indicating firms with declining employment has an expected positive sign. Finally, the wage variable is negative for the overall sample, but somewhat surprisingly positive for highly educated workers.

TABLE 5 HERE

The estimated coefficients for the regional dummies are plotted against regional labor mobility rates, defined as number of intraregional job switchers divided by overall regional employment, in Figure 2 and Figure 3.

FIGURE 2 HERE

FIGURE 3 HERE

The two variables follow each other closely, but not perfectly. The correlation between the estimated coefficients and the mobility rates are 0.79 and 0.94 for the overall sample and for the highly educated, respectively.

4.2 Regional productivity growth

Table 6 reports the result when the estimations are based on all individuals and Table 7 when the estimations are based on highly educated workers.

TABLE 6 HERE

TABLE 7 HERE

The most clear cut result from the regression analysis is the positive impact intraregional labor mobility has on productivity growth. This variable is highly significant for both the overall population and for the sub sample of highly educated workers, demonstrating the positive role labor mobility and its ensuing knowledge diffusion and labor market matching plays for economic development in the regions.

Another strong result is found for access to other regions' human capital. The accessibility variable is positive and highly significant in all regressions, which can be taken as evidence of interregional spillover effects. Thus, omitting this variable in the regression specification would render the assumption of an independently distributed error term in (3) false.

Next, turning to the control variables in vector **y**; the initial wage level has the expected negative sign, and is statistically significant in most regressions. Somewhat surprisingly, the share of highly educated workers turns up insignificant and negative. Given the role knowledge and human capital play in endogenous growth theory, we would expect a clear positive sign for this variable. The most likely explanation for the unexpected result is the strong correlation between the initial wage level and the share of highly educated workers as shown in Table 4. This is also verified by an inspection of the variance inflation factors, which show strong multicollinearity for these two variables. It is important to realize, however, that multicollinearity is not a violation of the underlying assumptions of the regression model but merely means that it is hard to separate between the effects of the initial wage level and the share of highly educated workers.

The three variables capturing the industry structure do not perform particularly well in the regressions. The knowledge-intensive service sector has the expected positive sign and is significant when the regressions are based on highly educated individuals, whereas the remaining variables lack significance. The two entrepreneurship variables vary in sign and are insignificant in all regression specifications, whereas the dummy variable for small regions is positive and statistically significant in all but one regression.

The overall explanatory power of the regressions is at a satisfactory level, ranging from 0.34 to 0.46 as indicated by the R-squared value. The F-test reported in Table 6 and 7 shows that the instruments are relevant, especially when the regressions are based on the highly educated part of the labor force. Since I have more instruments than endogenous variables I am also able to test the assumption that the instruments are uncorrelated with the error term in regression model (3). The null hypothesis for this test is that all instruments are exogenous and hence identify trouble free variation in the labor mobility variable. The null hypothesis is not rejected for any regression as shown by the insignificant J-statistic. In all, this indicates that density and density squared constitutes a good set of instruments for the labor mobility measure used in the present study. Finally, an inspection of Moran's I based on the residuals reveals no signs of remaining spatial autocorrelation.

5. Robustness test

The initial conditions/subsequent growth approach in Section 4 is a way of extracting the underlying structure for the variables of interest without having the result distorted by short term variations. However, it might be argued that the results obtained by the approach are biased due to omitted region-specific effects. I will therefore make use of the panel structure of the dataset and estimate the growth regression with fixed region-specific effects to check the validity of this argument. To do this I first need to re-estimate the probit model, interacting the regional dummies with time dummies to get annual mobility measures for the regions. The model to estimate is given by

$$\Pr\left(Mob_{i,t}=1\,|\,\tilde{\mathbf{x}}_{i,t}\right)=\Phi\left(\tilde{\mathbf{x}}_{i,t}'\tilde{\mathbf{\Gamma}}\right),$$
$$\tilde{\mathbf{x}}_{i,t}'\tilde{\mathbf{\Gamma}}=\tilde{\alpha}+\left(\mathbf{r}\otimes\mathbf{t}\right)'\tilde{\boldsymbol{\beta}}+\mathbf{z}_{i,t}'\tilde{\boldsymbol{\gamma}}+\tilde{\varepsilon}_{i,t} \tag{4}$$

where vector **r** comprises regional dummies, vector **t** time dummies and ⊗ is the Kronecker operator. Vector **z** contains the same variables as in Section 3. This model is only possible to estimate for the total labor force since many region-year combinations lack intraregional labor mobility for highly educated and hence cannot be estimated.[‡‡] The result from the estimation is reported in Table 8 and the relationship between the estimated regional dummies and the labor mobility rates is shown in Figure 4.

TABLE 8 HERE

FIGURE 4 HERE

The estimated coefficients for the regional dummies are again used to create a new mobility measure, $Mob_{r,t}$, which is included among the explanatory variables. The growth regression to estimate is now given by

[‡‡] It is not possible to estimate the coefficient for a variable when the dependent variable does not vary within one of the categories of the independent variable (Long and Freese, 2003, p. 117).

$$\ln\left(w_{r,t+1}\right)-\ln\left(w_{r,t}\right)=\tilde{\alpha}+\tilde{\beta}Mob_{r,t}+\tilde{\gamma}Access_{r,t}+\tilde{\mathbf{y}}'_{r,t}\tilde{\boldsymbol{\delta}}+\varepsilon_{r,t},$$
$$\varepsilon_{r,t}=\varepsilon_{r}+\eta_{r,t} \qquad (5)$$

where vector $\tilde{\mathbf{y}}$ contains the same variables as in Section 3 with two exceptions. First, the small regions dummy variable cannot be included when estimating a region-specific fixed effects model and second, the vector includes time dummies aimed at controlling for short term fluctuations caused by the business cycle. η_{rt} is assumed to be independently and identically distributed across regions and time with zero mean and variance $\tilde{\sigma}^2$.

Table 9 presents the estimation results.

TABLE 9 HERE

Labor mobility still has the expected positive sign, but is now only weakly significant. One explanation for the reduction in significance levels when using panel data could be that short term fluctuations in the variables make it hard to discern the underlying parameters of the model. The overall picture shown by the analysis in Section 4 and 5 still highlights the importance of labor mobility for economic growth.

Among the remaining explanatory variables in Table 9, only the initial wage and the accessibility measure are statistically significant. Both variables have the expected signs providing further support for the convergence hypothesis and stressing the importance of interregional spillover effects for productivity growth.

6. Conclusions

Human capital and knowledge diffusion are generally regarded as the prime means behind sustained economic growth – the engine of growth. Since knowledge diffusion is facilitated by, and in many cases requires, face-to-face interactions, this gives a central role to proximity in explaining growth. Previous studies support this view and show that density, measured along various dimensions, is positively related to productivity growth. However, the mechanisms through which this relationship works is usually left unexplained in the empirical literature or is only briefly commented upon.

The hypothesis pursued in this paper is that knowledge diffusion and labor market efficiency are higher in regions with higher labor mobility, and hence, that labor mobility constitutes a mechanism behind the observed relationship between density and growth. Evidence in favor of this hypothesis is obtained from regression analyses implemented on Swedish labor market regions. An additional result is that regions embedded in larger, knowledge abundant, areas tend to benefit from interregional spillover effects yielding further productivity growth.

References

Acs, Zoltan J. and Catherine Armington, (2004), "Employment growth and entrepreneurial activity in cities," *Papers on Entrepreneurship, Growth and Public Policy*, no. 2004-13.

Almeida, Rita, (2007), "Local economic structure and growth," *Spatial Economic Analysis*, Vol. 2(1), pp. 65–90.

Almeida, Paul and Bruce Kogut, (1999), "Localization of knowledge and the mobility of engineers in regional networks," *Management Science*, Vol. 45(7), pp. 905–917.

Andersson, Martin and Urban Gråsjö, (2009), "Spatial dependence and the representation of space in empirical models," *The Annals of Regional Science*, Vol. 43(1), pp. 159–180.

Andersson Martin and Per Thulin, (2009), "Labor mobility and agglomeration economies," Mimeo, Royal Institute of Technology.

Audretsch, David and Michael Fritsch, (2002), "Growth regimes over time and space," Regional Studies, Vol. 36(2), pp.113–124.

Audretsch, David, Max Keilbach and Erik Lehmann, (2006), *Entrepreneurship and economic growth*. New York: Oxford University Press.

Barro, Robert J., (1991), "Economic growth in a cross section of countries," *The Quarterly Journal of Economics*, Vol. 106(2), pp. 407–443.

Bleakly, Hoyt and Jeffrey Lin, (2007), "Thick-market effects and churning in the labor market: Evidence from U.S. cities," Working Paper no. 07-23, Research Department, Federal Reserve Bank of Philadelphia.

Braunerhjelm Pontus and Benny Borgman, (2004), “Geographical concentration, entrepreneurship and regional growth: evidence from regional data in Sweden, 1975–99,” *Regional Studies*, Vol. 38(8), pp. 929–947.

Carree, Martin A. and Roy Thurik, (2003), “The impact of entrepreneurship on economic growth,” in Acs, Zoltan and Audretsch, David (eds.), *Handbook of Entrepreneurship Research*, New York: Springer.

Ciccone, Antonio, (2002), ”Agglomeration effects in Europe,” *European Economic Review*, Vol. 46(2), pp. 213–227.

Ciccone, Antonio and Robert E. Hall, (1996), ”Productivity and the density of economic activity,” *American Economic Review*, Vol. 86(1), pp. 54–70.

Duranton, Giles and Diego Puga (2004), “Microfoundation of urban agglomeration economies”. In V. Henderson and J-F. Thisse (Eds). *Handbook of Regional and Urban Economics*, Vol. 4, Elsevier.

Farber, Henry S., (1994), ”The analysis of inter-firm worker mobility,” *Journal of Labor Economics*, Vol. 12(4), pp. 554–593.

Glaeser, Edward L., Jose A. Scheinkman and Andrei Shleifer, (1995), “Economic growth in a cross-section of cities,” *Journal of Monetary Economics*, Vol. 36(1), pp. 117–143.

Görg, Holger and Eric Strobl, (2005), ”Spillovers from foreign firms through worker mobility: An empirical investigation,” *Scandinavian Journal of Economics*, Vol. 107(4), pp. 693–709.

Long, J. Scott and Jeremy Freese, (2003), *Regression models for categorical dependent variables using STATA*. Texas: STATA Press.

Lucas, Robert E. Jr, (1988), ”On the mechanics of economic development,” *Journal of Monetary Economics*, Vol. 22(1), pp. 3–42.

Mankiw, Gregory M, David Romer and David N. Weil, (1992), “A contribution to the empirics of economic growth,” *The Quarterly Journal of Economics*, Vol. 107(2), pp. 407–437.

National Mediation Office, (2009), Annual report.

Oettl, Alexander and Ajay Agrawal, (2008), “International labor mobility and knowledge flow externalities,” *Journal of International Business Studies*, Vol. 39(8), pp. 1242–1260.

Romer, Paul M., (1986), ”Increasing returns and long-run growth,” *Journal of Political Economy*, Vol. 94(5), pp. 1002–1037.

Schumpeter, Joseph A., (1911/34), *The theory of economic development*. Cambridge, Mass: Harvard University Press.

Solow, Robert M., (1956), “A contribution to the theory of economic growth,” *The Quarterly Journal of Economics*, Vol. 70(1), pp. 65–94.

Topel, Robert H. and Michael P. Ward, (1992), ”Job mobility and the careers of young men,” *Quarterly Journal of Economics*, Vol. 107(2), pp. 439–479.

Appendix

Consider a simple Cobb-Douglas production function where output (Y) in region r is determined by the local supply of capital (K) and labor (L),

$$Y_r = A_r K_r^{\alpha} L_r^{\beta} . \tag{A.1}$$

A_r denotes total factor productivity in the region. Maximizing profits, taking the wage rate (w) and the interest rate (r) as given, yields the following first-order conditions,

$$\begin{aligned} &\beta A_r K_r^{\alpha} L_r^{\beta-1} - w_r = 0 \\ &\alpha A_r K_r^{\alpha-1} L_r^{\beta} - r = 0 \end{aligned} , \tag{A.2}$$

where I have assumed that the wage rate is locally determined and the interest rate nationally determined. Taking logs and time derivatives of (A.2) gives me two expressions for the growth rate of total factor productivity,

$$\frac{\dot{A}_r}{A_r} = \frac{\dot{w}_r}{w_r} + (1-\beta)\frac{\dot{L}_r}{L_r} - \alpha\frac{\dot{K}_r}{K_r} \tag{A.3}$$

$$\frac{\dot{A}_r}{A_r} = \frac{\dot{r}}{r} - \beta\frac{\dot{L}_r}{L_r} + (1-\alpha)\frac{\dot{K}_r}{K_r} \tag{A.4}$$

Solving (A.3) and (A.4) for the growth rate of capital and then substituting back into (A.3) gives us productivity growth as

$$\frac{\dot{A}_r}{A_r}=(1-\alpha)\frac{\dot{w}_r}{w_r}+\alpha\frac{\dot{r}}{r}+(1-\alpha-\beta)\frac{\dot{L}_r}{L_r}. \qquad \text{(A.5)}$$

Finally, imposing constant returns to scale on the Cobb-Douglas production function enables me to write the region's productivity growth as a weighted average of the factor prices' growth rates as,

$$\frac{\dot{A}_r}{A_r}=(1-\alpha)\frac{\dot{w}_r}{w_r}+\alpha\frac{\dot{r}}{r}. \qquad \text{(A.6)}$$

This condition is quite intuitive. If the right-hand side is larger than the left-hand side, factor remuneration would eventually make firms' profits negative. On the other hand, should the left-hand side be larger than the right-hand side, firms would be making positive profits. Neither of these two options is sustainable in the long-run since market forces would eventually make condition (A.6) hold.

Since the growth rate of the interest rate is assumed to be equal for all regions it will be captured by the intercept when using wage growth as a proxy for productivity growth in the regressions. Accordingly, I argue that wage growth serves as a good proxy for productivity growth in the econometric analysis.

Table 1. Intra- and interregional labor mobility in Swedish labor market regions 1997–2004

FA-region	Number of job switchers (1)	Number of intraregional job switchers (2)	Intraregional job switchers, share (3)	FA-region	Number of job switchers (4)	Number of intraregional job switchers (5)	Intraregional job switchers, share (6)
Stockholm	615,729	552,594	0.8975	Vetlanda	5,759	3,682	0.6393
Malmö	172,246	143,467	0.8329	Trollhättan	28,230	18,035	0.6389
Göteborg	209,925	170,515	0.8123	Ljusdal	2,571	1,637	0.6367
Östergötland	65,210	51,467	0.7893	Ljungby	6,548	4,126	0.6301
Skellefteå	9,247	7,208	0.7795	Nyköping	7,711	4,849	0.6288
Luleå	19,079	14,690	0.7700	Tranås	3,384	2,122	0.6271
Örnsköldsvik	7,411	5,589	0.7541	Strömstad	4,514	2,821	0.6249
Karlstad	30,703	22,937	0.7471	Sollefteå	1,895	1,182	0.6237
Sundsvall	22,760	16,958	0.7451	Lidköping	10,179	6,307	0.6196
Jönköping	35,152	26,084	0.7420	Jokkmokk	602	367	0.6096
Värnamo	21,279	15,764	0.7408	Karlskoga	5,832	3,533	0.6058
Gävle	22,208	16,406	0.7387	Torsby	1,261	760	0.6027
Umeå	16,125	11,858	0.7354	Vimmerby	4,118	2,473	0.6005
Östersund	15,653	11,458	0.7320	Sorsele	404	240	0.5941
Gotland	5,824	4,229	0.7261	Åsele	250	148	0.5920
Västerås	45,080	32,661	0.7245	Arjeplog	486	285	0.5864
Örebro	31,631	22,912	0.7244	Arvidsjaur	604	354	0.5861
Gällivare	2,160	1,549	0.7171	Älmhult	5,557	3,247	0.5843
Växjö	23,200	16,544	0.7131	Kramfors	2,097	1,216	0.5799
Skövde	21,858	15,416	0.7053	Avesta	4,830	2,769	0.5733
Kalmar	15,909	11,161	0.7016	Vansbro	1,009	575	0.5699
Halmstad	22,139	15,446	0.6977	Bengtsfors	2,164	1,229	0.5679
Falun/Borlänge	20,008	13,905	0.6950	Lycksele	1,691	937	0.5541
Mora	3,996	2,777	0.6949	Övertorneå	396	217	0.5480
Kiruna	2,330	1,604	0.6884	Överkalix	321	174	0.5421
Kristianstad	21,241	14,280	0.6723	Hagfors	1,059	569	0.5373
Blekinge	17,421	11,674	0.6701	Haparanda	673	359	0.5334
Söderhamn	8,651	5,787	0.6689	Storuman	700	373	0.5329
Eskilstuna	19,846	13,210	0.6656	Eda	814	421	0.5172
Borås	22,214	14,732	0.6632	Hällefors	867	448	0.5167
Oskarshamn	6,715	4,422	0.6585	Fagersta	2,520	1,259	0.4996
Årjäng	1,419	931	0.6561	Härjedalen	1,796	868	0.4833
Dorotea	333	218	0.6547	Pajala	360	170	0.4722
Västervik	4,152	2,704	0.6513	Filipstad	1,105	520	0.4706
Hudiksvall	5,050	3,244	0.6424	Vilhelmina	604	283	0.4685
Ludvika	6,698	4,291	0.6406	Malung	2,373	1,005	0.4235

Notes: Column 1 and 4 show the total number of job changes during the period 1997–2004. Correspondingly, column 2 and 5 show the number of job changes within respective region and column 3 and 6 their share of total job changes.

Table 2. Summary statistics for variables in the probit regression

	A. All individuals, 13,557,534 obs.				B. Highly educated individuals, 1,490,636 obs.			
	Mean (1)	Standard deviation (2)	Min (3)	Max (4)	Mean (5)	Standard deviation (6)	Min (7)	Max (8)
Intraregional labor mobility	0.0974	0.2965	0	1	0.1170	0.3214	0	1
Age	39.73	11.74	16	64	39.52	10.03	19	64
Male	0.6864	0.4639	0	1	0.6802	0.4664	0	1
Tenure	5.322	5.257	0	18	3.751	4.296	0	18
Declining employment	0.3536	0.4781	0	1	0.3533	0.4780	0	1
Wage, 1,000 SEK	249.9	179.2	0.1	43,400	397.8	361.9	0.1	28,300
Education dummies								
High school < 9 years	0.0745	0.2625	0	1	-	-	-	-
High school 9 or 10 years	0.1388	0.3457	0	1	-	-	-	-
Senior high school ≤ 2 years	0.3191	0.4661	0	1	-	-	-	-
Senior high school 3 years	0.2374	0.4255	0	1	-	-	-	-
University < 3 years	0.1202	0.3253	0	1	-	-	-	-
Univ. (excl. PhD) 3 years or longer	0.1053	0.3070	0	1	0.9579	0.2009	0	1

Table 3. Summary statistics for variables in the growth regression

	Mean (1)	Standard deviation (2)	Min (3)	Max (4)
Growth rate wage	0.1731	0.0318	0.1157	0.2857
Intraregional labor mobility, all individuals	-0.0641	0.1111	-0.2940	0.2822
Intraregional labor mobility, highly educated	0.0600	0.2070	-0.3731	0.5798
Initial wage 1,000 SEK, logarithm	5.292	0.0981	5.090	5.550
Highly educated, share	0.0372	0.0256	0.0057	0.1506
Access to highly educated	4.172	2.089	-1.958	7.583
High-tech manuf., share	0.0357	0.0399	0	0.2117
Low-skilled service, share	0.4048	0.1063	0.1833	0.6754
High-skilled service, share	0.1280	0.0637	0.0317	0.3417
New entrepr. high tech., share	0.0017	0.0013	0	0.0068
All entrepr. high tech., share	0.0133	0.0062	0.0031	0.0329
Dummy for regions with less than 1,000 employees	0.1571	0.3666	0	1

Notes: The mobility variables are the estimated coefficients for regional dummies in a probit estimation of labor mobility.

Table 4. Correlation table for variables in the growth regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Growth rate wages	1.00											
(2) Intraregional labor mobility, all individuals	-0.01	1.00										
(3) Intraregional labor mobility, highly educated	0.04	0.84	1.00									
(4) Initial wage, logarithm	-0.40	0.50	0.48	1.00								
(5) Highly educated, share	-0.07	0.67	0.62	0.73	1.00							
(6) Access to highly educated, logarithm	-0.02	-0.09	-0.09	0.35	0.06	1.00						
(7) High-tech manuf., share	-0.02	0.31	0.09	0.15	0.34	-0.05	1.00					
(8) Low-skilled service, share	0.37	0.01	0.05	-0.54	-0.11	-0.38	-0.04	1.00				
(9) High-skilled service, share	0.30	0.40	0.32	0.10	0.57	-0.23	0.20	0.41	1.00			
(10) New entrepr. high tech., share	0.33	0.11	0.23	-0.10	0.23	-0.12	-0.03	0.35	0.43	1.00		
(11) All entrepr. high tech., share	0.39	0.14	0.19	-0.24	0.10	-0.21	0.05	0.45	0.53	0.64	1.00	
(12) Dummy for regions with less than 1,000 employees	0.46	-0.36	-0.29	-0.68	-0.30	-0.29	-0.02	0.43	0.10	0.30	0.39	1.00

Table 5. Estimation results for intraregional labor mobility 1997–2005

Dependent variable: Probability of intraregional job change	All individuals (1)	Highly educated individuals (2)
Age	-0.0302	-0.0114
	(0.0004)	(0.0013)
Age squared	0.0002	-3.53e-06
	(4.41e-06)	(1.60e-06)
Male	0.0532	0.0143
	(0.0013)	(0.0033)
Tenure	-0.0483	-0.0395
	(0.0001)	(0.0005)
Declining employment	0.1383	0.1942
	(0.0011)	(0.0030)
Wage	-1.19e-07	4.54e-08
	(5.83e-09)	(3.91e-09)
Regional dummies	YES	YES
Time dummies	YES	YES
Industry dummies	YES	YES
Educational dummies	YES	YES
Number of observations	13,557,534	1,490,636
Number of individuals	2,630,270	317,614
Pseudo R^2	0.0878	0.0588

Notes: Robust standard errors, adjusted for clustering at the individual level, are reported in parentheses. Highly educated individuals have at least three years of university education. All reported variables, except squared age for highly educated individuals, are significant at the 1-percent level. Industry dummies refer to 2-digit NACE Rev.1 industries and educational dummies to six (1) and one (2) different educational lengths, respectively.

Table 6. Estimation results for regional wage growth 1998–2005 (intraregional labor mobility for all individuals)

	(1)	(2)	(3)	(4)	(5)	(6)
Labor mobility,	0.3232***	0.2659***	0.3528**	0.3953**	0.3925**	0.4031***
all individuals	(4.69)	(4.64)	(2.40)	(2.56)	(2.55)	(2.59)
Initial wage	-0.3124***	-0.1991***	-0.1678	-0.1494	-0.1475	-0.1445
	(-4.34)	(-2.61)	(-1.45)	(-1.17)	(-1.18)	(-1.11)
Highly educated,	-	-	-0.4671	-0.8340	-.8680	-0.8854
share			(-0.85)	(-1.52)	(-1.61)	(-1.54)
Access to	-	-	0.0055**	0.0068**	0.0068**	0.0070**
highly educated			(2.24)	(2.28)	(2.24)	(2.29)
High-tech	-	-	-	-0.1584	-0.1428	-0.1599
manuf., share				(-1.17)	(-1.01)	(-1.18)
Low-skilled	-	-	-	-0.0416	-0.0467	-0.0364
service, share				(-0.56)	(-0.65)	(-0.49)
High-skilled	-	-	-	0.1891	0.1746	0.2239
service, share				(1.02)	(0.94)	(1.13)
New entrepr.	-	-	-	-	2.941	-
high tech., share					(0.67)	
All entrepr. high	-	-	-	-	-	-0.6405
tech., share						(-0.60)
Small	-	0.0320**	0.0521**	0.0573***	0.0542**	0.0613**
		(2.33)	(2.24)	(2.60)	(2.43)	(2.48)
F-statistic for instruments	16.2***	13.9***	2.87*	2.70*	2.65*	2.67*
Hansen's J-statistic	1.18	2.38	0.35	0.57	0.74	0.40
R^2	0.34	0.36	0.39	0.45	0.46	0.46
Number of observations	70	70	70	70	70	70

Notes: z-statistics, based on robust standard errors, are reported in parentheses. The null for the F-test is that the instruments are uncorrelated with labor mobility and the null for Hansen's J-statistic is that all instruments are exogenous. Significance levels are reported as *, ** and *** for the 10-, 5- and 1 percent level, respectively.

Table 7. Estimation results for regional wage growth 1998–2005 (intraregional labor mobility for highly educated individuals)

	(1)	(2)	(3)	(4)	(5)	(6)
Labor mobility,	0.2050***	0.1825***	0.1792***	0.1336***	0.1368***	0.1425***
highly educated	(4.03)	(3.87)	(2.58)	(3.12)	(3.15)	(3.30)
Initial wage	-0.3383***	-0.2585***	-0.2390**	-0.1956*	-0.1963*	-0.1929*
	(-4.08)	(-2.63)	(-2.30)	(-1.81)	(-1.80)	(-1.72)
Highly educated,	-	-	-0.2136	-0.5101	-0.5283	-0.5901
share			(-0.52)	(-1.35)	(-1.40)	(-1.49)
Access to	-	-	0.0053**	0.0062***	0.0063***	0.0064***
highly educated			(2.03)	(2.58)	(2.58)	(2.63)
High-tech	-	-	-	0.0429	0.0452	0.0493
manuf., share				(0.47)	(0.48)	(0.53)
Low-skilled	-	-	-	-0.0466	-0.0483	-0.0443
service, share				(-0.81)	(-0.84)	(-0.75)
High-skilled	-	-	-	0.2428**	0.2441**	0.2838**
service, share				(2.17)	(2.12)	(2.27)
New entrepr.	-	-	-	-	0.0823	-
high tech., share					(0.03)	
All entrepr. high	-	-	-	-	-	-0.6741
tech., share						(-0.90)
Small	-	0.0225	0.0352*	0.0335**	0.0337**	0.0378**
		(1.45)	(1.88)	(2.33)	(2.26)	(2.38)
F-statistic for instruments	14.75***	10.30***	3.43**	7.04***	7.07***	7.28***
Hansen's J-statistic	0.44	1.16	0.73	2.43	2.32	2.03
R^2	0.35	0.37	0.38	0.43	0.44	0.45
Number of observations	70	70	70	70	70	70

Notes: z-statistics, based on robust standard errors, are reported in parentheses. The null for the F-test is that the instruments are uncorrelated with labor mobility and the null for Hansen's J-statistic is that all instruments are exogenous. Significance levels are reported as *, ** and *** for the 10-, 5- and 1 percent level, respectively.

Table 8. Estimation results for intraregional labor mobility 1997–2005

Dependent variable: Probability of intraregional job change	All individuals (1)
Age	-0.0301
	(0.0004)
Age squared	0.0002
	(4.42e-06)
Male	0.0530
	(0.0013)
Tenure	-0.0485
	(0.0001)
Declining employment	0.1407
	(0.0011)
Wage	-1.15e-07
	(5.79e-09)
Regional x time dummies	YES
Time dummies	YES
Industry dummies	YES
Educational dummies	YES
Number of observations	13,557,534
Number of individuals	2,630,270
Pseudo R^2	0.0894

Notes: Robust standard errors, adjusted for clustering at the individual level, are reported in parentheses. Highly educated individuals have at least three years of university education. All reported variables are significant at the 1-percent level. Industry dummies refer to 2-digit NACE rev.1 industries and educational dummies to seven different educational lengths.

Table 9. Panel estimation results for regional wage growth 1998–2005 (intraregional labor mobility for all individuals)

	(1)	(2)	(3)	(4)	(5)
Labor mobility, all individuals	0.2041	0.1820*	0.1366*	0.1335*	0.1757
	(1.63)	(1.88)	(1.72)	(1.67)	(1.44)
Initial wage	-0.6676***	-0.6442***	-0.6662***	-0.6687***	-0.6714***
	(-6.09)	(-5.75)	(-6.62)	(-6.78)	(-5.92)
Highly educated, share	-	-0.1677	-0.1209	-0.1261	-0.1529
		(-0.71)	(-0.61)	(-0.65)	(-0.67)
Access to highly educated	-	0.1035*	0.1038**	0.0992**	0.1000*
		(1.90)	(2.21)	(2.13)	(1.86)
High-tech manuf., share	-	-	0.0113	0.0335	-0.0141
			(0.06)	(0.19)	(-0.06)
Low-skilled service, share	-	-	-0.0508	-0.0511	-0.0544
			(-0.71)	(-0.73)	(-0.66)
High-skilled service, share	-	-	-0.0780	-0.1054	-0.1129
			(-0.74)	(-0.97)	(-0.87)
New entrepr. high tech., share	-	-	-	1.254	-
				(0.80)	
All entrepr. high tech., share	-	-	-	-	0.9401
					(0.75)
Time dummies	YES	YES	YES	YES	YES
F-statistic for instruments	3.59**	3.98**	3.96**	3.80**	2.39*
Hansen's J-statistic	0.12	1.79	1.17	1.26	0.88
R^2	0.66	0.67	0.68	0.68	0.68
Number of observations	420	420	420	420	420

Notes: z-statistics, based on robust standard errors, are reported in parentheses. The null for the F-test is that the instruments are uncorrelated with labor mobility and the null for Hansen's J-statistic is that all instruments are exogenous. Significance levels are reported as *, ** and *** for the 10-, 5- and 1 percent level, respectively.

Figure 1. The spatial distribution of economic activity, labor mobility and productivity

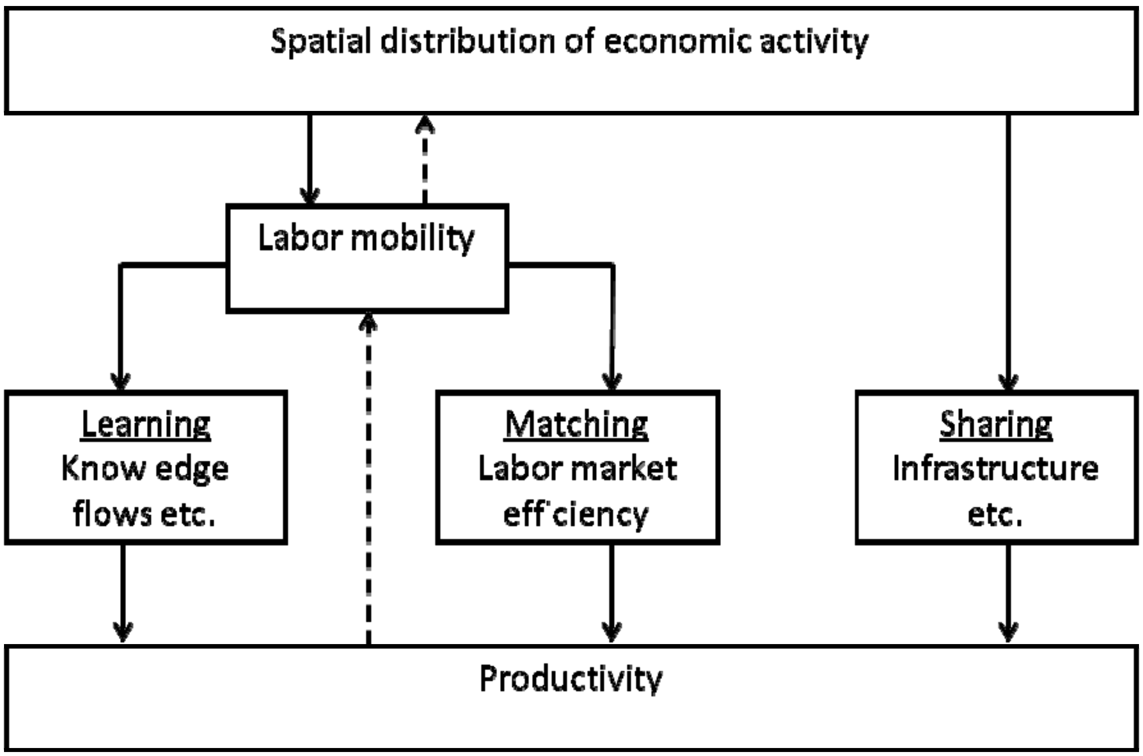

Figure 2. Relationship between intraregional labor mobility and estimated regional effects on labor mobility, all individuals

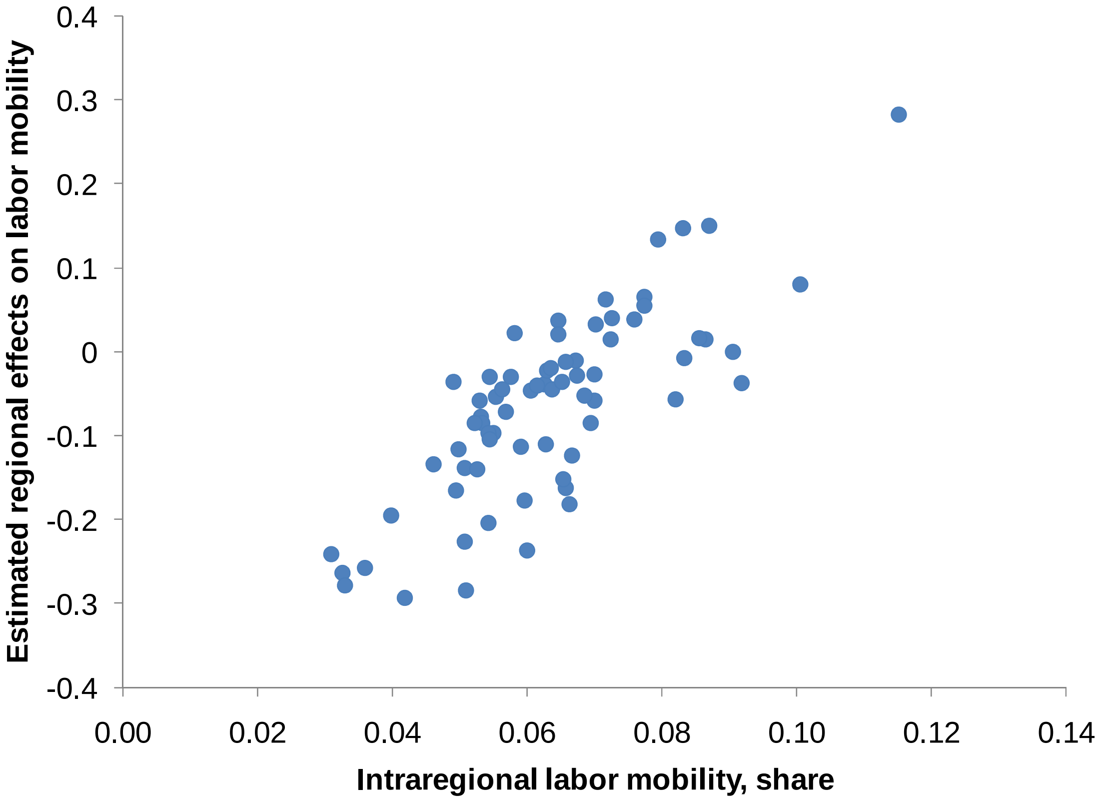

Figure 3. Relationship between intraregional labor mobility and estimated regional effects on labor mobility, highly educated individuals

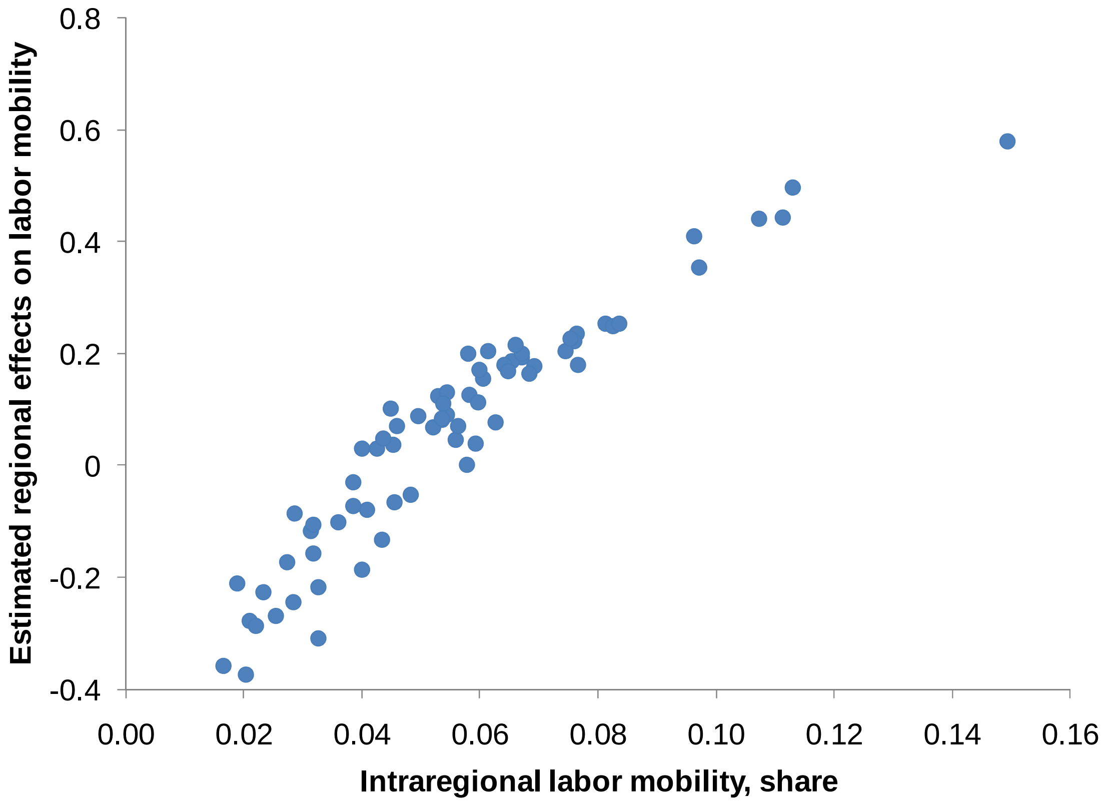

Figure 4. Relationship between intraregional labor mobility and estimated regional effects on labor mobility, all individuals