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Job Matching Efficiency in Skilled Regions: Evidence on the Microeconomic Foundations of Human Capital Externalities

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Abstract

Inspired by the literature on the role of local career networks for the quality of labour market matches we investigate whether human capital externalities arise from a higher job matching efficiency in skilled regions. Using two samples of workers in Germany we find that an increase in the regional share of highly qualified workers by one standard deviation is associated with between-job wage growth of about five per cent and with an increase in the annual probability of a job change of about sixty per cent. Wage gains are incurred only by workers changing jobs within industries. We find highly qualified workers in skilled regions to respond to these wage differentials by changing jobs more often within rather than between industries. Taken together, these findings suggest that human capital externalities partly arise because workers in skilled regions have better access to labour market information, which allows them to capitalize on their industry-specific knowledge when changing jobs.

Keywords: human capital externalities; job matching; career networks; spatial wage differences; skilled regions

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1. Introduction: The Microeconomics of Human Capital Externalities

> *It is now time to […] attempt to understand precisely how human capital externalities percolate. […] Most mechanisms generating local increasing returns to scale can be enriched to take human capital into account and generate external effects of human capital.*
> Duranton (2006: 35)

The idea that aggregate human capital matters for productivity and growth, which has gained prominence with the seminal contribution by Lucas (1988), has over time been established as one of the empirical regularities in economics. While macroeconomic studies show that economic growth increases with the national average level of education, more recent investigations on the matter have predominantly come from urban and regional economics. Empirical studies by Rauch (1993), Moretti (2004b), and Rosenthal and Strange (2008) provide robust evidence that aggregate regional education positively influences individual productivity and wages.[1] The core idea behind such external effects to education, which are frequently referred to as human capital externalities, is that workers incur productivity benefits by learning from the skills of others without compensating them (Arrow 1962).

In the literature, the occurrence of human capital externalities is usually assigned to spillovers of technological knowledge. In line with the notion that "the mysteries of the trade become no mysteries but are, as it were, in the air" (Marshall 1890: 271), a number of microeconomic papers have modelled the intensity of knowledge exchange as a function of local human capital endowments (Jovanovic and Rob 1989; Jovanovic and Nyarko 1995; Black and Henderson 1999). Based on this idea, numerous empirical studies have investigated the importance of local education levels for regional innovation and growth (see Audretsch and Feldman 2004 for a survey). Without denying the importance of spillovers of technical knowledge as a source of human capital externalities, Duranton (2006) emphasizes, however, that social returns to education are likely to arise from a more complex set of microeconomic mechanisms and points to the literature on agglomeration economies for inspiration.

Since Duranton and Puga (2004), the microeconomic mechanisms behind productivity enhancing effects from agglomeration are usually categorized along the lines of sharing, matching, and learning. Based on this taxonomy a number of studies have aimed to disentangle the sources of agglomeration economies as determinants of regional wages (Glaeser and Maré 2001; Yankow 2006; Wheeler 2006). In contrast, no such attempt has so far been made with respect to the microeconomic foundations of human capital externalities.[2]

Recognizing the lack of research on the foundations of human capital externalities this study investigates the role of a higher matching efficiency in skilled regions as a microeconomic source of human capital externalities. Closely related to the literature on knowledge spillovers, which argues that information about products and processes of production is transmitted more easily in skilled regions, the idea of matching externalities is that higher aggregate levels of education enhance the flow of information on job opportunities and thereby improve the quality of labour market matches in human capital rich regions. Thus, the core hypothesis here is that workers in skilled regions are better informed about potential career paths and efficient job matches and therefore incur higher wages when changing jobs.

This notion is intimately linked to the literature on career networks which, starting with Fischer (1982), has emphasized the importance of individual education for the size of social networks and, hence, for access to informal information. This literature consistently finds that “the more educated people are, the larger their personal network” (Grossetti 2007: 397), implying that the accessibility of labour market information not only depends on a worker’s own human capital but also on the range of direct and indirect contacts within his local network and, hence, on the local aggregate level of education.

The availability of information on job and career opportunities can in turn be expected to influence the efficiency of job matches within local labour markets (Jovanovic 1979), which finds its expression in the job change behaviour of workers and in the size of wage gains incurred by job changers (Bartel and Borjas 1981; Topel and Ward 1992). As argued by Johnson (1978), the availability of labour market information reduces the cost of job search and makes workers more likely to shop between jobs. At the same time, knowledge about efficient job matches allows workers to incur larger wage gains when changing jobs (Bartel 1980; Mincer and Jovanovic 1981). Based on these insights this study aims to shed light on the existence of matching externalities in skilled regions by examining whether workers in human capital rich regions (a) incur larger wage gains when changing jobs and (b) display a higher probability of changing jobs than workers in less skilled regions. Addressing these questions we estimate (a) Mincerian wage equations for job changers and job stayers and (b) Probit equations on the effect of local aggregate education on the probability of a job change.

In Section II we review the literature on career networks and local job matching efficiency; Section III describes the econometric approach and summarizes the data; in Sections IV and V we present the results on wage effects and on the probability of job changes in skilled regions; Section V concludes and discusses implications for the design of public policies.

2. Aggregate Local Education and Job Matching: Literature Review

The insight that local career networks matter for the incidence of job changes and for the quality of job matches goes back to the influential contribution by Granovetter (1974), who shows that more than fifty per cent of job changers have found their jobs through personal contacts. In general, personal networks reduce information gaps by providing informal information to workers and firms about unobservable characteristics of the other party (Montgomery 1991). The intuition that career networks improve the quality of job matches has inspired a voluminous empirical literature in economics and sociology, which is surveyed in Ioannides and Loury (2004).

The accessibility of information on job opportunities increases with the size of career networks (Calvo-Armegnol and Jackson 2004, 2007), because information is transmitted most efficiently in networks consisting of a large number of ‘weak’ ties (Boorman 1975; Granovetter 1983; Podolny and Baron 1997). Empirical studies support the idea that larger career networks increase matching efficiency by transmitting labour market information more effectively. Investigating the structure of informal networks of Mexican immigrants, Munshi (2003) shows that workers in exogenously larger networks earn significantly higher wages. Similarly, Datcher (1983) and Simon and Warner (1992) show that a larger number of informal contacts allow workers to acquire information about job and employer characteristics before taking up a job.

Studies from sociology (e.g., Fischer 1982; Grossetti 2007) and psychology (e.g., Ajrouch et al. 2005) provide evidence that the size of personal networks increases significantly with individual education, i.e., higher levels of individual education are associated with larger non-kin networks among men and women. Since the amount of information an individual has access to through second or third order ties increases with the level of education of other members in the network, the size and range of career networks can be expected to increase with the average level of education within a network. Accordingly, a number of theoretical models in economics have expressed the speed and the range of information diffusion as a function of local education levels (see, e.g., Jovanovic and Rob 1989).

Effective career networks are characterized by a pronounced local dimension. Models from information science (Watts and Strogatz 1998; Cowan and Jonard 2004), epidemiology (Jeger et al. 2007), and economics (Acemoglu et al. 2010) show that information is transmitted most efficiently in networks exhibiting distinct small world properties, meaning that about ninety per cent of contacts are regionalized, while the rest are of a long-distance nature. These theoretical insights are confirmed by a number of empirical studies on the geographical scope of career networks. Controlling for reverse causality and sorting effects, Bayer et al. (2008) show that individual career perspectives and wages are shaped through social interactions between workers within the same block of residence. Their study is complemented by a broad body of literature showing that face-to-face communication and peer effects within local environments enhance the diffusion of knowledge on job perspectives (Cutler and Glaeser 1997), entrepreneurial opportunities (Acs and Armington 2004), and innovation (Jaffe et al. 1993).[3] The local nature of career networks is underpinned by numerous case studies. Casper and Murray (2005) provide evidence on the regionalization of information flows by showing that career paths of highly qualified workers within biotechnology clusters in Cambridge, UK, and in Munich, Germany, are shaped through participation in strongly localized career networks. In the same vein, Combes et al. (2008) show that personal networks, which are of prime importance for candidates to be successful in the centralized hiring procedure of economics professors in France, are of a strong local nature, i.e., are usually located within economics departments.

Taken together, the existing literature suggests that labour market information can be regarded as a local public good which increases in supply with the density of localized social networks, i.e., the amount of labour market information a workers has access to rises not only with his own level of education, but also with the local aggregate level of human capital. Based on this consideration, Helsley and Strange (1990) argue that the availability of labour market information increases with the degree of agglomeration, leading to a higher matching efficiency in cities. A number of empirical studies in the literature on agglomeration externalities have thereafter addressed the question whether higher urban wages arise from better matching opportunities in cities.

These studies have usually resorted to the identification strategy by Topel and Ward (1992), i.e., they have examined whether wage gains of job changers and the probability of workers to change jobs increase with the local level of agglomeration. Within this literature, Glaeser and Maré (2001) and Wheeler (2006) show that wage gains of job changers are larger in cities than in the countryside. Accordingly, Bleakley and Lin (2007) and Finney and Kohlhase (2007) find that workers in cities change jobs more often than workers in rural areas. Similar results are obtained by Freedman (2008) who shows that the probability of intra-industry compared to inter-industry job changes is significantly higher in agglomerated areas.

While these results suggest that the efficiency of job matches rises with the regional degree of agglomeration, one may contest that improved matching opportunities are caused by urban density alone. In fact, the close correlation between agglomeration and aggregate education levels leaves room for human capital externalities as an explanation for a higher quality of job matches in cities. Since workers and firms usually possess only imperfect information about the respective other, the availability of knowledge about efficient matches is likely to be as important for matching efficiency as the availability of jobs and workers.

Based on this consideration we resort to the identification approach employed in the literature on agglomeration externalities in order to analyse whether matching efficiency in local labour markets rises with the local aggregate level of education.

3. Econometric Approach and Data

3.1. Identifying Matching Externalities: Two Approaches

To investigate whether wage gains of job changers are influenced by the local level of human capital, we first estimate Mincerian wage equations which are augmented by indicators for a job change and for regional human capital endowments, as well as by the interaction thereof.

$$w_{i,t} = \sum_{k=1}^{K} X_{k,i,t}\beta_k + \sum_{m=1}^{M} F_{m,f,t}\beta_m + \gamma A_{r,t} + \delta_1 J_{i,t} + \delta_2 HC_{r,t} + \delta_3 J_{i,t} \times HC_{r,t} + \phi_r + \phi_t + \varepsilon_{i,t} \quad (1)$$

More specifically, we estimate the wage w of individual *i* at time *t* as a function of *k* individual characteristics $X_{k,i,t}$, m firm characteristics $F_{m,f,t}$, the regional degree of agglomeration $A_{r,t}$, the incidence of a job change $J_{i,t}$ of individual *i* at time *t*, the share of highly qualified workers $HC_{r,t}$ in region *r* at time *t*, as well as the interaction between the latter two. In addition, we include region (ϕ_r) and time (ϕ_t) fixed effects in order to control for wage effects from macroeconomic and region-specific shocks. The prime parameter of interest is δ_3, which measures the extent to which wage gains incurred by job changers depend on the regional aggregate level of education.

Estimating Probit equations we then examine whether the probability of a worker to change jobs increases with the local aggregate level of education:

$$\Delta J_{i,t} = \sum_{h=1}^{H} X_{h,i,t}\theta_k + \sum_{n=1}^{N} F_{n,f,t}\beta_n + \vartheta A_{r,t} + \tau HC_{r,t} + \phi_r + \phi_t + \varepsilon_{i,t} \quad (2)$$

The incidence of a job change $\Delta J_{i,t}$ of individual *i* at time *t* is expressed as a function of *h* individual characteristics $X_{h,i,t}$, n firm characteristics $F_{n,f,t}$, the regional degree of agglomeration $A_{r,t}$, as well as of the share of highly qualified workers $HC_{r,t}$ in region *r* at time *t*. In addition, we control for region and time fixed effects. The main parameter of interest is τ, which indicates whether regional human capital influences the probability of a job change.

We define labour market regions along the lines of the 326 counties in Western Germany, which are equal to NUTSIII regions and are either made up by a single large city (*'Kreisfreie Stadt'*) or by an administrative unit of several smaller cities or towns (*'Landkreise'*).[4] Following Moretti (2004) and Rosenthal and Strange (2008) we employ the regional share of highly qualified workers as a measure of regional human capital. Regional agglomeration is measured by the number of workers per square kilometre within each of the 326 counties.

We restrict the analysis to workers who change jobs without changing regions. Focusing on intra-region job changers allows for identifying matching effects from regional human capital more clearly by avoiding bias from several confounding factors. The biggest threat to a proper identification of human capital externalities stems from the fact that regional human capital exhibits both amenity and productivity effects (Roback 1982). Thus, while the regional level of human capital increases a worker's productivity, it also constitutes an amenity inasmuch as workers might be willing to accept wage reductions in exchange for living and working in a more educated environment. Reducing the sample to workers changing jobs within regions ensures that wage reducing amenity effects do not affect wage growth on the incidence of a job change because pre-job change wages are already amenity adjusted.[5]

3.2. Data and Descriptives

The empirical analysis is based on the IABS data set provided by the Institute for Labour and Employment Research in Nuremberg. The IABS is a two per cent random sample of all workers in Germany holding a job subject to social security contribution and contains longitudinal information on workers' employment histories, as well as on further individual characteristics (see Drews 2007 for a description of the data). The definition of worker status along the lines of social security contributions excludes self-employed workers and public servants. From this spell data we construct a panel data set encompassing all observations made on the 30th of June of each year. This annualized panel data set contains more than 18 million observations for Western Germany between 1975 and 2004.

In addition to its panel structure, the main merit of the data set is that it is very reliable because these data provide the source for calculating social benefits entitlements, and employers are therefore obliged to submit them to the best of their knowledge. The drawback of data being generated from the employment register is that wages are top coded at the threshold of maximum social security payments.[6] We have therefore imputed wages above this threshold by predicting them from a full set of individual characteristics (see Gartner 2005). Throughout the paper wages are defined as gross daily wages, which are inflation adjusted to the 2004 Euro level.

The education variable is a six-stage indicator containing information on a worker's highest degree of formal education. We have corrected for inconsistent coding by using an improved variable provided by Fitzenberger et al. (2006) and Drews (2006). Part-time employees, apprentices, and trainees are excluded from the data, which leaves 12 million observations on about one million full time employees in Western Germany between 1975 and 2004. From these data we construct two subsamples.

Close to the approach by Jacobson et al. (1993), the first subsample contains a balanced panel of workers, encompassing all employees with a full set of observations between 1999 and 2004, i.e., workers with a total of six observations in this period. Since these workers are required to stay within one region, i.e., to neither change employers nor move houses between regions, all workers changing jobs or regions, except those changing jobs within regions in 2000, are excluded from the sample. This leaves 1,100,692 observations on 184,282 workers, out of which 11,240, i.e., 6.1 per cent, change firms in 2000 without changing regions.[7] We define a dummy variable which equals 1 (0) if a worker belongs to the group of job changers (job stayers). Earmarking the group of job changers over the whole period of investigation, rather than just for the year 2000, allows controlling for systematic and persistent unobservable differences between job changers and job stayers. Focusing on job changes occurring in 2000 eliminates bias from changing macroeconomic environments, or systematic changes of motives for job changes over time, e.g., due to business cycles.

While providing insight into the size of wage effects from aggregate human capital, the drawback of using a balanced panel containing just one job change within a given year is that it does not allow for employing time or region fixed effects when examining the influence of local education on the probability of a job or industry change. In order to examine this issue we construct a second sample which allows for tracking workers from their career start onwards. This sample contains only workers who show up for the first time in the data after 1975 (in order to avoid left-censoring), are below the age of thirty when observed for the first time, and who have a full set of observations until they either leave the local labour market or until the sample ends in 2004.[8] This sample contains 1,395,228 observations on 195,441 workers, i.e., workers are observed on average for a period of 7.1 consecutive years. Workers change jobs on average .63 times during the period of observation. Thus, the annual probability for a worker to change jobs is 8.8 per cent.

Table I contains descriptive statistics for both samples. Since the first sample is made up of workers of all ages while the second sample consists of workers at the start of their working life, workers in the first sample are on average older, earn higher wages and exhibit more years of experience and tenure. In addition, the regional share of highly qualified workers is two percentage points higher in the first sample, reflecting the fact that the overall level of education has increased over time.

Maps I and II provide evidence on the close correlation between the regional share of highly qualified workers and the average wage within each of the 326 regions. High average wages and human capital intensities follow the well-known 'hot banana pattern', i.e., they follow an imaginary line starting in the North-West in the Rhineland, crossing the Rhine-Main area and the automobile cluster around Stuttgart, and continuing down to the South-East to Bavaria. Employing an instrumental variable approach, Heuermann (2011) shows that while sorting effects play an important role for higher wages in human capital intensive regions, external effects from human capital raise wages by .75 per cent with each additional percentage point in the regional share of highly qualified workers. Thus, a rise in the share of highly qualified workers by one standard deviation is associated with an increase in average wages of about 3.5 per cent. In the subsequent analysis we investigate the extent to which wage effects from human capital externalities are attributable to a higher matching efficiency in skilled regions.

4. Matching as a Microeconomic Source of Human Capital Externalities

4.1. Between-Job Wage Growth

Graph I illustrates the evolution of average wages for job changers and job stayers in the balanced sample of workers. With the exception of 2004, average wages increase over the whole period of observation at an average annual rate of 2.6 per cent for job movers and of .5 per cent for job stayers. Of particular interest is the wage jump occurring at the time of a job change, i.e., between 1999 and 2000, where average wages rise of job changers rise by more than seven per cent from below 82 to above 88 Euros. In what follows we examine the extent to which this wage growth is driven by the local level of education.

Table II contains the results from estimating equation (1). All coefficients on individual characteristics are in line with the empirical literature, i.e., wages grow at a decreasing marginal rate with age, tenure and experience; they rise with individual education, and are about 35 per cent lower for women than for men. In addition, larger firms pay higher wages, as do younger firms and those with a higher share of highly qualified workers.

Column I shows that workers changing jobs in 2000 incur significant wage gains from human capital externalities. While the overall effect of the regional share of highly qualified workers on wages of all workers (‘*Regional Share HQ’*) is insignificant throughout all regressions, the significantly positive coefficient on the interaction term (*‘Job Change*Regional Share HQ’*) indicates that wages of job changers rise by .16 per cent with each additional percentage point of highly qualified workers in the local workforce. Thus, an increase in the share of highly qualified workers by one standard deviation (5.1 percentage points) is associated with .8 per cent higher wages for job changers.

In column II we differentiate the impact of regional human capital on wages of job changers by year to examine when exactly these wage gains arise. The first thing to note is that job changers and job stayers do not differ systematically from each other, as can be seen by the insignificant job move dummy (*‘Job Move’*). At the same time, however, job changers in skilled regions earn significantly less than job stayers in skilled regions before changing jobs (*‘Job Change*Regional Share HQ, 1999’*), a finding that is in line with the descriptive evidence on lower wages for job changers contained in Graph I. On the occasion of changing jobs (*‘Job Change*Regional Share HQ, 2000’*), job changers experience wage gains of between .82 and .85 per cent with each additional percentage point of highly qualified workers in the local workforce. Over the following two years these wage gains slightly increase. Over the whole period of investigation wages of job changers rise by about 4.7 per cent with an increase in the regional share of highly qualified workers by one standard deviation. The fact that wage gains arise on the incidence of a job change and remain largely constant thereafter provides evidence for a ‘level effect’ rather than a ‘growth effect’ (see Yankow 2006), i.e., these findings suggest that improved matching opportunities in skilled regions are of importance as a microeconomic mechanism behind the occurrence of human capital externalities.

In column III, we differentiate the impact of regional aggregate education (‘*Regional Share HQ’*) by year to control for changes in the size of human capital externalities over time which might be picked up by the interaction term. Coefficients, which are not shown here, are insignificant for each year. Finding the coefficients on the interaction terms to remain unchanged confirms that wage effects from human capital externalities are incurred exclusively by workers changing jobs.

In columns IV and V we examine whether wage effects from aggregate human capital differ by gender. Wage effects from changing jobs in skilled regions turn out to be larger for women than for men. In fact, over the whole period of observation wages of female job changers rise on average by about 6.2 per cent with an increase of the regional share by one standard deviation while those of men rise by only 3.3 per cent. This finding stands in contrast to prior results which show that women benefit on average to the same degree from job mobility as men do (see, e.g., Keith and McWilliams 1995; Valcour and Tolbert 2003). These results are unlikely to be driven by differences in observable characteristics, as male and female job changers in the sample show on average the same age, education, tenure and experience. However, as gender-related wage differences are partly driven by differences in employment histories and a number of unobservable factors (see Fuller 2008 for a survey) which we cannot control for, we leave the issue of gender-specific matching effects for further research.

In column VI we address the concern of a potential self-selection of job changers with respect to unobservable but productivity relevant characteristics such as motivation or ambition by means of worker fixed effects. When doing so, the job change dummy is dropped as it is perfectly collinear with the fixed effects, which pick up all individual time-constant characteristics including the fact that a person belongs to the group of job changers. With individual fixed effects now absorbing wage effects from a negative self-selection of job movers, the coefficients on wage effects from local human capital for job changers shift upwards. In sum, the results from this fixed effects model confirm that wages of job changers rise by close to five percent over the period of investigation compared to wages of job stayers.

Table III contains further robustness checks. As described in Section III.2., we have imputed top-coded wages, i.e., wages of workers earning above the maximum level of social security contribution. This applies to approximately nine per cent of the observation on wages. In order to corroborate that the results obtained so far are not driven by the method of imputation we have made sure that the findings also holds in the absence of any imputed wages. In fact, if the results are driven by the method of imputation alone, we should find no effects for a sample which consists only of workers earning wages below the threshold. Column I in Table III shows that this is not the case. In fact, dropping all observations encompassing censored wages does not alter the results on wage effects from local human capital levels.

Another threat to identification arises from the potential endogeneity of the regional share of highly qualified workers. We have addressed this issue by means of an instrumental variable approach. Similar to the geographic instruments employed by Rosenthal and Strange (2008) we use county area and water area within a county as instrumental variables for the regional share of highly qualified workers. For both instruments, an F-test confirms their joint relevance in the first stage estimation at the one per cent level. With respect to instrument exogeneity, a J-test of over-identifying restrictions confirms that the hypothesis of exogeneity holds at the one per cent level. The results from this approach, which are contained in column II in Table III show that wage effects from aggregate human capital are not driven by a potential endogeneity of the regional share of highly qualified workers.

In column III, we include industry dummies to control for wage effects which might arise if workers in skilled regions self-select into higher paying industries. We have not controlled for industry effects so far because the system of industry classifications changes between 2002 and 2003 and both systems are incongruent, i.e. the two variables cannot be merged into one. When controlling for a potential self-selection of workers the results remain constant, i.e., wages of job changers rise by about .8 per cent with an increase in the share of highly qualified workers in the local workforce by one standard deviation.

As wages might be influenced by the regional price level, we control for the effect of local price levels on individual wages in column IV. In the absence of regional consumer prices, we use the average annual price per square meter of sold land within a county, which is provided by the Federal Statistical Office, as a proxy for regional price levels. The results show that the impact of local human capital on individual wages is not driven by local price effects.

Finally, we make sure that our results do not hinge on the regional share of highly qualified workers as an indicator for the regional level of skills. In order to do so, we use the regional average number of school years of workers within a county as an alternative measure.[9] On average, workers in Germany have absolved 12.7 years of schooling with a standard deviation of .56 years. Column V shows that the results are robust to the choice of the education variable. In fact, wages of job changers rise by about .5 per cent with an increase in average years of education by one standard deviation.

In sum, the results obtained so far show that wages of job changers rise with the local level of education. Over the period of investigation, wages of job changers increase by about five per cent with an increase in the regional share of highly qualified workers by one standard deviation. A more detailed analysis indicates that the bulk of these wage gains occur at the time of a job change, a finding that provides evidence for the existence of ‘matching effects’ rather than ‘learning effects’. In the next section we examine whether workers respond to these wage differentials by changing job more often in skilled regions. Before doing so, however, some comments are in order with respect to the other regional variables.

First, we find the agglomeration variable to be insignificant throughout most wage regressions. This finding, which stands in contrast to prior findings for the US, is likely to be driven by the close collinearity between the local degree of agglomeration (as measured by the number of workers per square kilometre), the average level of skills (corr .78) and the regional fixed effects. In fact, as the area of a county is absorbed by the regional fixed effects because it does not change over time, the only source of variance in the agglomeration variable comes from changes in the local number of workers. These changes are probably too small to yield significant effects. We have addressed this issue by employing different indicators for regional agglomeration. First, we have used an agglomeration measure provided by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (*Bundesinstitut für Bau-, Stadt- und Raumforschung*), which classifies regions into nine different agglomeration types based on the size of the core city and the population density of the wider region. When converting this indicator into dummy variables, the coefficients for these dummy variables provide evidence for a positive influence of regional agglomeration on individual wages while leaving the effects of the regional level of skills unaffected. The drawback of these dummy variables is, however, that they are perfectly multi-collinear with the region fixed effects and, hence, cannot be used jointly with them. Using the regional number of workers or the logarithm thereof as alternative measures also does not qualitatively change the results provided so far. In sum, for econometric reasons we have not found a way to replicate the positive results on agglomeration effects provided by, e.g., Rosenthal and Strange (2008). However, this does not invalidate the findings obtained so far on wage effects from the local level of education. In fact, the results from the instrumental variable approach provide strong evidence that such effects are unlikely to be driven by a spurious correlation between the local level of skills and the degree of agglomeration.

Similarly, a word of caution is in order with respect to the insignificance of overall wage effects from aggregate human capital (i.e., wage effects from aggregate human capital incurred by all workers independent of whether they change jobs or not). Two potential reasons may apply here. First, taken at face value, the results suggest that human capital externalities are exclusively driven by matching effects in skilled regions and, hence, wage effects only accrue to job changers. Alternatively, the results may be rooted in the short time horizon the sample covers and the close co-linearity with the interaction term, rather than by the absence of genuine human capital externalities for job stayers. In fact, wage effects from aggregate human capital can arise only from intra-regional shifts in aggregate education since level effects are captured by regional fixed effects. As the sample covers a period of six years only, intra-regional variances in the share of highly qualified workers may be too small to yield significant effects. In what follows we discuss the relative importance of matching externalities as a microeconomic source of human capital externalities by referring to findings from existing studies on the size of wage effects from human capital externalities.

In the empirical literature, wage effects from the regional share of highly qualified workers have been shown to amount to around one per cent with each additional percentage point of highly qualified workers, independent of whether workers change jobs or not (see, e.g., Moretti 2004a; Moretti 2004b; Heuermann 2011). Such productivity enhancing effects are, however, prone to be underestimated since with the existence of amenity effects workers are willing to accept wage losses in return for being close to other skilled workers (Roback 1982). According to Shapiro (2006), productivity effects account for about two thirds of the social returns to human capital and amenity effects for the remaining third. Thus, productivity effects from aggregate human capital are likely to be in the range of 1.5 per cent for all workers. According to our results, job changers incur wage gains of about .8 per cent with each additional percentage point in the regional share of highly qualified workers at the time of changing firms. As workers in this sample change jobs only within regions, wage gains on the incidence of a job change are not influenced by amenity effects and simply reflect increases in productivity. Hence, comparing this result with the ones by Moretti and Heuermann suggests that matching effects from aggregate human capital may account for about half of overall productivity enhancing returns to human capital, which is in line with a dynamic interpretation of localized economies of scale. In fact, in the literature on agglomeration externalities it is increasingly acknowledged that productivity effects from economic density are mainly incurred by workers reaping the gains from better matching opportunities in urban areas. In this vein, Yankow (2006: 160) argues that “coordination efficiencies in dense urban settings have a prominent role to play in any comprehensive explanation of the urban wage premium”. Analogously, the results here suggest that human capital externalities partly arise from improved labour market coordination in skilled regions.

4.2. The Probability of Job Changes

Table IV contains the results from Probit regressions on individual and aggregate determinants of a job change using both samples of workers. The first sample is restricted to the year 2000, because due to the way the sample is constructed, job changes can only occur in that year. The subsample contains a cross-section of 184,282 workers, out of which 11,240 change jobs. As this restriction impedes the use of time or region fixed effects we also employ the second, unbalanced panel of workers, which encompasses 1,395,228 observations on workers out of which 123,420 are observations on job changes. The dependent variable throughout all regressions is the incidence of a job change.

Due to differences in the samples (with the first sample covering all workers in 2000 and the second sample consisting of observations on young workers between 1976 and 2004) the coefficients on individual variables vary between the two samples. However, all coefficients show similar signs across all regressions. The probability of changing jobs first decreases with age and tenure and then rises again. Experience, in contrast, follows an inverted U-shape pattern, indicating that the probability of a job change first increases with labour market experience and then declines again (see Battu et al. 2002 for similar results). Men change jobs more often than women; while in general the propensity of workers to change job increases with education, it is highest for workers with secondary education and subsequent vocational training.

Employing the first sample in column I, we find that the annual probability of workers to change jobs increases by 3.5 percentage points with a rise in the share of highly qualified workers by one standard deviation. This effect is, however, likely to be confounded by region and time specific shocks which cannot be controlled for by means of fixed effects in this cross-section. When using the second sample of workers and employing region and time fixed effects in column II, we find the effect of regional education levels on the probability of a job change to increase in size, i.e. a rise in the share of highly qualified workers by one standard deviation raises the annual probability of a job change by about 5.6 percentage points. With an annual average probability of about 8.8 per cent for a worker to change jobs, this corresponds to an increase of about sixty per cent. Controlling for firm characteristics in column III leaves this result unchanged.

When differentiating the results by gender we find that the results are entirely driven by male workers. Thus, despite the fact that women are slightly more likely to change jobs in a given year (women: 9.6 per cent; men: 8.1 per cent), the probability of men to change jobs rises by 7.7 percentage points with a rise in the regional share of highly qualified workers by one standard deviation while we find no significant effects for women. While this result renders our findings somewhere close to the insights by Simon and Warner (1992) who show that in the US ‘Old Boy Networks’ are important determinants of overall career paths, it is also in line with results from research on gender-related differences in job-change decisions which provides evidence that women’s career developments are more strongly influenced by family and marital circumstances than men’s are (see Fuller 2008 for an overview).

Graph II shows the results from a simulation of the probability of job change as a function of regional human capital endowments based on the specification in column III. The probability increases monotonically at a growing marginal rate within the observable range of regional human capital levels. Finding job change probabilities to increase more than proportionally with the local aggregate level of human capital suggests that career networks are predominantly an issue of a number of ‘high-skill hubs’ located at the upper end of the distribution, whereas for intermediate levels of aggregate human capital matching effects are not very large. Typically, regions with high shares of qualified workers are characterized by clusters of industries. Munich (share of highly qualified workers: 21.7 %; industry cluster: computer engineering), Frankfurt (18.7 %; banking), Stuttgart (15.7 %; automobile industry), and Ludwigshafen (15%; chemical industry) are a point in case here. Hence, it is likely that the size of matching effects does not only depend on the level of regional human capital, but also on the extent to which regional industrial compositions allow workers to change jobs within industries and to thereby capitalize on their industry-specific human capital. In line with this notion, Fallick et al. (2006) provide evidence that high job-hopping rates in Silicon Valley identified by Saxenian (1994) are entirely driven by job changes within the computer industry, while job changing rates within other industries are not significantly higher than elsewhere. In what follows we examine the importance of within-industry job changes for the occurrence of matching externalities.

5. Matching Externalities and the Transfer of Industry-Specific Knowledge

The results obtained so far support the idea that human capital externalities partly arise from an improved matching efficiency in skilled regions. Among other things, the quality of a labour market match depends on the extent to which workers can transfer their knowledge and experience to a new environment and thereby continue to use it productively. Studies in the literature on agglomeration externalities have shown that benefits from urban density are to some extent rooted in the fact that cities are home to larger industries, which facilitates the transfer of industry-specific knowledge between jobs (Freedman 2008; Wheeler 2008). Analogously, individual networks might allow workers in skilled regions to continue their career in the same industry and to thereby capitalize on their knowledge and experience obtained in past jobs. Examining this issue we first investigate whether wage gains from aggregate human capital are larger for workers changing jobs within industries. We then analyse whether workers are more likely to stay within an industry in human capital intensive regions when changing jobs than workers in less skilled regions.

Column I in Table V indicates that wage effects from aggregate human capital only arise for workers changing jobs within an industry. With respect to the importance of career networks, this finding suggests that such networks carry information about job opportunities within industries and thereby increase the chances of workers to capitalize on their industry-specific human capital early in their career. While it may be the case that intra-industry and between-industry changers differ systematically in their motives of changing jobs, such self-selection effects are likely to be captured by the job change dummy rather than by the interaction term, which is subject to the assumption that the unobserved heterogeneity between workers does not vary systematically with the density of human capital.

If wage gains only arise for workers changing jobs within an industry, workers in human capital intensive areas should be more likely to change jobs within industries in order to reap the gains from matching externalities. We examine this issue by estimating the probability of a worker to change industries (conditional on changing jobs) as a function of regional human capital. For this analysis the two samples are reduced to contain only job changers.

Column II in Table V shows that for the first sample the probability of a job changer to change industries declines with the regional share of highly qualified workers. The effects are, however, small and statistically significant only at the ten percent level. The results show that a rise in the regional share of highly qualified workers by one standard deviation is associated with a decrease in the probability of a worker to change industries by about one percentage point. Columns III and IV contain the results from the second sample with and without controlling for firm specific effects. While slightly more robust, the results are similar in size to the ones obtained from the first sample.

As the empirical literature on job change patters has provided evidence that the inter-sectoral mobility increases with the individual level of education (see, e.g., Fallick 1993; Magnani 2001), we examine in columns V and VI whether workers of different skill groups respond differently to wage effects from human capital externalities occurring within industries. We therefore re-estimate the regression contained in columns IV separately by highly qualified and non-highly qualified workers. The results show that the probability for highly qualified workers to change industries when changing jobs decreases by about eight percentage points with an increase of the share of highly qualified workers by one standard deviation. With job changers splitting equally into industry changers and non-industry changers this amounts to a decrease in the industry change probability of about sixteen per cent. We do, in contrast, not find significant effects for non-highly qualified workers.

In sum, the general picture emerging from this analysis is that job changers of all education levels incur larger wage gains in skilled regions if they change jobs within industries rather than between industries. At the same time, we find that the likelihood of responding to these wage differentials by changing jobs within industries in skilled regions increases with individual education. As a result, at least for highly qualified workers it seems that a high regional level of education enables them to gather information on superior job matches more quickly during their careers and to thereby capitalize on their industry-specific human capital. Hence, it is through the opportunity of changing jobs within industries that regional human capital allows these workers to climb up the income ladder more quickly in skilled regions.

6. Conclusion

In this study we set out with the intent to shed light on the microeconomic foundations of human capital externalities. Inspired by the literature on the importance of social networks for career perspectives we have investigated whether the local aggregate level of education unfolds productivity effects through an improved quality of job matches in human capital rich regions. Employing two samples of highly qualified workers in Germany we have examined the extent to which regional differences in between-job wage growth and in job changing behaviour are attributable to differences in regional educational endowments as measured by the share of highly qualified workers. Our results support the notion that regional human capital externalities are partly rooted in improved job matching opportunities in skilled regions. Four core findings emerge from the analysis:

First, an increase in the share of highly qualified workers by one standard deviation is associated with wage gains of job changers of about five per cent and, second, with an increase in the annual probability of a job change by about sixty per cent. Third, between-job wage gains accrue only to workers changing jobs within industries. Fourth, it seems that only highly qualified workers respond to this wage differential by changing jobs more often within industries. The latter two finding suggests that matching externalities partly arise because highly qualified workers in skilled regions are able to capitalize on their industry-specific human capital to a larger extent than workers in less skilled regions.

From these results three conclusions can be drawn with respect to the design of public policies. First, corroborating the existence of external returns to tertiary education, the present paper adds to the list of arguments put forth for public investment in colleges and universities. Second, the results contribute to the long standing debate on whether industrial clustering or industrial diversification is more desirable from the point of view of local economic development. Our results adds to the arguments being made for industrial clustering, as highly qualified workers capitalize on the local level of education by making their careers mainly within single industries. Third, from the viewpoint of efficiency it is desirable to maximize the number of persons benefitting from matching externalities. A potential way of achieving this would be an increased integration of local labour markets, e.g., by public investment into infrastructure which allow workers living in peripheral regions to commute to skilled regions. In an international setting, the close labour market integration between Trier and Luxemburg, made possible by the removal of legal and infrastructural borders between two nation states provides an excellent example for the benefits peripheral regions (Trier) can incur from gaining access to a skilled labour market (Luxemburg). In fact, with the process of European economic integration Trier has not only seen a substantial rise in wage levels, but has also increasingly become home to highly qualified workers. The strong skill base resulting from this process provides promising conditions for future economic growth.

Given the significance of improved job matching opportunities as a microeconomic foundation of human capital externalities, further research is encouraged to go beyond a mere quantification of external effects from human capital and to further our understanding of the microeconomic sources of human capital externalities. In this respect we regard the taxonomy by Duranton and Puga (2004) of sharing, matching, and learning mechanisms as particularly helpful because it not only furthers our understanding of how exactly human capital externalities come about, but are also instructive for the design of empirical strategies that are capable of identifying the ways through which human capital externalities arise. A closer look at these mechanisms also reveals that a proper identification necessitates the use of new and innovative data. In fact, while the use of individual wage date is helpful for identifying local matching effects, these data are less suited to examine the productivity effects from local knowledge spillovers. A promising approach for such an analysis has been provided by Jaffe et al. 1993 who have successfully introduced the use of patent data as a way of tracking the flow of knowledge. While their approach has by now become firmly established in empirical studies on knowledge spillovers, the empirical study by Charlot and Duranton (2004) that uses data on patterns of workplace communication for identifying learning effects can be regarded as an innovative complement which promises to further our understanding of how mutual learning between workers contribute to productivity gains in skilled regions.

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Appendix

Table I – Descriptive Statistics

	Sample I		Sample II	
	Mean	Standard Deviation	Mean	Standard Deviation
Daily Gross Wage	92.8	36.3	71.0	35.5
Age	42.3	9.6	27.8	7.6
Tenure	11.5	7.6	5.7	5.4
Experience	17.9	7.6	8.0	6.6
Share of Females	.40	-	.46	-
Share of Highly Qualified Workers	.10	.05	.08	.06
Regional Density	.89	1.96	.29	.73

	Job Changers		Job Stayers		Job Changers		Job Stayers	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Daily Gross Wage	89.2	35.9	93.0	36.3	73.9	34.2	66.8	36.7
Age	38.8	9.6	42.5	9.5	28.6	7.7	26.7	7.3
Tenure	3.8	3.5	11.9	7.5	5.2	4.8	6.3	6.0
Experience	15.1	7.7	18.1	7.5	9.1	6.7	6.4	6.0
Share of Females	.41	-	.40	-	.46	-	.46	-
Share of Highly Qualified Workers	.11	.04	.10	.05	.08	.06	.08	.06
Regional Density	.99	2.07	.89	1.95	.29	.71	.29	.71

	Correlations Sample I					
	Daily Gross Wage	Age	Tenure	Experience	Female	Share of HQ Workers
Age	.09	-	-	-	-	-
Tenure	.16	.44	-	-	-	-
Experience	.21	.65	.62	-	-	-
Female	-.44	.03	-.06	-.12	-	-
Share of Highly Qualified Workers	.20	.05	-.01	.01	.00	-
Regional Density	.08	.02	-.01	-.01	.00	.32

	Correlations Sample II					
	Daily Gross Wage	Age	Tenure	Experience	Female	Share of HQ Workers
Age	.63	-	-	-	-	-
Tenure	.46	.69	-	-	-	-
Experience	.56	.85	.78	-	-	-
Female	-.28	-.17	-.11	-.12	-	-
Share of Highly Qualified Workers	.19	.12	.01	.03	.00	-
Regional Density	.13	.11	.05	.08	.00	.37

Table II – Do Workers Benefit from Regional Human Capital when Changing Jobs?

Dependent Variable:	Ln(Individual Daily Gross Wage)					
	(I)	(II)	(III)	(IV)	(V)	(VI)
Age	.009 (.0004)***	.009 (.0004)***	.009 (.0004)***	.025 (.0004)***	-.005 (.0006)***	-
Age²	-.163 (.004)***	-.163 (.004)***	-.163 (.004)***	-.304 (.005)***	-.029 (.007)***	-.456 (.008)***
Experience	.018 (.0003)***	.018 (.0003)***	.018 (.0003)***	.026 (.0003)***	.008 (.001)***	.046 (.0008)***
Experience²	-.151 (.008)***	-.140 (.008)***	-.139 (.008)***	-.447 (.010)***	.123 (.015)***	-.209 (.011)
Tenure	.007 (.0002)***	.007 (.0002)***	.007 (.0002)***	.004 (.0002)***	.012 (.0004)***	.003 (.0005)***
Tenure²	-.116 (.007)***	-.128 (.007)***	-.129 (.007)***	-.024 (.007)***	-.256 (.014)***	-.028 (.009)***
Female	-.345 (.0007)***	-.345 (.0007)***	-.345 (.0007)***	-	-	-
No Formal Degree	-.264 (.002)***	-.264 (.002)***	-.264 (.002)***	-.229 (.002)***	-.273 (.003)***	-
Secondary School and Vocational Training	-.111 (.002)***	-.111 (.002)***	-.111 (.002)***	-.087 (.002)***	-.117 (.002)***	.737 (.008)***
Gymnasium with or w/o Vocational Training	-	-	-	-	-	.661 (.019)***
Tertiary Education	.202 (.002)***	.202 (.002)***	.202 (.002)***	.242 (.002)***	.161 (.002)***	1.04 (.028)***
Firm Size	.007 (.00009)***	.006 (.00009)***	.006 (.00009)***	.006 (.00009)***	.011 (.00002)***	.001 (.0005)**
Firm Age	-.005 (.0001)***	-.005 (.0001)***	-.005 (.0001)***	-.004 (.0002)***	-.007 (.0002)***	-.005 (.0007)***
Share of Highly Qualified Workers in the Firm	.539 (.004)***	.538 (.004)***	.538 (.004)***	.391 (.004)***	.771 (.007)***	.076 (.011)***
Regional Density	-.264 (.139)*	-.152 (.139)	-.021 (.143)	-.213 (.159)	.215 (.255)	.009 (.087)***
Job Change	.002 (.003)	.004 (.003)	.004 (.003)	-.010 (.004)***	.027 (.006)***	-
Regional Share HQ	-.177 (.237)	-.267 (.236)	Split up by Year, results not shown	Split up by Year, results not shown	Split up by Year, results not shown	Split up by Year, results not shown
Job Change*Regional Share HQ	.157 (.027)***	Split up by Year	Split up by Year	Split up by Year	Split up by Year	Split up by Year
Job Change*Regional Share HQ, 1999	-	-.597 (.041)***	-.611 (.041)***	-.473 (.048)***	-.814 (.071)***	.179 (.176)
Job Change*Regional Share HQ, 2000	-	.226 (.038)***	.236 (.038)***	.165 (.045)***	.269 (.063)***	.787 (.174)***
Job Change*Regional Share HQ, 2001	-	.287 (.037)***	.303 (.037)***	.221 (.044)***	.346 (.063)***	.854 (.174)***
Job Change*Regional Share HQ, 2002	-	.295 (.037)***	.312 (.037)***	.227 (.043)***	.353 (.062)***	.861 (.173)***
Job Change*Regional Share HQ, 2003	-	.326 (.036)***	.313 (.036)***	.181 (.043)***	.412 (.060)***	.850 (.173)***
Job Change*Regional Share HQ, 2004	-	.324 (.036)***	.309 (.036)***	.180 (.042)***	.399 (.061)***	.837 (.172)***
Sample	All Workers	All Workers	All Workers	Men	Women	All Workers (FE)
Adj. R²	.39	.39	.39	.31	.21	.11
No. of Observations	1,105,692	1,105,692	1,105,692	661,782	443,910	1,105,692

Notes: Robust standard errors in parentheses; ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively; all specifications contain Region and Year Fixed Effects; column (VI) additionally contains Worker Fixed Effects (FE); coefficients for constants are not reported here; *Female* equals 0 for *'Male'* and 1 for *'Female'*; *Secondary School* refers to *Volks-, Haupt-, and Realschule*; for reasons of readability of the table, coefficients and standard errors on *Age²*, *Experience²*, *Tenure²*, *Firm Size* and *Firm Age* are multiplied by 1,000.

Table III – Robustness Checks: Do Workers Benefit from Regional Human Capital when Changing Jobs?

Dependent Variable:	Ln(Individual Daily Gross Wage)				
	(I)	(II)	(III)	(IV)	(V)
Age	.013	.009	.014	.009	.009
	(.0004)***	(.0004)***	(.0005)***	(.0004)***	(.0003)***
Age²	-.216	-.158	-.206	-.158	-.163
	(.004)***	(.004)***	(.005)***	(.004)***	(.004)***
Experience	.017	.018	.022	.018	.018
	(.0003)***	(.0003)***	(.0004)***	(.0003)***	(.0003)***
Experience²	-.115	-.156	-.299	-.159	-.151
	(.008)***	(.008)***	(.011)***	(.008)***	(.008)***
Tenure	.008	.007	.007	.007	.007
	(.0002)***	(.0002)***	(.0003)***	(.0002)***	(.0002)***
Tenure²	-.124	-.109	-.149	-.112	-.116
	(.007)***	(.007)***	(.009)***	(.007)***	(.007)***
Female	-.341	-.355	-.322	-.356	-.345
	(.0007)***	(.0008)***	(.0009)***	(.0008)***	(.0007)***
No Formal Degree	-.370	-.463	-.249	-.463	-.264
	(.002)***	(.002)***	(.002)***	(.002)***	(.002)***
Secondary School and Vocational Training	-.217	-.316	-.092	-.316	-.111
	(.002)***	(.001)***	(.002)***	(.002)***	(.002)***
Gymnasium with or without Vocational Training	-.113	-.201	-	-.202	-
	(.002)***	(.002)***		(.002)***	
Tertiary Education	-	-	.223	-	.202
			(.002)***		(.002)***
Firm Size	.008	.005	.004	.006	-.006
	(.0009)***	(.0009)***	(.0001)***	(.0009)***	(.0009)***
Firm Age	-.005	-.005	-.002	-.005	-.005
	(.0001)***	(.0001)***	(.0002)***	(.0001)***	(.0001)***
Share of Highly Qualified Workers in a Firm	.710	.535	.413	.537	.539
	(.005)***	(.004)***	(.005)***	(.004)***	(.004)***
Regional Density	-.378	-.187	.016	-.168	-.178
	(.142)***	(.154)	(.182)	(.149)	(.139)
Regional Price Level	-	-	-	.0006	-
				(.0005)	
Job Change	.011	.0003	-.006	-.0003	-.171
	(.003)***	(.003)	(.004)	(.003)	(.031)***
Regional Share HQ	-.158	1.47	-.569	-.081	-
	(.241)	(1.75)	(.304)*	(.244)	
Job Change*Regional Share HQ	.111	.164	.153	.174	-
	(.028)***	(.028)***	(.033)***	(.029)***	
Average Year of Education	-	-	-	-	.085
					(.019)***
Job Change* Average Years of Education	-	-	-	-	.015
					(.002)***
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Region Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	Yes	No	No
Individual Fixed Effects	No	No	No	No	No
Type of Robustness Check	w/o Imputed Wages	Instrumental Variables	Industry Fixed Effects	Regional Price Levels	Average Years of Education
Adj. R^2	.37	.40	.41	.40	.39
No. of Observations	1,001,979	1,010,502	680,340	979,866	1,105,692

Notes: Robust standard errors in parentheses; ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively; coefficients for constants are not reported here; *Female* equals 0 for *'Male'* and 1 for *'Female'*; *Secondary School* refers to *Volks-, Haupt-, and Realschule*; for reasons of readability of the table, coefficients and standard errors on *Age²*, *Experience²*, *Tenure²*, *Firm Size*, *Firm Age* and *Regional Price Levels* are multiplied by 1,000.

Table IV – Does Regional Human Capital Increase the Probability of Intra-Regional Job Changes?

Dependent Variable:	Incidence of Job Change				
	(I)	(II)	(III)	(IV)	(V)
Age	-.012 (.006)**	-.222 (.020)	-.227 (.020)***	-.222 (.031)***	-.181 (.025)***
Age²	.004 (.007)	.004 (.0004)***	.004 (.0004)***	.004 (.0006)***	.003 (.0005)***
Experience	.901 (.021)***	1.54 (.102)***	1.54 (.102)***	1.22 (.140)***	1.77 (.141)***
Experience²	-.002 (.0005)***	-.056 (.004)***	-.056 (.004)***	-.046 (.005)***	-.063 (.005)***
Tenure	-.965 (.195)***	-4.45 (.275)***	-4.44 (.274)***	-3.64 (.394)***	-4.96 (.364)***
Tenure²	.032 (.007)***	.156 (.009)***	.155 (.009)***	.129 (014)***	.172 (.013)***
Female	-.003 (.015)	-.033 (.016)**	-.044 (.016)***	-	-
No Formal Degree	-.051 (.035)	-.783 (.066)***	-.976 (.079)***	-.822 (.101)***	-.882 (.099)***
Secondary School and Vocational Training	.055 (.028)	.492 (.048)***	.305 (.044)***	.275 (.042)***	.362 (.069)***
Gymnasium with or without Vocational Training	.003 (.032)	.061 (.040)	-.068 (.043)	-	-.106 (.072)***
Tertiary Education	-	-	-	.072 (.046)	-
Firm Size	-.00001 (.000004)***	-	-.00002 (.000003)***	-.00002 (.000004)***	-.00003 (.000005)***
Firm Age	-.000006 (.000002)**	-	.00004 (.000004)***	.00002 (.000004)	.00006 (.000006)***
Share of Highly Qualified Workers in a Firm	.096 (.069)	-	-.767 (.099)***	-.347 (.097)***	-1.21 (.175)***
Regional Density	-.011 (.004)***	-.137 (.025)***	-.154 (.026)***	-.095 (.028)***	-.202 (.042)***
Regional Share HQ	.683 (.215)***	1.03 (.423)**	.999 (.425)**	1.37 (.477)***	.456 (.699)
Year Dummies	No	Yes	Yes	Yes	Yes
Region Dummies	No	Yes	Yes	Yes	Yes
Sample	Sample I	Sample II	Sample II	Sample II, Men	Sample II, Women
Pseudo- R²	.54	.54	.54	.56	.52
No. of Observations	184,282	1,395,228	1,395,228	755,749	639,479

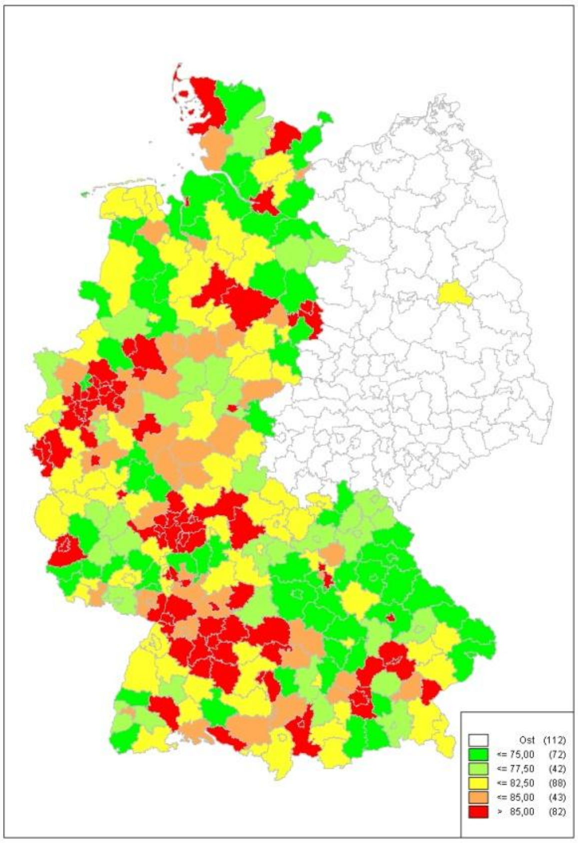
Notes: Robust standard errors in parentheses; ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively; coefficients for constants are not reported here; *Female* equals 0 for *'Male'* and 1 for *'Female'*; *Secondary School* refers to *Volks-, Haupt-, and Realschule*; for reasons of readability of the table, all coefficients and standard errors are multiplied by 1,000.

Table V – Is There Evidence for Matching Effects from Industry-Specific Human Capital?

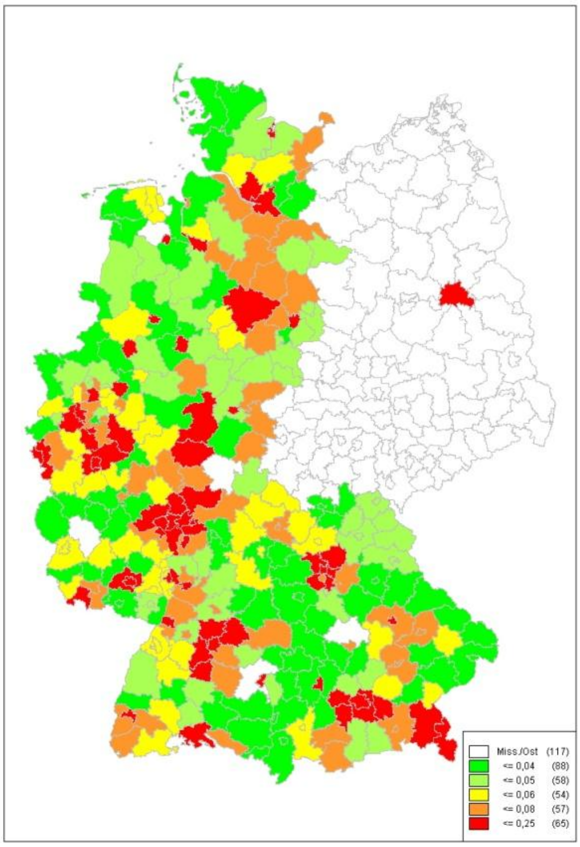
Dependent Variable:	Ln(Individual Daily Gross Wage)	Incidence of Industry Change, conditional on Job Change				
	(I)	(II)	(III)	(IV)	(V)	(VI)
Age	.019 (.0005)***	.027 (.004)***	.023 (.002)***	.024 (.002)***	-.017 (.013)	.029 (.002)***
Age²	-.276 (.006)***	-.361 (.056)***	-.334 (.036)***	-.344 (.036)***	.133 (.199)	-.415 (.041)***
Experience	.021 (.0004)***	-.015 (.003)***	-.014 (.001)***	-.014 (.001)***	.002 (.005)	-.016 (.001)***
Experience²	-.239 (.012)***	.225 (.110)**	.299 (.056)***	.289 (.056)***	.045 (.246)	.351 (.060)***
Tenure	.008 (.0003)***	-.030 (.007)***	-.028 (.003)	-.045 (.003)***	-.029 (.011)***	-.045 (.003)***
Tenure²	.148 (.009)***	.886 (.381)**	1.49 (.212)***	1.98 (.216)***	1.47 (.703)**	1.96 (.228)***
Female	-.328 (.001)***	-.061 (.010)***	-.077 (.003)***	-.078 (.003)***	-.018 (.014)	-.083 (.003)***
No Formal Degree	-.241 (.003)***	-	.083 (.008)***	.156 (.008)***	-	.083 (.007)***
Secondary School and Vocational Training	-.084 (.002)***	-.052 (.017)	.029 (.007)***	.092 (.008)***	-	.019 (.006)***
Gymnasium with or without Vocational Training	-	-.069 (.013)***	.035 (.008)***	.092 (.008)***	-	-
Tertiary Education	.135 (.003)***	-.074 (.023)***	-	-	-	-
Firm Size	.005 (.0001)***	-.001 (.0004)***	-	-.003 (.0006)***	-.001 (.001)	-.003 (.0006)***
Firm Age	-.002 (.0002)***	-.026 (.002)***	-	-.024 (.005)***	-.016 (.002)***	-.025 (.006)***
Share of Highly Qualified Workers in a Firm	.563 (.006)***	.149 (.043)***	-	.295 (.016)***	.097 (.029)***	.383 (.021)***
Regional Density	-.174 (.212)	-.001 (.003)	-.018 (.005)***	-.009 (.005)*	-.019 (.017)	-.010 (.005)*
Regional Share HQ	-.825 (2.69)	-.189 (.105)*	-.170 (.091)*	-.191 (.092)**	-1.35 (.385)***	-.104 (.096)
Job Change	.006 (.002)***	-	-	-	-	-
Intra-Industry Job Change* Regional Share HQ	.469 (.047)***	-	-	-	-	-
Inter-Industry Job Change* Regional Share HQ	-.011 (.050)	-	-	-	-	-
Year Dummies	Yes	No	Yes	Yes	Yes	Yes
Region Dummies	Yes	No	Yes	Yes	Yes	Yes
Sample	Sample I; Instruments, w/o Imputed Wages	Sample I	Sample II	Sample II	Sample II, HQ Workers	Sample II, Non-HQ Workers
Adj. R² / Pseudo-R²	.40	.05	.06	.07	.09	.07
No. of Observations	557,525	11,240	123,420	123,420	7,950	115,470

Notes: Robust standard errors in parentheses; ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively; coefficients for constants are not reported here; *Female* equals 0 for *'Male'* and 1 for *'Female'*; *Secondary School* refers to *Volks-*, *Haupt-, and Realschule*; for reasons of readability of the table, coefficients and standard errors on *Age²*, *Experience²*, *Tenure²*, *Firm Size* and *Firm Age* are multiplied by 1,000

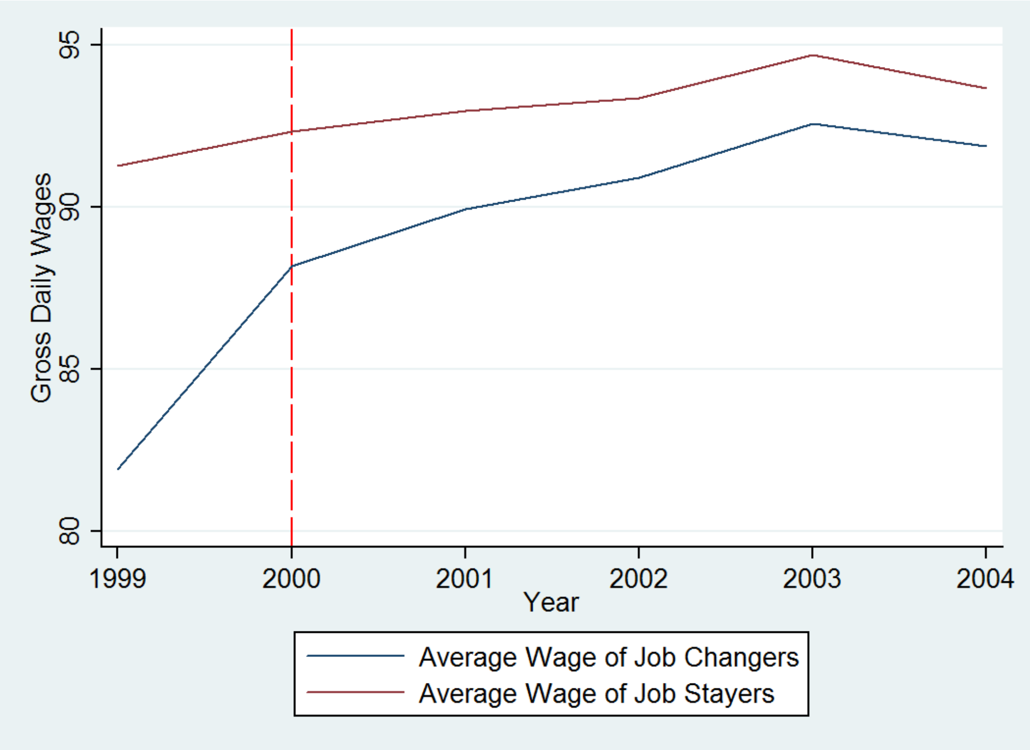
Map I: Average Regional Wages, 2001



Map II: Regional Share of Highly Qualified Workers, 1992

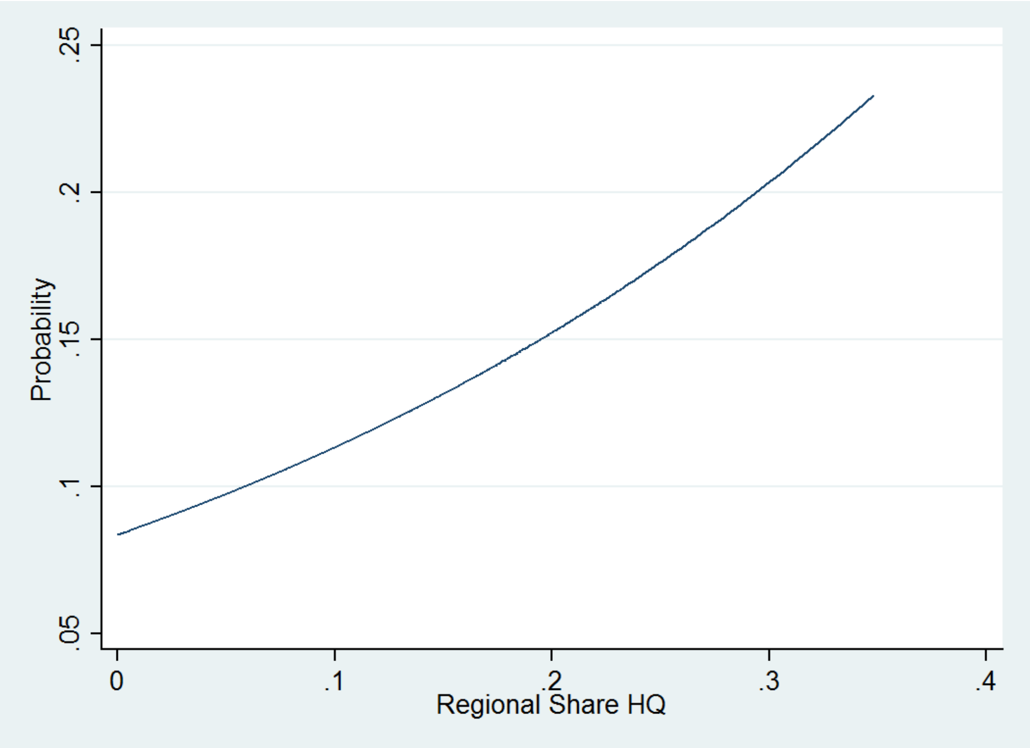


Graph I: Wage Development of Job Changers and Job Stayers



The graph displays annual average wages of all individuals changing jobs in 2000 (blue line) and of all individuals not changing jobs at all during the period of observation (red line).

Graph II: The Probability of a Job Change as a Function of Regional Human Capital



The graph displays the results from a simulation of the probability of a job change as a function of regional human capital endowments, based on the results contained in column III in Table IV.

Endnotes

[1] The relationship between aggregate human capital and employment growth has been investigated among others by Simon and Nardinelli (2002) and Glaeser and Shapiro (2003); see Davies (2002) and Moretti (2004a) for a survey of the empirical literature on human capital externalities.

[2] See Heuermann et al. (2010) for a comparison of the empirical literatures on the urban wage premium and on human capital externalities.

[3] See Brock and Durlauf (2001) for a comprehensive survey of the literature on social interaction.

[4] We focus on regional wage differentials and matching externalities across regions in Western Germany. We exclude Eastern Germany for two reasons. First, data on Eastern Germany are available only from 1992 onwards, whereas data are available for Western Germany from 1975 until today. Second, due to a large-scale devaluation of educational degrees in Eastern Germany at the time of reunification, information on the highest degree of education are incommensurable between workers in Eastern and Western Germany. Since our analysis relies on educational degrees as a core variable, we exclude Eastern Germany in order to avoid inconsistent or biased results.

[5] Another problem we eliminate when restricting the sample to workers changing jobs within regions is that workers moving regions are sometimes compensated for their moving efforts by their future employer. Since these one-time payments cannot be identified in the data, ruling out the occurrence of moves across regions reduces the threat from upward bias in the estimations on matching effects.

[6] The ten per cent of workers earning wages above this threshold, which increases annually approximately in line with overall wage growth, are free to choose to either pay the maximum amount of social security payments, or to leave the public system and insure privately.

[7] A job change is defined as a change of employers (on plant level).

[8] Quits from the sample can occur if workers change into the public service, become self-employed, become unemployed, or leave the labour force altogether.

[9] Educational degrees are translated into years of schooling as follows: ‘no formal education’ (9 years); ‘degree from Volks-/Haupt-/Realschule and subsequent vocational training’ (12 years); ‘Gymnasium with vocational training’ (16 years), ‘degree from a technical college or from university’ (20 years).