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Benefits of dense labour markets - Evidence from transitions to employment in Germany

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Benefits of dense labour markets - Evidence from transitions to employment in Germany

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Abstract

Agglomeration economies may impact on productivity in different ways. Up to now, only a few papers try to provide evidence on the underlying mechanisms that might give rise to a positive correlation between agglomeration and wages. In this analysis we focus on the matching mechanism, i.e. the hypothesis that the size of the local labour market allows for better matching of job seekers and vacancies. Better matches in turn are supposed to give rise to higher productivity. We aim at providing new evidence on the importance of the matching mechanism and investigate the effects of the density of local labour markets on the wages of new employment relationships. The analysis is based on a large micro data set that offers detailed information on labour market biographies of workers in Germany. We apply the two-stage regression approach proposed by Combes et al. (2008) and distinguish between different types of transition, i.e. job-to-job transitions as well as transitions from short- and long-term unemployment. The results point to rather small positive effects on productivity: a doubling of the employment density increases the productivity of new employment relationships by 1.1% to 1.4%. Moreover, the findings indicate that the benefits of a better match might only accrue to persons with a job-to-job transition as well as short-term unemployed. We detect no important impact of agglomeration for transitions from long-term nonemployment.

JEL classification: R23, J31

Keywords: Agglomeration economies, matching, transitions to employment

1 Introduction

A voluminous literature provides robust evidence for an urban wage premium. In the urban economics literature these disparities are explained by agglomeration economies. Density of the local economy might, however, impact on productivity in different ways. Duranton and Puga (2004) distinguish three basic mechanisms that might cause a positive correlation between density and productivity: sharing, matching and learning. While there is comprehensive empirical evidence on a positive impact of agglomeration on productivity of workers and firms (Combes et al., 2008; Glaeser and Maré, 2001), much less is known about the significance of different mechanisms as noted by Rosenthal and Strange (2004) and Combes and Gobillon (2015). Moreover, only a few studies explicitly differentiate between static and dynamic effects of agglomeration (De la Roca and Puga, 2013; Matano and Naticchioni, 2015) and allow for heterogenous effects across individual and firm characteristics. However, the identification of mechanisms that give rise to significant productivity effects of agglomeration is crucial from policy perspective because the market failures associated with alternative channels differ and therefore implications with respect to corrective policies vary (Duranton and Puga, 2004).

This study aims at providing new empirical evidence on the importance of the matching mechanism and investigates the effect of the density of local labour markets on the wages of new employment relationships. We investigate the hypothesis that the size of the local labour market allows for better matching of job seekers and vacancies. Better matches in turn are supposed to give rise to higher productivity and wages. The analysis is based on a micro data set that offers detailed information on labour market biographies of workers in Germany. More precisely, we use a 5% sample of the Integrated Employment Biographies (IEB) of the Institute for Employment Research (IAB) to identify more than 1,000,000 transitions to full-time employment between 2005 and 2011. We apply the two-stage regression approach proposed by Combes et al. (2008) to estimate the impact of the employment density on wages associated with these transitions. We distinguish between different types of transition: job-to-job transitions as well as transitions from short- and long-term nonemployment. In order to deal with unobserved heterogeneity, i.e. composition effects due to spatial sorting on individual characteristics, we include worker fixed effects. A second econometric issue concerns the endogeneity of the pivotal explanatory variable: density and productivity are simultaneously determined and, thus, OLS estimates of the elasticity of productivity with respect to employment density will be biased. We apply instrument variable (IV) estimation to arrive at unbiased estimates using historical population data as well as soil characteristics as instruments.

In the empirical literature, the estimated elasticity of productivity with respect to local density typically ranges between 0.04 and 0.10 (Combes et al., 2010), indicating that an increase of the density by 1% gives rise to an increase in productivity by up to 0.1% or, in other words, a doubling of the density causes a rise of productivity by around 7% at the maximum. Our results indicate that there are rather small positive effects on productivity associated with transitions from job search to employment: the estimates suggest that a doubling of the employment density increases the productivity of new employment relationships by 1.1% to 1.4%. Moreover, the density effects are heterogeneous. The findings indicate that the benefits of a better match might only accrue to persons with a job-to-job transition and short-term unemployed. We detect no important positive impact of agglomeration for transitions from long-term nonemployment. Furthermore, the regression results suggest a slightly larger impact on migrants as compared to stayers.

The focus of our analysis is on the static agglomeration effect that results from a better matching of workers and jobs. The empirical strategy thus aims at excluding or controlling the impact of other

mechanisms that generate agglomeration economies. The first-stage regression therefore provides some evidence on other channels and on dynamic effects resulting from agglomeration. We detect a highly significant impact of the previous work experience in dense labour markets pointing to the importance of dynamic learning effects. This confirms evidence provided by De la Roca and Puga (2013) for Spain. Our estimates indicate that every additional year of work experience gathered in a large city increases the wage by 0.8%. Moreover, knowledge spillovers and complementarities seem to matter since the share of high-skilled workers in the firm and the local industry tend to increase the wages associated with transitions to employment as well.

In contrast to most previous studies we control more comprehensively for the labor market biography of the workers because this might significantly impact on productivity and wages. Workers likely accumulate firm-specific human capital because the employer might offer training and acquire skills via learning by doing. This should increasingly influence the productivity and wages as tenure rises but is not directly related to the matching. Furthermore, in order to approach benefits associated with a better matching of workers and jobs we identify transitions to new employment relationships and focus on the reported wages associated with these transitions. Finally, only a few studies allow for heterogeneous effects of agglomeration. A small number of studies provide corresponding evidence with respect to the skill level of workers (Andersson et al., 2014; Bacolod et al., 2009). To the best of our knowledge this analysis is the first that considers differences with respect to the pre-employment status of the workers.

The structure of the paper is as follows. In Section 2, we review the corresponding literature with a focus on studies that consider benefits caused by the matching mechanism. In the section 3 and 4, we describe our empirical strategy and the data set. We discuss the main results of the regression analysis in Section 5. Section 6 concludes.

2 Literature

Many studies find evidence for the existence of the urban wage premium (Combes et al., 2008; Glaeser and Maré, 2001; Glaeser and Resseger, 2010). The urban economics literature offers theoretical explanations for the stylized fact that workers in bigger cities earn significantly more than workers employed in other areas. Obviously, there are productivity advantages of urban regions that give rise to higher earnings of workers. The theoretical arguments for these agglomeration economies go back to Marshall (1890). Duranton and Puga (2004) combine the various explanations into three main channels and provide microfoundations for these mechanisms that generate agglomeration. They differentiate between sharing, learning and matching. We refrain from a detailed discussion of these well-known mechanisms and focus on matching in the following and in particular to productivity gains that result from the better match of workers and jobs in thick markets.

Kim (1990) develops a model of an urban labor market that explains the static matching effect. The approach is characterized by increasing returns to scale, specialized production methods and heterogeneous workers. Increasing the size of the regional labour market in this setting improves the match between specialized workers and the heterogeneous skill requirement of firms. Differences in skills do not refer to the level of educational attainment, i.e. skills are horizontally differentiated. The jobs require specific skill characteristics and in case the workers is not equipped with the corresponding requirements costly training is needed. Highest productivity is achieved if the worker exactly meets the skill requirements of

the workplace. As the distance between worker skills and job requirements increases, necessary training costs rise. The worker chooses the firm that offers the highest net wage (gross wage minus training costs) if this amount is at least equal to her reservation wage. The firm in turn will hire the job candidate if her marginal value product with the firm exceeds the required training cost.

In a large market more diverse job requirements are available. Kim (1990) argues that in a large urban labor market the proximity of workers and firms promotes a specialized labor market. The model predicts a positive correlation between worker productivity and the size of the local labor market because the specialization associated with a larger market reduces the average cost of mismatch between the skill characteristics of workers and the job requirements of firms. Moreover, Kim (1989) shows that workers tend to invest more in the depth of human capital as opposed to the breadth as the local market becomes larger. This will give rise to a more specialized human capital in these markets.¹ In line with this theoretical argument Kok (2014) shows that jobs in large cities consists of less sub-tasks and are thus more specialized. The theoretical models also suggest that workers who experience a significant depreciation of human capital due to an extensive period of non-employment might not benefit from market size because their specific skills deteriorate. Thus, we might expect significant differences in the static agglomeration effect across types of transitions that differ with respect to length of preceding nonemployment.

An important differentiation is between static and dynamic agglomeration effects. For instance, benefits caused by learning are considered to be dynamic in a sense that it might take some time for these effects to show up and that they increase with the time spent in agglomerations. In contrast, static gains from better matching are instantaneous (Combes et al., 2010). Furthermore, the matching advantage has a quantitative and a qualitative dimension. The large number of job seekers and job offers in a dense urban labor markets reduce search frictions and increase the probability of a match of workers and firms. Correspondingly, a thick labor market tends to show more frequent job changes and also a higher quality of matches which should materialize in terms of high productivity and wages (Duranton and Puga, 2004). This differentiation between the quantitative and qualitative element of the matching mechanism carries over to the empirical literature. There are studies that analyse the probability of finding a job (a match) and investigations that focus on the frequency of job changes and worker mobility across occupations and industries. In contrast, other papers concentrate on different aspects of matching quality.

Turning to the empirical literature, Di Addario (2011) investigates the factors that impact on the probability for non-employed to find a job in Italy and detects a significant positive effect of market size. Other studies examine whether agglomeration increases the frequency of job changes. Bleakley and Lin (2012) prove with US data a negative effect of employment density on industry and occupation changes. However, for younger workers the correlation between density and corresponding job changes is positive. The latter finding is confirmed by several studies. Andersson and Thulin (2013) show that in Sweden the positive impact of density on job changes is more important for young educated workers than for other groups of workers. Similarly, Wheeler (2008) examines the relationship between density, industrial diversity and job mobility for the US. He finds that industry changes occur more often in large, diverse markets. However, once a number of changes have occurred, the relationship between diversity and the probability of an industry change becomes negative.

¹ Sato (2001) considers the significance of search friction in this context. In this search model matches are random and workers don't necessarily find their most suitable jobs. The results indicate that agglomerations economies can emerge notwithstanding the existence of frictions if the search technology exhibits increasing returns to scale.

Other studies focus on the quality of the match. Harmon (2013) investigates job search outcomes in Denmark. He finds that job seekers in large labour markets find jobs that are better matches given their skills and previous industry experience. Büchel and van Ham (2003) uses overeducation as an indicator for match quality. Investigating the German context his results indicate that the risk of overeducation declines as market size increases. Other authors analyse the degree of assortative matching in thick markets, i.e. complementarity between worker and firm quality in production and whether this is influenced by the size of the market. While Mion and Naticchioni (2009) detect a negative relationship between assortative matching and density in Italy, findings by Melo and Graham (2014) and Andersson et al. (2007) point to a higher degree of assortative matching in thicker markets.

Finney and Kohlhase (2008) conclude that productivity advantages of U.S. cities derive from greater coordination in large labour markets. More precisely, highly urbanized regions give young workers the opportunity to try various jobs in search of a closer match. Boualamy (2014) examines the propensity that entrants to the French labour market get a job related to their field of education. Controlling for individual, regional, occupational and educational characteristics, his results show that agglomeration enhances the quality of job matches.

Aside from studies which deal with the matching advantage associated with dense markets there is a large body of literature that focuses on the relationship between productivity and agglomeration. The seminal contribution by Ciccone and Hall (1996) addresses the static effects of agglomeration on productivity. Using aggregate data for the US, they find that a doubling of employment density increases average labour productivity by around 6%. A drawback of studies which base on aggregate data is, however, that they cannot for the effect of sorting of workers across locations. This problem was first tackled by Glaeser and Maré (2001) applying information on workers in the U.S. and regression models that include individual fixed effects and thereby control for a possible sorting of high-ability workers into big cities. Their results suggest that the wage premium reflects static agglomeration effects as well as a wage premium that seems to accumulate over time and is maintained when workers leave cities, indicating wage growth effects.

Also other authors have investigated the role of static and dynamic agglomeration economies. Combes et al. (2008) provides evidence on static advantages associated with bigger cities in France. Lehmer and Möller (2010) find for Germany that only dynamic effects occur once firm size and individual fixed effects are taken into account. D'Costa and Overman (2014) show for the UK that having worked in a city at some point in the past affects longer-term wage growth. Wheeler (2006) concludes that faster wage growth in dense metropolitan areas in the US is due to between-job wage growth rather than wage growth experienced on the job. However, results by Yankow (2006) suggest that a higher frequency of job changes in agglomerations result in an urban wage growth premium, rather than between-job wage growth.

A small number of recent studies consider heterogeneous agglomeration effects, in particular with respect to the skill level of the workers. Bacolod et al. (2009) and Andersson et al. (2014) identify an important urban wage premium only for workers with high cognitive skills in the U.S. and Sweden respectively. This is in line by findings of a study by Matano and Naticchioni (2015). The authors also consider heterogenous effects of agglomeration. Their focus is, however, on disentangling static and dynamic effects for skilled and unskilled workers. Their results indicate that skilled workers in Italy benefit from important static and dynamic agglomeration effects, whereas unskilled workers only experience a significant wage growth effect that might be caused by learning effects in dense labor markets. who

conclude that in dense areas less skilled worker do not benefit from job changes while skilled workers enjoy a wage premium by exploiting matching opportunities. Combes and Gobillon (2015) summarize that there is only scarce evidence on heterogenous agglomeration gains across demographic groups. Moreover, frequently studies that allow for heterogenous effects do not take into account simultaneously the endogeneity issues brought about by reverse causality and omitted variables.

Evidently, there is a considerable amount of empirical evidence proving the existence of agglomeration economies and in particular positive effects of agglomeration on productivity.² However, the size of the reported estimates vary a lot due to difference in applied data and estimation methods. Melo et al. (2009) review the corresponding literature and report elasticities of wages with respect to city size vary between 0.088 and 0.194. Combes and Gobillon (2015) state that typical values, when controlling for some local characteristics (but ignoring problems of reverse causality and spatial sorting), range from 0.04 to 0.10. This implies that a doubling of density leads to an increase in productivity of 3% to 7%.

Apart from varying results and more important with regard to the empirical evidence for agglomeration effects: the underlying mechanisms remain a black box in almost all empirical studies (Puga, 2010; Combes and Gobillon, 2015). As regards the impact on productivity there are two rare exceptions. De la Roca and Puga (2013) aim at disentangling static from dynamic effects and provide evidence on the significance of dynamic learning effects using information on work experience in big cities in Spain. They show that working experience acquired in the largest Spanish cities has a significantly higher value than experience acquired in the rest of the county. Based on results obtained for three different classes of cities, they conclude that about one half of the productivity gains are immediate static effects while another half of the wage premium is dynamic as workers accumulate experience in big cities and take these gains with them when they leave the city. Matano and Naticchioni (2015) also try to separate the channels that generate agglomeration economies. They analyse the wage dynamics of different groups of migrants who move from lower to higher density areas in Italy. They show that job changes have no static effect on wages for unskilled workers. These employees rather benefit from dynamic wage growth due to human capital accumulation in dense areas. In contrast, for skilled workers job tenure plays a minor role and their wage premium in dense areas results primarily from better matching opportunities.

However, altogether corresponding evidence is scarce and Combes and Gobillon (2015) thus conclude that most of analyses identify an overall impact but do not offer findings on the importance specific mechanisms that generate agglomeration effects. Only a few papers try to provide evidence on the underlying mechanisms that give rise to agglomeration economies and their impact on wages.³ More empirical investigations are still needed in order to better disentangle the different short-term dynamics from long-term effects. As the identification of the mechanisms that generate agglomeration economies is one of the current concerns in the literature we focus on the importance of matching mechanisms.

² Fingleton and Longhi (2013) is one of the few studies that failed to prove general positive relationship between wages and density.

³ There is a related strand of literature on specific mechanisms behind agglomeration economies that does not, however, investigate the effects on productivity. For instance, Overman and Puga (2010) provide evidence on the importance of labor market pooling by showing that industries whose establishments experience more idiosyncratic shocks are more spatially concentrated. We refrain from a detailed review of this literature and refer to comprehensive surveys by Combes and Gobillon (2015).

3 Data

To determine the impact of labour market density on matching quality we analyse wages of 1,073,158 new employment relationships in Germany covering the period between 2005 and 2011. Detailed information on individual labour market biographies enables us to identify these new employment relationships and to differentiate between different types of transition to employment, i.e. job-to-job transitions as well as transitions after short- and long-term nonemployment.

The information bases on the Integrated Employment Biographies (IEB) of the IAB. The IEB contains detailed and very reliable micro data on employment, job-search status, benefit receipt, and participation in measures of active labour market policy. It comes from the integrated notification procedure for health, pension and unemployment insurance and the corresponding administrative procedures from the Federal Employment Agency. Our data set comprises a 5% random sample of all employees with at least one notification to social security between 2005 and 2011. For this sample of workers our data set captures all information from the IEB that refers to the period 2000 to 2011. Using the individual employment spells, we are able to identify new employment relationships. We restrict our analysis to new full-time employment subject to social security contributions outside the public sector and the temporary work sector with a length of at least seven days.⁴

For the new employment relationships we observe the corresponding gross daily wage⁵ as well as further information on the new job (e.g. occupation, occupational status) and important characteristics of the worker, like age, educational attainment and sex. Since the wage that is paid by a new employer likely depends on previous jobs of the worker and previous periods of unemployment, we use the information on the individual labour market biographies to generate additional control variables, e.g. the labour market status before the considered transition to employment, recent (occupation specific) labour market experience, and the number of different employers in the past. Detailed information on all variables that we use in our analysis is provided in Table A.1 in the appendix. Summary statistics can be found in Table A.2 and Table A.3, respectively.

The establishment identifier in the IEB is used to add important information on the establishment such as industry, establishment size and skill structure of the staff to our individual level data set. The data is taken from the Establishment History Panel (BHP) of the IAB.⁶ Since the location of the establishment is also available we are able to assign each transition to employment to one of 141 German regional labour markets. The delineation of these regions bases on commuter flows.⁷

Finally, we enrich our individual data set with detailed information on the regional labour market. Our pivotal variable is labour market density. Figure 1 shows the correlation between the density of the local

⁴ Apprenticeships are not considered as well as new employment relationships which start simultaneously with an other employment relationship or with a measure of active labour market policy since we cannot ensure that this employment is not publicly subsidised. Moreover, we exclude new employment relationships with a wage below two times the limit for marginally employed as well as recalls, i.e. cases in which a worker starts to work in an establishment in which she was working already at least once during the previous 28 days. If a worker is already employed at the starting date of the new employment relationship in an other establishment we consider the new employment relationship only if the previous employment spell ends at the latest 7 days later.

⁵ The spell of a new employment relationship in the IEB ends at the latest at December, 31st of the year in which the new employment relationship starts. The daily wages are calculated by dividing the reported total earnings from this spell by the length of the spell. Information on actual working days or contract hours is not available.

⁶ Different units of a firm that are located in different municipalities are considered as independent establishments. Unfortunately, it is not possible to identify whether different establishments belong to the same firm.

⁷ See Kosfeld and Werner (2012) for a detailed description.

labour markets and the average wages of new employment relationships. In the regression analysis we take into account systematic differences between East and West German regions since wages in East Germany are still lower than in West Germany. However, for both sub-samples there is a strong positive correlation between density and wage level. The labor market density explains more than 30% of the variation of regional wages in a simple model with density as the only regressor. The elasticity is roughly 0.11 for East as well as the West German sub-sample. Since there are also other regional characteristics

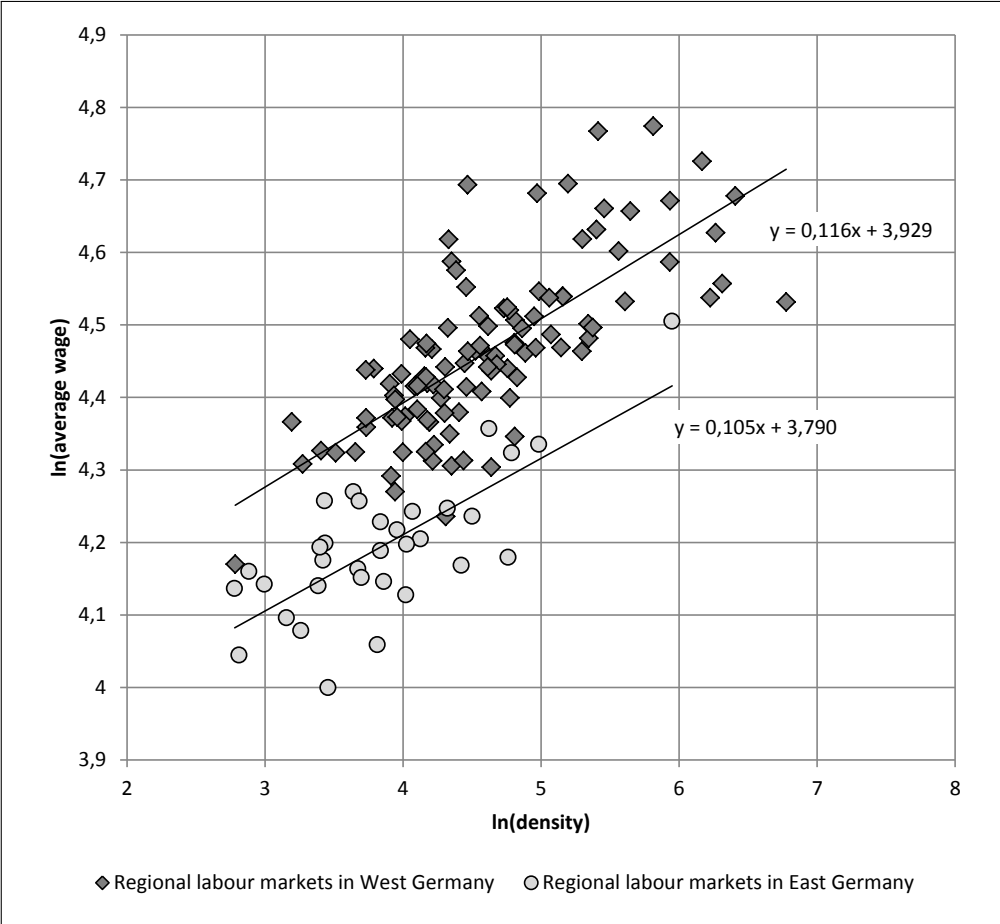


Figure 1: Correlation between labour market density and wages after transitions to employment (2005-2011 averages, in 2011 prices)

Note: Some regional labour markets along the former inner-German border capture parts of East and West Germany and are according to their economic centers considered as West German regions.

that might impact on wages, we also consider information on characteristics of the local industry, regional unemployment rates by skill level, as well as indicators for the attractiveness of the region (amenities).

Firms report earnings only up to the upper limit for social security contributions, such that the wage information in the IEB is right censored. Therefore, we partly impute the wages. We follow Reichelt (2015) and apply interval regression, a generalisation of tobit regression, to predict the wages above the threshold (about 6% of the observations).⁸

We use historical population density and information on the nature of soils as instrument variables for labor market density. The historical regional population density refers to 1871, 1880, 1890, 1900, 1910,

⁸ See Reichelt (2015) for a detailed description on how interval regression is applied to impute right censored wages. The results of our regression analysis do not change when we use the reported wages as dependent variable instead of the imputed wages in the first stage regression.

1925, and 1933 and is provided by Rothenbacher (2002). The soil data comes from the European Soil Database. We aggregate the available raster data at the regional level and use the same characteristics as Combes et al. (2010).

4 Empirical Strategy

We apply the two-stage regression approach proposed by Combes et al. (2008) to estimate the impact of the employment density on wages associated with transitions to new employment relationships. In the first stage we regress individual wages on a set of region-time fixed effects while controlling for worker, job, firm and region characteristics (see equation (1)). In the second stage, we regress the region-time fixed effects on our measure of regional labor market size, i.e. the employment density (equation (2)). This gives us the elasticity of the wage premium with respect to the size of the regional labor market. The first-stage wage regression is given by:

$$w_{irst} = \alpha_i + x_{it}'\beta + z_{rst}'\gamma + u_{rt}'\delta + \theta_{rt} + \varepsilon_{irst} \quad (1)$$

where w_{irst} is the log wage of worker i in region r , sector s and year t . The vector x_{it} captures time-varying worker characteristics, α_i is a worker fixed effect, and ε_{irst} is the error term. Individual characteristics also comprise detailed information on the labor market biography, the pre-employment status and the participation in programs of active labour market policies. Apart from worker characteristics we control for some firm characteristics such as sector, firm size and skill structure. The vector u_{rt}' includes characteristics of the regional labor market like skill-specific unemployment rates, whereas z_{rst}' to local characteristics of the sector in which the new employment relationship is established.⁹ The latter are supposed to control for mechanisms other than matching that give rise to agglomeration benefits. The vector z_{rst}' includes the local employment share of the sector, the number the establishments and the skill structure of the local industry.

The time-varying region fixed effect θ_{rt} capture the impact of observed and unobserved regional factors on worker productivity. We also estimate specifications with a time-invariant region fixed effect θ_r . On the second stage we regress the region fixed effects on the measure of regional labor market size and some control variables. The corresponding regression model is given by:

$$\theta_{rt} = \zeta + D_{rt}\lambda + C_{rt}'\gamma + \varphi_t + e_{rt} \quad (2)$$

where D_{rt} is the log employment density of the regional labor market, φ_t are time fixed-effects, and e_{rt} is the error term that is assumed to be i.i.d. across regions and years. The main interest of this analysis is to provide an unbiased estimate of λ , the elasticity of wages with respect to labor market size. We also consider some control variables C_{rt}' in the second stage in order to allow for the impact of amenities that may be capitalized into wages as argued by Combes et al. (2008). To account for systematic differences between East and West German labor markets (see Figure 1), we include a corresponding dummy vari-

⁹ We control for skill-specific unemployment rates because there is an extensive literature on the wage curve suggesting a robust negative relationship between wages and unemployment (Blanchflower and Oswald, 1990). Baltagi et al. (2009) provide corresponding evidence for Germany.

able in some specifications. Agglomeration economies that might spill over the boundaries of regional labor markets are captured by a spatial lag of D_{rt} .

There are two important econometric issues: selection effects and the endogeneity of the size of the labor market. We will discuss these problem very briefly here because comprehensive discussions of these topics are available (Combes and Gobillon, 2015; Combes et al., 2010). Firstly, the estimate of the elasticity might be severely upward biased due to unobserved heterogeneity, i.e. more able workers might select into large regions. We apply the standard solution and include worker fixed effects in the regression models. However, in order estimate fixed effects models we need to observe at least two transitions to a new employment relationship for a worker. Secondly, large regions which are marked by a high productivity will be attractive locations and thus likely experience significant in-migration. This will in turn impact on the size of the labor market. Therefore we need to account for reverse causality to arrive at unbiased estimates. To identify the causal effect of labor market density on wages of new employment relationships we apply instrument variable estimation techniques. Following Ciccone and Hall (1996) and Combes et al. (2008), we use historical population density and information on the nature of soils as instrument variables for labor market density. Combes et al. (2010) provide a detailed discussion of the relevance and exogeneity of these instruments.

Our main interest is in identifying the importance of the static matching effect. By considering the wages associated with new employment relationships we focus on mechanisms which have instantaneous effects on productivity, in contrast to other channels such as learning that take some time to materialize.¹⁰ Moreover, as tenure increases other factors, e.g. training on the job and professional training offered by the firm, will gain in importance for productivity. But normally these effects are unobserved by the econometrician. In the first-stage estimation we also include several variables that are supposed to capture other agglomeration effects in order to isolate the static matching effect. Even in the fixed effects model the corresponding estimate may be biased when learning effects, i.e. dynamic benefits due to work experience in dense labor market are ignored (De la Roca and Puga, 2013). In order to deal with this issue we consider the work experience in dense labor markets as an important control variable in the first-stage regression. To account for other urbanization and localization economies that might impact on the productivity associated with new employment relationships the employment share and the number of establishments of the local industry as well as industrial diversity are included in the regression model. Human capital externalities and complementarities are captured by the human capital of the local industry and the qualification structure of the firms's workforce. Wheeler (2006) shows that job changes positively impact on wage growth. Therefore the number of job changes during the last five years also enters.¹¹

In contrast to most previous studies we control more comprehensively for the labor market biography of the workers because this might significantly impact on productivity and wages.¹² Ignoring important time-varying worker characteristics will bias the estimation of the region-time fixed effects and may thus lead to incorrect inference regarding the significance of the matching benefits. However, we cannot entirely rule out the existence of other unobserved time-varying factors that are correlated with the error term in equation (1) will bias the estimation of the region-time fixed effects.¹³

¹⁰ This is in contrast to most previous studies which use information on employment at a reference date.

¹¹ See appendix for a detailed description of all variables

¹² See Lesner (2014) for a recent survey of the corresponding labor economics literature. The author also provides empirical evidence on the important role of the labor market history for transitions between labor market states and wages in Denmark.

¹³ See Combes et al. (2008) for a detailed discussion of corresponding econometric issues.

We also allow for heterogeneous effects across groups of workers. Whereas Andersson et al. (2014) focus on heterogeneity with respect to the skill level, i.e. vertical differentiation, we consider differences in the length of nonemployment before the match. This seems to be more in line with the specificity of worker skills and requirements of jobs discussed by Kim (1990). We assume that the specificity of skills declines as the period of non-employment before the new employment relationship increases because human capital depreciates. Mincer and Ofek (1982) show that career interruptions due to unemployment, sick leave or other reasons cause a significant decline in wages that is interpreted as indicating human capital depreciation. Görlich and de Grip (2009) argue that not using or updating skills during periods of nonemployment may result in a significant decline because they may be subject to technical and economic obsolescence. The authors provide corresponding evidence for Germany with a focus on the impact of parental leave on earnings and consequences for occupational segregation by gender.

In order to analyze whether the benefits of matching in dense labor markets differ with the length of nonemployment we investigate the relationship between the productivity of new employment relationships and density for three different types of transition: job-to-job transitions, employment relationships that are established after a short-term unemployment (up to 12 months) and transitions after long-term nonemployment (more than 12 months).¹⁴

5 Results

Table 1 summarizes some first results of the two-stage regression approach described in Section 3. We only display the estimates of the second stage and report bootstrapped standard errors in order to account for the two-stage nature of the regression approach.¹⁵ The regression results rely on all transitions to employment and we consider region-specific effects as the dependent variable at the second stage. In the first column a rather simple model that only includes worker characteristics is estimated on the first stage. In line with previous studies we detect a highly significant positive effect of density on productivity. However, compared with the raw elasticity of roughly 0.11 (see Figure 1) the impact of labor market size almost halves once we take worker characteristics into account. This implies that the sorting of workers across regions on observable characteristics is an important econometric issue. The estimated elasticity is located in the typical range of corresponding results (0.04 and 0.10 according to Combes et al. (2010)). The coefficient slightly declines if we augment the model by including the labor market biography and other agglomerations effects.

Although the results in column (3) base upon a model that includes a considerable number of control variables they might still be biased because these estimates don't take into account the possible sorting on unobserved worker characteristics. The positive correlation between employment density and productivity might at least partly be caused by the sorting of more able workers into larger labor markets. The standard approach to solve this problem is to estimate a fixed effects model as it allows to control for time-invariant individual unobserved heterogeneity (Combes et al., 2008; Mion and Naticchioni, 2009). In the present setting fixed effects imply that we can only consider workers with a minimum of two transitions to employment. This approach significantly reduces the number of observations (see Table A.4

¹⁴ The last group is likely the most heterogeneous category since it encompasses long-term unemployed as well as workers who have been inactive for at least one year, e.g. due to parental leave or on grounds of ill health.

¹⁵ Robust and clustered standard errors are of similar size. First-stage estimates of different specifications are summarized in Table A.4 in the appendix.

in the appendix). The corresponding estimate of the elasticity in column (4) confirms previous findings regarding the importance of sorting since the coefficient of density significantly declines.

Table 1: Second stage results for region fixed effects (OLS)

	(1)	(2)	(3)	(4)
ln(Employees per km ²)	0.068*** (0.008)	0.063*** (0.008)	0.065*** (0.009)	0.044*** (0.006)
Constant	0.170*** (0.020)	0.156*** (0.019)	0.161*** (0.021)	0.111*** (0.014)
Observations	141	141	141	141
R ²	0.321	0.301	0.293	0.317
Adjusted R ²	0.316	0.296	0.288	0.312
First stage: Individual characteristics	Yes	Yes	Yes	Yes
First stage: Biography	No	Yes	Yes	Yes
First stage: Agglomeration variables	No	No	Yes	Yes
First stage: Worker fixed effects	No	No	No	Yes
Second stage: Additional control variables	No	No	No	No

* p<0.05, ** p<0.01, *** p<0.001. Bootstrap standard errors in parentheses (clustered at regional level, 500 replications).

A drawback of the result in column (4) is that the time-invariant region-specific effect is entirely identified by new employment relationships that involve a change of the regional labor market, i.e. by migrants, because with worker fixed effects we cannot estimate region fixed effects based on workers who are always observed in the same regional labor market. De la Roca and Puga (2013) note that this can be a source of concern as migrants might not be representative for the broader worker population. To derive more general results we use region-time effects as dependent variable in Table 2. The impact of agglomeration is now estimated on the basis of both migrants and workers who experience a change in labor market density without relocating. Correspondingly the number of observations in the second stage increases from 141 to 987.

Table 2: Second stage results for region-time fixed effects (OLS)

	(1)	(2)	(3)	(4)
ln(Employees per km ²)	0.033*** (0.003)	0.020*** (0.002)	0.017*** (0.003)	0.015*** (0.003)
East Germany		-0.060*** (0.005)	-0.055*** (0.006)	-0.053*** (0.006)
W x ln(Employees per km ²)				0.006 (0.004)
Constant	0.156*** (0.007)	0.136*** (0.005)	-0.016 (0.043)	0.005 (0.044)
Observations	987	987	987	987
R ²	0.823	0.898	0.908	0.909
Adjusted R ²	0.822	0.897	0.907	0.908
Additional control variables	No	No	Yes	Yes

* p<0.05, ** p<0.01, *** p<0.001. Bootstrap standard errors in parentheses (clustered at regional level, 500 replications). All first stage regression models include time-varying worker and job characteristics, worker fixed effects, information on the labor market biography and variables that refer to the local industry and regional labor market conditions. All second stage regression models include time fixed effects.

Comparing the estimate in the first column of in Table 2 with the elasticity detected for the migrants

(column (4), Table 1) points to some heterogeneity in the static benefits of dense labor markets. Migrants seem to profit more from taking up a new job in a large urban region. As Figure 1 shows an important wage gap between East and West German regions we control for corresponding differences in column (2). As regards the elasticity with respect to labor market size this constitutes a conservative approach because the employment density of East German regions tends to be relatively low. However, we still detect a highly significant effect of agglomeration on productivity.¹⁶ This also applies if we add additional controls and a spatial lag of the employment density in the columns (3) and (4). The latter is included to account for the fact that agglomeration economies might spill over the boundaries of the regions.¹⁷ But the advantages of large labor markets seem to be highly localized as the coefficient of the spatial lag does not significantly differ from zero. Altogether our preferred estimate in column (4) is somewhat below the lower limit of previous findings on static agglomeration effects, suggesting that we should not overrate the size of the static matching benefit.

Table 3 summarizes results for different groups of workers. The columns (1) and (2) show the estimates for job-to-job transitions that clearly confirm our previous findings displayed in Table 2. The elasticity of productivity with respect to density is somewhat larger than the average effect identified for the entire sample of transitions. Furthermore, the relevant spatial scale of the effects seems to be slightly more extensive for job-to-job transitions. The estimate of the spatial lag of the employment density indicates that the size of neighboring labor markets matters as well for the productivity of these newly established employment relationships. In contrast, for the other groups of transitions we don't find significant spill over effects. As regards transitions from short periods of unemployment the impact of local labor market size does not differ from the effect associated with job-to-job transitions. However, the regression results suggest that workers who take up a job after a longer period of nonemployment don't benefit from a better matching quality in large markets. It is interesting to see that the East German wage gap also differs across transition groups. The disadvantage of accepting a job in East Germany deepens as the spell of nonemployment increases. In view of the relatively low employment density of East German regions, this corroborates our findings on differentiated agglomeration effects for distinct transition types.

The differences between transition types suggest that workers who experienced an extensive period of nonemployment do not benefit from static matching effects in large labor market due to a significant deterioration their specific skills as discussed in Section 2.¹⁸ The results are also consistent with the idea that these workers are not able to take advantage of referrals by current employees and (former) co-workers because they are at the margin of the labour market. Brown et al. (2015) show that referred candidates are more likely to be hired and that hired referred workers experience an initial wage advantage relative to nonreferred workers. Dustmann et al. (2015) provide similar evidence on the importance of referral-based job search networks in Germany. As proximity likely impacts on the interaction in these social networks, referrals might be understood as one channel behind static matching benefits. In fact, Dustmann et al. (2015) investigate search networks in a few metropolitan labour markets in Germany.

Table 4 gives the second stage results of the instrument variable estimation. We instrument for both employment density and the spatial lag of density. Several tests in the lower panel of the table suggest

¹⁶ It is noteworthy that this fairly simple model has considerable explanatory power as indicated by the adjusted R^2 .

¹⁷ We restrict spill over effects to neighboring labor markets that share a common border.

¹⁸ When we focus on transitions from long-term nonemployment some region-time fixed effects base only on few transitions. For some region-time combinations we cannot even estimate a fixed effect due to missing transitions. Therefore, we also estimate models that base on a first stage that includes region fixed effects instead of region-time fixed effects. Our main results are confirmed by these robustness checks. The corresponding results are available from the authors upon request.

Table 3: Second stage results for region-time fixed effects by type of transition (OLS)

	Job-to-Job transitions		Transitions after short term nonemployment		Transitions after long term nonemployment	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Employees per km ²)	0.020*** (0.003)	0.017*** (0.004)	0.020*** (0.005)	0.017** (0.005)	-0.025 (0.024)	-0.030 (0.025)
East Germany	-0.035*** (0.006)	-0.032*** (0.007)	-0.091*** (0.008)	-0.089*** (0.009)	-0.127*** (0.031)	-0.123*** (0.031)
W x ln(Employees per km ²)		0.012** (0.005)		0.010 (0.006)		0.015 (0.021)
Constant	0.042 (0.047)	0.082 (0.050)	-0.105 (0.057)	-0.073 (0.059)	-0.097 (0.207)	-0.045 (0.221)
Observations	987	987	987	987	959	959
R ²	0.889	0.891	0.632	0.637	0.268	0.269
Adjusted R ²	0.887	0.889	0.627	0.631	0.257	0.258

* p<0.05, ** p<0.01, *** p<0.001. Bootstrap standard errors in parentheses (clustered at regional level, 500 replications). All first stage regression models include time-varying worker and job characteristics, worker fixed effects, information on the labor market biography and variables that refer to the local industry and regional labor market conditions. All second stage regression models include time fixed effects and further control variables.

Table 4: Second stage results for region-time fixed effects (2SLS)

	Transitions after. . .			
	All transitions (1)	Job-to-Job transitions (2)	short term nonemployment (3)	long term nonemployment (4)
ln(Employees per km ²)	0.014** (0.004)	0.015** (0.005)	0.017* (0.007)	-0.016 (0.029)
W x ln(Employees per km ²)	0.008 (0.005)	0.014** (0.005)	0.009 (0.007)	0.005 (0.021)
East Germany	-0.053*** (0.006)	-0.033*** (0.006)	-0.089*** (0.009)	-0.119*** (0.032)
Observations	987	987	987	959
R ²	0.664	0.468	0.631	0.117
Adjusted R ²	0.658	0.459	0.625	0.102
F test [†] for density	20.345	20.345	20.345	19.561
F test [†] for spatial lag	22.314	22.314	22.314	22.476
Kleibergen-Paap LM rk statistic (p-value)	0.008	0.008	0.008	0.008
Kleibergen-Paap Wald rk F statistic	22.596	22.596	22.596	22.617
Sargan statistic (p-value)	0.210	0.201	0.341	0.499

[†] Angrist-Pischke multivariate F test of excluded instruments. * p<0.05, ** p<0.01, *** p<0.001. Bootstrap standard errors in parentheses (clustered at regional level, 500 replications). Exogenous instruments: Historic population density (1871-1933), spatial-lag of the historic population density & information from the European Soil Data base. All first stage regression models include time-varying worker and job characteristics, worker fixed effects, information on the labor market biography and variables that refer to the local industry and regional labor market conditions. All second stage regression models include time fixed effects and further control variables.

that our instruments are valid, i.e. relevant and uncorrelated with the error term. The Angrist-Pischke F-statistics of excluded instruments as well as the Kleibergen-Paap Wald test indicate that the partial correlation between instruments and endogenous regressor is sufficient to ensure unbiased estimates and relatively small standard errors. The Kleibergen-Paap F statistic is well above the thresholds proposed by Stock and Yogo (2005) for the maximal relative bias of 5%.¹⁹ The Kleibergen-Paap LM test confirms the relevance of the instruments as we can reject the null that the model is underidentified at the 5%-level. And finally the results of the Sargan test suggest that we can not reject the hypothesis that the instruments are exogenous.

The results of the IV regressions indicate that endogeneity due to reverse causality, omitted variables or measurement errors is unlikely to be a major problem in this setting. Comparing OLS and 2SLS estimates points to a minor bias as differences between the coefficients are small. This applies to employment density as well as the corresponding spatial lag and is in line with previous evidence provided by De la Roca and Puga (2013) and Combes et al. (2010). They conclude that endogeneity of region size is not a crucial issue when estimating the effects of agglomeration.

So far, our discussion of the regression results has focused on the elasticity of wages with respect to labor market density and on static matching benefits. However, the first stage regressions also provide evidence on other mechanisms that generate agglomeration economies (see Table A.4 in the appendix). We detect a highly significant impact of the previous work experience in dense labour markets pointing to the importance of dynamic learning effects. This confirms findings by De la Roca and Puga (2013) for Spain. Our estimates indicate that every additional year of work experience within an agglomeration in the last 5 years increases the wage by 0.8%. These dynamic agglomeration benefit also seem to differ across types of transition. We detect significant effects for job-to-job transitions and, interestingly, for transitions after a longer period of nonemployment. Thus, while the latter group does not benefit from static agglomeration effects they can take advantage of learning from working in large cities. In fact, they seem to achieve above average benefits as every additional year of work experience in large labor markets increases the wage by 1.6% after long-term nonemployment. In contrast, no significant effects show up for transitions after short term nonemployment.

Moreover, there is indication of important localisation economies that impact on the productivity of new employment relationships. Again, only workers with job-to-job transitions and those with a short period of nonemployment seem to benefit from these agglomeration economies. Only for these groups we estimate a significant positive effect of the employment share of the local industry. And finally the regression analysis points to significant knowledge spillovers and complementarities: the share of high-skilled workers in the firm and the local industry tends to increase the wages associated with transitions to employment as well. In contrast, the industrial diversity of the local economy does not impact on productivity of new employment relationships.

With respect to the interpretation of the estimates as pointing to static matching benefits there are some caveats to bear in mind. We try to control for other static and dynamic effects of agglomeration by considering the wage a newly established employment relationships and via control variables. However, we cannot rule out that our estimate of the static matching effect also comprises the impact of other mechanisms related to agglomeration. For instance, the productivity effect of sharing a good infrastructure endowment likely shows up immediately after the establishment of the employment relationship. We

¹⁹ With two endogenous regressors and 40 excluded instruments the critical values are 21.37 for a maximum bias of 5 percent of the IV estimator relative to the OLS and 11.22 for a maximum bias of 10 percent.

might somehow capture the impact of a specialized infrastructure (localization economies) by including the local size of the industries in the first stage regression. In contrast, the influence of general infrastructure facilities cannot be differentiated from the static matching effects. This also refers to the local monopsony power of the firm. Combes and Gobillon (2015) note that regional wage differences might to some extent reflect a spatial variation in the degree of competition on local labor markets. If the monopsony power of firms decreases with the size of the local market, higher wages in dense urban regions might be partly caused by the relatively high competitive pressure in these regions. However, the importance of the monopsony effect should decline with increasing labor mobility, i.e. workers should c.p. move to locations characterized by a relatively small monopsony power. Moreover, relocation of firms is also relevant in this context. Firm might move to regions that offer a higher mark-up of productivity over wages. Thus, mobility of firms and workers should decrease differences in monopsony power and the importance of corresponding wages disparities across regions.

6 Conclusions

STILL TO BE WRITTEN

7 Appendix

Table A.1: Variables - definitions and sources

Variable	Definition	Source
ln(imputed gross daily wage)	The IEB captures only right censored information on earnings. The first employment spell in the IEB of a new employment relationship ends at the latest at December, 31st of the year in which the new employment relationship starts. The (censored) daily wages are calculated by dividing the reported total earning from this spell by the length of the spell. The wages above the censoring limit (about 6%) are estimated applying interval regression as described by Reichelt (2015).	Integrated Employment Biographies (IEB)
Educational level of the worker	Categorical variables that combine information on the highest school leaving certificate, completed vocational training and university degree. In some employment spells the information is missing. Then, we take the information from previous employment spells following Fitzenberger et al. (2005).	IEB
Gender, nationality		IEB
Lifetime working experience	Approximated by the difference between the considered date of transition to employment and the date of the first employment spell within the IEB. Since the IEB do not capture employment spells before January, 1th 1975 this variable is right censored.	IEB

Table A.1 continued

Variable	Definition	Source
Recent working experience	Years of employment measured on a daily bases within the previous five years. Marginal employment is not considered as well as employment spells that refer to measures of active labour market policy. We distinguish total, occupation specific, and region specific working experience, as well as working experience achieved in agglomerations. Occupation specific working experience is measured on an aggregate level that distinguishes 21 occupational segments (see Matthes et al., 2008), region specific working experience refers to previous employment in the regional labour market in which the new employer is located, and for working experience achieved in agglomeration a definition of the Federal Institute for Research on Building, Urban Affairs and Spatial Development is applied that bases on the population share living in cities, the existence of large cities within the region, and population density.	IEB
Number of employers	We count the number of different establishment identifiers within the previous five years.	IEB
Pre-employment status	Dummy variables referring to the previous 28 days before the considered transition to employment <ul style="list-style-type: none"> - unemployment benefit (Arbeitslosengeld I) - unemployment assistance (Arbeitslosengeld II / Arbeitslosenhilfe). - unemployed and registered as a job seeker - not unemployed, but registered as a job seeker - participation in measures of active labour market policy. 	IEB
Occupational status	Categorical variable that distinguished white-collar employees and blue-collar workers based on the type of pension insurance institution (vom Berge et al., 2013). Blue-collar workers are in addition classified according to the activity: unskilled workers, skilled workers, and master craftsman / foreman. In December 2011 a new occupational classification was introduced. Therefore, for some observations the occupational status is unknown.	IEB
Firm characteristics	Number of employees, employment growth (dummy variable), share of workers with a university degree, share of workers with no completed vocational training / no university degree. The information refers to the last reference date (June 30th) before the considered transition.	Establishment History Panel (BHP)
Industry share	Logarithm of the employment share of the industry (2-digit level: 88 industries) in total regional employment.*	Employment statistics of the Federal Employment Agency (FEA)
Industrial diversity	Inverse Herfindahl index based on the employment shares of the different industries in total regional employment. The own industry is excluded when the inverse Herfindahl index is calculated.*	FEA
ln(Number of establishments within the local industry)	Number of establishments with at least one employee subject to social security at June 30th in t-1. Only firms that belong to the same industry and are located in the same regional labour market are considered.*	FEA

Table A.1 continued

Variable	Definition	Source
Human capital within the local industry	Share of workers with a university degree in total employment and share of workers without completed vocational training / university degree within the same industry and the same regional labour market.*	FEA
Skill specific unemployment rate of the regional labour market	The share of persons that are registered as unemployed in the number of persons who are registered as unemployed or employed in the region. We distinguish three groups: persons with a university degree, persons with a completed vocational training, and persons without completed vocational training / university degree.*	(Un-)employment statistics of the Federal Employment Agency
Industry fixed effects	We include fixed effects for 88 distinct industries (2-digit level according to the classification from 2008). In 2008 there was a change in the industry classification. If an establishment is observed before and after 2008 we assign the employment spells from 2005-2007 to the industry that the firm reports in 2008 (or later). If an establishment identifier shows up only 2005-2007 we use a correlation matrix between the old and new industry classification as described by Eberle et al. (2011).	IEB
Occupation fixed effects	We include fixed effects for 21 distinct occupational segments.	IEB
Region-Year fixed effects	We include region-year fixed effects (in some specifications region fixed effects) for the location of the establishment, in which a person starts to work. The location refers to one of 141 functional labour markets which are defined according to commuting intensity between NUTS 3-regions (see Kosfeld and Werner, 2012).	IEB
Ln(Employment density)	Logarithm of the working population per km ² .	The Regional Database Germany (TRDG)
Ln(Spatial lag of employment density)	Logarithm of the spatial lag of the regional employment density. The spatial lag is calculated applying a binary neighbouring matrix.	TRDG
Weather	The information has been collected between 1999-2009 at 71 weather stations. For each regional labor market we use the data from that weather station which is nearest to the geographical center of the region. We use the average temperature, average number of hours of sunshine, and the average precipitation amount.	DWD
Restaurant workers	Number of restaurant workers defined by KldB 1988 (classification of occupations) codes 912 (waiters) and 411 (cooks) in total regional population.	FEA
Share of recreation area	The share of urban green space, parks, allotment gardens, sport fields and campsites in total area.	TRDG
Coast	Dummy that indicates that the region is at a coast.	

Table A.1 continued

Variable	Definition	Source
Historical population density	Historical population density is available for 111 historic regions. We use this information to approximate the historic population density for our 141 regional labour market regions. In the cases where one labour market region comprise (parts of) several historic regions we calculate the average of the density of the different historic regions. Based on the data for 1871, 1880, 1890, 1900, 1910, 1925, and 1933 we generate a panel data set with seven waves that is used as instrument variable for the employment density 2005-2011.	Rothenbacher (2002)
Soil data	We use the following indicators: topsoil and subsoil mineralogy, dominant parent material (high and low aggregate), topsoil and subsoil water capacity, depth to rock, soil differentiation, erodibility, carbon content, hydrogeological class, ruggedness. The European Soil Database captures raster data. All indicators above (except ruggedness) are categorical variables. Based on the raster data we choose the modal value to aggregate the information at the level of each regional labour market.	European Soil Database

* The information refers to June 30th in t-1.

Table A.2: Summary statistics, first stage variables

	All transitions				Only transitions that are considered on the first stage with individual FE			
	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.
<i>Individual characteristics</i>								
ln(imputed gross daily wage)	4.128	0.499	3.267	7.573	4.122	0.487	3.267	7.573
Education:								
Secondary/intermediate school leaving certificate								
without completed vocational training	0.103	0.304	0.000	1.000	0.092	0.288	0.000	1.000
with completed vocational training	0.638	0.481	0.000	1.000	0.664	0.472	0.000	1.000
Upper secondary school leaving certificate								
without completed vocational training	0.021	0.144	0.000	1.000	0.016	0.127	0.000	1.000
with completed vocational training	0.083	0.276	0.000	1.000	0.082	0.274	0.000	1.000
Completion of a university of applied sciences	0.045	0.208	0.000	1.000	0.045	0.207	0.000	1.000
College/university degree	0.109	0.312	0.000	1.000	0.101	0.302	0.000	1.000
Female worker	0.337	0.473	0.000	1.000	0.300	0.458	0.000	1.000
Foreign worker	0.084	0.278	0.000	1.000	0.080	0.271	0.000	1.000
Years of lifetime working experience	14.388	9.598	0.000	36.975	14.475	9.171	0.000	36.969
Years of recent working experience	3.187	1.703	0.000	4.999	3.301	1.547	0.000	4.999
Length of employment spell in the year of transition in month	6.041	3.631	0.033	12.000	5.816	3.558	0.033	12.000
Years of recent occupation specific working experience	2.201	1.982	0.000	4.999	2.251	1.897	0.000	4.999
Years of recent employment within the region	2.080	1.938	0.000	4.999	2.073	1.854	0.000	4.999
Years of recent employment within agglomerations	1.705	1.971	0.000	4.999	1.733	1.927	0.000	4.999
Number of different firms in previous 5 years*	1.913	1.739	0.000	41.000	2.274	1.891	0.000	41.000
Unemployment benefit (ALG I)	0.234	0.424	0.000	1.000	0.281	0.450	0.000	1.000
Unemployment assistance (ALG II, ALHI)	0.083	0.275	0.000	1.000	0.078	0.268	0.000	1.000
No unemployment benefit / assistance	0.683	0.465	0.000	1.000	0.641	0.480	0.000	1.000
Unemployed and registered as a job seeker	0.313	0.464	0.000	1.000	0.356	0.479	0.000	1.000
Not unemployed, but registered as a job seeker	0.098	0.297	0.000	1.000	0.102	0.302	0.000	1.000
Not registered as a job seeker	0.589	0.492	0.000	1.000	0.542	0.498	0.000	1.000

Table A.2 continued

	All transitions				Only transitions that are considered on the first stage with individual FE			
	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.
Participation in measures of active labour market policy	0.055	0.227	0.000	1.000	0.056	0.230	0.000	1.000
Occupational status:								
Unskilled worker	0.243	0.429	0.000	1.000	0.254	0.435	0.000	1.000
Skilled worker	0.224	0.417	0.000	1.000	0.251	0.434	0.000	1.000
Master craftsman, foreman	0.009	0.095	0.000	1.000	0.009	0.096	0.000	1.000
Employee	0.443	0.497	0.000	1.000	0.414	0.493	0.000	1.000
unknown (only 2011)	0.081	0.273	0.000	1.000	0.072	0.258	0.000	1.000
<i>Establishment characteristics</i>								
ln(Number of workers within the establishment)	3.971	1.955	0.000	10.875	3.830	1.893	0.000	10.875
Share of high skilled within establishment	0.121	0.210	0.000	1.000	0.111	0.204	0.000	1.000
Share of low skilled within establishment	0.156	0.217	0.000	1.000	0.158	0.221	0.000	1.000
Number of workers within the establishment is increasing	0.417	0.493	0.000	1.000	0.418	0.493	0.000	1.000
<i>Regional characteristics</i>								
ln(Employment share of the industry within the region)	-3.528	1.056	-12.732	-0.855	-3.535	1.049	-12.732	-0.855
ln(Number of establishments within the local industry)	6.346	1.667	0.000	9.646	6.380	1.643	0.000	9.646
Industrial diversity without own industry within the region	21.177	5.571	4.238	34.853	21.069	5.566	4.238	34.853
Share high-skilled workers within the local industry	0.109	0.111	0.000	1.000	0.102	0.107	0.000	1.000
Share low-skilled workers within the local industry	0.188	0.091	0.000	1.000	0.190	0.092	0.000	1.000
Local unemployment rate among high-skilled labour [†]	7.464	3.117	1.342	17.087	7.427	3.106	1.342	17.087
Local unemployment rate among skilled labour [†]	11.654	5.976	2.666	32.605	11.723	6.050	2.666	32.605
Local unemployment rate among low-skilled labour [†]	31.045	11.435	9.439	73.208	30.819	11.405	9.439	73.208
Transitions	1,073,158				681,650			

* For less than 1% of the observations the number of previous employers exceeds 7.

[†] The statistics on the local unemployment rate among high-skilled labor base only on observations of workers with a university degree. The same applies to the local unemployment rates of the other skill groups.

Table A.3: Summary statistics, second stage variables

	Mean	SD	Min.	Max.
ln(Thousand Employees per km ²)	-2.475	0.783	-4.152	-0.118
W x ln(Thousand Employees per km ²)	-2.237	0.587	-3.878	-0.689
East Germany	0.234	0.424	0.000	1.000
Average precipitation amount per year 1999-2009	828.043	308.323	466.250	1855.150
Average hours of sunshine per year 1999-2009	1677.156	111.491	1357.610	1916.750
Average temperature 1999-2009	9.196	1.804	2.950	11.360
Coast (Yes / No)	0.085	0.279	0.000	1.000
Restaurant workers per 1,000 inhabitants	69.487	25.066	0.000	150.324
Share of recreation area	1.406	1.220	0.186	7.400
ln(Historical population density)	4.670	0.607	3.497	8.476
W x ln(Historical population density)	4.848	0.628	3.829	7.797
Region-year observations	987			

Table A.4: First stage results with region-time fixed effects for ln(imputed gross daily wage)

	All transitions			Job-to-Job transition	After short term nonemployment	After long term nonemployment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Individual characteristics</i>							
Education, reference: Secondary/intermediate school leaving certificate with completed vocational training							
Secondary/intermediate school leaving certificate without completed vocational training	-0.044*** (0.004)	-0.032*** (0.004)	-0.042*** (0.004)	-0.005 (0.006)	0.022* (0.010)	0.015 (0.012)	-0.023 (0.052)
Upper secondary school leaving certificate without completed vocational training	0.015* (0.006)	0.066*** (0.006)	0.052*** (0.006)	-0.097*** (0.010)	-0.011 (0.017)	-0.075* (0.033)	-0.112 (0.068)
Upper secondary school leaving certificate with completed vocational training	0.107*** (0.002)	0.109*** (0.002)	0.106*** (0.002)	0.015*** (0.004)	0.017** (0.006)	0.002 (0.011)	0.021 (0.029)
Completion of a university of applied sciences	0.287*** (0.005)	0.306*** (0.005)	0.293*** (0.005)	0.129*** (0.007)	0.092*** (0.012)	0.099*** (0.024)	0.206*** (0.052)
College/ university degree	0.426*** (0.005)	0.448*** (0.005)	0.431*** (0.005)	0.182*** (0.007)	0.141*** (0.012)	0.114*** (0.026)	0.234*** (0.052)
Female worker	-0.206*** (0.001)	-0.199*** (0.001)	-0.199*** (0.001)				
Foreign worker	0.005* (0.002)	0.021*** (0.002)	0.020*** (0.002)	-0.002 (0.003)	-0.004 (0.006)	-0.000 (0.006)	-0.006 (0.024)
Years of lifetime working experience	0.021*** (0.000)	0.010*** (0.000)	0.010*** (0.000)	0.056*** (0.002)	0.076*** (0.003)	0.017*** (0.004)	0.049** (0.017)
(Lifetime working experience) ²	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.000*** (0.000)	-0.001*** (0.000)
Length of employment spell within the year of transition		0.008*** (0.000)	0.008*** (0.000)	0.008*** (0.002)	0.007*** (0.000)	0.006*** (0.000)	0.008*** (0.002)
Years of recent working experience		0.051*** (0.000)	0.048*** (0.001)	0.033*** (0.001)	0.034*** (0.001)	0.012*** (0.002)	0.000 (0.007)
Years of recent occupation specific working experience		0.019*** (0.000)	0.017*** (0.000)	0.006*** (0.000)	0.004*** (0.000)	0.006*** (0.001)	0.020*** (0.005)
Years of recent employment within the region		-0.016*** (0.000)	-0.018*** (0.000)	-0.004*** (0.000)	-0.003*** (0.000)	-0.002** (0.001)	-0.010 (0.005)

Table A.4 continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Years of recent employment within agglomerations			0.014*** (0.000)	0.008*** (0.001)	0.006*** (0.001)	0.003 (0.002)	0.016* (0.007)
Number of different employers in previous 5 years			-0.011*** (0.001)	0.001* (0.000)	-0.002*** (0.001)	0.001 (0.001)	0.003 (0.003)
Public assistance benefits, reference: no benefit							
Unemployment benefit (ALG I)		-0.036*** (0.001)	-0.037*** (0.001)	-0.010*** (0.001)	-0.003 (0.003)	0.003 (0.003)	-0.001 (0.013)
Unemployment assistance (ALG II, ALHI)		-0.034*** (0.002)	-0.034*** (0.002)	-0.008*** (0.002)	-0.004 (0.005)	-0.004 (0.003)	-0.017 (0.012)
Pre-employment status, reference: not registered as job seeker							
Unemployed and registered as a job seeker		-0.068*** (0.001)	-0.065*** (0.001)	-0.028*** (0.001)	-0.041*** (0.003)	0.002 (0.003)	-0.007 (0.011)
Not unemployed, but registered as a job seeker		-0.079*** (0.001)	-0.076*** (0.001)	-0.023*** (0.001)	-0.037*** (0.002)	0.010** (0.004)	-0.002 (0.014)
Participation in measures of active labour market policy		-0.034*** (0.001)	-0.032*** (0.001)	-0.018*** (0.001)	-0.015*** (0.004)	-0.012*** (0.002)	-0.002 (0.010)
Occupational status, reference: low skilled worker							
Skilled worker	0.076*** (0.002)	0.043*** (0.002)	0.042*** (0.002)	0.018*** (0.001)	0.012*** (0.002)	0.018*** (0.002)	0.025* (0.010)
Master craftsman, foreman	0.293*** (0.004)	0.238*** (0.004)	0.234*** (0.004)	0.062*** (0.005)	0.042*** (0.007)	0.062*** (0.010)	0.060 (0.044)
Employee	0.224*** (0.002)	0.176*** (0.002)	0.171*** (0.002)	0.025*** (0.002)	0.018*** (0.003)	0.023*** (0.004)	0.026 (0.014)
unknown (only 2011)	0.242*** (0.003)	0.165*** (0.003)	0.159*** (0.003)	0.063*** (0.002)	0.049*** (0.004)	0.051*** (0.004)	0.056* (0.023)
<i>Establishment characteristics</i>							
In(Number of workers within the establishment)	0.043*** (0.001)	0.037*** (0.001)	0.035*** (0.001)	0.016*** (0.000)	0.011*** (0.000)	0.021*** (0.001)	0.024*** (0.003)
Share of high skilled within establishment	0.222*** (0.006)	0.209*** (0.005)	0.195*** (0.005)	0.056*** (0.003)	0.055*** (0.004)	0.026** (0.008)	0.040 (0.026)
Share of low skilled within establishment	-0.074***	-0.067***	-0.065***	-0.030***	-0.022***	-0.034***	-0.048**

Table A.4 continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.016)
Number of workers within the establishment is increasing	-0.029***	-0.014***	-0.012***	-0.004***	-0.002	-0.003*	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.007)
<i>Regional characteristics</i>							
ln(Employment share of the industry within the region)			0.019***	0.007***	0.007***	0.010***	-0.001
			(0.002)	(0.001)	(0.002)	(0.002)	(0.009)
ln(Number of establishments within the local industry)			-0.015***	-0.007***	-0.009***	-0.006**	-0.003
			(0.002)	(0.001)	(0.001)	(0.002)	(0.009)
Share high-skilled workers within the local industry			0.210***	0.074***	0.088***	0.023	0.080
			(0.019)	(0.009)	(0.013)	(0.024)	(0.076)
Share low-skilled workers within the local industry			0.035**	-0.012	-0.013	-0.006	0.009
			(0.014)	(0.008)	(0.013)	(0.017)	(0.071)
Industrial diversity within the region without own industry			-0.002*	-0.001	0.000	-0.003	0.010
			(0.001)	(0.001)	(0.001)	(0.002)	(0.006)
Local unemployment rate among high-skilled labour	-0.008***	-0.007***	-0.005***	-0.012***	-0.009***	-0.008**	-0.009
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.007)
Local unemployment rate among skilled labour	-0.002***	-0.000	0.000	-0.004***	-0.003***	-0.003*	-0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.004)
Local unemployment rate among low-skilled labour	-0.000	0.000	0.001**	-0.001***	-0.002***	-0.001**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)
Constant	3.746***	3.659***	3.864***	3.454***	3.361***	3.824***	3.185***
	(0.014)	(0.012)	(0.024)	(0.031)	(0.053)	(0.068)	(0.263)
Transitions	1,073,158	1,073,158	1,073,158	681,650	261,484	168,399	12,607
Workers	642,273	642,273	642,273	250,765	108,240	61,020	6,222
Transitions per worker (Min.)				2	2	2	2
Transitions per worker (Mean)				2.72	2.42	2.76	2.03
Transitions per worker (Max.)				47	36	23	4
Adjusted R^2	0.542	0.595	0.599	0.150	0.132	0.095	0.220
Individual fixed effects	No	No	No	Yes	Yes	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses. (1)-(3) standard errors clustered at firm level. (4)-(7) Huber/White/sandwich estimator.

All models include region-time fixed effects, industry fixed effects as well as occupation fixed effects.

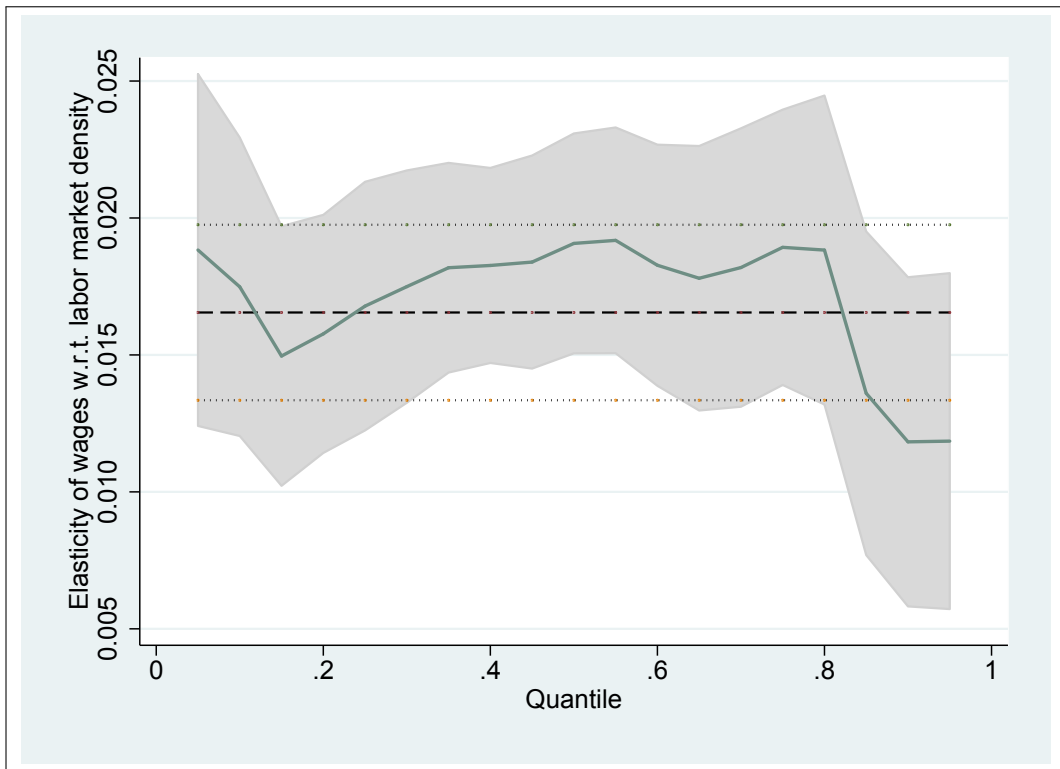


Figure A.1: Impact of labour market density on wages after transition to employment: Result of a quantile regression that correspond to (3) in Table 2

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