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Benefits of dense labour markets

Evidence from transitions to employment in Germany

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Mit der Reihe „IAB-Discussion Paper“ will das Forschungsinstitut der Bundesagentur für Arbeit den Dialog mit der externen Wissenschaft intensivieren. Durch die rasche Verbreitung von Forschungsergebnissen über das Internet soll noch vor Drucklegung Kritik angeregt und Qualität gesichert werden.

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Contents

Abstract

We analyse whether the size of the local labour market allows for better matching between job seekers and vacancies, which is thought to enhance productivity. This analysis is based on a large data set providing detailed micro-level information on new employment relationships in Germany. Our results suggest rather small matching benefits. Doubling employment density increases the productivity of new employment relationships by 1.1% to 1.2%. Moreover, the findings indicate that the benefits accrue only to persons experiencing job-to-job transitions and short-term unemployed. We detect no important impact of agglomeration on transitions from long-term non-employed.

Zusammenfassung

Wir untersuchen, ob die Größe des lokalen Arbeitsmarktes die Qualität von Matches zwischen Arbeitsuchenden und offenen Stellen verbessert, welches sich in einer höheren Produktivität widerspiegeln sollte. Die Analyse basiert auf einem umfangreichen Individualdatensatz mit detaillierten Informationen zu einzelnen Beschäftigungsaufnahmen in Deutschland. Unsere Ergebnisse deuten auf eher geringe Matchingvorteile hin. Eine Verdoppelung der Beschäftigungsdichte erhöht die Produktivität neuer Beschäftigungsverhältnisse um 1,1% bis 1,2%. Allerdings profitieren den Resultaten zufolge ausschließlich Personen mit einem Job-to-Job Wechsel oder einer Beschäftigungsaufnahme nach einer kurzen Beschäftigungsunterbrechung. Die Produktivität nach einer langen Beschäftigungsunterbrechung wird nicht von der Dichte des lokalen Arbeitsmarktes beeinflusst.

JEL classification: R23, J31

Keywords: Agglomeration economies, matching, urban wage premium, transitions to employment

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1 Introduction

A voluminous literature provides robust evidence of an urban wage premium. In the urban economics literature, these disparities are explained by agglomeration economies. The density of the local economy might, however, impact productivity in different ways. Duranton/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 of a positive impact of agglomeration on worker and firm productivity (Combes/Duranton/Gobillon, 2008; Glaeser/Maré, 2001), much less is known about the significance of different mechanisms, as noted by Rosenthal/Strange (2004) and Combes/Gobillon (2015). Moreover, only a few studies explicitly differentiate between static and dynamic effects of agglomeration (De la Roca/Puga, 2013; Matano/Naticchioni, 2016) 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 a policy perspective because the market failures associated with alternative channels differ, and therefore, the implications for corrective policies vary (Duranton/Puga, 2004).

This study aims to provide new empirical evidence of the importance of the matching mechanism, investigating the effects of local labour market density on wages in new employment relationships. We test the hypothesis that the size of the local labour market allows for better matching between job seekers and vacancies. Better matches in turn are thought to give rise to higher productivity and wages. This analysis is based on micro-level data that offer detailed information on labour market biographies for workers in Germany. More precisely, we use a sample of 5% 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/Duranton/Gobillon (2008) to estimate the impact of employment density on the wages associated with these transitions. We distinguish among different types of transitions: job-to-job transitions, as well as transitions from short- and long-term non-employment. To address 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: as density and productivity are simultaneously determined, OLS estimates of the elasticity of productivity with respect to employment density will be biased. Thus, we apply an instrument variable (IV) estimation to arrive at unbiased estimates using historical population data and soil characteristics as instruments.

In the empirical literature, the estimated elasticity of productivity with respect to local density typically varies between 0.04 and 0.10 (Combes et al., 2010), indicating that a density increase of 1% gives rise to an increase in productivity of up to 0.1%. In other words, doubling the density increases productivity by approximately 7% at the maximum. Our results indicate rather small positive effects on productivity associated with transitions from job searching to employment: the estimates suggest that a doubling of the employment density increases the productivity of new employment relationships by 1.0% to 1.2%. Moreover, the density effects are heterogeneous. The findings indicate that the benefits of a better match might accrue only to persons experiencing job-to-job transitions and short-term unemployed. We detect no important positive impact of agglomeration on transitions from long-term non-employment. Furthermore, the regression results suggest a slightly larger impact on migrants than on stayers.

The focus of our analysis is on the static agglomeration effect that results from better matching between workers and jobs. The empirical strategy thus aims to exclude or control for the impact of other mechanisms that generate agglomeration economies. The first-stage regression provides some evidence of other channels and of dynamic effects resulting from agglomeration. We detect a highly significant impact of previous work experience in dense labour markets, indicating the importance of dynamic learning effects. This result confirms evidence provided by De la Roca/Puga (2013) for Spain. Our estimates indicate that every additional year of work experience obtained in a large city increases the wage by 0.8%. Moreover, knowledge spillovers and complementarities seem to matter because the shares of high-skilled workers in the firm and in the local industry also tend to increase the wages associated with transitions to employment.

In contrast to most previous studies, we control more comprehensively for the labour market biographies of the workers because these might significantly impact their productivity and wages. Workers are likely to accumulate firm-specific human capital because employers may offer training and workers can acquire skills via learning-by-doing. This human capital should increasingly influence productivity and wages with increasing tenure, but it is not directly related to matching. In order to determine the benefits associated with better matches between workers and jobs, we identify new employment relationships and focus on the reported wages associated with these transitions. Finally, only a few studies consider heterogenous effects of agglomeration. A small number of studies provide evidence with respect to the skill level of workers (Andersson/Klaesson/Larsson, 2014; Bacolod/Blum/Strange, 2009). In contrast, this analysis 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 the benefits of the matching mechanism. In Sections 3 and 4, we describe the empirical strategy and the data set. We discuss the main results of the regression analysis in Section 5. Section 6 concludes.

2 Literature

2.1 Theoretical Arguments

Many studies find evidence of an urban wage premium (Combes/Duranton/Gobillon, 2008; Glaeser/Maré, 2001). The urban economics literature offers theoretical explanations for the stylised fact that workers in larger cities earn significantly more than workers in other areas. Obviously, there are productivity advantages of urban regions that give rise to higher earnings. The theoretical arguments for these agglomeration economies go back to Marshall (1890). Duranton/Puga (2004) combine various explanations into three main channels and provide micro-foundations for distinct mechanisms that generate agglomeration benefits. They differentiate among sharing, learning and matching. We refrain from discussing these well-known mechanisms in detail and focus on matching in the following, particularly on the productivity gains that result from a better match between workers and jobs in dense markets.

Kim (1990) develops a model of an urban labour market that explains a static matching advantage. The approach is characterised by increasing returns to scale, specialised production methods and heterogeneous workers. Increasing the size of the regional labour market in this setting improves the match between specialised workers and firms' heterogeneous skill requirements. Differences in skills do not refer to levels of educational attainment, i.e., skills are horizontally differentiated. Jobs require specific skills, and if the worker is not equipped with these required skills, costly training is needed. The highest productivity is achieved when the worker exactly meets the skill requirements of the workplace. As the distance between worker skills and job requirements increases, 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 will hire a candidate if her marginal value product exceeds the cost of training her.

In a large market, more diverse job requirements are available. Furthermore, Kim (1990) argues that in a large, urban labour market, the proximity of workers and firms promotes specialised labour markets. The model predicts a positive correlation between worker productivity and the size of the local labour market because the specialisation associated with a larger market reduces the average cost of mismatch between the skills of workers and the requirements of firms. Moreover, Kim (1989) shows that workers tend to invest more in human capital depth rather than breadth as the local market becomes larger. This tendency will give rise to more specialised human capital in these markets.[1] Kok (2014) shows, in line with this theoretical argument, that jobs in large cities consists of fewer sub-tasks and are thus more specialised. The theoretical models also suggest that workers who experience a significant human capital depreciation due to extensive periods of non-employment might not benefit from market size because their specific skills deteriorate. Thus, we might expect significant differences in matching benefits across transitions that differ with respect to the length of time of non-employment.

An important distinction exists between static and dynamic agglomeration effects. For instance, the benefits of learning are considered to be dynamic in the sense that it might take some time for these effects to show up, they increase with the amount of time spent in agglomerations and give rise to growth effects. In contrast, static gains from better matching are instantaneous and associated with level effects (Combes et al., 2010). Furthermore, the matching advantage has both quantitative and qualitative dimensions. The quantitative dimension refers to the probability of finding a job and the number of job, occupation or industry changes. We expect that the quality of a match is reflected e.g. by the productivity of a new employment relationship. The large number of job seekers and job offers

[1] Sato (2001) considers the significance of search friction in this context. In this search model, matches are random, and workers do not necessarily find the most suitable job. The results indicate that agglomerations economies can emerge regardless of frictions if the search technology exhibits increasing returns to scale.

in a dense urban labour markets reduces search friction and increases the probability of a match between workers and firms. Correspondingly, a dense labour market tends to exhibit more frequent job changes and higher quality matches, which should materialise as higher productivity and wages (Duranton/Puga, 2004). The difference between these aspects is, however, not always clear. For instance, according to the coordination hypothesis, more frequent job changes in cities might lead to higher matching quality (Wheeler, 2006; Yankow, 2006).

2.2 Empirical Evidence

The distinction between quantitative and qualitative elements 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. Starting with the empirical literature on the quantitative dimension, Di Addario (2011) investigates the factors that impact the probability that a non-employed worker finds a job in Italy and detects a significant positive effect of market size. Other studies examine whether agglomeration increases the frequency of job changes. In the U.S., Bleakley/Lin (2012) find evidence of a negative effect of the employment density on industry and occupation changes. However, for younger workers, the correlation between density and corresponding job changes is positive. This is confirmed by Andersson/Thulin (2013), who 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) finds that industry changes occur more often in large, diverse markets. Finney/Kohlhase (2008) argue that the productivity advantages of U.S. cities derive from a coordination advantage of large labour markets. More precisely, highly urbanised regions give young workers opportunities to try various jobs in search of a closer match. Furthermore, Wheeler (2006) concludes that the faster wage growth in dense metropolitan areas is due to between-job wage growth rather than on-the-job wage growth. Likewise, Yankow (2006) stresses that the high frequency of job changes in agglomerations is an important source of urban wage growth.

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 matched to their skills and previous industry experience. Büchel/van Ham (2003) use over-education as an indicator of match quality and show that in Germany, the risk of over-education declines as market size increases. Boualamy (2014) examines the propensity that entrants to the French labour market find a job related to their field of education. Controlling for individual, regional, occupational and educational characteristics, his results indicate that agglomeration enhances the quality of job matches. Other scholars analyse assortative matching in dense markets, i.e., the complementarity between worker and firm quality, and consider whether this correlates with market size. While Mion/Naticchioni (2009) detect a negative relationship between assortative matching and density in Italy, Melo/Graham (2014) and Andersson/Burgess/Lane (2007) point to a higher degree of assortative matching in large markets.

Aside from studies that focus on the matching advantage associated with dense markets, a large body of literature focuses on the relationship between productivity and agglomeration without considering the mechanisms behind the agglomeration benefits. The seminal contribution of Ciccone/Hall (1996) addresses the static effects of agglomeration on productivity. Using aggregate data for the U.S., they find that doubling the employment density increases average labour productivity by approximately 6%. A drawback of studies based on aggregate data, however, is that they cannot control for the effects of worker sorting across locations. This problem was first addressed by Glaeser/Maré (2001) using information on workers in the U.S. and regression models that include individual fixed effects.[2] Their results suggest that the urban 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.

Several authors investigate the significance of static and dynamic agglomeration economies for productivity. Combes/Duranton/Gobillon (2008) provide evidence of static advantages associated with larger cities in France. Figueiredo/Guimarães/Woodward (2014) investigate the impact of agglomeration on worker productivity in Portugal. However, they focus on the effects of spatial clustering among firms within the same industry, i.e., localisation economies. Lehmer/Möller (2010) find that only dynamic effects seem to matter in Germany after firm size and individual fixed effects are taken into account. D'Costa/Overman (2014) show that in the UK, having previously worked in a city affects long-term wage growth.

A few recent studies consider heterogeneous agglomeration effects, in particular, with respect to the skill level of workers. Bacolod/Blum/Strange (2009) and Andersson/Klaesson/Larsson (2014) identify an important urban wage premium only for workers with high cognitive skills in the U.S. and Sweden, respectively. These results are in line with findings by Matano/Naticchioni (2016) for Italy. Combes/Gobillon (2015) conclude that there is scarce evidence of heterogenous agglomeration gains across demographic groups. Moreover, studies that allow for heterogenous effects frequently do not take into account endogeneity issues from reverse causality and omitted variables.

Evidently, there is a considerable amount of empirical evidence demonstrating the existence of agglomeration economies, particularly of the positive effects of agglomeration on productivity.[3] However, the size of the estimates varies considerably due to differences in the data and estimation techniques applied. Melo/Graham/Noland (2009) report elasticities of wages with respect to city size ranging between 0.088 and 0.194. Combes/Gobillon (2015) find that typical values, controlling for some local characteristics (but ignoring reverse causality and spatial sorting problems), range from 0.04 to 0.10. This implies that doubling the density leads to a productivity increase of 3% to 7%.

However, evidence of the significance of the underlying mechanisms remains scarce (Puga, 2010; Combes/Gobillon, 2015). Regarding the impact of agglomeration on productivity,

[2] Using a large micro-level data set for Italy, Matano/Naticchioni (2012) show that the significance of sorting might differ by sector.

[3] Fingleton/Longhi (2013) is one of the few studies that does not provide robust evidence of a positive relationship between wages and density.

there are a few exceptions.[4] De la Roca/Puga (2013) aim to disentangle static from dynamic effects and to provide evidence of significant dynamic learning effects using information on work experience in large Spanish cities. They show that working experience acquired in the largest Spanish cities has a significantly higher value than experience acquired in the rest of the country. Matano/Naticchioni (2016) also try to separate the channels that generate agglomeration economies. Their results indicate that skilled workers in Italy benefit from important static and dynamic agglomeration effects, whereas unskilled workers only experience significant wage growth effects that might be caused by learning effects in dense labour markets. For skilled workers, job tenure plays a minor role, and in dense areas, their wage premium results primarily from better matching opportunities. Altogether, the corresponding evidence is scarce, and Combes/Gobillon (2015) conclude that most studies identify an overall impact but do not offer findings on the importance of specific mechanisms that generate agglomeration benefits. This study therefore aims to provide new evidence of the importance of the matching mechanism. We focus on static effects and on the quality of a match, as indicated by the productivity of a new employment relationship.

3 Data

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

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

For new employment relationships, we observe the corresponding gross daily wage and particulars of the new job, such as occupation and occupational status, and important worker characteristics, such as age, educational attainment and sex. As the wage that is

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

paid by a new employer likely depends on the worker's previous jobs and previous periods of unemployment, we use information from the individual labour market biographies to generate additional control variables, e.g., labour market status before the considered transition to employment, recent (occupation-specific) labour market experience, and the number of different previous employers. Details for all the variables used in this analysis are provided in Table B.1 of the appendix. Summary statistics can be found in Table B.2 and Table B.3.

The establishment identifier in the IEB is used to match important information about the establishment, such as industry, establishment size and skill structure of the staff, to the individual-level data set. The data is taken from the IAB's Establishment History Panel (BHP).[5] We use a region identifier to assign each transition to employment to one of 141 German regional labour markets.[6] We enrich our individual data set with detailed information on the regional labour market. Our pivotal variable is employment density. Figure 1 shows the correlation between the density of the local labour market and the average wage of new employment relationships. The regression analysis takes into account systematic differences between East and West Germany because 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. Labour market density explains more than 30% of the variation in regional wages in a simple model where density is the only regressor. The elasticity is approximately 0.11 for both the East and West German sub-samples. As there are other regional characteristics that might also impact wages, we consider local industry characteristics, regional unemployment rates by skill level, and indicators of regional attractiveness (amenities).

We use historical population density and soil characteristics as instrumental variables for current employment density. Historical regional population density is measured in 1871, 1880, 1890, 1900, 1910, 1925, and 1933 and is provided by Rothenbacher (2002). The soil data come from the European Soil Database. We aggregate the available raster data at the regional-level using the same characteristics as Combes et al. (2010).

[5] Firm units that are located in different municipalities are considered independent establishments. Unfortunately, it is not possible to identify whether different establishments belong to the same firm.

[6] The delineation of these regions is based on commuter flows; see Kosfeld/Werner (2012) for a detailed description.

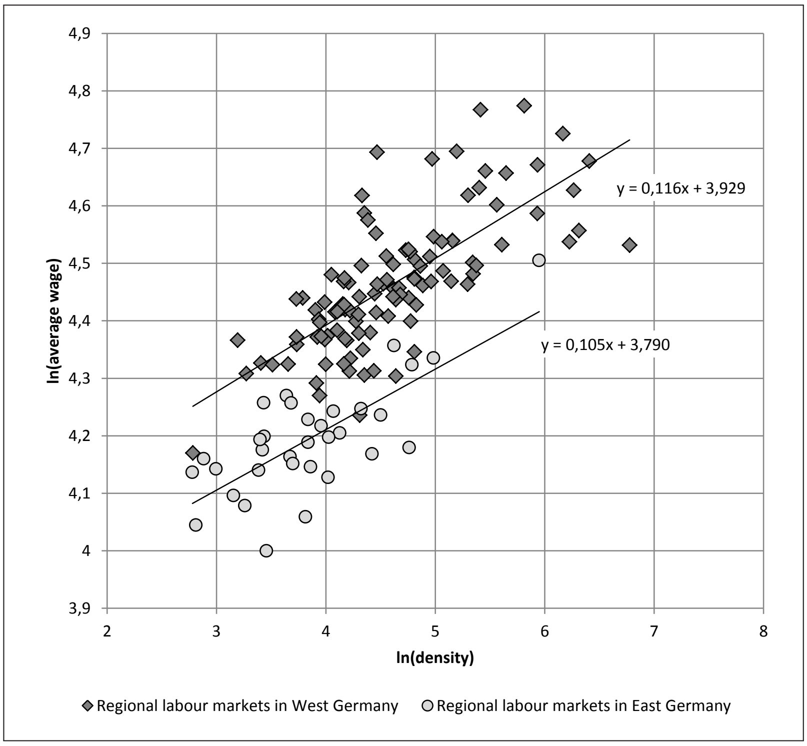

Figure 1: Correlation between employment density and wages in new employment relationships

Note: Average wages based on transitions to employment during the period from 2005 to 2011. Gross daily wages are measured in 2011 prices. Some regional labour markets along the former inner-German border include parts of both East and West Germany. They are considered West German regions based on their economic centres.

4 Empirical Strategy

We apply the two-stage regression approach proposed by Combes/Duranton/Gobillon (2008) to estimate the impact of the employment density on the 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 labour market size, i.e., employment density (equation (2)). This gives us the elasticity of the wage premium with respect to the size of the regional labour market. The first-stage wage regression is given by:

$$w_{irst} = \alpha_i + x'_{it}\beta + z'_{rst}\gamma + u'_{rt}\delta + \theta_{rt} + \epsilon_{irst} \tag{1}$$

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 include detailed information from the labour market biographies, pre-employment status and participation in active labour market policy programs. Apart from worker characteristics, we control for firm characteristics such as sector, firm size and skill structure. The vector u'_{rt} includes characteristics of the regional labour market such as skill-specific unemployment rates, whereas z'_{rst} refers to local characteristics of the sector in which the new employment relationship is established.[7] 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} captures the impact of observed and unobserved regional factors on worker productivity. We also estimate specifications with a time-invariant region fixed effect θ_r. In the second stage, we regress the region fixed effects on the measure of regional labour market size and some control variables. The corresponding regression model is given by:

$$\theta_{rt} = \zeta + D_{rt}\lambda + C'_{rt}\gamma + \varphi_t + e_{rt} \tag{2}$$

where D_{rt} is the log employment density of the regional labour market, φ_t are time fixed effects, and e_{rt} is an 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 labour market size. We also consider some control variables C'_{rt} in the second stage to allow for the impact of amenities that may be capitalised into wages, as argued by Combes/Duranton/Gobillon (2008). To account for systematic differences between East and West German labour markets (see Figure 1), we include a corresponding

[7] 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/Oswald, 1990). Baltagi/Blien/Wolf (2009) provide corresponding evidence for Germany.

dummy variable in some specifications. Agglomeration economies that might spill over the boundaries of regional labour 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 labour market. We will discuss these problem very briefly here because comprehensive discussions of these topics are available (Combes/Gobillon, 2015; Combes/Duranton/Gobillon, 2011; Combes et al., 2010). First, the estimated 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, to estimate fixed effects models, we need to observe at least two new employment relationships for a worker, that is, two transitions. Second, large regions that are characterised by high productivity will be attractive locations and are thus likely to experience significant in-migration. This will in turn impact the size of the labour market. Therefore, we need to account for reverse causality to obtain unbiased estimates. To identify the causal effect of labour market density on wages in new employment relationships, we apply instrument variable estimation techniques. Following Ciccone/Hall (1996) and Combes/Duranton/Gobillon (2008), we use historical population density and soil characteristics to instrument for labour 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 that have instantaneous effects on productivity unlike other channels, such as learning, that take some time to materialise.[8] Moreover, as tenure increases, other factors, e.g., on-the-job and professional development training offered by the firm, will gain importance for productivity. Normally, these effects are unobserved by the econometrician.

In the first-stage estimation, we 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 labour market, are ignored (De la Roca/Puga, 2013). To address this issue, we consider work experience in dense labour markets to be an important control variable in the first-stage regression. To account for other urbanisation and localisation economies that might impact the productivity of new employment relationships, the employment share, the number of establishments in the local industry and 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 firm's workforce. As Wheeler (2006) shows that job changes positively impact wage growth, the number of job changes over the last five years is also included.[9]

In contrast to most previous studies, we control more comprehensively for the labour market biography of a worker because this might significantly impact productivity and wage.[10]

[8] This feature contrasts with most previous studies, which use information on employment at a reference date.

[9] See the appendix for a detailed description of the variables.

[10] See Lesner (2014) for a recent survey of the related labour economics literature. The author also provides

Ignoring important time-varying worker characteristics will bias the estimation of the region-time fixed effects and may thus lead to incorrect inferences 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) and will bias the estimation of the region-time fixed effects.[11]

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

To analyse whether the benefits of matching in dense labour markets differ with the length of non-employment, we investigate the relationship between the productivity of new employment relationships and labour market density for three different types of transitions: job-to-job transitions, transitions from short-term unemployment (up to 12 months) and transitions from long-term non-employment (more than 12 months).[12]

5 Results

Table 1 summarises the preliminary results of the two-stage regression approach described in Section 4. We display only the estimates of the second stage and report bootstrapped standard errors to account for the two-stage nature of the regression approach.[13] The regression results rely on all transitions to employment, and we consider region-specific effects as the dependent variable in the second stage. In the first column, a rather simple model that includes only worker characteristics is estimated in 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 approximately 0.11 (see Figure 1), the impact of labour market size decreases by nearly one-half after we take worker characteristics into

empirical evidence for the important role of labour market history in transitions between labour market states and in wages in Denmark.

11 See Combes/Duranton/Gobillon (2008) for a detailed discussion of the corresponding econometric issues.

12 The latter group is likely the most heterogeneous, as it encompasses long-term unemployed workers and those who have been inactive for at least one year, e.g., due to parental or medical leave.

13 Robust and clustered standard errors are of similar size. This also applies to the nonparametric covariance matrix estimator introduced by Driscoll/Kraay (1998), which provides heteroscedasticity-consistent standard errors that are also robust to very general forms of spatial and temporal dependence. The first-stage estimates of different specifications are summarised in Table B.4 in the appendix.

account. This implies that the sorting of workers across regions on observable characteristics is an important econometric issue. The estimated elasticity is in the typical, previously reported range (between 0.04 and 0.10 according to Combes et al. (2010)). The coefficient slightly declines if we augment the model by including labour market biography and other agglomeration effects (columns (2) and (3)).

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

	(1)	(2)	(3)	(4)
ln(density)	0.068^{***}	0.063^{***}	0.065^{***}	0.044^{***}
	(0.008)	(0.008)	(0.009)	(0.006)
Constant	0.170^{***}	0.156^{***}	0.161^{***}	0.111^{***}
	(0.020)	(0.019)	(0.021)	(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 the regional level, 500 replications).

Although the results in column (3) are based on a model that includes a considerable number of control variables, they might still be biased because these estimates do not take into account possible sorting on unobserved worker characteristics. The positive correlation between employment density and productivity might be at least partly caused by the sorting of more able workers into large labour markets. The standard approach solving this problem is to estimate a fixed effects model that allows to control for time-invariant individual unobserved heterogeneity (Combes/Duranton/Gobillon, 2008; Mion/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 B.4 in the appendix). The corresponding estimate of the elasticity in column (4) confirms previous findings regarding the importance of sorting because the coefficient of the density significantly declines.

A drawback of the model 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 labour market, i.e., migration, because worker fixed effects do not allow estimates of region fixed effects based on workers who are always observed in the same regional labour market. De la Roca/Puga (2013) note that this can be a source of concern, as migrants might not be representative of the broader worker population. To derive more general results, we use region-time effects as the 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 labour market density without relocating. Correspondingly, the number of observations in the second stage increases from 141 to 987.

Comparing the estimate in the first column of Table 2 with the elasticity detected for migrants (column (4), Table 1) suggests some heterogeneity in the static benefits of dense labour markets. Migrants seem to profit more from taking new jobs in large urban regions. As Figure 1 shows an important wage gap between East and West Germany, we control for these differences in column (2). As regards the elasticity with respect to labour 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.[14] This also applies if we include additional controls and a spatial lag of the employment density in columns (3) and (4). The latter is included to account for the fact that agglomeration economies might spill over regional boundaries.[15] However, the advantages of large labour markets seem to be highly localised, as the coefficient of the spatial lag does not significantly differ from zero. Overall, our preferred estimates in columns (3) and (4) are somewhat below the lower limits of previous findings on static agglomeration effects, suggesting that we should not overstate the static matching benefit.

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

	(1)	(2)	(3)	(4)
ln(density)	0.033^{***}	0.020^{***}	0.017^{***}	0.015^{***}
	(0.003)	(0.002)	(0.003)	(0.003)
East Germany		-0.060^{***}	-0.055^{***}	-0.053^{***}
		(0.005)	(0.006)	(0.006)
W_ln(density)				0.006
				(0.004)
Constant	0.156^{***}	0.136^{***}	-0.016	0.005
	(0.007)	(0.005)	(0.043)	(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 the regional level, 500 replications). All first-stage regression models include time-varying worker and job characteristics, worker fixed effects, information on labour market biographies and local industry and regional labour market conditions. All second-stage regression models include time fixed effects. The second-stage regression includes controls for first and second nature amenities. See Table B.1 in the appendix for details.

We apply the quantile regression approach introduced by Koenker/Bassett (1978) to address the effects of outlying observations and parameter heterogeneity, i.e., the question of whether the size of the matching advantage differs between high- and low-productivity regions. The results are summarised in Figure 2 and indicate that the elasticity of wages with respect to labour market density is rather constant over the entire distribution and that the OLS coefficient is an appropriate approximation. The OLS estimate (dashed line) is always within the 95% confidence interval obtained by the quantile regression. Thus, there are no important differences in the size of the static agglomeration economies along the productivity distribution.

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

[15] We restrict spillover effects to neighbouring labour markets that share a border.

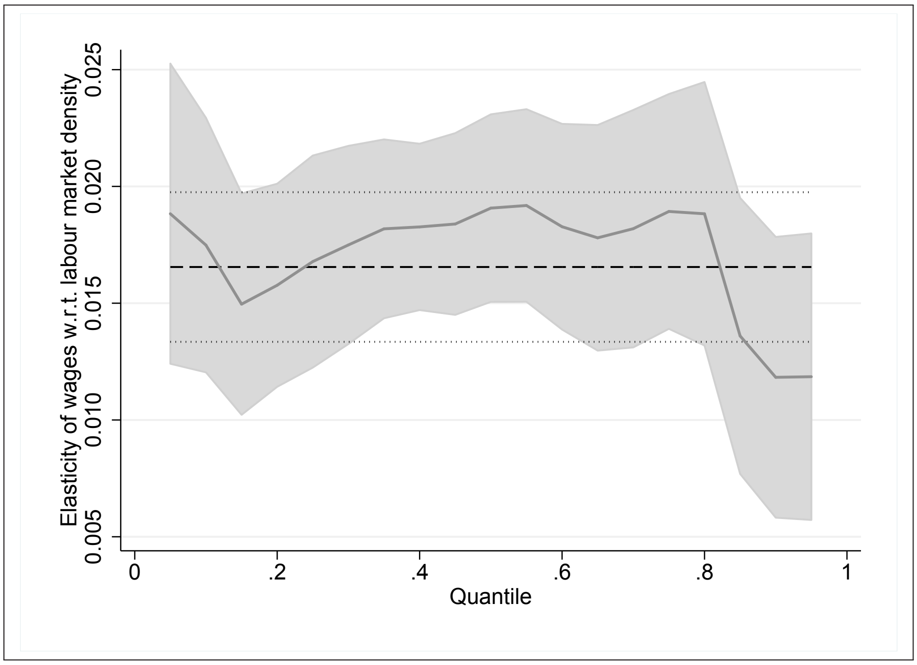

Figure 2: Impact of labour market density on wages – quantile regression results

Note: The results of the quantile regression correspond to the model in column (3) in Table 2. The solid line represents to the coefficients of a bootstrapped quantile regression with increments of 0.05 and 500 replications. The shaded area indicates the 95% confidence interval. By comparison, the dashed and dotted lines refer to the OLS coefficients and corresponding confidence interval, respectively.

Table 3 summarises the results for different groups of workers. Columns (1) and (2) show estimates for job-to-job transitions that clearly confirm the 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 neighbouring labour markets also matters for the productivity of these newly established employment relationships. In contrast, for the other groups of transitions, we do not find significant spill over effects. Regarding transitions from short periods of unemployment, the impact of local labour market size does not differ from the effect associated with job-to-job transitions. However, the regression results suggest that workers who obtain jobs after longer periods of non-employment do not benefit from better match 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 length of the spell of non-employment increases. In view of the relatively low employment density of East German regions, this corroborates our findings on differentiated agglomeration effects by transition type.

The differences between transition types suggest that workers who experience an extensive period of non-employment do not benefit from static matching effects in large labour markets due to the significant deterioration of their specific skills, as discussed in Section 2.[16] The results are also consistent with the idea that these workers are not able

[16] When we focus on transitions from long-term non-employment, some region-time fixed effects are based only on a few transitions. For some region-time combinations, we cannot even estimate a fixed effect due

to take advantage of referrals from current employees and (former) co-workers because they are at the margin of the labour market. Brown/Setren/Topa (2015) show that referred candidates are more likely to be hired and that hired referred workers experience an initial wage advantage relative to non-referred workers. Dustmann et al. (2016) provide similar evidence on the importance of referral-based job search networks in Germany. As proximity likely impacts interactions in these social networks, referrals might be understood as one channel of static matching benefits. In fact, Dustmann et al. (2016) investigate search networks in a few metropolitan labour markets in Germany.

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

	Job-to-job transitions		Transitions after short-term non-employment		Transitions after long-term non-employment	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(density)	0.020^{***}	0.017^{***}	0.020^{***}	0.017^{**}	-0.025	-0.030
	(0.003)	(0.004)	(0.005)	(0.005)	(0.024)	(0.025)
East Germany	-0.035^{***}	-0.032^{***}	-0.091^{***}	-0.089^{***}	-0.127^{***}	-0.123^{***}
	(0.006)	(0.007)	(0.008)	(0.009)	(0.031)	(0.031)
W_ln(density)		0.012^{**}		0.010		0.015
		(0.005)		(0.006)		(0.021)
Constant	0.042	0.082	-0.105	-0.073	-0.097	-0.045
	(0.047)	(0.050)	(0.057)	(0.059)	(0.207)	(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 the regional level, 500 replications). All first-stage regression models include time-varying worker and job characteristics, worker fixed effects, information on labour market biographies and variables that capture local industry and regional labour market conditions. All second-stage regression models include time fixed effects and control variables.

Table 4 provides the second-stage results of the instrument variable estimation. We instrument for both the employment density and the spatial lag of density. Several tests in the lower panel of the table suggest that our instruments are valid, i.e., relevant and uncorrelated with the error term. The Angrist-Pischke F statistics of excluded instruments and the Kleibergen-Paap Wald test indicate that the partial correlation between instruments and endogenous regressors is sufficient to ensure unbiased estimates and relatively small standard errors. The Kleibergen-Paap F statistic is above the thresholds proposed by Stock/Yogo (2005) for a maximum relative bias of 5%.[17] The Kleibergen-Paap LM test confirms the relevance of the instruments, as we can reject the null that the model is under-identified at the 5% level. Finally, the results of the Sargan test suggest that we can not reject the hypothesis that the instruments are exogenous.[18]

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. Compar-

to missing transitions. Therefore, we also estimate models based 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.

[17] With two endogenous regressors and 40 excluded instruments, the critical values are 21.37 for a maximum bias of 5 per cent of the IV estimator relative to the OLS and 11.22 for a maximum bias of 10 per cent.

[18] The results of the Sargan test are displayed because we use bootstrapped standard errors. They are confirmed by the corresponding Hansen tests if we apply robust standard errors. These results available from the authors upon request.

ing the OLS and 2SLS estimates points to minor bias, as the differences between the coefficients are small.[19] This applies to employment density as well as to the corresponding spatial lag and is in line with previous evidence presented by De la Roca/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.

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

			Transitions after...	
	All transitions	Job-to-job transitions	short-term non-employment	long-term non-employment
	(1)	(2)	(3)	(4)
ln(density)	0.014^{**}	0.015^{**}	0.017^{*}	-0.016
	(0.004)	(0.005)	(0.007)	(0.029)
W_ln(density)	0.008	0.014^{**}	0.009	0.005
	(0.005)	(0.005)	(0.007)	(0.021)
East Germany	-0.053^{***}	-0.033^{***}	-0.089^{***}	-0.119^{***}
	(0.006)	(0.006)	(0.009)	(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

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

† Angrist-Pischke multivariate F-test of excluded instruments. Instruments: historic population density (1871-1933), spatial lag of the historic population density, information on soil characteristics from the European Soil Data base. All first-stage regression models include time-varying worker and job characteristics, worker fixed effects, information on the labour market biographies and variables that refer to local industry and regional labour market conditions. All second-stage regression models include time fixed effects and further control variables.

So far, our discussion of the regression results has focused on the elasticity of wages with respect to labour market density and on static matching benefits. However, the first-stage regressions also provide evidence of other mechanisms that generate agglomeration economies (see Table B.4 in the appendix). We detect a highly significant impact of previous work experience in dense labour markets, suggesting the importance of dynamic learning effects. This result confirms findings by De la Roca/Puga (2013) for Spain. Our estimates indicate that every additional year of work experience in an agglomeration over the last 5 years increases wages by 0.8%. These dynamic agglomeration benefit also seem to differ by transition type. We detect significant effects for job-to-job transitions and, interestingly, for transitions after longer periods of non-employment. Thus, while the latter group does not benefit from static agglomeration effects, they can take advantage of learning from working in large cities.[20] In fact, they seem to achieve above-average benefits, as each additional year of work experience in large labour markets increases wages by 1.6% after long-term non-employment. In contrast, no significant effects are observed for

[19] In order to check whether the results are sensitive to weak instruments, we also apply limited information maximum likelihood (LIML) estimation. The LIML estimates confirm the 2SLS results. These regression results are available upon request.

[20] These differences are in line with findings by Matano/Naticchioni (2016) for distinct skill groups (see Section 2.2)

transitions after short-term non-employment.

Moreover, there is evidence of important localisation economies that impact the productivity of new employment relationships. Again, only workers with job-to-job transitions and those with short periods of non-employment seem to benefit from these agglomeration economies. For only these groups, we observe a significant positive effect of the employment share of the local industry. This result is in line with evidence provided by Figueiredo/Guimarães/Woodward (2014) that the quality of a firm-worker match tends to increase with firm clustering within the same industry. However, the size of the corresponding effect is moderate. Our results also suggest that specialisation per se is not beneficial. While the impact of the employment share on productivity is positive, we detect a negative correlation between wages and the number of establishments in the local industry. Finally, the regression analysis points to significant knowledge spillovers and complementarities: the share of high-skilled workers in the firm and the local industry also tends to increase the wages associated with transitions to employment. In contrast, the industrial diversity of the local economy does not impact the productivity of new employment relationships.

With respect to the interpretation that the estimates point to static matching benefits, there are some caveats. We try to control for other static and dynamic effects of agglomeration by considering the wage of newly established employment relationships and by including control variables. However, we cannot rule out that our estimate of the static matching effect also includes the impact of other mechanisms related to agglomeration. For instance, the productivity effect of sharing a suitable infrastructure endowment likely shows up immediately after the establishment of the employment relationship. We might somehow capture the impact of a specialised infrastructure (localisation 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 in this analysis. This also refers to the local monopsony power of the firm. Combes/Gobillon (2015) note that regional wage differences might, to some extent, reflect spatial variation in the degree of competition in local labour markets. If the monopsony power of firms decreases with the size of the local market, the higher wages observed in dense urban regions might be partly caused by relatively high competitive pressure in these regions. However, the importance of monopsony effects should decline with increasing labour mobility, i.e., workers should, ceteris paribus, move to locations characterised by a relatively little monopsony power. Moreover, the relocation of firms is also relevant in this context. Firms might move to regions that offer higher mark-ups of productivity over wages. Thus,firm and worker mobility should decrease the differences in monopsony power and the importance of corresponding wages disparities across regions.

6 Conclusions

In this paper, we investigate the importance of the static agglomeration effect that results from a better match between workers and jobs in large urban labour markets. In contrast to previous studies, we focus on the impact on wages in newly established employment relationships and consider differences with respect to pre-employment status. The regression analyses provide robust evidence of a positive effect of employment density on wages. Our preferred estimates indicate, however, that we should not overstate the size of the static matching benefit. Our estimates suggest that doubling the employment density increases the productivity of new employment relationships by 1.0% to 1.2%, whereas results for the static agglomeration effect typically range between 2.8% and 7% (Combes et al., 2010). This confirms the assessment by Baum-Snow/Pavan (2012) that the immediate effect of a good match seems to be moderate relative to the impact of other channels and dynamic effects.

Altogether, the regression results suggest that the advantage of working in a large urban labour market includes various components. We identify static and dynamic effects of agglomeration in line with findings of Matano/Naticchioni (2016) and De la Roca/Puga (2013). Apart from sorting effects, the urban wage premium seems to be caused by accumulating work experience in large urban labour markets and by matching advantages that materialise instantaneously. However, workers benefit not only from working in large cities but also from working with high-skilled workers. Human capital externalities and complementarities are at work within establishments and at the city level. Furthermore, our findings indicate that both localisation and urbanisation economies matter for the productivity of newly established employment relationships.

The differences across types of transitions to employment show that not all workers benefit from static matching advantages. While we detect significant matching advantages for job-to-job transitions and after short periods of unemployment, workers do not seem to benefit from obtaining a job in a large labour market after a long spell of non-employment. This result is in line with theoretical arguments proposed by Kim (1990) and Kim (1989) that the advantages of a large urban labour market materialise when specialised workers are matched with the heterogenous skill requirements of firms. The depreciation of human capital after an extensive period of non-employment might inhibit matching benefits. Likewise, there is no indication of important human capital externalities or localisation economies for this group of workers. However, this does not imply that agglomeration economies do not matter at all after a significant career interruption. In fact, we find that important learning benefits of larger cities appear even after long periods of non-employment.

Appendix

A Definition of new employment relationships and censored wages

The units of observation in our analysis are new employment relationships. We focus on new employment spells with a length of at least seven days that refer to full-time employment subject to social security contributions outside the public sector and the temporary work sector. Apprenticeships are not considered, nor are new employment relationships that start simultaneously with another employment relationship or with an active labour market programme, as we cannot ensure that this employment is not publicly subsidised. Moreover, we exclude new employment relationships with wages below two times the limit for marginal employment as well as recalls, i.e., cases in which a worker starts to work in an establishment in which she worked 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 within 7 days.

We use the wages of new employment relationships as the dependent variable in the first-stage regression. The first employment spell in the IEB of a new employment relationship ends, at the latest, by December 31st of the year in which the new employment relationship starts. Daily wages are calculated by dividing the reported total earning from this spell by the length of the spell. Information on actual working days or contract hours is not available. 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 estimate an interval regression, a generalisation of Tobit regression, to predict wages above the threshold (approximately 6% of the observations). See Reichelt (2015) for a detailed description of 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.

B Tables and Figures

Table B.1: Variables – definitions and sources

Variable	Definition	Source
Gross daily wage	Daily wages are calculated by dividing the reported total earning from employment spell by the length of the spell.	Integrated Employment Biographies (IEB)
Educational level of worker	A categorial variable that combines information on highest school leaving certificate, completed vocational training and university degree. For some employment spells, this information is missing. If so, we use the information from previous employment spells following Fitzenberger/Osikominu/Völter (2005).	IEB
Gender		IEB

Table B.1 continued

Variable	Definition	Source
Nationality		IEB
Experience	The difference between the considered date of transition to employment and the date of the first employment spell in the IEB. This variable is right censored because the IEB data do not capture employment spells before January 1, 1975.	IEB
Recent work experience	Years of employment measured on a daily basis for the five years before the considered transition to employment. Marginal employment is not included, nor are employment spells that are combined with active labour market policies. We distinguish total, occupation-specific, and region-specific work experience, as well as work experience acquired in agglomerations. Occupation-specific experience is defined with respect to 21 occupational segments (see Matthes/Burkert/Biersack, 2008). Region-specific experience refers to previous employment in the regional labour market in which the new employer is located, and experience acquired in agglomerations is classified based on the Federal Institute for Research on Building, Urban Affairs and Spatial Development, which is based on the population share living in cities, the existence of large cities within the region, and the population density.	IEB
Number of employers	The number of unique establishment identifiers over the previous five years.	IEB
Pre-employment status	Dummy variables referring to the 28 days before the considered transition to employment - unemployment benefits (Arbeitslosengeld I) - unemployment assistance (Arbeitslosengeld II/Arbeitslosenhilfe). - unemployed and registered as a job seeker - not unemployed but registered as a job seeker - participating in active labour market policy programmes.	IEB
Occupational status	Categorical variable that distinguishes white-collar and blue-collar workers based on the type of pension insurance institution (vom Berge/Burghardt/Trenkle, 2013). Blue-collar workers are also classified by 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 30) before the considered transition.	Establishment History Panel (BHP)

Table B.1 continued

Variable	Definition	Source
Industry share	Logarithm of the employment share of the industry (2-digit level: 88 industries) of total regional employment.*	Employment statistics of the Federal Employment Agency (FEA)
Industrial diversity	Inverse Herfindahl index based on the employment shares of industries of total regional employment. The own industry is excluded when the inverse Herfindahl index is calculated.*	FEA
Number of establishments of the local industry	Number of establishments with at least one employee subject to social security on June 30 at t-1. Only firms in the same industry and same regional labour market are considered.*	FEA
Human capital of the local industry	Share of workers with a university degree of total employment and share of workers without completed vocational training/university degree in the same industry and regional labour market.*	FEA
Skill-specific unemployment rate of the regional labour market	Share of persons registered as unemployed of 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 completed vocational training, and persons without completed vocational training/university degree. Information refers to June 30 at t-1	(Un-)Employment statistics of the FEA
Industry fixed effects	Fixed effects for 88 distinct industries (2-digit level according to the industry 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 for 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	Fixed effects for 21 distinct occupational segments.	IEB
Employment density	Working population per square kilometre .	Regional Database Germany (RDG) of the Federal Statistical Office
Weather indicators	Information covering the period 1999–2009 collected at 71 weather stations. For each regional labour market we use data from the weather station which is nearest to the geographical centre of the region. We use the average temperature, average number of hours of sunshine, and average precipitation.	Deutscher Wetterdienst

Table B.1 continued

Variable	Definition	Source
Restaurant workers	Share of restaurant workers defined according to the 1988 classification of occupations (codes 912 - waiters, 411 - cooks) of the total regional population.	FEA and RDG
Share of recreation area	The share of urban green space, parks, allotment gardens, sport fields and campsites of the total area.	TRDG
Coast	A dummy variable that indicates whether the region is located on the coast.	
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. If one labour market region includes (parts of) several historic regions, we calculate the weighted 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 to instrument for the employment density over 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, and ruggedness. The European Soil Database provides raster data. All indicators (except ruggedness) are categorical variables. Based on the raster data, we choose the modal value to aggregate the information at the regional labour market level.	European Soil Database

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

Table B.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.
Individual characteristics								
ln(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
Degree of 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
Experience (in years)	14.388	9.598	0.000	36.975	14.475	9.171	0.000	36.969
Work experience (in years)	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 months)	6.041	3.631	0.033	12.000	5.816	3.558	0.033	12.000
Occupation specific work experience (in years)	2.201	1.982	0.000	4.999	2.251	1.897	0.000	4.999
Work experience in region (in years)	2.080	1.938	0.000	4.999	2.073	1.854	0.000	4.999
Work experience in agglomerations (in years)	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

Table B.2 continued

	All transitions				Only transitions that are considered on the first stage with individual FE			
	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.
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
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
Establishment characteristics								
ln(Number of workers)	3.971	1.955	0.000	10.875	3.830	1.893	0.000	10.875
Share of high-skilled workers	0.121	0.210	0.000	1.000	0.111	0.204	0.000	1.000
Share of low-skilled workers	0.156	0.217	0.000	1.000	0.158	0.221	0.000	1.000
Increasing employment (Y/N)	0.417	0.493	0.000	1.000	0.418	0.493	0.000	1.000
Regional characteristics								
ln(Employment share of local industry)	-3.528	1.056	-12.732	-0.855	-3.535	1.049	-12.732	-0.855
ln(Number of establishments of local industry)	6.346	1.667	0.000	9.646	6.380	1.643	0.000	9.646
Industrial diversity	21.177	5.571	4.238	34.853	21.069	5.566	4.238	34.853
Share high-skilled workers of local industry	0.109	0.111	0.000	1.000	0.102	0.107	0.000	1.000
Share low-skilled workers of 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			

Table B.2 continued

	All transitions				Only transitions that are considered on the first stage with individual FE			
	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.

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

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

Table B.3: Summary statistics, second stage variables

	Mean	SD	Min.	Max.
ln(density)	-2.475	0.783	-4.152	-0.118
W_ln(density)	-2.237	0.587	-3.878	-0.689
East Germany	0.234	0.424	0.000	1.000
Average annual precipitation amount 1999–2009	828.043	308.323	466.250	1855.150
Average annual hours of sunshine 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_ln(historical population density)	4.848	0.628	3.829	7.797
Region-year observations	987			

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

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

Table B.4 continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.005)
Work experience in the region		-0.016^{***}	-0.018^{***}	-0.004^{***}	-0.003^{***}	-0.002^{**}	-0.010
		(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.005)
Work experience in agglomerations			0.014^{***}	0.008^{***}	0.006^{***}	0.003	0.016^{*}
			(0.000)	(0.001)	(0.001)	(0.002)	(0.007)
Number of different employers in previous 5 years			-0.011^{***}	0.001^{*}	-0.002^{***}	0.001	0.003
			(0.001)	(0.000)	(0.001)	(0.001)	(0.003)
Public assistance benefits, reference: no benefit							
Unemployment benefit (ALG I)		-0.036^{***}	-0.037^{***}	-0.010^{***}	-0.003	0.003	-0.001
		(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.013)
Unemployment assistance (ALG II, ALHI)		-0.034^{***}	-0.034^{***}	-0.008^{***}	-0.004	-0.004	-0.017
		(0.002)	(0.002)	(0.002)	(0.005)	(0.003)	(0.012)
Pre-employment status, reference: not registered as job seeker							
Unemployed and registered as a job seeker		-0.068^{***}	-0.065^{***}	-0.028^{***}	-0.041^{***}	0.002	-0.007
		(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.011)
Not unemployed but registered as a job seeker		-0.079^{***}	-0.076^{***}	-0.023^{***}	-0.037^{***}	0.010^{**}	-0.002
		(0.001)	(0.001)	(0.001)	(0.002)	(0.004)	(0.014)
Participation in measures of active labour market policy		-0.034^{***}	-0.032^{***}	-0.018^{***}	-0.015^{***}	-0.012^{***}	-0.002
		(0.001)	(0.001)	(0.001)	(0.004)	(0.002)	(0.010)
Occupational status, reference: low-skilled worker							
Skilled worker	0.076^{***}	0.043^{***}	0.042^{***}	0.018^{***}	0.012^{***}	0.018^{***}	0.025^{*}
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.010)
Master craftsman, foreman	0.293^{***}	0.238^{***}	0.234^{***}	0.062^{***}	0.042^{***}	0.062^{***}	0.060
	(0.004)	(0.004)	(0.004)	(0.005)	(0.007)	(0.010)	(0.044)
Employee	0.224^{***}	0.176^{***}	0.171^{***}	0.025^{***}	0.018^{***}	0.023^{***}	0.026
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.014)
unknown (only 2011)	0.242^{***}	0.165^{***}	0.159^{***}	0.063^{***}	0.049^{***}	0.051^{***}	0.056^{*}
	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)	(0.023)
Establishment characteristics							

Table B.4 continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln(Number of workers in establishment)	0.043^{***}	0.037^{***}	0.035^{***}	0.016^{***}	0.011^{***}	0.021^{***}	0.024^{***}
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.003)
Share of high-skilled workers in establishment	0.222^{***}	0.209^{***}	0.195^{***}	0.056^{***}	0.055^{***}	0.026^{**}	0.040
	(0.006)	(0.005)	(0.005)	(0.003)	(0.004)	(0.008)	(0.026)
Share of low-skilled workers in establishment	-0.074^{***}	-0.067^{***}	-0.065^{***}	-0.030^{***}	-0.022^{***}	-0.034^{***}	-0.048^{**}
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.016)
Increasing employment in establishment	-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)
Regional characteristics							
ln(Employment share of local industry)			0.019^{***}	0.007^{***}	0.007^{***}	0.010^{***}	-0.001
			(0.002)	(0.001)	(0.002)	(0.002)	(0.009)
ln(Number of establishments in 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 in 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 in local industry			0.035^{**}	-0.012	-0.013	-0.006	0.009
			(0.014)	(0.008)	(0.013)	(0.017)	(0.071)
Industrial diversity			-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

Table B.4 continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
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.

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