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What Explains the Urban Wage Premium? Sorting, Non-Portable or Portable Agglomeration Effects?

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Hanna Frings and Rebecca Kamb[1]

What Explains the Urban Wage Premium? Sorting, Non-Portable or Portable Agglomeration Effects?

Abstract

Using administrative data for West Germany, we study the relative importance of different determinants of the urban wage premium. More explicitly, we distinguish worker sorting, as well as portable and non-portable agglomeration effects. Our results indicate that worker sorting explains about two thirds of the urban-rural wage gap. We show that the estimated fraction of the urban wage premium attributed to worker sorting differs considerably depending on the selectivity of the sample used for identification and provide guidance how this selectivity can be reduced. Agglomeration effects explain about one third of the urban wage premium, with portable and non-portable agglomeration effects being of similar importance.

JEL-Code: R23, J31, J60

Keywords: Urban wage premium; sorting; agglomeration

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1 Hanna Frings, RWI and IZA; Rebecca Kamb, RWI and RUB. - We are grateful to Ronald Bachmann, Thomas K. Bauer, Wolfgang Dauth, Boris Hirsch, Sandra Schaffner, Miguel Zerecero, and participants at the BeNA labour Economics Workshop 2017, the 10th Interdisciplinary Ph.D. Workshop on Perspectives on (Un-) Employment 2018, the Verein fur Socialpolitic Annual Meeting 2018, the 6th PhD Workshop in Empirical Economics 2019, the 1st FDZ Ruhr Regional Disparity Workshop 2019, the Workshop on Worker Flows, Match Quality and Productivity, and the Spring Meeting of Young Economists 2021 as well as seminar participants at RWI for valuable comments and suggestions. Financial support by the Leibniz Association (Project: Worker Flows, Match Quality and Productivity – Evidence from European Micro Data) is gratefully acknowledged. All remaining errors are our own. This paper uses confidential data from the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) (project number fdz1378). The data can be obtained by submitting an application to the Research Data Centre (FDZ). Details on applying for the dataset and possibilities for data processing can be found on the FDZ homepage (https://fdz.iab.de/en.aspx).– All correspondence to: Rebecca Kamb, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, e-mail: rebecca.kamb@rwi-essen.de

1 Introduction

It is an established empirical fact that workers in larger cities earn higher wages than those employed in less populated regions (e.g. Glaeser & Maré, 2001; Combes *et al.*, 2008; Di Addario & Patacchini, 2008; De La Roca & Puga, 2017; Dauth *et al.*, 2019; Moretti, 2011). This is an odd result at first sight, since theory suggests that mobility of workers and firms should equalize any regional wage differences in equilibrium. Urban economics has thus focused on two main explanations for the urban wage premium that both assume productivity differences between rural and urban regions. First, more productive workers may systematically sort into cities, thereby explaining the observed urban wage premium (e.g. Combes *et al.*, 2008; Dauth *et al.*, 2019). Second, cities may increase the productivity of workers and firms due to agglomeration effects (e.g. Greenstone *et al.*, 2010; De La Roca & Puga, 2017; Dauth *et al.*, 2019). Agglomeration effects can be further distinguished into non-portable and portable productivity differences. Non-portable productivity differences may exist due to higher match quality in more urban areas or knowledge spillovers and sharing gains between firms operating in the same industry and region. Portable productivity differences arise mainly due to faster human capital accumulation in more populated areas (Glaeser & Maré, 2001).

These explanations for the urban wage premium are not mutually exclusive, but have different policy implications. In general, policies aiming at decreasing regional wage disparities will only be effective if the channels determining the urban wage premium are well understood. For example, Fajgelbaum & Gaubert (2020) suggest policies providing incentives for high-skilled workers to relocate to smaller cities. Such policies are clearly different in nature from those aiming at establishing regional clusters of the same industry in order to facilitate knowledge spillovers and sharing gains between firms.

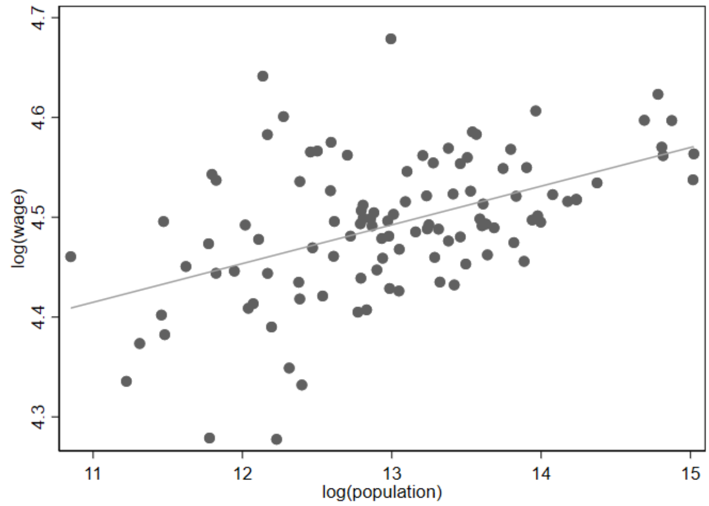
Despite the high policy relevance of understanding the relative importance of worker sorting, portable, and non-portable agglomeration effects, the existing literature mostly investigates the sorting and agglomeration channels separately. This hinders effective policy design as each study only provides one piece of the puzzle. This paper therefore considers worker sorting and agglomeration effects in one empirical framework, which allows us to make statements about the relative importance of the different explanations. To this end, we first estimate how much of the urban wage premium can be explained by worker sorting. Second, we analyse the degree to which the remaining part of the urban wage premium is determined by portable and non-portable agglomeration effects.

In addition, we are – to the best of our knowledge – the first study to explicitly acknowledge that estimates of the urban wage premium net of worker sorting rest on a selective sample of workers relocating to another region when changing jobs (hereafter referred to as region movers). Much of the existing literature first estimates wage regressions including region fixed effects and then correlates the estimated region fixed effects with a population measure to obtain an estimate of the urban wage premium. Adding worker fixed effects in the first stage accounts for worker sorting, but also limits the identifying variation for the region fixed effects to the sample of region movers. We tackle this problem by analysing worker sorting using all job movers, instead of region movers only, and show that the proportion of the urban wage premium that is explained by worker sorting changes considerably. We achieve this goal by using firm fixed effects instead of region fixed effects as the dependent variable, which are identified by all job movers even after adding worker fixed effects. We are able to do so as we use high-quality, representative, administrative linked employer-employee data for Germany that is sampled in such a way to ensure high observed mobility of workers between firms (LIAB Mover Model).

Figure 1 shows the correlation of log(wage) and log(population) at the level of local labour market regions and averaged across the time period 1993 to 2008. Regressing log(wage) on log(population) results in a statistically significant coefficient of 0.0394, implying that an increase in population by 1% is associated with an increase in wages by 0.039%. This positive correlation between wages and population is an established finding in the literature. Using German data that are similar to ours, Hirsch *et al.* (2020) report an elasticity of 0.034 and Dauth *et al.* (2019) find an elasticity of 0.037 after controlling for observable worker characteristics. The same relationship has also been found in other countries e.g. Glaeser & Maré (2001) for the US, D'Costa & Overman (2014) for the UK, and De La Roca & Puga (2017) for Spain.

Even though the vast majority of existing studies concludes that worker sorting matters, the degree to which sorting explains the urban wage premium varies significantly from 20% to 80%. This is also true for studies covering the same countries and using similar data. For Germany, Hirsch *et al.* (2020) report that only 20% of the urban wage premium are explained by

Figure 1: The Correlation between Wages and Population



Notes: Each value indicates log(population) and log(wage) of the 108 labour market regions defined according to Kosfeld & Werner (2012). The regression coefficient of log(wage) on log(population) is 0.0394 with an R^2 of 0.0110.
Source: Calculations based on LIAB-Mover-Model 9308. Population data from Statistisches Bundesamt (2020).

worker sorting, while Dauth *et al.* (2019) attribute 50% of the urban-rural wage gap to worker sorting. Glaeser & Maré (2001) and D'Costa & Overman (2014) conclude that this fraction amounts to 80% in the US and UK, respectively. De La Roca & Puga (2017) and Combes *et al.* (2008) state that half of the urban wage gap in Spain and France, respectively, is explained by worker sorting. As this study shows, part of this high variation is due to the selectivity of region movers that identify the urban wage premium net of worker sorting. This observation has been neglected in the literature up to now.

In comparison to the literature mentioned before, that mainly deals with worker sorting for explaining the urban wage premium, another strand of literature concentrates on the relative importance of portable and non-portable agglomeration effects. Based on data for the US, Glaeser & Maré (2001), Yankow (2006) and Baum-Snow & Pavan (2012) find evidence for both types of agglomeration effects. Baum-Snow & Pavan (2012) stress that portable agglomeration effects are more important for wage differences between large and small cities, while non-portable agglomeration effects are more relevant for wage gaps between medium and small cities. De La Roca & Puga (2017) indicate that both types of agglomeration effects each explain about one-half of higher earnings in Spanish cities. In comparison to that D'Costa & Overman (2014) conclude for the UK that non-portable agglomeration effects are generally more important, but young male workers benefit additionally from portable agglomeration effects. Wheeler (2006) finds a comparable result for the US.

Our results show that an increase in population by 1% is associated with an increase in wages by 0.036%, which is comparable in magnitude to estimates in the existing literature. Additionally controlling for time-constant observable characteristics reduces the wage premium slightly to 0.032. Worker sorting along observable characteristics thus only explains a small part of the urban wage premium. Adding worker fixed effects, and thereby controlling for worker sorting along unobservable characteristics, reduces the urban wage premium by 67%. Hence, worker sorting explains more than half of the observed urban wage premium. This result is obtained using all job movers for identification. Using only the sample of region movers - as usually done in the literature - results in an urban wage premium that is reduced by 85% after controlling for worker sorting along unobservable characteristics. This shows clearly that region movers are a more selective sample than job movers, and offers one explanation for the high variation of existing estimates on the importance of worker sorting for the urban wage premium. The remaining 33% of the urban wage premium can be explained by agglomeration effects. Differentiating agglomeration effects into portable and non-portable agglomeration effects shows that both effects are existent and of similar magnitude. When focusing on workers entering and exiting the biggest cities, we find that non-portable agglomeration effects are somewhat more important than portable agglomeration effects.

The remaining paper is organized as follows. Section 2 provides a detailed overview of the empirical strategy and Section 3 describes the used data set. In Section 4 we present the empirical results on sorting of workers and agglomeration effects as explanations for the urban wage premium. Section 5 concludes.

2 Empirical Strategy

We apply two well established empirical strategies to analyse the relative importance of worker sorting, portable, and non-portable agglomeration effects for the urban wage premium. First, we follow Combes *et al.* (2008) in differentiating between worker sorting and agglomeration effects using a two step procedure. The first step consists of regressing individual level wages on observable worker and firm characteristics as well as region and worker fixed effects. In the second step, the estimated region fixed effects are regressed on log(population) to obtain a measure of the urban wage premium. Second, we follow Glaeser & Maré (2001) in differentiating between portable and non-portable agglomeration effects by estimating wage-tenure profiles for region movers. This section and the discussion of the results are both structured in subsections that correspond to these two empirical strategies.

We advance both strategies by additionally including firm and match effects. First, this allows us to differentiate between worker sorting and agglomeration effects based on all job movers, instead of the more selective sample of region movers only. Second, the wage-tenure profiles only measure portable agglomeration effects when additionally controlling for firm and match effects, which enables us to properly differentiate between portable and non-portable agglomeration effects.

2.1 Worker Sorting vs. Agglomeration Effects

The relative importance of worker sorting and agglomeration effects has already often been analysed in the literature (e.g. Hirsch *et al.* (2020)) using a two-step procedure. We therefore closely follow previous work in our empirical methodology. The first step consists of decomposing individual-level wages to estimate region fixed effects.

$$w_{ijrt} = \alpha + x_{ijt}\beta + \underbrace{\delta_r}_{\text{Agglomeration effects}} + \underbrace{\theta_i}_{\text{Worker sorting}} + \epsilon_{ijrt} \quad (1)$$

where w_{ijrt} is the log daily wage of worker i at firm j in region r at time t.[1] x_{ijt} are time-varying individual and firm characteristics, more precisely age, age^2, tenure, firm size, as well as industry, occupation, and year dummies. The region fixed effects δ_r account for time-constant, regional differences of 108 labour market regions in West Germany. Likewise, the worker fixed effects θ_i capture time-constant unobservables at the individual level leading to wage differences.

In a second step, we regress the estimated region fixed effects on log(population).

[1] We follow the literature in urban economics in using nominal wages that are not adjusted for local price differences. Among others, De La Roca & Puga (2017) and Hirsch *et al.* (2020) argue that spatial differences in nominal wages reflect productivity differences, while spatial differences in real wages reflect the utility of workers due to amenities of cities.

$$\hat{\delta}_r = \alpha + \gamma_1\, log(pop)_r + \epsilon_r \tag{2}$$

where $log(pop)_r$ is defined as the population of each labour market region averaged across the years 1995 to 2008[2]. Population is thus a time-constant characteristic of each labour market region. The associated coefficient γ_1 measures the size of the urban wage premium. If worker fixed effects are excluded in Equation 1, this corresponds to the urban wage premium caused jointly by worker sorting and agglomeration effects. Including worker fixed effects in Equation 1 implies that we estimate region fixed effects net of worker sorting, and therefore obtain a measure of the urban wage premium purely due to agglomeration effects. A comparison of the two coefficients shows the relative importance of worker sorting and agglomeration effects for the urban wage premium.

We proceed by acknowledging that the region fixed effects in Equation 1 are only identified by the selective sample of region movers as soon as worker fixed effects are added to account for worker sorting. This peculiarity of the identifying variation has been omitted by the existing literature. We propose to include firm and match effects, instead of region fixed effects, in the wage composition in the first step and to regress the estimated firm fixed effects on log(population) in the second step to obtain a less biased estimate of the urban wage premium net of worker sorting.

$$w_{ijrt} = \alpha + x_{ijt}\beta + \underbrace{\theta_i}_{\text{Worker sorting}} + \underbrace{\psi_{jr}}_{\text{Agglomeration effects}} + \lambda_{ijr} + \epsilon_{ijrt} \tag{3}$$

$$\hat{\psi}_{jr} = \alpha + \gamma_2\, log(pop)_{jr} + \epsilon_{jr} \tag{4}$$

It is possible to replace region with firm fixed effects, because firms are not regionally mobile (see Section 3) and region fixed effects are therefore fully captured by the firm fixed effects. That is, the firm fixed effects of all firms j in region r contain a common component that is due to agglomeration effects present in that specific region. To make the estimates of the urban wage premium based on region and firm fixed effects comparable to each other, we apply weights to the regressions using firm fixed effects as the dependent variable that are defined

[2]The average population in each labour market region is based on data from 1995 and not 1993 onwards, because several district reforms took place before and therefore the comparability between districts is not possible.

as the inverse of the number of firms observed in a region.

The inclusion of firm fixed effects in Equation 3 corresponds to an AKM decomposition of wages (Abowd *et al.*, 1999). We additionally apply an extension proposed by Woodcock (2008, 2015) that decomposes the variation in wages into a worker, firm and match component. The incorporation of match effects in Equation 3 is important from a technical perspective. Omitting match effects results in biased estimation of the worker and firm effects if the match effects are non-zero (Woodcock, 2015). Indeed, there are many reasons to expect non-zero match effects, either due to synergies of specific employer-employee matches where the worker's human capital in combination with the firm's production technology increases productivity, due to portable human capital (see Section 1) that leads to high post-transition match effects for urban-rural movers, or more generally due to endogenous job mobility of workers, relating to the observation that workers only accept jobs at low-paying firms if they are compensated with higher match effects.

Jinkins & Morin (2018) show that job-to-job transitions of workers in Denmark are endogenous to the wage earned in the new job as wage losses - net of worker and firm fixed effects - of workers moving to lower-paying firms are lower than wage gains - net of worker and firm fixed effects - of workers moving to higher-paying firms. Stated differently, workers moving to lower-paying firms are compensated for this move with higher match effects. Applying this finding to our context, we expect that workers moving to more rural regions are compensated with a higher match effect, while such a compensation is not to be expected for workers relocating to more urban regions. This implies that urban-rural movers may chose their employer endogenously due to job opportunities and location-specific amenities (Huttunen *et al.*, 2018).

The identification of multiple, higher-order fixed effects is non-trivial (Abowd *et al.*, 1999, 2002; Woodcock, 2015).[3] We opt for the algorithm provided by Mittag (2019) that was developed specifically for the estimation of match effects. Match effects have the particular property that they nest in the firm and worker fixed effects, i.e. they represent their interaction. The joint identification of all three sets of fixed effects therefore requires certain normalizations. First, the worker fixed effects are estimated without any standardization. Second, the firm fixed effects are standardized to sum to zero across all firms. And third, the match effects are normalized to sum to zero for each worker and for each firm. This last standardization is most important for

[3] See Andrews *et al.* (2006) and Abowd *et al.* (2008) for more details on estimation and computation.

the interpretation of our results, as it implies that we are only able to estimate match-specific deviations from the worker's (or firm's) average match quality, which is inseparable from the worker's (or firm's) fixed effect.

The algorithm by Mittag (2019) enables us to conduct further analysis based on the worker, firm and match effects, as it provides explicit estimates of all three sets of fixed effects. We can therefore not only control for worker sorting when estimating the urban wage premium (and thereby isolate agglomeration effects), but we are also able to describe the sorting of high-wage individuals into urban regions. Furthermore, the estimated worker fixed effects can be used to analyse how workers select into job and regional mobility, including the decision to move to a more urban or a more rural region. Finally, the estimated firm fixed effects are used to provide some suggestive evidence on the role of sharing gains for non-portable agglomeration effects.

2.2 Non-Portable vs. Portable Agglomeration Effects

To further differentiate between portable and non-portable agglomeration effects, we follow a different empirical strategy that involves estimating wage-tenure profiles for region movers. Portable agglomeration effects mainly relate to faster human capital accumulation in cities (Glaeser & Maré, 2001; De La Roca & Puga, 2017), while non-portable agglomeration effects refer to any factor associated with the region itself or with the firms located in cities (see Section 1 for more details). Both types of agglomeration effects have specific implications for the expected wage-tenure profile of workers moving between regions with different degrees of urbanity. First, non-portable agglomeration effects lead to a sudden increase (decrease) in wages as workers move to more urban (rural) regions. Such effects are therefore also referred to as wage-level effects. Second, portable agglomeration effects imply that wages grow faster in cities than in rural regions as human capital accumulates more quickly. In contrast to non-portable agglomeration effects this process takes time and workers do not lose the accumulated human capital once they relocate to a more rural region. These effects are therefore also known as wage-growth effects.

By examining the wage-tenure profile of region movers while differentiating between moving to a more or less populated labour market region, we are able to study the relative importance of both types of agglomeration effects. To be more precise, we estimate the following specification:

$$w_{ijt} = \alpha + x_{ijt}\beta + \underbrace{\theta_i}_{\text{Worker sorting}} + \underbrace{\sum_k \sigma_k^{increase} I_k^{increase} + \sum_k \sigma_k^{decrease} I_k^{decrease}}_{\text{Agglomeration effects}} + \epsilon_{ijt} \tag{5}$$

where the vector x_{ijt} includes age, age^2, firm size, as well as industry, occupation, and year dummies[4] and θ_i stands for worker fixed effects. Following Glaeser & Maré (2001), we define dummy variables for the time before and after the transition, respectively. More specifically, $I_k^{increase}$ is a set of eight dummy variables, each taking the value one in a specific time period k before and after the transition[5] for region movers relocating to more urban labour market regions. The dummy variables $I_k^{decrease}$ are defined likewise, but for workers moving to less urban labour market regions. The coefficients $\sigma_k^{increase}$ therefore measure wage growth in each time period k for rural-urban movers and the coefficients $\sigma_k^{decrease}$ measure the wage growth in time period k for urban-rural movers. In comparison to Equation 1, the two sets of dummy variables capture any agglomeration effects that were previously measured by the inclusion of region fixed effects (or firm fixed effects) in Equation 3.

The explicit modelling of the wage-tenure profile allows us to differentiate between portable and non-portable agglomeration effects. If non-portable agglomeration effects exist, $\sigma_{k=1}^{increase}$ is expected to be large and positive, hence a direct wage increase would be observed. In addition, we would expect $\sigma_{k=1}^{decrease}$ to be large and negative, indicating a direct wage decrease after the move. This would indicate the existence of the wage-level effect. Portable agglomeration effects imply wage gains that accumulate slowly and persist when leaving urban areas. Thus, in $k = 1$ there would be no strong effect. Instead, we should observe a higher wage growth for workers after moving to a job in a more highly populated area in comparison to a worker switching to a job in a less populated area, $\sigma_k^{increase} > \sigma_k^{decrease}$ for $k > 0$. In a similar vein, before the move the wage growth is expected to be higher for the workers still working in the more urban area, thus $\sigma_k^{increase} < \sigma_k^{decrease}$ for $k < 0$.

We then advance the estimation strategy proposed by Glaeser & Maré (2001) by addition-

[4] We do not control for tenure here as it is perfectly collinear with the wage-tenure profile dummy variables.

[5] $k = -1$ covers the year before the transition and is omitted as a reference category. $k = -2$ covers the time period 1-3 years before the transition, $k = -3$ covers the time period 3-5 years before the transition, and $k = -4$ covers any time period exceeding 5 years before the transition. The time periods after the transition are defined in the same manner.

ally adding firm fixed effects and match effects to Equation 5:

$$w_{ijt} = \alpha + x_{ijt}\beta + \underbrace{\theta_i}_{\substack{\text{Worker}\\\text{sorting}}} + \underbrace{\psi_j}_{\substack{\text{Non-portable}\\\text{agglomeration effects}}} + \lambda_{ij} + \underbrace{\sum_k \sigma_k^{increase} I_k^{increase} + \sum_k \sigma_k^{decrease} I_k^{decrease}}_{\text{Portable agglomeration effects}} + \epsilon_{ijt} \quad (6)$$

where the inclusion of firm fixed effects, ψ_j, captures any non-portable agglomeration effect attached to the firm or the labour market region. The match effects, λ_{ij}, take away any wage variation associated with a specific job.[6] Importantly in our context, this includes unusually high wages - given the worker and firm fixed effects - of post-transition jobs for urban-rural movers that might be caused by portable human capital. Therefore, $\sigma_k^{increase}$ and $\sigma_k^{decrease}$ now only show the potential wage-growth effect net of any wage-level effect. We are thus able to clearly separate portable from non-portable agglomeration effects.

3 Data

The empirical analysis is based on the LIAB-Mover-Model 9308 provided by the Research Data Centre (FDZ) of the Federal Employment Agency at the Institute for Employment Research (IAB) (Heining *et al.*, 2012).[7] The data cover the time period from 1993 to 2008. It is a linked-employer-employee data set and consists of survey data on firms and administrative employment histories for workers. The data are sampled such as to maximize the observed number of workers moving between firms. That is, only firms are included between which at least once a mover is observed. Next to the movers up to 500 workers per firm are included. This feature of the data allows us to rule out the limited mobility bias which occurs when only few movers between firms are observed in a sample (Andrews *et al.*, 2008). Thus, the LIAB-Mover-Model provides a large connected sample with high realized mobility that is needed for the identification of worker and firm fixed effects. A disadvantage of the LIAB-Mover-Model is that large firms in the manufacturing sector are over-sampled. We therefore control for firm size and

[6] The coefficients $\sigma_k^{increase}$ and $\sigma_k^{decrease}$ are only identified by within-match wage variation in this specification. We therefore additional omit $I_{k=1}^{increase}$ and $I_{k=1}^{decrease}$ as reference categories.

[7] More explicitly, data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and subsequently remote data access.

industry dummies in all specifications.

The LIAB-Mover-Model includes, on the one hand, firm information like the industry, the average wage paid by the firm and its workforce composition. On the other hand, the administrative data cover information such as age, gender, education, wage and occupation of the workers. In addition, the place of work is available for each individual at the district level. We focus on West Germany[8] and aggregate the district information to 108 labour market regions (LMR). Following Kosfeld & Werner (2012), labour market regions are defined by close commuter links and they account for moving decisions motivated by labour market reasons instead of housing decisions (Eliasson *et al.*, 2003).

Finally, we restrict the sample to full-time employees in West Germany aged 16-65 years on 1.1.2000 and only keep matches of individuals working at firms included in the survey ("Betriebspanel-firms").[9] This ensures that the sample continues to be characterized by high mobility of workers between firms. In addition, we drop spells that are shorter than three days and drop individuals with more than 300 spells, as these spells show unrealistic patterns. In addition, we only keep a connected sample, which - due to the sampling procedure described above - amounts to 99.99% of the original sample. Thus, we observe one spell per worker, firm and year in our final data set, which consists of $2,488,842$ individuals and $17,009$ firms overall.

The estimation of the urban wage premium rests on different samples of workers, depending on whether the estimate accounts for worker sorting and on whether the agglomeration effects are captured via region or firm fixed effects (refer to Section 2 for more details). One contribution of this study is to analyse the selectivity of these different samples in order to assess possible biases in the estimated wage premium. In order to do so, we need to define the different groups unambiguously. We first define every worker either as a job mover or as a job stayer. If a worker is observed at only one firm, this individual is defined as a job stayer. Workers that change their employer at least once are defined as job movers, who are further divided into region stayers and region movers, depending on whether or not the worker moves to a different LMR when changing jobs.

[8]We exclude East Germany from the analysis for two reasons: First, there are some problems with the wage variable shortly after German reunification in the early 90s. Second, East Germany is much more rural than West Germany. At the same time, an East-West wage-gap exists that is independent of the urban wage premium, but will bias its estimate if not properly controlled for.

[9]We restrict the sample to full-time employees as we only have information about daily wages and not working hours and are therefore not able to calculate reliable wages for part-time employees.

Our estimates of the wage-tenure profiles in Section 4.3 require to distinguish between region movers in more detail. We therefore define subgroups depending on whether the worker moves to a LMR with more or less population than the current LMR. In doing so, we use population data on district level from Statistisches Bundesamt (2020) that are available from 1995 to 2008 and calculate the average population in each labour market region over time. Based on this time-constant characteristic of each LMR, we define two groups of region movers. The first group categorises every region move as a move to a labour market region with less or more population than the original region. Thus, every job move that goes along with a region move is categorised into a population decrease or increase, as no two labour market regions have the exact same number of inhabitants. Following Glaeser & Maré (2001), the second definition is based on the upper end of the distribution of labour market regions by urbanity. We first divide the labour market regions into deciles according to their population. We then focus on workers that either exit or enter the highest decile, i.e. the highest 10% of all labour market regions in terms of population. Thus, this group of region movers is a subgroup of the first group differentiating only between moving to a more or less populated labour market region.

Table 1: Summary Statistics

	Job stayer	**Job mover**				
		Region stayer	**Region mover**			
			Pop. increase	Pop. decrease	Enter top 10%	Exit top 10%
	(1)	(2)	(3)	(4)	(5)	(6)
Log(wage) - avg.	4.5148	4.5482	4.6247	4.6307	4.6495	4.6491
Log(wage) - before	-	4.5132	4.5710	4.5884	4.5874	4.6152
Log(wage) - after	-	4.5966	4.6759	4.6666	4.7138	4.6767
Avg. age	40.5085	38.8746	36.0904	36.7400	36.2618	37.1544
Males (%)	0.6681	0.7606	0.7448	0.7625	0.7396	0.7604
Non-Germans (%)	0.0830	0.0926	0.0618	0.0657	0.0614	0.0727
Low Educ. (%)	0.1513	0.1335	0.0495	0.0492	0.0404	0.0429
Med. Educ. (%)	0.7137	0.6976	0.5598	0.5566	0.5505	0.5472
High Educ. (%)	0.1351	0.1689	0.3907	0.3942	0.4091	0.4099
Tenure (in years) - avg.	10.4090	5.8820	4.4137	4.4830	4.6786	4.3651
Tenure (in years) - before	-	7.6764	5.3870	5.2850	5.9355	4.8906
Tenure (in years) - after	-	4.4430	3.4850	3.8023	3.3759	3.9377
Firm size below 11 - avg. (%)	0.0076	0.0168	0.0079	0.0074	0.0060	0.0063
Firm size 11-50 - avg. (%)	0.0656	0.0558	0.0435	0.0403	0.0362	0.0365
Firm size 51-250 - avg. (%)	0.3067	0.1961	0.2016	0.1922	0.1955	0.1850
Firm size 250-500 - avg. (%)	0.2067	0.1521	0.1598	0.1545	0.1628	0.1490
Firm size 501-1000 - avg. (%)	0.1804	0.1793	0.1891	0.1831	0.1911	0.1809
Firm size above 1000 - avg. (%)	0.2329	0.3999	0.3981	0.4225	0.4084	0.4423
No. of observations	15,470,809	2,322,270	452,784	463,564	199,978	195,446
No. of matches	2,095,214	504,199	123,733	125,660	53,779	53,828
No. of workers	2,095,214	261,604	65,494	66,530	28,473	28,474

Notes: Job stayers and job movers are mutually exclusive groups. Job movers are further divided into region stayers and region movers, whereas region movers can relocate to a more populated ("pop. increase") or to a less populated ("pop. decrease") region. Those workers entering the top 10% biggest regions are a subgroup of "pop. increase", while those workers exiting the top 10% biggest regions are a subgroup of "pop. decrease".
Source: Calculations based on LIAB-Mover-Model 9308.

Table 1 shows the mean values of observable characteristics for the different groups of individuals used in the analysis. The comparison of log(wage) before and after the job change shows that all job movers earn higher wages in their new job. The extent to which this increase is bigger for urban-rural movers (i.e. "population increase" and "entering top 10%") than for rural-urban movers (i.e. "population decrease" and "exiting top 10%") is the (raw) underlying variation identifying the urban wage premium net of worker sorting.

Similarly, the comparison of log(wage) across the different groups of job movers provides first suggestive evidence that region movers are more positively selected than job movers, who in turn are a positively selective group in comparison to job stayers. In terms of observables, region movers are younger, more often male, less often of foreign nationality and posses a higher education than job stayers. Lastly, a high share of workers is observed in (very) large firms, while the probability to work in a large firm is highest for region movers and lowest for job stayers.

4 Results

Section 4.1 discusses the results of the two-step procedure aiming at distinguishing worker sorting from agglomeration effects as determinants of the urban wage premium (cf. Section 2.1). Section 4.2 provides suggestive evidence on the role of sharing gains for non-portable agglomeration effects. Section 4.3 turns to differentiating between portable and non-portable agglomeration effects by estimating wage-tenure profiles of all region movers (cf. Section 2.2).

4.1 The Relative Importance of Worker Sorting and Agglomeration Effects

We start by estimating the urban wage premium by following a two-step procedure. The first step corresponds to a wage decomposition into region fixed effects, worker, and firm characteristics (cf. Equation 1), which is shown in Table A.1 in the appendix. As expected, wages increase with age, tenure, firm size and education. Further, women and non-Germans generally earn lower wages. In the second step, we regress the estimated region fixed effects on log(population), thereby obtaining a measure for the urban wage premium (cf. Equation 2).

Column (1) of Table 2 shows that the urban wage premium - net of age, tenure, firm size, as well as occupation, industry, and year dummies - amounts to 0.0356. Note that not controlling for any individual and firm level characteristics results in a wage premium of 0.0394 (cf. Figure 1). Controlling additionally for time-constant, observable worker characteristics (education, sex, and nationality) in the wage decomposition also only slightly decreases the urban wage premium to 0.0322 (Column (2) of Table 2). In conclusion, worker sorting along observable characteristics and observable firm characteristics only explain a relatively small part of the urban-rural wage gap observed in West Germany.

The estimated coefficient of 0.0322 is economically meaningful in its magnitude. It implies that an increase in population by 10% is associated with an increase in wages by 0.32%. A worker living in Bonn (population in LMR: 1 mill.) instead of Darmstadt (population in LMR: 500.000) thus receives a wage that is 3.2% higher, all else equal. Or, working in Cologne (population in LMR: 2 mill.) instead of Bonn (population in LMR: 1 mill.) is rewarded with a wage increase of 3.2%. In general, from the smallest LMR (Vulkaneifel, 64.000 inhabitants) to the biggest LMR (Hamburg, 3.2 million inhabitants) the population increases by factor 50. This is associated with an increase in wages by 160%, all else equal.[10]

The size of the estimated wage premium is in line with the existing national and international literature. First, Hirsch *et al.* (2020) find an urban wage premium of 0.034 for Germany. Second, Dauth *et al.* (2019) estimate an urban wage premium of 0.037 for Germany. A similar urban wage premium can also be observed for other countries. For example, De La Roca & Puga (2017) find an earnings premium with respect to city size of 0.0455 for Spain. Based on French data, Combes *et al.* (2008) report an elasticity of 0.049.

However, this correlation between wages and population may not be causal, as individuals most likely sort into urban regions along unobservable characteristics. These workers may be the ones with high ability and high productivity, thereby explaining the urban wage premium. To tackle this question the established solution from the literature is to add worker fixed effects (e.g. Glaeser & Maré, 2001; Yankow, 2006; Hirsch *et al.*, 2020). Column (3) of Table 2 shows the respective results after controlling for worker fixed effects in the wage decomposition (cf. Equation 2). The urban wage premium is indeed reduced by 85%, from 0.0356 to 0.0052. This suggests that sorting of high-wage workers into urban regions plays a decisive role in explaining the urban wage premium in West Germany.

[10] This number should be interpreted with care. First, it assumes a linear relationship between the population of a LMR and its wage level. Second, the estimated elasticity of 0.0322 does not account for sorting of workers and firms yet, so the "true" urban wage premium may be much smaller.

Table 2: The Elasticity of Wages to Population

	Region fixed effects			Firm fixed effects	
	(1)	(2)	(3)	(4)	(5)
Log(population)	0.0356***	0.0322***	0.0052**	0.0117***	0.0111***
	(0.0053)	(0.0047)	(0.0024)	(0.0034)	(0.0035)
Constant	-0.4902***	-0.4427***	-0.0676**	-0.1470***	-0.1391***
	(0.0725)	(0.0644)	(0.0315)	(0.0463)	(0.0468)
R^2	0.2712	0.2625	0.0336	0.0035	0.0031
N	108	108	108	17,009	17,009
Included controls for heterogeneity in the wage decomposition					
Observable worker characteristics	No	Yes	No	No	No
Worker fixed effects	No	No	Yes	Yes	Yes
Firm fixed effects	No	No	No	Yes	Yes
Match effects	No	No	No	No	Yes
Region fixed effects	Yes	Yes	Yes	No	No

Notes: Results from regression of region fixed effects and firm fixed effects on log(population). The dependent variable are the region fixed effects and the firm fixed effects from the corresponding specifications in Table A.1. The regressions in Columns (4) and (5) are weighted such to ensure that each region has the same weight as in Columns (1) to (3). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are enclosed in parentheses.
Source: Calculations based on LIAB-Mover-Model 9308.

The existing literature finds a reduction of the urban wage premium after controlling for worker fixed effects between 20% and 80%. Hence, our result can be classified in the upper end of the findings in the literature and is closely related to Glaeser & Maré (2001) and D'Costa & Overman (2014), who state for the US and UK, respectively, a reduction of 60-80% of the urban wage premium after controlling for worker sorting. In addition, Mion & Naticchioni (2009) estimate that three quarters of wage differences can be explained by worker sorting in Italy, while Hirsch *et al.* (2020) find the smallest reduction of the urban wage premium due to sorting of about 20%. Dauth *et al.* (2019) and De La Roca & Puga (2017) report a reduction of about 50% after controlling for worker fixed effects.

We then proceed by replacing region fixed effects with firm fixed effects in the wage decomposition (cf. Equation 3). Therefore, any regional differences are now fully captured in the firm fixed effects and we regress the firm fixed effects on log(population) to obtain the urban wage premium (cf. Equation 4). Interestingly, the estimated urban wage premium net of worker sorting is almost twice as large when using firm fixed effects instead of region fixed effects as the dependent variable (compare Column (3) and Column (4) of Table 2). This is also true after the inclusion of match effects in the wage decomposition (compare Column (4) and (5)), which ensures unbiased estimation of the firm fixed effects. We prefer the estimation via firm fixed effects because they are identified by all job movers in the wage decomposition, while region fixed effects are only identified by region movers. The latter group is potentially a more selective sample of workers than the former group.

The explicit estimation of the worker fixed effects in the wage decomposition allows us to study this potential selectivity. Table 3 shows the respective average worker fixed effects for the different groups identifying the urban wage premium. In comparison to job stayers, job movers are a positively selected group as their average wage is about 2% (or 0.0229 log points) higher. If the urban wage premium is estimated via region fixed effects, only region movers - instead of all job movers - provide the identifying variation. The selectivity for region movers is considerably stronger than for job movers: Their average wage is about 6% (or 0.0599 log points) higher than the average wage of job stayers (Table 3).

This simple analysis of the average worker fixed effects by mobility group clearly shows that the estimation of the urban wage premium net of worker sorting rests on selective samples, and that the selectivity is much stronger for the estimation via region fixed effects in comparison to firm fixed effects. While the differences in worker fixed effects do by definition not directly enter the estimation of the urban wage premium, the higher selectivity of region movers compared to job movers is a likely explanation for the different estimates of the urban wage premium reported in Table 2. For example, the importance of agglomeration effects for individual-level wages might simply be much smaller for high-ability, high-wage workers in comparison to all workers, thereby leading to a much smaller estimate of the urban wage premium net of worker sorting. Due to the lower selectivity of job movers in comparison to region movers, we prefer the estimation of the urban wage premium via firm fixed effects over the estimation via region fixed effects.

Table 3: Selection into Regional Mobility

	Mean of worker fixed effect	N
Job stayer	4.5963	2,095,214
Job mover	4.6192	393,628
Region stayer	4.6006	261,604
Region mover	4.6562	132,024

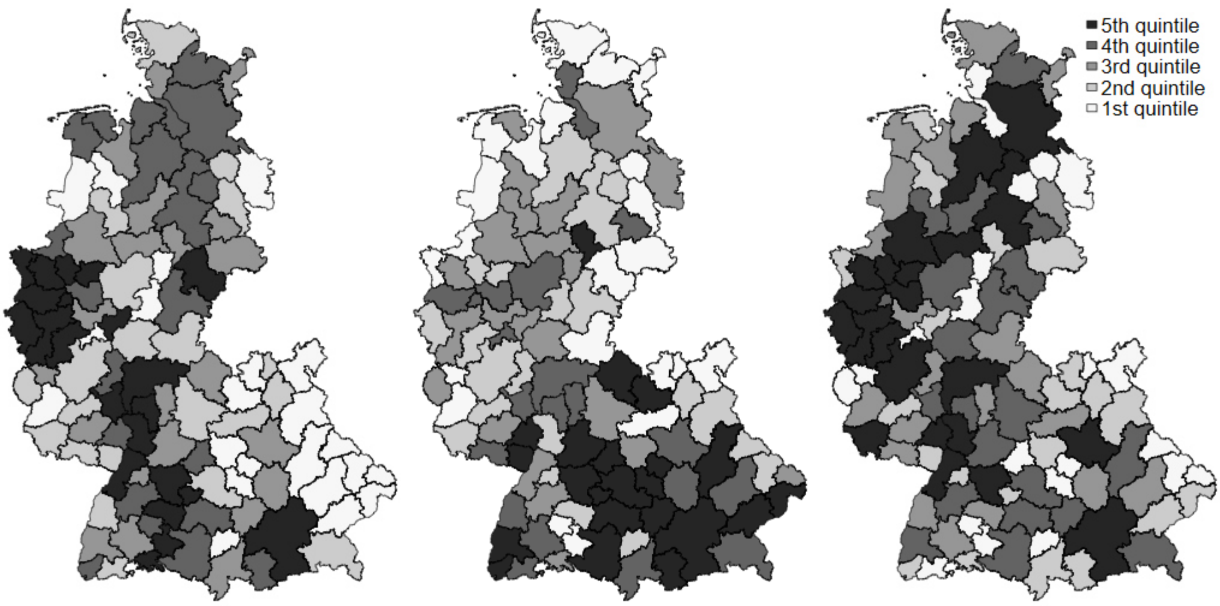
Notes: Mean values of the worker fixed effects from Specification (5) in Table A.1. The worker fixed effect for the following groups are significantly different from each other with a p-value < 0.01: (1) Job movers vs. job stayers; (2) Region movers vs. region stayers.
Source: Calculations based on LIAB-Mover-Model 9308.

In Figure A.1 we show the boxplots of the worker, firm and match fixed effects from Equation 3. Figure A.1a shows the distribution of worker fixed effects. As wages enter the wage decomposition in logs, all fixed effects are also measured in log points. The worker fixed effects show a relatively large spread: The 25th and the 75th percentile are about 0.5 log points apart. Thus, a worker located at the 75th percentile earns a wage that is 1.5 times higher than a worker located at the 25th percentile, only due to time-constant, (mostly) unobservable worker characteristics. Further, the distribution has long tails, that is, the spread in worker fixed effects is especially large at both ends of the distribution. Firm fixed effects are distributed around mean zero, as they are standardized to sum to zero across all firms (Figure A.1b). Apart from this standardization, the spread in firm fixed effects is much smaller compared to worker fixed effects. Finally, Figure A.1c shows that match effects are normalized to sum to zero for every worker and firm (Mittag, 2019). Thus, we are able to compare pre- and post-transition match effects for each worker and make statements about the relative change. However, it is not possible to analyse the level of the match effect, since it nests within the worker and firm fixed effects. This implies that we are not able to make any statements on average match quality observed in a specific region based on the match effects. We can, however, analyse how match effects change when workers move from rural (urban) to urban (rural) regions. We will make use of this in Section 4.3.

Figure 2 additionally presents the regional distribution of worker and firm fixed effects (Panels (a) and (b)), as well as the average population in each LMR (Panel (c)). The urban centres, such as Munich, Stuttgart, Rhein-Main Area and Rheinland, are clearly visible in Figure 2a. This confirms the result that high-wage workers are more often situated in urban LMR. However, this correlation is not perfect. First, there are many high-wage workers in the federal state of Baden-Württemberg, even in relatively rural LMR. Second, there are too few high-wage workers in North-Rhine Westphalia and northern Germany in general, given the urbanity of these regions. Figure 2b shows the regional distribution of firm fixed effects, net of worker sorting and match quality. There is no obvious visual correlation between the average firm fixed effect and the population across LMR (cf. Figure 2c). Instead, there appears to be a cluster of high-wage firms in Bavaria and Baden-Württemberg.

We proceed by regressing the estimated worker fixed effects on log(population) and time-

Figure 2: Regional Distribution of Worker and Firm Fixed Effects



(a) Worker fixed effects (b) Firm fixed effects (c) Average population

Notes: Panel (a) shows the average worker fixed effects and Panel (b) the average firm fixed effects from Specification (5) in Table A.1. Panel (c) shows the time-averaged population.
Source: Calculations based on LIAB-Mover-Model 9308 and Statistisches Bundesamt (2020).

constant individual characteristics. The results confirm the finding that high-wage workers sort into urban regions, i.e. one percent increase in population is associated with an increase of 0.0503 in the average worker fixed effect (Table 4). Since worker fixed effects are estimated in log-wage points, this implies an increase in wages of 0.05%, all else equal. Additionally controlling for individual-level, time-constant variables slightly increases the R^2 and reduces the coefficient of log(population) by 15% to 0.0428. The result shows that high wage workers are more likely to be highly educated, male and possess the German nationality. However, these observables only explain a comparably small fraction of the sorting across regions and into urban regions specially. Thus, we conclude that unobservables are more important than observables for explaining the urban wage premium and hence it is not enough to control for observables to account for worker sorting.

Table 4: Regression of Worker Fixed Effects on Population

	(1)	(2)
Log(population)	0.0503***	0.0428***
	(0.0008)	(0.0008)
Base category: Intermediate/upper secondary school		
Vocational training	-	0.0408***
		(0.0016)
University degree	-	0.3386***
		(0.0020)
Women	-	-0.2129***
		(0.0011)
Foreign	-	-0.1253***
		(0.0019)
Constant	3.9106***	4.0119***
	(0.0111)	(0.0108)
R^2	0.0077	0.0988
N	2,488,842	2,488,842

Notes: The dependent variable are the worker fixed effects from Specification (5) in Table A.1. The regressions are weighted such to ensure that each region has the same weight. * p < 0.10, ** p < 0.05, *** p < 0.01. Robust standard errors are enclosed in parentheses.
Source: Calculations based on LIAB-Mover-Model 9308.

In conclusion, sorting of workers is an important determinant of the urban wage premium as it explains about 67%[11] of the urban-rural wage gap. The remaining part of the premium is

[11]The estimation via region fixed effects suggested that 85% of the urban wage premium are due to worker sorting. As explained above, we prefer the estimation via firm fixed effects, implying that a smaller share of the urban-rural wage gap is explained by workers sorting.

due to agglomeration effects.[12] Therefore, the next section will look at one type of such effects, namely non-portable agglomeration effects.

4.2 Non-Portable Agglomeration Effects: The Role of Sharing Gains

The firm fixed effects in the wage decomposition capture all types of agglomeration effects, such as sharing, matching and learning. We proceed by analyzing the importance of sharing gains for the urban wage premium. A necessary - but not sufficient - condition for sharing gains to be realized is a relatively large number of firms operating in the same industry cluster regionally. We are therefore interested in how the urban wage premium changes once we control for the composition of firms in terms of industry at the regional level. Table 5 shows the regression of firm fixed effects on log(population) only[13] and on log(population) and industry dummies, whereby the corresponding firm fixed effects are net of worker sorting.

As soon as we control for industry dummies (Table 5, Column 2)), the correlation between firm fixed effects and log(population) increases from 0.0111 to 0.0178. Thus, the regional distribution of high-wage firms is strongly determined by industry clusters, but these are not necessarily found in the largest cities. Thus, agglomeration effects cannot be explained by high-paying industries concentrating in highly populated areas. Further, the majority of industries, except for mining and quarrying, electricity, gas and water supply, and financial intermediation, have statistically significantly lower firm fixed effects than the manufacturing sector.

In Column (3) of Table 5, we add interaction terms between log(population) and the industry dummies in order to analyse if and to what extent the urban wage-premium differs between industries. The wage differences between industries are much smaller when compared only within rural regions. Only firms operating in agriculture, financial intermediation, as well as real estate, renting and business activities have statistically significantly lower firm fixed effects compared to firms in manufacturing. The elasticity of wages to population, i.e. the interaction of the industry dummies and log(population), is much higher in these industries

[12]Table B.4 in the supplementary material replicates Table 2, but only for men. The estimated elasticity of wages to population is somewhat lower in all specifications. More importantly, the share of the urban wage premium that can be explained by worker sorting is slightly larger at 71%. Still, full-time employed women generally appear to behave similarly as full-time employed men. We therefore continue to provide results for both genders in order to keep the estimation sample as broad as possible.

[13]This is a replication of Column (5) of Table 2.

Table 5: Regression of Firm Fixed Effects on Population

	(1)	(2)	(3)
Log(population)	0.0111***	0.0178***	0.0179***
	(0.0035)	(0.0034)	(0.0056)
Base category: Manufacturing			
Agriculture and Fishing	-	-0.1873***	-1.1500***
		(0.0297)	(0.4362)
Mining and quarrying	-	0.0313	0.6477*
		(0.0242)	(0.3758)
Electricity, gas, and water supply	-	0.0575***	0.3306
		(0.0144)	(0.2320)
Construction	-	-0.0178*	-0.1064
		(0.0106)	(0.1927)
Wholesale and retail trade	-	-0.0931***	-0.0623
		(0.0077)	(0.1463)
Hotels and restaurants	-	-0.2245***	0.1815
		(0.0207)	(0.3456)
Transport, storage and communication	-	-0.0889***	0.0925
		(0.0133)	(0.3290)
Financial intermediation	-	-0.0160	-0.2902*
		(0.0111)	(0.1762)
Real estate, renting and business activity	-	-0.1238***	-0.4713***
		(0.0096)	(0.1752)
Public administration and defence	-	-0.0684***	0.0384
		(0.0065)	(0.1173)
Education	-	-0.0832***	-0.0691
		(0.0210)	(0.4622)
Health and social work	-	-0.0963***	0.0190
		(0.0080)	(0.1782)
Other community, social and personal sector	-	-0.0756***	0.1110
		(0.0115)	(0.1574)
Extra-territorial organizations	-	-0.1298***	-0.0212
		(0.0230)	(0.2462)
Interaction of log(population) and...			
Agriculture and Fishing	-	-	0.0726**
			(0.0318)
Mining and quarrying	-	-	-0.0467*
			(0.0276)
Electricity, gas, and water supply	-	-	-0.0208
			(0.0171)
Construction	-	-	0.0069
			(0.0144)
Wholesale and retail trade	-	-	-0.0023
			(0.0108)
Hotels and restaurants	-	-	-0.0311
			(0.0253)
Transport, storage and communication	-	-	-0.0138
			(0.0243)
Financial intermediation	-	-	0.0209
			(0.0129)
Real estate, renting and business activity	-	-	0.0260**
			(0.0127)
Public administration and defence	-	-	-0.0082
			(0.0087)
Education	-	-	-0.0011
			(0.0339)
Health and social work	-	-	-0.0089
			(0.0133)
Other community, social and personal sector	-	-	-0.0143
			(0.0115)
Extra-territorial organizations	-	-	-0.0081
			(0.0193)
Constant	-0.1391***	-0.1730***	-0.1745**
	(0.0468)	(0.0459)	(0.0749)
R^2	0.0031	0.1018	0.1062
N	17,009	17,009	17,009

Notes: The dependent variables are the firm fixed effects from Specification (5) in Table A.1. The regressions are weighted such to ensure that each region has the same weight. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are enclosed in parentheses.
Source: Calculations based on LIAB-Mover-Model 9308.

at the same time. One interpretation is that firms in these industries benefit more from agglomeration in comparison to firms in manufacturing and the remaining industries. Possible mechanisms are sharing or improved match quality in the labour market.

4.3 The Relative Importance of Non-Portable and Portable Agglomeration Effects

So far our results indicate that sorting of high-wage workers into densely populated areas explains about 67% of the urban wage premium. Thus, 33% of the urban wage premium is due to agglomeration effects of any kind. In this section, we will analyse the relative importance of non-portable and portable agglomeration effects (cf. Section 2.2).

Non-portable agglomeration effects relate to any factor that is attached to the region itself. Examples include higher match quality in cities or knowledge spillovers between firms. These sources of the urban wage premium lead to an immediate increase in wages for rural-urban movers, and likewise, to an immediate decrease in wages for urban-rural movers. Further, there is no reason to expect differences in wage growth in regions characterized by different degrees of urbanity. Consequently, non-portable agglomeration effects are also referred to as wage-level effects.

Portable agglomeration effects relate to faster learning in cities, implying higher wage growth in urban regions that slowly accumulates over time to significant wage differences (Duranton & Puga, 2004). Glaeser & Maré (2001) therefore refer to portable agglomeration effects as a wage-growth effect. Further, wages do not immediately react when workers change regions, and urban-rural movers do not experience a decrease in wages, as the human capital accumulated in the urban region still earns returns in the more rural region.

We will analyse the wage-tenure profile of region movers before and after the job transition to shed light on this differentiation. The obtained results should be understood as a proxy for the relative importance of both agglomeration effects, and not as an exact measure, for two reasons. First, the analysis is based completely on the sample of region movers, which is a highly selective group. Second, we simply compare the wage-tenure profile of rural-urban and urban-rural movers, but we do not take into account by what degree population changes.[14]

[14]Those workers, who move to more populated LMR mainly move to the big cities, independently of where they were working before (Table B.3). In contrast, those workers, who move to less populated LMR mainly only move to a slightly smaller LMR, but the difference in population is much less pronounced (cf. Table B.2).

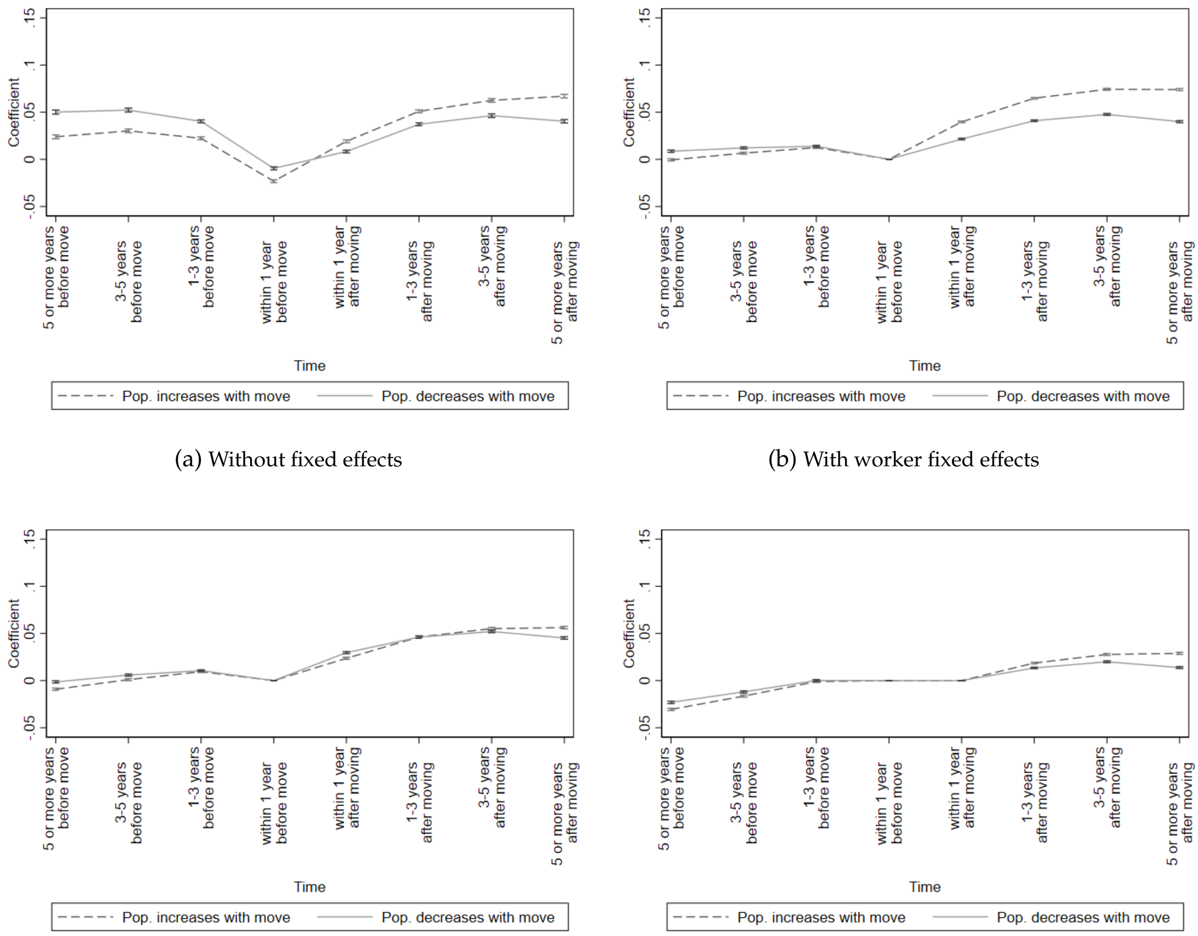
As before, we control for different sets of fixed effects in a step-wise fashion which changes the interpretation of the wage-tenure profile. First, the addition of worker fixed effects accounts for the selectivity of region movers in comparison to region stayers. Second, firm fixed effects absorb non-portable agglomeration effects and therefore ensure that the wage-tenure profile only captures portable agglomeration effects. Third, additionally including match effects allows to focus on within-job wage growth which is important due to the portability of human capital from urban to rural regions. The relative importance of portable agglomeration effects is thus given by a comparison of the wage-tenure profile only controlling for worker fixed effects (cf. Equation 5) and the wage-tenure profile controlling for worker, firm, and match effects (cf. Equation 6). The latter is free of any non-portable agglomeration effects.

Figure 3a shows all sources of the urban wage premium, but only for region movers. First, worker sorting into urban regions is contained in the difference between the two lines (selection into moving to a more or less urban region) as well as the slope of both lines (selection into regional mobility in comparison to staying in the same region). Second, non-portable agglomeration effects determine how steep wages increase (decrease) when relocating to a more (less) urban region in the first year after the transition. And third, portable agglomeration effects are captured by differences in the slopes in the post-transition period (i.e. differences in wage growth) and the wage increase in the first period after the relocation.

Indeed, the difference between the two lines after more than 5 years post transition roughly corresponds to the urban wage premium identified only by region movers and including worker sorting. That is, the urban wage premium in Column (2) of Table 2 equals 0.0322, and the difference between the two lines in Figure 3a amounts to 0.0266 (0.0670-0.0404; refer to Table A.2).

Still, as the discussion above has shown, Figure 3a does not allow us to differentiate between portable and non-portable agglomeration effects because worker sorting as well as both types of agglomeration effects determine post-transition wage growth. We now add the three sets of fixed effects to clearly identify the different sources of the urban wage premium. Adding worker fixed effects eliminates the effect associated with the selectivity of workers who relocate regionally (cf. Equation 5). Stated differently, instead of comparing wages between region stayers and the two different types of region movers, respectively, we now only use within-

Figure 3: Wage-Tenure Profiles for all Region Movers



(a) Without fixed effects

(b) With worker fixed effects

(c) With worker and firm fixed effects

(d) With worker, firm, and match effects

Notes: The figures show the wage-tenure profile of region movers for the different specifications in Table A.2.
Source: Calculations based on LIAB-Mover-Model 9308.

worker variation in wage growth. Note that the selectivity of workers moving to a more urban region in comparison to workers moving to a less urban region is still contained in the comparison of the two lines. It is not possible to solve this selectivity in what follows.

Figure 3b shows that rural-urban movers experience a wage growth of 4% and urban-rural movers of 2.2% within one year after the job transition. The observation that wage growth within the first year after the transition is higher for rural-urban movers can be interpreted as first suggestive evidence for a wage-level effect of 1.8%.[15] Further, we also observe a wage-growth effect: Rural-urban movers enjoy higher wage growth in their new job in comparison to urban-rural movers. One possible explanation is faster learning in cities. For workers moving to more urban regions wages additionally increase by 3.4 percentage points (0.0740-0.0397) until the end of our observation window. For workers moving to less urban regions wages additionally increase by about 1.9% (0.0400-0.0215) (cf. A.2). The difference between the two groups of 1.5 percentage points can be regarded as first evidence for the existence of a wage-growth effect. Note that the wage-growth and the wage-level effect are broadly of the same importance (1.5 vs. 1.8 percentage points).

Figure 3c additionally controls for firm fixed effects (cf. Equation 6). Again the year before the transition is the reference category. Most notably, the wage increase in the first year after the transition for rural-urban movers that could be observed in Figure 3b disappears completely. The underlying reason is that any wage-level effect is now completely captured by the firm fixed effects.

More surprisingly, the wage-tenure profile of both types of region movers appears to be almost identical. This could be interpreted as evidence that the wage-growth effect does not exist after all. However, recall that the wage-growth effect not only implies higher wage growth in urban regions, but also the portability of accumulated human capital to more rural regions. Urban-rural movers therefore obtain unusually high wages in their new job, especially given relatively low firm fixed effects (i.e. rural stayers in the same firm earn much lower wages, all else equal). This explains why wage growth within the first year after the transition is equal for both types of region movers: Rural-urban movers benefit from the generally higher wage-growth rates in urban regions compared to rural regions, while urban-rural movers are

[15] The size of this estimate is not directly comparable with the aggregate estimates presented previously, because we do not account for the magnitude of the change in urbanity here.

compensated for their accumulated human capital.

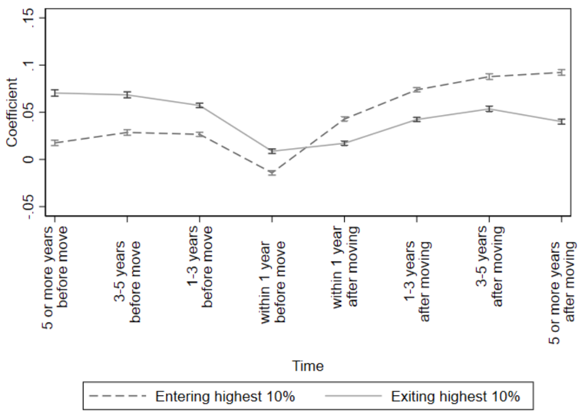
Figure 3d confirms this hypothesis by additionally including match effects, thereby ensuring that the unusually high wage level of urban-rural movers in their new job is no longer contained in the wage-tenure profile, but is now captured by the match effects. When focusing on within-match wage growth, we indeed observe higher wage growth rates for rural-urban movers in the post-transition period. After five years, these differences have accumulated to a difference in wages of 1.5 percentage points (0.0289-0.0138; cf. A.2), which can directly be interpreted as the contribution of the wage-growth effect to the urban wage premium. Thus, our naive estimate of the relative magnitude of the wage-growth vs. the wage-level effect based on Figure 3b is confirmed.

In conclusion, the results indicate the existence of the wage-growth and the wage-level effect that are of similar magnitude. Hence, portable and non-portable productivity differences both exist and contribute to the urban wage premium. So far, we have focused on all region movers, independent of the degree of urbanity of the initial and the target region. This implicitly assumes a linear relationship between the speed of human capital accumulation and the degree of urbanity. In contrast, De La Roca & Puga (2017) suggest that faster human capital accumulation is especially prevalent in large cities. Figure 4 therefore focuses on workers entering and existing the top 10% biggest cities.

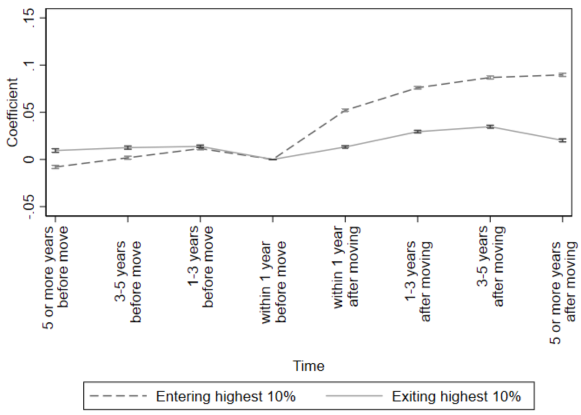
Generally, Figure 4 leads to exactly the same conclusion as Figure 3. The main difference is that all effects are much stronger in magnitude. This is to be expected as theory suggests that portable agglomeration effects are especially relevant in big cities.

Figure 4b again provides us with a naive estimate of the relative importance of both effects of interest. One year after the transition, wages have increased by an additional 3.9 percentage points (0.0520-0.0132; cf. Table A.3) for workers entering in comparison to workers leaving the biggest cities. This is the wage-level effect. The wage-growth effect is measured by the difference between the gap in wage growth after five years and after one year. It amounts to 3.1 percentage points ((0.0896-0.0202)-(0.0520-0.0132); cf. Table A.3). Non-portable agglomeration effects therefore appear to be about 1.3 times as important as an explanation for the urban wage premium in comparison to portable agglomeration effects. Note that this statement is only true for the specific sample of region movers entering and exiting the top 10% biggest

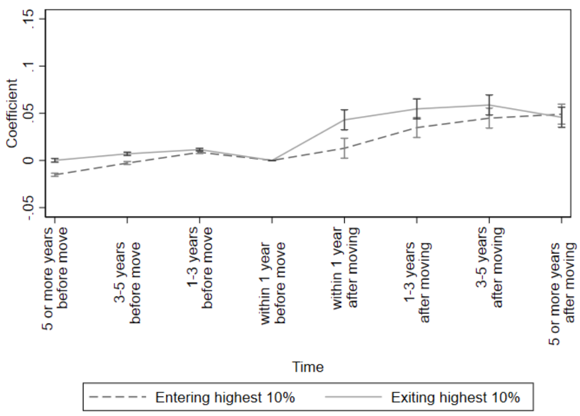
Figure 4: Wage-Tenure Profiles for Workers Entering and Exiting the Biggest Cities



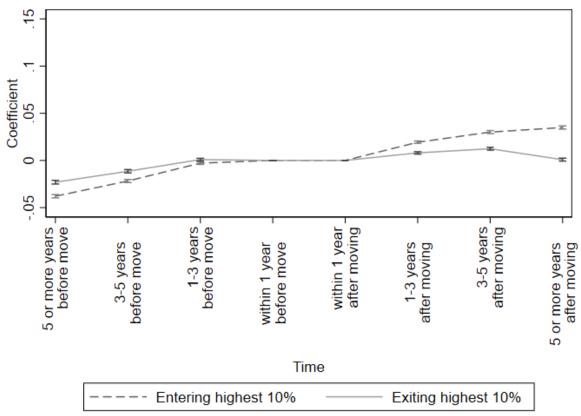
(a) Without fixed effects



(b) With worker fixed effects



(c) With worker and firm fixed effects



(d) With worker, firm, and match effects

Notes: The figures show the wage-tenure profile of region movers for the different specifications in Table A.3.
Source: Calculations based on LIAB-Mover-Model 9308.

cities in West Germany.

As before, Figure 4d provides a more exact estimate of the wage-growth effect, because it allows us to focus on within-match wage growth only. Interestingly, the wage-growth effect now appears to be smaller at 2.8 percentage points (0.0349-0.0070; cf. Table A.3). Figure 4c offers an explanation for the different estimates of the wage-growth effect. The wage-tenure profiles of the specification including firm fixed effects, but no match effects, suggest that workers leaving the biggest cities enjoy significantly higher wage growth within the first year after the transition than workers entering the biggest cities. This result can be easily explained by portable human capital, for which workers receive returns independently of the urbanity of the region. This effect is also present in Figure 4b and thereby biases the naive estimate of the wage-growth effect.

In summary, for workers entering and leaving the top 10% biggest cities in West Germany, the wage-level effect and the wage-growth effect are both important determinants of the urban wage premium. The wage-level effect at 3.9 percentage points seems somewhat more important in terms of magnitude than the wage-growth effect at 2.8 percentage points. This finding for the existence for the wage-level and wage-growth effect has already been established in the literature (e.g. Glaeser & Maré, 2001; Yankow, 2006; De La Roca & Puga, 2017), while D'Costa & Overman (2014) only find evidence for the wage-level effect.

Table 6: Change in Firm and Match Effects for Region Movers

	Before the move	After the move	Difference
Average firm fixed effect			
Population increases with the move	0.0584	0.0755	0.0171
Population decreases with the move	0.0709	0.0669	-0.0004
Enter top 10%	0.0595	0.0873	0.0278
Exit top 10%	0.0808	0.0657	-0.0151
Average match fixed effect			
Population increases with the move	-0.0147	0.0039	0.0186
Population decreases with the move	-0.0156	0.0053	0.0209
Enter top 10%	-0.0151	0.0054	0.0205
Exit top 10%	-0.0159	0.0056	0.0215

Notes: Mean values of the firm and match fixed effects from specification (4) in Table A.2 and A.3.
Source: Calculations based on LIAB-Mover-Model 9308.

Another way of showing the importance of including firm and match effects for the estimation of the urban wage premium is to analyse the change in these fixed effects with job transitions for the different types of region movers. Table 6 shows the average fixed effects by time period and type of region mover.

The upper panel shows the firm fixed effects. As suggested by the wage-level effect, workers relocating to a more urban region experience an increase in the firm fixed effect, i.e. they move to a firm that pays higher wages to all workers. The opposite is true for workers relocating to a more rural region: The firm fixed effect decreases after the job transition. This difference corresponds to non-portable agglomeration effects that are fully captured by the firm fixed effects. In line with the results of the wage-tenure profiles, this effect is more pronounced when comparing workers entering and exiting big cities in comparison to all region movers. In both cases, the difference in the change between the groups is statistically significant at the one percent level. Noticeably, the decrease for urban-rural movers is much smaller than the increase in firm fixed effects for rural-urban movers. This can be regarded as evidence of endogenous job mobility, i.e. workers only relocate to more rural regions if they can match with relatively high wage firms.

The lower panel shows the match effects. Each job move is associated with an increase in match effects, independently of the change in urbanity. This suggests that job mobility is generally related with an increase in match quality. This finding fits to the literature stating that a large part of the wage growth experienced through a job-to-job move can be explained by increased match quality (e.g. Jinkins & Morin, 2018). The increase in match effects is larger in magnitude for workers moving to a more rural region. The reason is the portability of human capital accumulated in the more urban regions. Stated differently, urban-rural movers earn relatively high wages in comparison to other workers in the firm, who stayed in the more rural region during the observation period.

5 Conclusion

In this paper we study the urban wage premium in West Germany based on administrative linked employer-employee data. Further, we disentangle the different explanations, namely sorting and agglomeration effects, and focus on the relative importance of each effect.

Our results confirm the existence of the urban wage premium, namely an increase in population by 10% is associated with an increase in wages by 0.36%. We find that worker sorting due to observable characteristics is not very important for explaining the urban wage premium. However, when controlling for sorting by including worker fixed effects the urban wage premium is reduced by 67%. Hence, worker sorting explains two thirds of the observed urban wage premium. As worker sorting takes place mainly along unobservable worker characteristics, the inclusion of worker fixed effects is inevitable. However, the identification of the urban wage premium rests on the selective sample of region movers in this case. We suggest to pay more attention to this bias, and to minimize it by identifying the urban wage premium net of worker sorting using all job movers instead. We provide direct evidence that the selectivity of job movers is much smaller compared to the selectivity of region movers.

The remaining 33% of the urban wage premium can be explained by agglomeration effects. Differentiating agglomeration effects into portable and non-portable agglomeration effects shows that both effects are existent and of similar magnitude. Non-portable agglomeration effects are somewhat more important than portable agglomeration effects when concentrating on the workers entering and exiting the biggest cities. Therefore, between 15% to 20% of the urban wage premium is caused by non-portable agglomeration effects, i.e. factors that are completely independent of the worker, but are attached to the region or the firm instead.

Still, most existing policies aimed at decreasing regional wage disparities target firms and regions, but less so workers. While this is not problematic in itself, it does mean that the effectiveness and efficiency of such policies is limited. This leaves policy makers with two options. Either regional wage disparities may simply be accepted to the degree that they are caused by differences in workers' productivity. Or policy should aim additionally at providing incentives to high-productivity workers to relocate to more rural regions.

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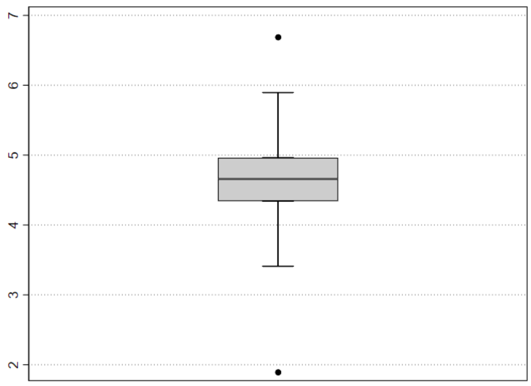
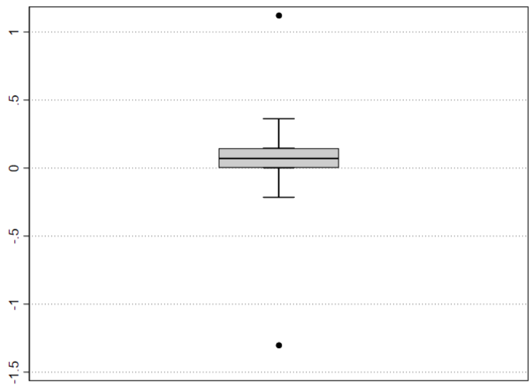
A Appendix

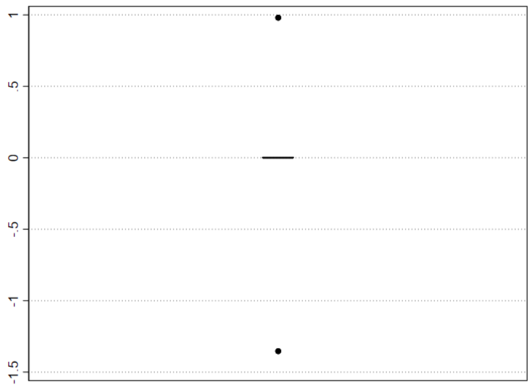
Figure A.1: Boxplots of Worker, Firm and Match Effects



(a) Worker fixed effect



(b) Firm fixed effect



(c) Match fixed effect

Notes: Boxplots show worker, firm and match fixed effects from specification (5) in Table A.1.
Source: Calculations based on LIAB-Mover-Model 9308.

Table A.1: Wage Decomposition into Fixed Effects

	(1)	(2)	(3)	(4)	(5)
Age	0.0435***	0.0348***	-0.0043***	-0.0039***	-0.0001
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Age^2	-0.0005***	-0.0004***	-0.0004***	-0.0004***	-0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tenure	0.0044***	0.0062***	0.0015***	0.0033***	0.0065***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Firm size	0.0101***	0.0071***	0.0042***	0.0068***	0.0070***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Base category: Intermediate/upper secondary school					
Vocational training	-	0.1445***	not	not	not
		(0.0002)	applicable	applicable	applicable
University degree	-	0.4022***	not	not	not
		(0.0002)	applicable	applicable	applicable
Women	-	-0.1876***	not	not	not
		(0.0001)	applicable	applicable	applicable
Foreign	-	-0.0413***	not	not	not
		(0.0002)	applicable	applicable	applicable
Base category: Manufacturing					
Agriculture and Fishing	-0.1427***	-0.1413***	-0.0858***	-	-
	(0.0013)	(0.0011)	(0.0027)		
Mining and quarrying	-0.0241***	-0.0316***	-0.0417***	-	-
	(0.0007)	(0.0006)	(0.0012)		
Electricity, gas, and water supply	0.1174***	0.0800***	-0.0184***	-	-
	(0.0005)	(0.0004)	(0.0011)		
Construction	-0.0108***	-0.0330***	-0.0074***	-	-
	(0.0004)	(0.0004)	(0.0009)		
Wholesale and retail trade	-0.0955***	-0.0926***	-0.0369***	-	-
	(0.0003)	(0.0002)	(0.0005)		
Hotels and restaurants	-0.4003***	-0.3374***	-0.1481***	-	-
	(0.0003)	(0.0007)	(0.0016)		
Transport, storage and communication	-0.0089***	-0.0308***	-0.0509***	-	-
	(0.0003)	(0.0003)	(0.0006)		
Financial intermediation	0.0885***	0.0619***	-0.0251***	-	-
	(0.0003)	(0.0003)	(0.0009)		
Real estate, renting and business activity	-0.0352***	-0.0775***	-0.0925***	-	-
	(0.0003)	(0.0002)	(0.0004)		
Public administration and defence	-0.0963***	-0.1020***	-0.1046***	-	-
	(0.0003)	(0.0002)	(0.0007)		
Education	-0.0726***	-0.1233***	-0.1467***	-	-
	(0.0005)	(0.0004)	(0.0008)		
Health and social work	-0.1364***	-0.0896***	-0.1014***	-	-
	(0.0003)	(0.0003)	(0.0008)		
Other community, social and personal sector	-0.0822***	-0.0789***	-0.0891***	-	-
	(0.0004)	(0.0003)	(0.0008)		
Extra-territorial organizations	-0.1934***	-0.1494***	-0.0886***	-	-
	(0.0021)	(0.0018)	(0.0058)		
Base category: Production of raw materials and goods, and manufacturing					
Agriculture, forestry, farming, and gardening	-0.0908***	-0.0705***	-0.0264***	-0.0187***	-
	(0.0008)	(0.0007)	(0.0013)	(0.0013)	
Construction, architecture, surveying and technical building services	0.0345***	0.0085***	-0.0024***	-0.0045***	-
	(0.0004)	(0.0003)	(0.0005)	(0.0005)	
Natural sciences, geography and informatics	0.1407***	0.1041***	0.0105***	0.0087***	-
	(0.003)	(0.0002)	(0.0004)	(0.0004)	
Traffic, logistics, safety and security	-0.1383***	-0.0886***	-0.0230***	-0.0178***	-
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	
Commercial services, trading, sales, the hotel business and tourism	0.0412***	0.0699***	0.0160***	0.0249***	-
	(0.0003)	(0.0003)	(0.0005)	(0.0005)	
Business organisation, accounting, law and administration	0.0522***	0.1027***	0.0147***	0.0165***	-
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	
Health care, the social sector, teaching and education	0.1083***	0.1251***	0.0079***	0.0131***	-
	(0.0003)	(0.0003)	(0.0007)	(0.0007)	
Philology, literature, humanities, social sciences, economics, media, art, culture, and design	0.2045***	0.1276***	0.0148***	0.0211***	-
	(0.0006)	(0.0005)	(0.0008)	(0.0008)	
Constant	3.4011***	3.4628***	-	-	-
	(0.0009)	(0.0008)			
R^2	0.3057	0.4895	0.9284	0.9317	0.9378
N	18,709,427	18,709,427	18,709,427	18,709,427	18,709,427
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	No	No
Worker fixed effects	No	No	Yes	Yes	Yes
Firm fixed effects	No	No	No	Yes	Yes
Match fixed effects	No	No	No	No	Yes

Notes: Results from regression log(wage) on log(population). Tenure is calculated in years. The firm size is measured in 1000. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are enclosed in parentheses.
Source: Calculations based on LIAB-Mover-Model 9308.

Table A.2: Wage-Tenure Profiles for all Region Movers

	(1)	(2)	(3)	(4)
Population increases with move				
5 or more years before move	0.0239***	-0.0006	-0.0092***	-0.0306***
	(0.0010)	(0.0006)	(0.0006)	(0.0006)
3-5 years before move	0.0302***	0.0066***	0.0010*	-0.0165***
	(0.0010)	(0.0005)	(0.0005)	(0.0006)
1-3 years before move	0.0223***	0.0125***	0.0094***	-0.0011**
	(0.0008)	(0.0004)	(0.0004)	(0.0004)
within 1 year before move	-0.0232***	not	not	not
	(0.0008)	applicable	applicable	applicable
within 1 year after moving	0.0191***	0.0397***	0.0236***	not
	(0.0008)	(0.0004)	(0.0006)	applicable
1-3 years after moving	0.0509***	0.0648***	0.0462***	0.0186***
	(0.0008)	(0.0004)	(0.0006)	(0.0004)
3-5 years after moving	0.0625***	0.0743***	0.0551***	0.0277***
	(0.0010)	(0.0005)	(0.0007)	(0.0005)
5 or more years after moving	0.0670***	0.0740***	0.0561***	0.0289***
	(0.0010)	(0.0006)	(0.0007)	(0.0006)
Population decreases with move				
5 or more years before move	0.0501***	0.0086***	-0.0014**	-0.0231***
	(0.0011)	(0.0006)	(0.0006)	(0.0006)
3-5 years before move	0.0522***	0.0121***	0.0058***	-0.0120***
	(0.0010)	(0.0006)	(0.0005)	(0.0006)
1-3 years before move	0.0403***	0.0139***	0.0106***	0.0001
	(0.0008)	(0.0004)	(0.0004)	(0.0005)
within 1 year before move	-0.0096***	not	not	not
	(0.0008)	applicable	applicable	applicable
within 1 year after moving	0.0083***	0.0215***	0.0296***	not
	(0.0007)	(0.0004)	(0.0006)	applicable
1-3 years after moving	0.0372***	0.0410***	0.0461***	0.0134***
	(0.0007)	(0.0004)	(0.0006)	(0.0004)
3-5 years after moving	0.0463***	0.0476***	0.0520***	0.0199***
	(0.0010)	(0.0005)	(0.0007)	(0.0005)
5 or more years after moving	0.0404***	0.0400***	0.0452***	0.0138***
	(0.0009)	(0.0005)	(0.0007)	(0.0005)
Age	0.0383***	0.0602***	-0.0033***	0.0003***
	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Age^2	-0.0004***	-0.0004***	-0.0004***	-0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Firm size	0.0087***	0.0036***	0.0067***	0.0070***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Base category: Intermediate/upper secondary school				
Vocational training	0.1417***	not	not	not
	(0.0002)	applicable	applicable	applicable
University degree	0.3869***	not	not	not
	(0.0002)	applicable	applicable	applicable
Women	-0.1884***	not	not	not
	(0.0001)	applicable	applicable	applicable
Foreign	-0.0246***	not	not	not
	(0.0002)	applicable	applicable	applicable
Base category: Manufacturing				
Agriculture and Fishing	-0.1425***	-0.0964***	-	-
	(0.0012)	(0.0025)		
Mining and quarrying	-0.0566***	-0.0237***	-	-
	(0.0006)	(0.0011)		
Electricity, gas, and water supply	0.0888***	-0.0199***	-	-
	(0.0004)	(0.0010)		
Construction	-0.0379***	-0.0111***	-	-
	(0.0004)	(0.0008)		
Wholesale and retail trade	-0.0921***	-0.0389***	-	-
	(0.0002)	(0.0005)		
Hotels and restaurants	-0.3362***	-0.1445***	-	-
	(0.0007)	(0.0014)		
Transport, storage and communication	-0.0317***	-0.0522***	-	-
	(0.0003)	(0.0006)		
Financial intermediation	0.0847***	-0.0247***	-	-
	(0.0003)	(0.0008)		
Real estate, renting and business activity	-0.0796***	-0.0972***	-	-
	(0.0002)	(0.0003)		
Public administration and defence	-0.0977***	-0.1073***	-	-
	(0.0002)	(0.0006)		
Education	-0.1280***	-0.1474***	-	-
	(0.0004)	(0.0007)		
Health and social work	-0.1016***	-0.1063***	-	-
	(0.0003)	(0.0007)		
Other community, social and personal sector	-0.0779***	-0.0960***	-	-
	(0.0003)	(0.0008)		
Extra-territorial organizations	-0.1510***	-0.0673***	-	-
	(0.0019)	(0.0052)		
Base category: Production of raw materials and goods, and manufacturing				
Agriculture, forestry, farming, and gardening	-0.0772***	-0.0270***	-0.0202***	-
	(0.0007)	(0.0012)	(0.0013)	
Construction, architecture, surveying and technical building services	0.0047***	-0.0008*	-0.0039***	-
	(0.0003)	(0.0004)	(0.0005)	
Natural sciences, geography and informatics	0.1117***	0.0107***	0.0086***	-
	(0.0002)	(0.0004)	(0.0004)	
Traffic, logistics, safety and security	-0.0952***	-0.0244***	-0.0189***	-
	(0.0002)	(0.0003)	(0.0003)	
Commercial services, trading, sales, the hotel business and tourism	0.0725***	0.0139***	0.0227***	-
	(0.0003)	(0.0005)	(0.0005)	
Business organisation, accounting, law and administration	0.1098***	0.0120***	0.0140***	-
	(0.0002)	(0.0003)	(0.0003)	
Health care, the social sector, teaching and education	0.1281***	0.0079***	0.0143***	-
	(0.0003)	(0.0007)	(0.0007)	
Philology, literature, humanities, social sciences, economics, media, art, culture, and design	0.1340***	0.0144***	0.0196***	-
	(0.0005)	(0.0007)	(0.0008)	
Constant	3.3963***	2.8274***	not	not
	(0.0008)	(0.0007)	applicable	applicable
R^2	0.4538	0.9253	0.9316	0.9383
N	19,399,583	19,131,448	19,399,583	19,399,583
Year fixed effects	Yes	Yes	Yes	Yes
Worker fixed effects	No	Yes	Yes	Yes
Firm fixed effects	No	No	Yes	Yes
Match fixed effects	No	No	No	Yes

Notes: Results are obtained from OLS regressions and the dependent variable is log(wage). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are enclosed in parentheses. The observation numbers are slightly higher than in Table A.1 because the correct identification of the coefficients of the time dummies modelling wage growth requires the duplication of multiple region movers.
Source: Calculations based on LIAB-Mover-Model 9308.

Table A.3: Wage-Tenure Profiles for Workers Entering and Exiting the Biggest Cities

	(1)	(2)	(3)	(4)
Population increases with move				
5 or more years before move	0.0175***	-0.0080***	-0.0152***	-0.0379***
	(0.0015)	(0.0009)	(0.0009)	(0.0009)
3-5 years before move	0.0286***	0.0018**	-0.0028***	-0.0218***
	(0.0015)	(0.0008)	(0.0008)	(0.0008)
1-3 years before move	0.0266***	0.0115***	0.0086***	-0.0029***
	(0.0011)	(0.0007)	(0.0007)	(0.0007)
within 1 year before move	-0.0142***	not	not	not
	(0.0012)	applicable	applicable	applicable
within 1 year after moving	0.0428***	0.0520***	0.0129**	not
	(0.0012)	(0.0007)	(0.0054)	applicable
1-3 years after moving	0.0738***	0.0760***	0.0348***	0.0193***
	(0.0012)	(0.0007)	(0.0054)	(0.0007)
3-5 years after moving	0.0877***	0.0868***	0.0448***	0.0300***
	(0.0015)	(0.0008)	(0.0054)	(0.0008)
5 or more years after moving	0.0922***	0.0896***	0.0490***	0.0349***
	(0.0015)	(0.0009)	(0.0054)	(0.0009)
Population decreases with move				
5 or more years before move	0.0704***	0.0094***	0.0001	-0.0231***
	(0.0017)	(0.0010)	(0.0010)	(0.0010)
3-5 years before move	0.0684***	0.0125***	0.0070***	-0.0115***
	(0.0016)	(0.0009)	(0.0009)	(0.0009)
1-3 years before move	0.0572***	0.0138***	0.0115***	0.0009
	(0.0012)	(0.0007)	(0.0007)	(0.0007)
within 1 year before move	0.0087***	not	not	not
	(0.0012)	applicable	applicable	applicable
within 1 year after moving	0.0171***	0.0132***	0.0430***	not
	(0.0011)	(0.0007)	(0.0054)	applicable
1-3 years after moving	0.0423***	0.0294***	0.0546***	0.0080***
	(0.0011)	(0.0007)	(0.0054)	(0.0006)
3-5 years after moving	0.0535***	0.0347***	0.0587***	0.0124***
	(0.0015)	(0.0008)	(0.0054)	(0.0008)
5 or more years after moving	0.0401***	0.0202***	0.0457***	0.0008
	(0.0013)	(0.0008)	(0.0054)	(0.0008)
Age	0.0384***	0.0605***	-0.0036***	0.0001*
	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Age^2	-0.0004***	-0.0004***	-0.0004***	-0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Firm size	0.0088***	0.0037***	0.0068***	0.0070***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Base category: Intermediate/upper secondary school				
Vocational training	0.1418***	not	not	not
	(0.0002)	applicable	applicable	applicable
University degree	0.3880***	not	not	not
	(0.0002)	applicable	applicable	applicable
Women	-0.1887***	not	not	not
	(0.0001)	applicable	applicable	applicable
Foreign	-0.0247***	not	not	not
	(0.0002)	applicable	applicable	applicable
Base category: Manufacturing				
Agriculture and Fishing	-0.1427***	-0.0954***	-	-
	(0.0012)	(0.0025)		
Mining and quarrying	-0.0560***	-0.0300***	-	-
	(0.0006)	(0.0011)		
Electricity, gas, and water supply	0.0885***	-0.0193***	-	-
	(0.0004)	(0.0010)		
Construction	-0.0380***	-0.0117***	-	-
	(0.0004)	(0.0008)		
Wholesale and retail trade	-0.0921***	-0.0386***	-	-
	(0.0002)	(0.0005)		
Hotels and restaurants	-0.3364***	-0.1459***	-	-
	(0.0007)	(0.0014)		
Transport, storage and communication	-0.0317***	-0.0526***	-	-
	(0.0003)	(0.0006)		
Financial intermediation	0.0846***	-0.0255***	-	-
	(0.0003)	(0.0008)		
Real estate, renting and business activity	-0.0798***	-0.0975***	-	-
	(0.0002)	(0.0004)		
Public administration and defence	-0.0980***	-0.1071***	-	-
	(0.0002)	(0.0006)		
Education	-0.1282***	-0.1502***	-	-
	(0.0004)	(0.0007)		
Health and social work	-0.1014***	-0.1065***	-	-
	(0.0003)	(0.0007)		
Other community, social and personal sector	-0.0782***	-0.0954***	-	-
	(0.0003)	(0.0008)		
Extra-territorial organizations	-0.1512***	-0.0707***	-	-
	(0.0019)	(0.0052)		
Base category: Production of raw materials and goods, and manufacturing				
Agriculture, forestry, farming, and gardening	-0.0773***	-0.0273***	-0.0203***	-
	(0.0007)	(0.0012)	(0.0013)	
Construction, architecture, surveying and technical building services	0.0047***	-0.0008*	-0.0037***	-
	(0.0003)	(0.0004)	(0.0005)	
Natural sciences, geography and informatics	0.1118***	0.0108***	0.0086***	-
	(0.0002)	(0.0004)	(0.0004)	
Traffic, logistics, safety and security	-0.0952***	-0.0244***	-0.0189***	-
	(0.0002)	(0.0003)	(0.0003)	
Commercial services, trading, sales, the hotel business and tourism	0.0727***	0.0141***	0.0230***	-
	(0.0003)	(0.0005)	(0.0005)	
Business organisation, accounting, law and administration	0.1100***	0.0124***	0.0143***	-
	(0.0002)	(0.0003)	(0.0003)	
Health care, the social sector, teaching and education	0.1285***	0.0076***	0.0140***	-
	(0.0003)	(0.0007)	(0.0007)	
Philology, literature, humanities, social sciences, economics, media, art, culture, and design	0.1342***	0.0139***	0.0194***	-
	(0.0005)	(0.0007)	(0.0008)	
Constant	3.3956***	2.8197***	not	not
	(0.0008)	(0.0007)	applicable	applicable
R^2	0.4536	0.9252	0.9315	0.9382
N	19,399,583	19,131,448	19,399,583	19,399,583
Year fixed effects	Yes	Yes	Yes	Yes
Worker fixed effects	No	Yes	Yes	Yes
Firm fixed effects	No	No	Yes	Yes
Match fixed effects	No	No	No	Yes

Notes: Results are obtained from OLS regressions and the dependent variable is log(wage). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are enclosed in parentheses. The observation numbers are slightly higher than in Table A.1 because the correct identification of the coefficients of the time dummies modelling wage growth requires the duplication of multiple region movers.
Source: Calculations based on LIAB-Mover-Model 9308.

B Supplementary Material

B.1 Additional Tables

Table B.1: Wage-Tenure Profile Specifications - Observation Numbers

	Increase/decrease (1)	Enter/exit top 10% (2)
Population increases with move		
5 or more years before move	14,119	5,520
3-5 years before move	24,897	10,070
1-3 years before move	46,395	19,222
within 1 year before move	67,086	29,190
within 1 year after moving	67,086	29,190
1-3 years after moving	49,063	22,143
3-5 years after moving	29,383	13,535
5 or more years after moving	18,965	9,173
Population decreases with move		
5 or more years before move	13,381	6,777
3-5 years before move	23,824	11,577
1-3 years before move	45,544	20,863
within 1 year before move	68,039	29,173
within 1 year after moving	68,039	29,173
1-3 years after moving	51,369	21,502
3-5 years after moving	31,423	12,751
5 or more years after moving	20,922	8,094

Notes: Number of individuals for each dummy variable in the wage-tenure profile specifications in Table A.2 and A.3.
Source: Calculations based on LIAB-Mover-Model 9308.

Table B.2: Transition Matrix - Population Decrease

	1	2	3	4	5	6	7	8	9	10
1	1.0000									
2	0.8167	0.1833								
3	0.1300	0.6400	0.2300							
4	0.2086	0.2127	0.2311	0.3476						
5	0.0544	0.1609	0.4237	0.1657	0.1953					
6	0.1178	0.0648	0.1661	0.1543	0.3839	0.1130				
7	0.0134	0.0816	0.1347	0.1216	0.2129	0.3173	0.1185			
8	0.0246	0.0928	0.0723	0.1089	0.1570	0.1810	0.2364	0.1270		
9	0.0244	0.0150	0.1453	0.0678	0.0496	0.0803	0.2257	0.2810	0.1109	
10	0.0133	0.0195	0.0292	0.0318	0.0710	0.0742	0.1241	0.1575	0.2534	0.2259

Notes: Share of individuals moving to less populated labour market regions according to the decile of the start and destination labour market region.
Source: Calculations based on LIAB-Mover-Model 9308.

Table B.3: Transition Matrix - Population Increase

	1	2	3	4	5	6	7	8	9	10
1	0.0404	0.0339	0.0202	0.0657	0.0375	0.1919	0.0260	0.0765	0.1739	0.3341
2		0.0039	0.0557	0.0465	0.0857	0.0649	0.0944	0.1869	0.0823	0.3797
3			0.0127	0.0320	0.0860	0.0806	0.0868	0.0964	0.3588	0.2467
4				0.0576	0.0382	0.1206	0.0744	0.1769	0.2159	0.3163
5					0.0333	0.1639	0.1394	0.1283	0.1298	0.4053
6						0.0504	0.1391	0.1752	0.2009	0.4344
7							0.0408	0.1276	0.3633	0.4683
8								0.0654	0.4047	0.5299
9									0.1481	0.8519
10										1.0000

Notes: Share of individuals moving to more populated labour market regions according to the decile of the start and destination labour market region.
Source: Calculations based on LIAB-Mover-Model 9308.

Table B.4: The Elasticity of Wages to Population - For Men Only

	Region fixed effects			Firm fixed effects	
	(1)	(2)	(3)	(4)	(5)
Log(population)	0.0316***	0.0294***	0.0046*	0.0093***	0.0093***
	(0.0051)	(0.0048)	(0.0026)	(0.0032)	(0.0032)
Constant	-0.4334***	-0.4026***	-0.0601*	-0.1142***	-0.1153***
	(0.0692)	(0.0654)	(0.0350)	(0.0435)	(0.0435)
R^2	0.2259	0.2169	0.0238	0.0024	0.0024
N	108	108	108	16,397	16,397
Included controls for heterogeneity in the wage decomposition					
Observable worker characteristics	No	Yes	No	No	No
Worker fixed effects	No	No	Yes	Yes	Yes
Firm fixed effects	No	No	No	Yes	Yes
Region fixed effects	Yes	Yes	Yes	No	No

Notes: Results from regression of region fixed effects and firm fixed effects on log(population). The regressions in Columns (4) and (5) are weighted such to ensure that each region has the same weight as in Columns (1) to (3). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are enclosed in parentheses.
Source: Calculations based on LIAB-Mover-Model 9308.

B.2 Data Preparation

This section offers some additional details on data preparation that might be useful for refereeing purposes, but that are not of general interest to the reader.

B.2.1 Mobility of Firms

- Despite the comparably long observation period of 15 years, regional mobility of firms is rarely observed. Only 199 out of 20,742 firms change their LMR during the observation period. We therefore restrict these 199 firms not to be regionally mobile in order to ensure that regional agglomeration effects are fully captured by the firm fixed effects.
- We do so following a two-step procedure. First, we observe that in 78 out of 199 cases firms relocate to a neighbouring LMR. In these cases we assume that the firm did not in fact relocate and extrapolate the first LMR, in which the firm was observed. Second, the remaining 121 out of 199 firms relocate to a more distant LMR. These firms have to be excluded from the analysis and are therefore dropped from the dataset.

B.2.2 Extrapolating of Missing Values and Procedures for Data Correction

- We correct the nationality if it changes within a person with the prevailing information for the respective individual.
- Along the same lines, we correct the industry affiliation if it changes within a firm with the prevailing information for the respective firm.
- The education variable is corrected following Fitzenberger *et al.* (2006).
- We extrapolate missing wage information with the last available wage at the respective employer.
- When two parallel employment episodes are existent, we only keep the episodes with the higher daily wage and drop spells with a daily wage of zero. Further, for data cleaning reasons the lowest percentile of the earnings distribution is dropped.

B.2.3 Identifying Worker-Firm Matches and Regional Mobility

- In order to deal with multiple spells for the same year-worker-firm combination we drop 156,585 persons and 308,800 matches. The spells that have been dropped are characterised with a huge gap to the next observed spell and/or huge wage deviations to the other spells. These extreme gaps in time and/or wage make it impossible to treat the spells as one continuous employment relationship.
- Workers that change their employer at least once are defined as job movers, whereas we restrict the gap between changing the employer to 365 days. Individuals that change the employer with a gap larger than 365 days are defined as separate job stayers. If individuals change their employer more than once, they count as several separate individuals in order to ensure that we can always identify pre- and post-transition employment spells. Due to the fact that we allow for a gap of up to 365 days between observed employment spells, the transitions can be either direct employment to employment transitions, but also employment-unemployment-employment transitions or other transitions that we can not observe.

- For the wage-tenure profile specification we need to ensure the clear identification of the dummy variables before and after the job transition. Considering that, we redefine job movers such that we can always identify the dummies defining the duration before and after the transition correctly. Therefore, the number of observation differs between the aggregate specifications and the wage-tenure profile specifications, however the sample consists of the same individuals and firms.