University of Zurich[UZH]

URPP Equality of Opportunity

Job Mobility and Wage Growth between Regions

Julius Lüttge

Equality of Opportunity Research Series #8
November 2022

University of Zurich[UZH]

URPP Equality of Opportunity

URPP Equality of Opportunity Discussion Paper Series No.8, November 2022

Job Mobility and Wage Growth between Regions

Julius Lüttge
University of Zurich
julius luettge@econ.uzh.ch

The University Research Priority Program "Equality of Opportunity" studies economic and social changes that lead to inequality in society, the consequences of such inequalities, and public policies that foster greater equality of opportunity. We combine the expertise of researchers based at the University of Zurich's Faculty of Arts and Social Sciences, the Faculty of Business, Economics and Informatics, and the Faculty of Law.

Any opinions expressed in this paper are those of the author(s) and not those of the URPP. Research published in this series may include views on policy, but URPP takes no institutional policy positions.

URPP Discussion Papers often represent preliminary work and are circulated to encourage discussion. Citation of such a paper should account for its provisional character.

URPP Equality of Opportunity, University of Zurich, Schoenberggasse 1, 8001 Zurich, Switzerland
info@equality.uzh.ch, www.urpp-equality.uzh.ch

Job Mobility and Wage Growth between Regions

Julius Lüttge*

November 18, 2022

Abstract

Individual wage growth is higher in more densely populated regions. Using data on detailed labour market biographies from Germany, this paper shows that job mobility contributes to this urban premium in wage growth. In urban regions, wage growth is higher both within jobs and between jobs. The higher between-job wage growth is driven by a combination of higher frequency of job changes and a higher payoff of moving between jobs. This finding is consistent with better coordination in denser labour markets. Further evidence shows that the gain from higher urban wage growth is not lost upon moving across regions, suggesting that a better job match results in higher human capital accumulation.

*University of Zurich, Department of Economics. julius.luettge@uzh.ch.

1 Introduction

Urban labor markets are different from those in less densely populated areas. Wages are higher, workers have more employment options, and they earn particularly valuable experience, leading to higher wage growth. The drivers behind the dynamic factor, higher urban wage growth, are not well understood. This paper studies one potential driver: job mobility. Do workers in urban areas make use of the thicker labor market where they have more potential employers to choose from? Do they move to better jobs more often? And if they do, does this result in higher wage gains? Finally, does this higher wage growth reflect human capital accumulation or merely a better job match?

To study these questions, I examine the German case. First, I confirm wage growth in regions with higher population density to be higher. I then decompose it into wage growth that workers accrue *within* the same job versus wage growth that workers gain when moving *between* jobs. This between-job wage growth can be further split into the frequency of job moves and the wage payoff of job mobility. In the second part of the analysis, I address the question whether the wage growth obtained by higher job mobility within a region is portable across geographic regions. If it is not lost upon moving away, this would suggest job mobility to a better-matching job does not just provide a transient benefit, but it provides workers with more valuable experience.

Regional wage disparities have been widely documented: wages in cities (or in more densely populated regions more generally) tend to be higher (e.g., Combes et al., 2008; Duranton and Puga, 2004; Glaeser and Resseger, 2010; Glaeser, 2012; Grujovic, 2020). In part, higher wages in urban areas compensate for higher living costs. They also reflect higher productivity (Henderson, 2003; Moretti, 2011; Combes et al., 2012). The drivers behind higher urban wages can be broken down into sorting (e.g., Glaeser and Maré, 2001; Yankow, 2006; Combes et al., 2008), static productivity benefits, and dynamic benefits that accrue over time (Baum-Snow and Pavan, 2012; De la Roca and Puga, 2017; Lüttge, 2022).

While most studies on regional wage disparities focus on differences in the wage level, the dynamic benefits imply higher urban wage growth (studied explicitly, for instance, by Glaeser, 1999; Glaeser and Maré, 2001). The determinants of wage growth over the life-cycle have been studied in many contexts. Wage growth has been found to be higher for younger workers, those with more education, those with higher tenure, and for men (e.g., Borjas, 1981; Bartel and Borjas, 1981; Topel and Ward, 1992; Lazear, 1976; Loprest, 1992; Dustmann and Pereira, 2008; Manning and Swaffield, 2008; Dustmann and Meghir, 2005; Rubinstein and Weiss, 2006).

Regional disparities in wage growth are likely explained - at least in part - by faster human capital accumulation in certain regions: workers in urban areas becoming more productive faster, that is to say, it is an effect of a higher degree of 'learning' in the labour market. We can call this the 'learning hypothesis'. Learning is shown to be a factor in De la Roca and Puga (2017), Glaeser and Maré (2001), and Glaeser (1999). Another possible explanation is described by the 'coordination hypothesis': cities offer more options on the labour market, so that workers can match to more suitable jobs (Dauth et al., 2022, show that this contributes to wage level differences). While this benefit of a thicker labour market may result in a better job match for some workers in their first local job (which would be a static effect), there may also be a dynamic factor as workers move to a better-matching position over time. Search behaviour and job mobility patterns have been shown to be different depending on local labour market characteristics (e.g., Petrongolo and Pissarides, 2006; Yankow, 2009; Di Addario, 2011; Bleakley and Lin, 2012; Andersson and Thulin, 2013; Petrongolo and Ronchi, 2020).

These two hypotheses - the learning hypothesis and the coordination hypothesis - differ in their prediction regarding the portability of wage growth. If higher wage growth in cities is the result of higher human capital accumulation - as described by the learning hypothesis - workers moving from a city to a small region will be not be expected earn lower wages in the small region in their previous city job. If, however, higher urban wage growth is the result of coordination, this coordination benefit will not be transferable between regions, so we would expect a worker moving from a city to a small region to earn a lower wage in their new job. However, these two factors - learning and coordination - need not be understood as alternative explanations for higher wage growth. It is possible that coordination effects and matching in thicker markets aids learning. Nonetheless, we can interpret the portability of urban wage growth as evidence for learning.

In this paper, I document higher wage growth in more densely populated regions. By decomposing this wage growth into a within-job component and a between-job component, I show that job mobility plays a role for urban wage premia. This higher between-job wage growth in urban areas is driven by both higher frequency of job changes and by a higher payoff of moving between jobs. This supports the coordination hypothesis, as higher mobility contributes to higher wage growth in urban areas. In the second part of the analysis, I examine how coordination and learning interact. Workers with higher job mobility within regions do not lose their higher resulting wage growth upon moving to another region. This suggests that learning occurs not only on the job but finding a better-matching job can contribute to human capital accumulation. Coordination is therefore not a transient benefit of denser regions.

The remainder of the paper is structured as follows. Section 2 presents the data and descriptive statistics. Section 3 shows a simple analysis of how wage growth over the life-cycle develops in regions of different sizes. Section 4 describes how wage growth can be decomposed into its component parts and shows the results on wage growth. Section 5 analyses the portability of wage growth between workers with different job mobility history in order to examine whether coordination and learning are complementary.

2 Data

The main data source is the Sample of Integrated Labour Market Biographies (SIAB Regional File 7517, Antoni et al., 2019) based on German social security data, and provided by the Institute of Employment Research (IAB). This is a 2 per cent random sample drawn from all employees in the years 1975 to 2017. It excludes civil servants, military personnel, and the self-employed.

The key advantage of this data set is that it includes very accurate wage data. However, wages are top-coded at the threshold for social security contributions. To address this, I simulate censored wages, following the procedure by Card et al. (2013), which is based on Dustmann et al. (2009): I fit a series of Tobit models to log daily wages, and then impute an uncensored value for each censored observation using the estimated parameters of these models and a random draw from the associated (left-censored) distribution. Wages are then deflated to 2015 prices using the CPI.

For each worker, the data include the location of the establishment in one of 328 regions. These are based on the 401 German administrative districts ('Landkreise' and 'kreisfreie Städte'), which are aggregated such that each region contains at least 100,000 inhabitants. As a measure of population density, I compute population within 10 km of the average resident for each region, using grid cell data from GEOSTAT (2006). Since the population density data are from 2006, the analysis is restricted to the years 1995 to 2017. East German regions are excluded from the analysis because of the large wage adjustments after unification.

For a simple comparison of regions, I also use an alternative size measure for parts of the analysis. For this purpose, I define the largest regions that are home to a quarter of workers as 'large' (38 regions). The next smaller regions home to a quarter of workers are defined as 'medium' (62 regions). And the smallest regions home to the remaining half of workers are defined as 'small' (167 regions).

The data are recorded to daily accuracy. To define wage growth over time, I convert it to quarterly data, including all employment spells that include 15 January, 15 April, 15 July, or 15 October. This way, any quarterly wage growth can be classified either as within-job (if the worker works at the same establishment as three months prior) or as between-job (if the worker has moved establishment). For the annual wage growth measure, quarterly log wage growth is summed over the past four quarters. Using quarterly data to compute wage growth has the advantage that it limits noise introduced by very short employment periods.

Since the analysis is focused on market wages, I exclude certain sectors with regulated wages: public administration, education, and medicine. Agriculture is also excluded because it is naturally a non-urban industry. Similarly, workers on apprenticeship or internship contracts are excluded. Since work hours are not recorded in the data, only workers on full-time contracts are included in the analysis. An observation is excluded if any of these restrictions holds in any of the prior three quarters. Also excluded are episodes with very low wages (under ten Euros per day), and workers who are observed in fewer than two of the past three quarters.

Table 1 shows summary statistics. There are over 4 million observations in the data. 14 per cent have a university degree, and 77 per cent have vocational training. The share of women in the data is 27 per cent. The low share of women in the data is partly explained by their lower labor market participation and partly by higher incidence of part-time work among women, which is excluded from the sample.

The average real annual log wage growth is 1.19 log points, i.e., about 1.20 per cent. Most of this wage growth is accrued within the same job (1.09 log points). The remainder is accrued between jobs (.10 log points). Each quarter, 4.19 per cent of workers in the sample change their jobs[1] and 10.96 per cent of workers change their jobs each year. Quarterly wage growth averages 0.24 per cent. Between periods when workers change jobs however, it averages 7.16 log points (7.42 per cent).

[1] A job move is defined as moving to a different establishment. Position changes within the same establishment cannot be reliably identified. Owing to the data, we cannot distinguish job moves between different firms versus job moves between establishments of the same firm.

Table 1. Summary statistics

	Mean
Age	40.59
Education: % vocational training	76.51
Education: % university degree	14.43
% female	27.44
Δ Log wage, year-on-year	1.19
Δ Log wage, annual, within same job	1.09
Δ Log wage, annual, between jobs	0.10
Job mobility rate, quarterly, in %	4.19
Job mobility rate, annual, in %	10.96
Δ Log wage, quarterly	0.24
Δ Log wage, quarterly, conditional on job move	7.16
Observations	4,545,446

Notes: Summary statistics all sampled workers. Data from the 2nd quarter of each year. Wage changes are shown in log points $\times$ 100. That is, a 1.19 log point wage change corresponds to approximately 1.19 per cent wage growth. Mobility rates are shown in per cent.

3 Wage profiles and wage growth

For a simple comparison of wages across regions, I plot average real wages by age for each region size group in Figure 1. While wages at age 20 are very similar across regions, there are wide regional wage differences by mid-career. Individual wage growth after age 40 is low in all regions, so the regional wage differences do not widen further. Wage growth is strong in all regions in a worker's early career but it flattens out earlier in smaller regions. The gap between regions, then, widens most starkly between ages 30 and 40.

The wages shown in Figure 1 are raw averages, and are not adjusted for differences in the types of jobs carried out in each region size group. Appendix Figure B.1 shows composition-adjusted wage profiles. Here, the education-occupation-industry-gender composition is held fixed across regions within each age group. This attenuates the differences between regions somewhat but the pattern remains: wage growth in larger regions is steeper in the first half of workers' careers.

Figure 2 emphasises the differential personal wage growth between regions, showing average annual wage growth by age in each region size group. Annual wage growth is decomposed into wage growth accrued on the job and wage growth accrued between jobs. Each quarter, we observe a worker i's wage growth, $\Delta \ln w_{i,t} = \ln w_{i,t} - \ln w_{i,t-1}$. And we observe whether the worker works in a different establishment than in the previous quarter, $\mathbb{1}(\text{job}_{i,t} \neq \text{job}_{i,t-1})$. Within-job

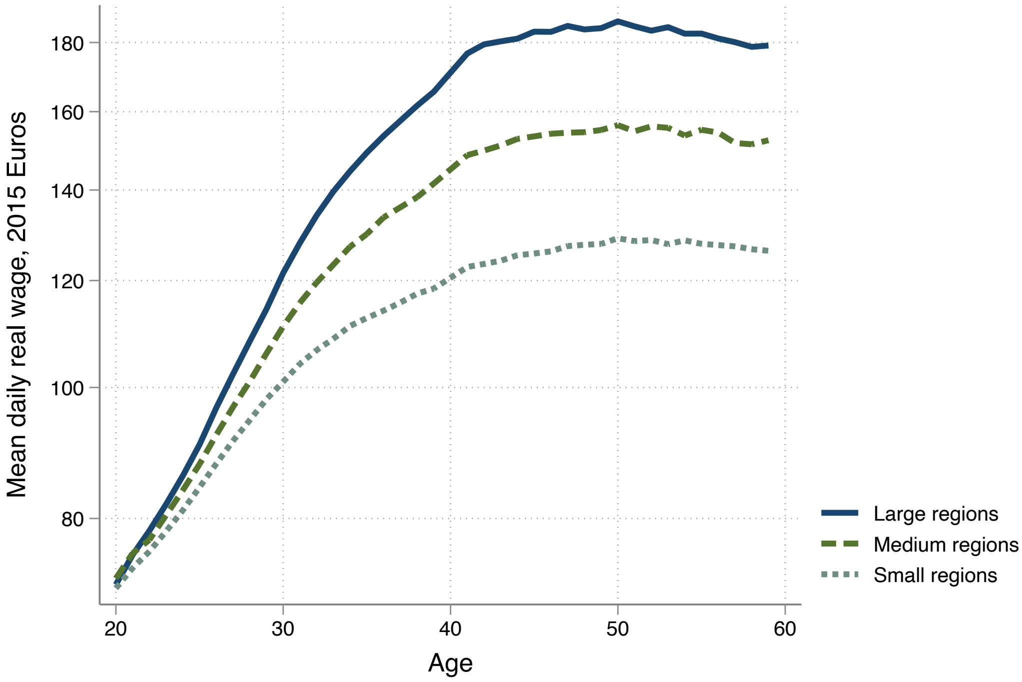

Figure 1. Raw average wages by age and region size

Notes: Raw mean daily wages by age and region size, shown on a log scale. Large regions: densest regions that contain 25% of workers. Medium regions: next densest regions that contain next 25% of workers. Small regions: remaining regions that contain remaining 50% of workers.

wage growth is then the sum of the prior year's wage growth episodes that occurred on the same job: $\sum_{t=t-3}^{t}(\Delta \ln w_{i,t} \times \mathbb{1}(\text{job}_{i,t} = \text{job}_{i,t-1}))$. Between-job wage growth, similarly, is the sum of the prior year's wage growth episodes that occurred in quarters when the worker changed jobs: $\sum_{t=t-3}^{t}(\Delta \ln w_{i,t} \times \mathbb{1}(\text{job}_{i,t} \neq \text{job}_{i,t-1}))$.

Since workers change jobs infrequently, it is not surprising that within-job wage growth accounts for most of total wage growth. It is higher earlier in the career, and it is positive until age 55, whereas average between-job wage growth is slightly negative after age 40. The figure also shows that within-job growth is consistently higher in larger regions until around age 40. This hierarchy largely holds also for between-job wage growth but the difference is less striking. After age 40, the patterns by region size disappear.[2]

[2]To allow comparison between regions, observations following a worker's geographic move between regions are not included. Since this lowers the observed frequency of job moves, it attenuates the observed between-job wage growth. However, including geographic moves would only slightly change the figure.

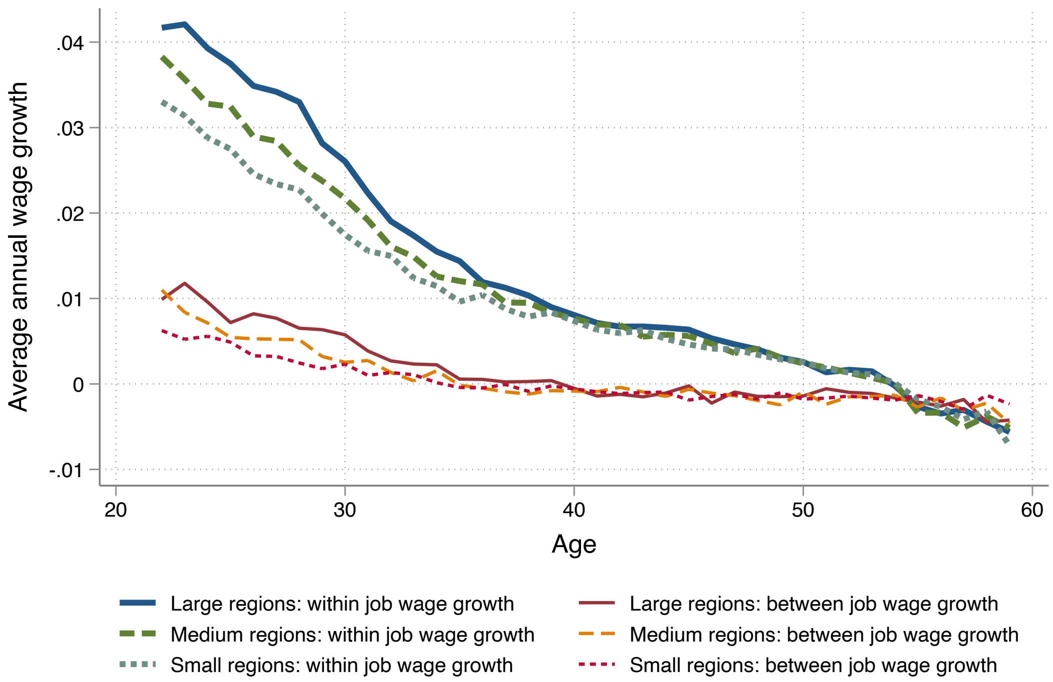

Figure 2. Wage growth by age, for three region size groups

Notes: Log wage growth is decomposed into within-job wage growth (thicker lines) and between-job wage growth (thinner lines). Taking a worker's quarterly wage growth for four consecutive quarters, annual within-job wage growth is defined as the sum of all quarterly wage growth incidences that occurred without a job change. Annual between-job wage growth is defined as the sum of all quarterly wage growth incidences that occurred with a job change. Between-job wage growth therefore incorporates both a frequency of job-change and a payoff-at-job-change effect. Observations that succeed a move between regions are excluded.

4 Decomposing wage growth

4.1 Estimation

The above figures showed that raw wage growth is higher in larger regions, both between jobs and within jobs. For a more systematic analysis of the types of wage growth between regions, we can regress annual wage growth on region size:

$$\Delta \ln w_{it} = \beta \ln \text{size}_{r(i,t-1)} + \epsilon_{it} \tag{1}$$

where $\Delta \ln w_{it} = \ln w_{it} - \ln w_{it-1}$ is the wage difference to last year's wage, and $\text{size}_{r(i,t-1)}$ is region r's log population density with mean zero (of the region in which worker i worked in $t-1$).[3] $\hat{\beta}$ estimates how wage growth varies with region density: comparing two regions A and B, where A is twice as large as B, wage

[3]Population density is defined as the number of residents within 10 km of the average resident in a region, as described in section 2. Since we are here concerned with within-region wage growth, the sample is restricted to within-region job moves only, so $r(i,t) = r(i,t-1)$.

growth is estimated to be $\hat{\beta}$ log points higher in A than in B. Without further controls, this specification simply allows comparison of average wage growth across regions of different sizes.

Alternatively, we can control for personal characteristics and a time effect:

$$\Delta \ln w_{it} = \alpha + \beta \ln \text{size}_{r(i,t-1)} + x'_{i,t-1}\psi + \delta_t + \epsilon_{it} \tag{2}$$

Note that equation 2 is similar to a Mincer equation in first differences. Take a wage equation with time-constant characteristics x'_i and time-varying personal characteristics x'_{it}: $\ln w_{it} = \alpha + x'_i\boldsymbol{\beta} + x'_{it}\boldsymbol{\gamma} + \epsilon_{it}$. In first differences, the time-constant characteristics drop out, and only changes of time-varying characteristics would remain. In our setting, this specification would not be able to pick up differences in wage growth for workers who work and stay in the same region between periods.

In equations 1 and 2, the outcome variable is year-on-year wage growth. We can estimate similar equations with within- and between-job wage growth as the dependent variable. The resulting $\hat{\beta}$ is an estimate of how each type of wage growth varies with region density.

Having documented the contribution of differential job mobility to the wage growth differential between regions of different sizes, we can decompose between-job wage growth further. Between-job wage growth is composed of the frequency of job changes and the payoff at job change. To evaluate how the frequency of job changes varies between regions of different sizes, we estimate a version of equations 2 and 1 with the job mobility hazard rate as the outcome variable. This is defined as the probability a worker changes their job in each period.

To assess whether the wage payoff at job mobility varies with region size, we can regress wage growth on a job move indicator, region size, and an interaction of the two:

$$\begin{aligned} \Delta \ln w_{it} = \beta_0 &+ \beta_1 \ln \text{size}_{r(i,t)} + \beta_2 \mathbb{1}(\text{new job}_{it}) \\ &+ \beta_3 \ln \text{size}_{r(i,t)} \mathbb{1}(\text{new job}_{it}) + x'_{it-1}\psi + \delta_t + \epsilon_{it} \end{aligned} \tag{3}$$

where $\mathbb{1}(\text{new job}_{it})$ is a binary variable indicating that worker i moved between jobs between $t-1$ to t.

Unlike in regressions 1 and 2 where the outcome variable is defined year-on-year, it is defined as quarterly wage change in equation 3. This is because I want to capture the wage change right at the moment the worker changes the job. This way, β_1 captures how quarterly within-job wage growth varies with region size; β_2 captures the average wage gain between jobs in the average sized region; and β_3

captures how the average wage gain between jobs varies by region size. Results are presented in the next section.

4.2 Results on wage growth

Table 2 shows results from the specifications above, without any controls. Column 1 shows regional variation in annual personal wage growth. Average personal annual wage growth in the sample is 1.195 log points. In a region twice as large as the average region, annual total wage growth is 0.169 percentage points higher. Annual wage growth in the largest region is therefore estimated to be 0.38 percentage points higher.[4] This means annual wage growth in Munich is estimated to be 32 per cent higher than in the median region.

Columns 2 shows regression results with within-job wage growth as the outcome variable. Within-job wage growth is defined as the sum of the past year's quarterly wage growth episodes that occurred without job changes. On average, this accounts for over 90 per cent of total personal wage growth (1.093 per cent a year). It is also significantly higher in larger regions. The estimate of 0.120 implies within-job wage growth is estimated to be 25 per cent higher in the largest region compared to a median sized region ($0.120 \times 2.25/1.093$).

In column 3, the outcome variable is between-job wage growth, defined as the sum of the last year's quarterly wage growth episodes that occurred when changing the job. While most wage growth occurs within the same job, the region gradient in between-job wage growth is large. In a region twice as large, between-job wage growth is 0.046 log points higher, which is 48 per cent higher than the national average between-job wage growth of 0.096 log points. Comparing the largest city to a median region, between-job wage growth in the largest city is more than twice as high.

Between-job wage growth may be higher in cities for two reasons: either workers change their jobs more frequently, or the payoff when changing the job is higher. Columns 4 and 5 examine these two possible drivers. In column 4, a job mobility indicator is regressed on region size in a linear probability model. At the average, this gives us a hazard rate of 8.824 per cent, meaning that on average 8.8 per cent of workers move between jobs in a given year in our sample. In larger cities, worker mobility is higher. The coefficient of 0.945 implies that job mobility is estimated to be 24 per cent higher in the largest region than in the average region.

[4] The population size measure for the smallest region, Vulkaneifel, is 22,338 . For the largest region, Munich, it is 973,778. In logs, this is a 3.77 point difference. The log point difference between the median size regions (Peine and Lörrach) and the largest region is 2.25 log points.

The average payoff of job changes is estimated in column 5. As opposed to columns 1 to 4, the outcome variable is quarterly wage growth because job mobility is observed at quarterly frequency. Average quarterly wage growth in the sample is 0.34 per cent. When a worker changes their job, this is 7.02 log points higher. This payoff at a job move is 0.439 percentage points higher in a region twice as large, which means it is estimated to be 14 per cent higher in the largest region in comparison to an average region.

Table 2. Wage growth components; no controls

	(1) Δ Log wage, year-on -year	(2) Δ Log wage, within job	(3) Δ Log wage, between jobs	(4) Job mobility hazard rate	(5) Δ Log wage, quarterly
Log region size	0.169***	0.120***	0.046***	0.945***	0.006***
	(0.027)	(0.025)	(0.011)	(0.071)	(0.002)
Job move × Log region size					0.439***
					(0.113)
Job move					7.021***
					(0.130)
Year FEs	No	No	No	No	No
Mean dep. var	1.195	1.093	0.096	8.842	0.244
R^2	0.000	0.000	0.000	0.001	0.034
Observations	3,942,396	3,939,307	3,936,833	4,437,049	4,103,737

Notes: Regression results based on specification 1 (columns 1 to 4) and 3 (column 5). All regressions include a constant but no further controls. The sample is restricted to workers in full-time employment on 15 April in each year. Log region size is defined as the number of residents within 10 km of the average resident. Job move is a binary variable indicating whether a worker has changed job in the past quarter. The outcome variable in column 1 is the change in log wage to the previous year. The outcome variable in column 2 is the change in log wage to the previous year that occurred within the same job, computed on quarterly wage growth episodes. The outcome variable in column 3 is the change in log wage to the previous year that occurred between jobs, computed on quarterly wage growth episodes. The outcome variable in column 4 is a binary variable indicating whether a worker has changed their job between 15 January and 15 April of the year. The outcome variable in column 5 is the log wage growth between those two dates. Coefficients are reported with standard errors in parentheses, clustered at the region level. ***, **, and * indicate statistical significance at the 1, 5, and 10% levels.

Overall, the findings from Table 2 show that wage growth is higher in larger regions both within the same job and between jobs. This between-job wage growth premium is partly due to higher frequency of job changes, and partly due to a higher payoff at job mobility.

Appendix Table B.3 shows corresponding results where each regression also includes year fixed effects. This accounts for national shocks in wage growth, but does not meaningfully affect wage any of the between-region estimates.

Figures 1 and 2 show that wage growth is particularly high for young workers. Appendix Table B.4 is equivalent to Appendix Table B.3 but is restricted to workers under 40. Indeed, the estimates in columns 1 to 3 are all higher than for the full sample, confirming that both types of wage growth is higher for younger workers in larger regions. However, in percentage terms, the additional within-job wage growth observed in larger regions does not differ meaningfully for the two samples.

When workers change jobs, a part of the wage growth is likely explained by changes in the observable characteristics of the job, such as occupation or industry. The results in Table 3 control for changes in the occupation and industry between two jobs. I follow Loprest (1992) and construct two one-dimensional indices that capture the expected wage growth from an occupation change or an industry change, respectively. To do this, I estimate a wage regression with occupation and industry fixed effects,[5] and define the index for an occupation pair as the distance between the estimated fixed effects for those two occupations (and analogously for industries). For a worker who does not change occupation (or industry) during a job move, this index is zero. For a worker who moves occupation (or industry) during a job move, the index expresses the expected wage gain or loss associated with that move. Occupation and industry only change when a worker changes her job, so the occupation and industry indices are only included in columns 1, 3, and 5, which include between-job movement. Since we know that young workers who are more mobile between jobs have higher wage growth, the estimates in Table 3 also include full age fixed effects.

The results in Table 3 show that job moves upward on the industry- or occupation scale are indeed associated with significant wage growth. If there was no variation in wages within each occupation-industry cell, the estimated coefficients for an occupation move as well as an industry move would be 100: moving to an occupation in which the mean wage is twice as high would be expected to double a worker's wage. The estimated coefficients are lower than that, which is in line with the findings by Groes et al. (2015): workers leaving an occupation tend to be from the tails of the wage distribution within an occupation. The variation by region size is overall similar to that reported in Table 2: a little stronger for within-job wage growth, and somewhat attenuated for job mobility and for wage growth between jobs.

[5] I regress log wages on age, age^2, tenure, tenure^2, gender, education dummies, year dummies, as well as 120 occupation and 10 industry dummies.

Table 3. Wage growth components: including controls

	(1) Δ Log wage, year-on -year	(2) Δ Log wage, within job	(3) Δ Log wage, between jobs	(4) Job mobility hazard rate	(5) Δ Log wage, quarterly
Log region size	0.205***	0.156***	0.045***	1.075***	0.008***
	(0.018)	(0.017)	(0.012)	(0.063)	(0.002)
Job move × Log region size					0.367***
					(0.109)
Job move					6.463***
					(0.129)
Occupation index	25.864***		23.081***		19.323***
	(0.572)		(0.622)		(0.740)
Industry index	77.662***		72.948***		50.614***
	(2.039)		(1.912)		(1.453)
Age FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Mean dep. var	1.195	1.093	0.096	8.842	0.244
R^2	0.045	0.019	0.048	0.014	0.059
Observations	3,926,706	3,939,307	3,921,201	4,437,049	4,097,485

Notes: Regression results based on specifications 1 (columns 1 to 4) and 3 (column 5). All regressions include a constant and a year fixed effect. The sample is restricted to workers in full-time employment on 15 April in each year. Log region size is defined as the number of residents within 10 km of the average resident. Job move is a binary variable indicating whether a worker has changed job in the past quarter. The occupation and industry indices capture the expected wage change associated with a job move, based on a standard wage regression of log wages on personal characteristics and industry and occupation fixed effects. The outcome variable in column 2 is the change in log wage to the previous year that occurred within the same job, computed on quarterly wage growth episodes. The outcome variable in column 3 is the change in log wage to the previous year that occurred between jobs, computed on quarterly wage growth episodes. The outcome variable in column 4 is a binary variable indicating whether a worker has changed their job between 15 January and 15 April of the year. The outcome variable in column 5 is the log wage growth between those two dates. Coefficients are reported with standard errors in parentheses, clustered at the region level. ***, **, and * indicate statistical significance at the 1, 5, and 10% levels.

5 Portability of experience

The results presented above show that higher wage growth in larger regions is driven both by higher wage growth on the job and higher wage growth between jobs. The higher wage growth between jobs, in turn, is driven by both higher job mobility and by a higher payoff of job mobility.

We know from previous work (De la Roca and Puga, 2017; Lüttge, 2022) that big city experience commands a premium. Not only do workers earn more in cities, and their wage growth is higher in cities, workers with city experience also benefit from a wage premium after leaving high-wage cities. This implies that experience acquired in cities is portable.

This section explores whether these portability results hold for both types of wage growth: wage growth acquired on the job and wage growth acquired between jobs. The answer to this question may help us adjudicate between two possible causes of dynamic urban wage premia. The learning hypothesis holds that workers in cities earn higher wages and experience higher wage gain because they acquire more valuable experience than in a small region. The coordination hypothesis, on the other hand, holds that wages are higher in cities because workers find better-matching jobs. This may lead to a static difference in wages between regions if workers find an initial better match in a thicker labour market, as well as to a dynamic urban wage premium if workers search on-the-job and leverage thicker labour markets to find even better matches over time (for a discussion of the learning hypothesis vs the coordination hypothesis, see Glaeser and Maré, 2001).

If city experience is portable, i.e., if workers' city-experience is more valuable not only in the region in which it was acquired but also helps workers find better-paid jobs when they leave a large city, this supports the learning hypothesis: workers learn more in cities, and acquire stable higher human capital. If, on the other hand, the dynamic urban wage premium is partly driven by higher between-job wage growth (as documented in section 4), this supports the coordination hypothesis, namely that city-workers benefit from better-matching opportunities over time.

However, it is also possible that both hypotheses hold: First, the dynamic urban wage premium may simply be multicausal. Second, workers may acquire more valuable experience in better job matches. In other words, there could be learning via coordination.

5.1 Job mobility: a framework

Workers are more likely to take a new job if it offers a higher wage. The same is true for moves to a job in a new region. As a consequence, we do not observe the full distribution of each worker's best wage offer in a different region but merely the upper tail of this distribution which contains the wage offers that were accepted. This type of self-selection would be particularly problematic for the interpretation of mobility results if the degree of selection varied systematically with prior mobility. For instance, it may be that workers who are more mobile within regions require a larger wage gain in order to move across regions. A separate consideration is that workers may not only differ in the magnitude of the wage gain that is needed to entice them to move but they may vary in their propensity for receiving outside offers.

To guide the interpretation of the results on regional job mobility and wage growth between workers with different local job mobility history, consider a simple framework: Assume there are two types of workers: high-mobility workers H and low-mobility workers L, which differ in terms of their prior within-region mobility. Each quarter, each worker draws a number of job offers from some distribution, and accepts the job if the wage gain from this offer exceeds a reservation value. More formally:

$$L \text{ gets } n \text{ draws of } \Delta w_i \sim D(0, \sigma), \text{ accepts if best offer } \Delta w_i > k.$$

$$H \text{ gets } n + \delta \text{ draws of } \Delta w_i \sim D(\omega, \sigma), \text{ accepts if best offer } \Delta w_i > k + \rho.$$

Job offers for L workers (and for H workers if $\omega = 0$) are sampled from a mean-zero distribution with standard deviation σ. This means that workers get offers for jobs that are similar to their current one in terms of wage.

The number of draws, the mean of the offer distribution, and the reservation wage are allowed to vary across worker type. Using this framework, we can derive predictions for both the frequency of job mobility and the expected wage growth conditional on job mobility, depending on the parameters δ, ω, and ρ.

A parameter $\delta > 0$ implies that H workers obtain more wage offers than L workers. This may be the case because workers with frequent past job mobility search more intensely for a new job, or by having had multiple past employers, they have more connections in the labour market - we may call this 'relationship capital'. Since H workers receive more offers when $\delta > 0$, they have a higher chance of getting an offer with a very large wage gain. As a result, H workers would be more likely to move, and have larger average wage gains conditional on moving. If $\delta < 0$, type H workers search less intensely. This is less plausible. It would have the opposite effect: lower hazard rate, and lower expected wage gain at job mobility.

The parameter ω governs the mean of the wage offer distribution of type H workers. $\omega < 0$ would imply that type H workers receive worse job offers on average than type L workers. This would be the case if the higher past within-region mobility of H workers generated location-specific wage gains that are not portable across space. In the $\omega < 0$ case, we would thus expect that H workers have a lower propensity to move and lower wage gains conditional on moving. If instead, all wage gains from past within-region mobility are portable, then both H and L workers would get outside wage offers that are similar to their current wage, so that $\omega = 0$. The case $\omega > 0$ would lead to the same prediction as $\delta > 0$, but it is less plausible: while workers with elevated past mobility may get more wage offers, it is less clear why such wage offers would be sampled from a more favourable distribution.

The parameter ρ indicates whether H workers seek a different wage gain than L workers in order to be induced to move. If $\rho > 0$, high-mobility workers require a higher wage gain to accept a job. This would result in a lower hazard rate, but a higher expected wage gain when they accept a job. Conversely, $\rho < 0$ would mean that high-mobility workers are more willing to accept offers with a lower wage gain. This would imply a higher hazard rate and a lower expected wage gain at job mobility.

This simple framework produces a key insight: If the H and L groups differ in their propensity to select into migration ($\rho > 0$ or $\rho < 0$), then the differential effects for H workers in terms of migration propensity and wage gain conditional on migration will have *opposing signs*. If, however, these two outcomes have the *same sign*, then the results are consistent with either different frequencies of obtaining wage offers ($\delta > 0$ or $\delta < 0$) or different underlying wage offer distributions ($\omega > 0$ or $\omega < 0$). While the δ and ω parameters can generate the same outcomes, it is arguably more plausible to assume $\delta > 0$ than $\omega > 0$, and more plausible to assume $\omega < 0$ than $\delta < 0$.

5.2 Wage growth and hazard rates by mobility type

Before assessing the portability of types of experience, we need to confirm that workers who change their jobs more often do indeed experience wage growth that is higher than or similar to those who do not.

Table 4 shows results from regressions of wage growth on categorical job mobility terms and a constant. The sample is restricted to all workers who are observed in full-time employment for at least five years in an origin region o (notwithstanding potential intermittent non-employment spells), and are observed moving to a destination region d in the sixth year. In Table 4, we only consider wage growth in the origin region in the five years leading up to the move to region d.

Table 4. Within-region wage growth before a regional move

	(1) Mean Δ Log wage, within job	(2) Mean Δ Log wage, between jobs	(3) Mean Δ Log wage, total
One job move in 5 years	-0.112***	3.766***	-0.027
	(0.032)	(0.269)	(0.032)
Two job moves in 5 years	-0.193***	5.383***	0.183***
	(0.061)	(0.347)	(0.062)
Three+ job moves in 5 years	-0.549***	4.894***	0.219***
	(0.101)	(0.429)	(0.073)
Constant	0.532***		0.532***
	(0.008)		(0.008)
R^2	0.001	0.028	0.000
Observations	89,208	17,986	89,208

Notes: The table shows results from a regression of different types of wage growth on a categorical job mobility counter. The sample is restricted to workers who have held a full-time job in the same region for at least five years, starting from 1995, and who moved to another region afterwards. The outcome variable in column 1 is a worker's mean quarterly log wage growth in periods without a job change, computed over a worker's last five years in a region. The outcome variable in column 2 is a worker's mean quarterly log wage growth in periods with a job change, computed over their last five years in a region. The outcome variable in column 3 is a worker's total mean quarterly log wage growth over all periods, computed over their last five years in a region. Log changes are multiplied by 100 so that coefficients are approximately equivalent to percentage point changes. Job mobility is a count of the times a worker has changed their job within the region during the last five years before moving to another region. Since 99.8 per cent of workers in the sample change their jobs fewer than once per year, worker with more frequent job changes are grouped with workers who changed their job four times in the five-year period. Coefficients are reported with robust standard errors in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10% levels.

In column 1, the outcome variable is within-job wage growth.[6] The constant in column 1 shows that mean quarterly wage growth for workers who did not change their job in the five years leading up to a region move was about 0.53 per cent. For workers with job moves within the origin region, the wage growth within each job is lower. The more jobs they held, the shorter was the average tenure per job, and the lower was the average wage growth within each job. This result of lower

[6] As before, this is defined as a worker's mean quarterly log wage growth in periods without a job change, computed over a worker's last five years in a region.

within-firm wage growth for workers with high job mobility is well known (e.g., Topel and Ward, 1992). It is also not surprising: First, low wage growth may be a reason for workers to search for an alternative job. Second, wage growth may be institutionally linked to seniority and only be realized after some minimum tenure. Third, employers are unlikely to increase wages of workers they do not intend to employ for long. Figure 3 shows the relationship between wage growth and final job tenure. For all workers with total tenure over two years, average quarterly wage growth within the job is near 0.4 per cent. For workers with shorter tenure, it is significantly lower, and even negative on average for workers whose total tenure remains under a year.

Column 2 of Table 4 shows the average wage gain per job move by job mobility. The wage gain is between 3 and 6 per cent on average, each time a worker moves to a new job. Given the lower within-firm wage growth for frequent job movers, the total wage gain is not ex-ante obvious. Column 3 shows that the higher between-job wage growth of job movers counteracts lower within-job wage growth. Total wage growth over the five-year period of workers with job mobility, then, is higher than or roughly the same as that of workers with no job mobility.

Having shown that within-region wage growth of workers who are more mobile between jobs is at least as high as of those who do not change jobs, we can now turn to the question whether there is a difference in the portability of this wage gain between these groups of workers when they move between regions. This requires estimating the two components described above: wage growth at job mobility and the regional move hazard rate.

First, we compare the immediate payoff of regional mobility of workers with varying prior job mobility. Again, I consider all workers who are observed in full-time employment for at least five years in an origin region o, and are observed moving to a destination region d in the sixth year. During the five-year period, we observe how often the worker has moved between jobs within region o. Using quarterly data, the maximum possible number of job moves in a five-year period is 19. However, job moves are rare, so over 99.8 per cent of workers change jobs fewer than once per year.

We can then compare the payoff of moving to region d of workers of different prior mobility by estimating a regression of the following type:

$$\ln \text{wage}_{i,t,r=d} - \ln \text{wage}_{i,t-1,r=o} = \alpha + \beta_1 \text{jobmoves}_{i,t-1,r=o} + x_{it}'\gamma + \epsilon_{it} \quad (4)$$

The outcome variable is the difference between a worker's first wage in the destination region and their last wage in the origin region. $\text{jobmoves}_{i,t-1,r=o}$ is the

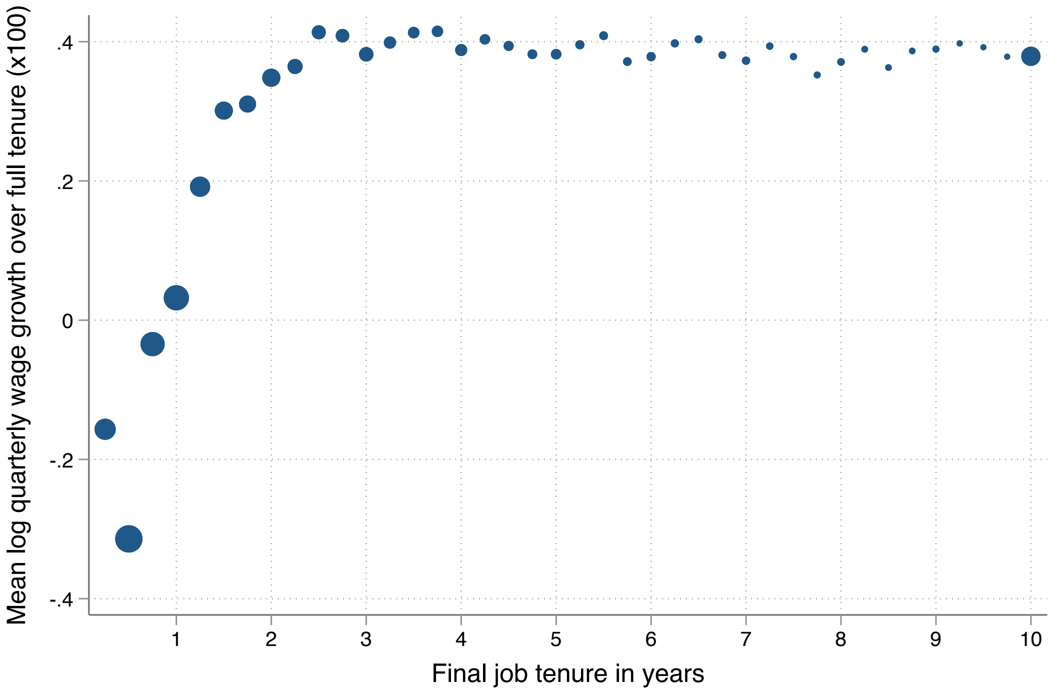

Figure 3. Average within-job wage growth by eventual job tenure duration
Notes: The figure plots the average log quarterly wage growth by eventual job tenure duration. The sample includes all workers in full-time employment between 1995 and 2017, whose tenure is fully observed. The horizontal axis shows the final job tenure duration. Job tenure spells of over 10 years are grouped with those that lasted 10 years. The vertical axis shows the mean quarterly log wage growth over the full tenure period (multiplied by 100, so that values are approximately equivalent to percentage changes). The size of the dots represents the size of each quarter-length tenure duration cell.

count of job moves in the origin region in the five years leading up to the regional move. Part of the wage change at job mobility is likely explained by changes in the job characteristics, such as occupation, industry, or by static differences in wages between regions. The regressions include indices that account for this: These are based on a regression of log wage levels on personal characteristics (age, age-squared, tenure, tenure-squared, education level, and a gender dummy), year fixed effects, and occupation-, industry-, and region- fixed effects. These fixed effects capture the wage level differences in each category. The index is computed as the difference in the fixed effect between the new job's characteristics (occupation/industry) in destination region d and the old job's in origin region o. The occupation- and industry-indices therefore control for any part of the wage change that is explained by changes in the job characteristics. The region index controls for the expected wage-level change between regions. Since we know that wage growth is higher for younger workers, and they are also more mobile between jobs, all regressions include age fixed effects.

Table 5 shows results of regression 4. In column 1, the regression includes categorical terms of prior job mobility. The constant estimates that for workers with no recent prior job mobility in the origin region, a job move across regions is associated with a 3 per cent increase in wages. For workers with prior job mobility, this is higher. They gain an additional two to four percentage points when moving between regions.[7]

In column 2, the specification includes a linear term in prior job mobility instead of categorical terms. In column 3, this linear term is interacted with a binary variable indicating whether the worker moved to a larger region or to a smaller region. The coefficients show that workers with prior job mobility receive a slightly higher wage gain when moving to a larger region than when moving to a smaller region. However, the difference between the two coefficients is not statistically significant.

To assess whether the higher between-region wage growth of more mobile workers is driven by time-invariant personal characteristics, we can estimate regression 5 including worker fixed effects. When estimating this regression, β_1, the additional wage growth associated with a regional move for workers with prior job mobility in comparison to those without prior job mobility, would then only be estimated on the basis of those workers with multiple region moves. Unfortunately, this reduces the sample size significantly, since few workers are observed for multiple full five-year periods in a region and a move to another one. To have enough power for such a regression, we can reduce the cutoff period in origin region o. This increases the sample size significantly. Table 6 shows such results where the sample is restricted to prior 4-year, 3-year, and 2-year periods.

In columns 1 and 2 of Table 6, the sample includes all workers who are observed for a continuous 2-year period in a region o preceding a move to a region d. Apart from the sample and the period in which prior job mobility is measured, the estimation in column 1 is identical to column 2 of Table 5. The estimated regional

[7] It may seem surprising that the wage gain at job mobility within a region reported in Table 3 is higher than the wage gain associated with a geographical move reported in Table 5. Since a worker moving across regions faces moving costs, one might expect regional mobility to be associated with a larger wage gain than a job move within the same region. Upon closer inspection, this is also borne out by the data. The samples and specifications in the two tables mentioned are not directly comparable. In Table 3, the sample includes all workers in full-time employment, whereas the sample in Table 5 is restricted to workers who have stayed in a region for five years. The correct comparison group to the wage gain at the regional move reported in Table 5 would be the same workers' previous within-region job moves. This is shown in Appendix Table B.7. The sample in column 1 includes the five years within a region before a geographical move. The workers' average quarterly within-job wage growth in this time was 0.498 per cent. And their average wage growth when changing the job was 3.681 log points higher, which implies a wage growth of 4.26 percentage points. In column 2, the next period (containing the geographical move), is included. Now the wage gain is estimated to be 0.749 percentage points higher than in the periods before.

Table 5. Wage growth at regional mobility by prior within-region job mobility

	Δ Log wage, quarterly		
	(1)	(2)	(3)
One job move in 5 years	2.071***		
	(0.246)		
Two job moves in 5 years	2.534***		
	(0.399)		
Three+ job moves in 5 years	3.334***		
	(0.646)		
Job mobility, 5-year		1.338***	
		(0.135)	
Job mobility, 5-year × Move to larger region			1.210***
			(0.185)
Job mobility, 5-year × Move to smaller region			1.441***
			(0.176)
Occupation index	12.157***	12.148***	12.150***
	(0.882)	(0.882)	(0.882)
Industry index	27.730***	27.786***	27.774***
	(1.261)	(1.261)	(1.261)
Region index	17.077***	17.101***	17.434***
	(1.095)	(1.095)	(1.162)
Constant	3.022***	3.170***	3.172***
	(0.131)	(0.124)	(0.124)
Age FEs	Yes	Yes	Yes
R^2	0.023	0.023	0.023
Observations	89,208	89,208	89,208

Notes: The table shows results from regression 4. The sample is restricted to workers who have held a full-time job in the same region for at least five years, starting from 1995, and who moved to another region afterwards. The outcome variable in all columns is the log wage change between the last quarter in the origin region and the first quarter in the destination region. The log wage gain is multiplied by 100 so that coefficients are approximately equivalent to percentage point changes. Job mobility is defined as the count of the times a worker has changed their job within the region during the last five years before moving to another region. In column 2, the job mobility coefficient is estimated separately for workers who moved to a larger region and workers who moved to a smaller region. In column 3, the job mobility count in the origin region is estimated non-parametrically. All columns include occupation, industry, and region indices, which capture the expected wage change associated with the move to the new job in the new region. These are based on a regression of log wages on personal characteristics, and occupation, industry, and region fixed effects. Coefficients are reported with robust standard errors in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10% levels.

mobility wage premium is higher for workers with prior job mobility - just as in Table 5. In column 2, the regression includes worker fixed effects. So now, the sample is reduced to only those workers who fulfilled the 2-year residency requirement at least twice, and the job mobility coefficient is estimated only on the basis of the within-person difference in job mobility prior to a regional move. Following a 2-year period within a region, which contained job changes, the wage gain upon moving to a new region is estimated to be higher than following a period with no job changes. So the inclusion of worker fixed effects does not meaningfully change the results.

Columns 3 and 4 repeat the same two regressions where the residency requirement is 3 continuous years. And in columns 5 and 6, the residency requirement is 4 continuous years. The estimates follow the same pattern: the job-mobility coefficients are positive in both the specification with and the specification without worker fixed effects; when controlling for within-worker and time-constant characteristics, the wage growth coefficients are somewhat attenuated. This suggests that worker-specific characteristics such as job-search proficiency may play a role in between-job wage growth. However, it does not explain a large part of the higher between-region wage growth after episodes with job mobility.

The other component of the analysis is the frequency of regional job moves by mobility type. This is straightforward as we can simply compare the region move hazard rates for workers with different local mobility histories. These are shown in Table 7. The region move hazard rate for workers without a job move in the past five years is 0.58 per cent and it is higher for workers with prior job mobility. In column 2, the regression includes age fixed effects. This does not change the pattern. So workers with higher job mobility within a region are also more likely to move between regions. Column 3 includes worker fixed effects and thus controls for time-invariant personal characteristics. This reduces the difference between the hazard rates of workers with different prior job mobility but a significant difference remains. This tells us that while the higher hazard rate is partly explained by unobserved characteristics, it remains higher following a period with more job mobility.

5.3 Implications for portability of wage growth

Tables 5 and 7 show that workers with higher job mobility within a region experience higher wage gains when moving between regions. They are also more mobile between regions.

To interpret this finding, we can apply the framework from section 5.1. It predicts the outcome we find in the case where $\omega > 0$ or $\delta > 0$. Again, $\omega > 0$ means that high-mobility workers draw from a higher-mean wage offer distribution, while $\delta > 0$ means that they draw more frequent job offers. Out of these two scenarios, $\delta > 0$ is the much more plausible one.

While this analysis cannot offer hard evidence for the portability of wage growth, it makes clear that the scenario in which wage growth that workers accrued by moving between jobs reflects location-specific human capital that cannot be transferred when they move between regions is unlikely. Instead, the analysis in section 4 showed that workers make use of the thicker labour market in larger cities by moving between jobs more often, which affords them larger wage gains. This supports the coordination hypothesis which posits that labour markets in larger cities offer more options for workers that land them in better jobs. We already know from previous work (De la Roca and Puga, 2017; Lüttge, 2022) that the experience acquired in larger cities is portable between regions. The analysis in this section shows that the additional wage growth that is obtained via job mobility (that is, coordination) as opposed to via learning on the job is also likely portable between regions. We can conclude that coordination and learning are not competing explanations for higher urban wage growth. Instead, they complement each other.

Table 6. Wage growth at regional mobility by prior job mobility, alternate definitions

	Δ Log wage, quarterly					
	(1)	(2)	(3)	(4)	(5)	(6)
Job mobility, 2-year	1.898***	1.581***				
	(0.136)	(0.320)				
Job mobility, 3-year			1.701***	1.211***		
			(0.134)	(0.360)		
Job mobility, 4-year					1.660***	1.123***
					(0.135)	(0.415)
Occupation index	11.205***	9.027***	11.070***	10.134***	11.806***	12.804***
	(0.488)	(0.969)	(0.559)	(1.288)	(0.638)	(1.691)
Industry index	28.197***	17.346***	27.813***	18.633***	28.110***	20.651***
	(0.721)	(1.454)	(0.828)	(1.912)	(0.946)	(2.483)
Region index	18.007***	13.726***	17.919***	13.171***	17.384***	12.813***
	(0.710)	(1.322)	(0.817)	(1.733)	(0.933)	(2.250)
Constant	4.656***	3.905***	4.069***	3.351***	3.576***	2.838***
	(0.081)	(0.141)	(0.095)	(0.187)	(0.110)	(0.242)
Worker FEs	No	Yes	No	Yes	No	Yes
Age FEs	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.026	0.428	0.024	0.451	0.024	0.469
Observations	176,383	76,718	137,800	48,439	110,396	31,088

Notes: The table shows results from regression 4. The sample is restricted to workers who have held a full-time job in the same region for at least 2 years (columns 1 and 2), at least 3 years (columns 3 and 4), or at least 4 years (columns 5 and 6), starting from 1995, and who moved to another region afterwards. The outcome variable in all columns is the log wage change between the last quarter in the origin region and the first quarter in the destination region. The log wage gain is multiplied by 100 so that coefficients are approximately equivalent to percentage point changes. Job mobility is defined as the count of the times a worker has changed their job within the region during the last five years before moving to another region. In columns 2, 4, and 6, the regressions include worker fixed effects. As a result, the sample is reduced to workers moving between regions at least twice after satisfying the residence requirement of 2, 3 or 4 years. All columns include occupation, industry, and region indices, which capture the expected wage change associated with the move to the new job in the new region. These are based on a regression of log wages on personal characteristics, and occupation, industry, and region fixed effects. Coefficients are reported with robust standard errors in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10% levels.

Table 7. Region mobility hazard rate by job mobility

	Region move hazard		
	(1)	(2)	(3)
One job move in 5 years	0.415***	0.343***	0.217***
	(0.007)	(0.007)	(0.007)
Two job moves in 5 years	0.631***	0.535***	0.290***
	(0.014)	(0.014)	(0.012)
Three+ job moves in 5 years	0.455***	0.465***	0.248***
	(0.006)	(0.007)	(0.007)
Constant	0.580***	0.588***	0.630***
	(0.002)	(0.002)	(0.002)
Age FEs	No	Yes	Yes
Worker FEs	No	No	Yes
R^2	0.0006	0.0018	0.0723
Observations	20,549,830	20,549,830	20,528,568

Notes: The table shows the regional mobility hazard rate by past job mobility within a region. In a linear probability model, a worker's regional mobility in the next quarter is regressed on indicators of the worker's prior job mobility within the region in the past five years. In column 1, the regression includes no fixed effects. In column 2, age fixed effects are included. In column 3, age and worker fixed effects are included. The sample includes all workers who held a full-time job for at least five years in a region. The constant of 0.58 indicates that out of all workers who held a full-time job in a region for five years or more and have not changed their job in the past five years, 0.58 per cent move to another region in the next quarter. Coefficients are reported with robust standard errors in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10% levels.

6 Conclusion

This paper has documented the important role of job mobility for personal wage growth, and its contribution to the difference in wage profiles in different regions. The higher wage growth in more densely populated regions is mostly driven by higher wage growth within jobs, but higher between-job wage growth also plays a role. This, in turn, is driven by the combination of higher job mobility and a higher wage gain at job mobility.

The finding of higher job mobility in larger regions points to workers making use of thicker regional labour markets by finding a better-matching job over time. The wage gain that results from this process is stable and does not disappear after workers have moved to other regions. This suggests that job mobility can help human capital accumulation. Labour market coordination is therefore not an alternative explanation for the presence of dynamic urban wage premia but is rather one of the channels through which greater learning in concentrated labour markets occurs.

Bibliography

Andersson, Martin and Per Thulin, "Does Spatial Employment Density Spur Inter-Firm Job Switching?," *The Annals of Regional Science*, August 2013, *51* (1), 245–272.

Antoni, Manfred, Philipp vom Berge, and Andreas Ganzer, "Factually Anonymous Version of the Sample of Integrated Labour Market Biographies (SIAB-Regionalfile) – Version 7517 V1," Technical Report, Research Data Centre of the Federal Employment Agency (BA) at the Institute for Employment Research (IAB) 2019.

Bartel, Ann and George Borjas, "Wage Growth and Job Turnover: An Empirical Analysis," in Sherwin Rosen, ed., *Studies in Labor Markets*, Chicago: University of Chicago Press, 1981.

Baum-Snow, Nathaniel and Ronni Pavan, "Understanding the City Size Wage Gap," *The Review of Economic Studies*, January 2012, *79* (1), 88–127.

Bleakley, Hoyt and Jeffrey Lin, "Thick-Market Effects and Churning in the Labor Market: Evidence from US Cities," *Journal of Urban Economics*, September 2012, *72* (2-3), 87–103.

Borjas, George J., "Job Mobility and Earnings over the Life Cycle," *Industrial and Labor Relations Review*, 1981, *34* (3), 365–376.

Card, David, Jörg Heining, and Patrick Kline, "Workplace Heterogeneity and the Rise of West German Wage Inequality," *The Quarterly Journal of Economics*, 2013, *128* (3), 240–266.

Combes, Pierre-Philippe, Gilles Duranton, and Laurent Gobillon, "Spatial Wage Disparities: Sorting Matters!," *Journal of Urban Economics*, March 2008, *63* (2), 723–742.

_ , _ , _ , Diego Puga, and Sébastien Roux, "The Productivity Advantages of Large Cities: Distinguishing Agglomeration From Firm Selection," *Econometrica*, 2012, *80* (6), 2543–2594.

Dauth, Wolfgang, Sebastian Findeisen, Enrico Moretti, and Jens Suedekum, "Matching in Cities," *Journal of the European Economic Association*, 2022, pp. 1–44.

De la Roca, Jorge and Diego Puga, "Learning by Working in Big Cities," *The Review of Economic Studies*, January 2017, *84* (1), 106–142.

Di Addario, Sabrina, "Job Search in Thick Markets," *Journal of Urban Economics*, May 2011, *69* (3), 303–318.

Duranton, Giles and Diego Puga, "Micro-Foundations of Urban Agglomeration Economies," in J. Vernon Henderson and Jacques-Francois Thisse, eds., *Handbook of Regional and Urban Economics*, Vol. 4, Elsevier, 2004, pp. 2063–2117.

Dustmann, Christian and Costas Meghir, "Wages, Experience and Seniority," *Review of Economic Studies*, 2005, *72*, 77–108.

_ **and Sonia C Pereira**, "Wage Growth and Job Mobility in the United Kingdom and Germany," *Industrial & Labor Relations Review*, 2008, *61* (3), 374–393.

_ **, Johannes Ludsteck, and Uta Schönberg**, "Revisiting the German Wage Structure," *The Quarterly Journal of Economics*, 2009, *124* (2), 843–881.

GEOSTAT, Eurostat, "GEOSTAT 2006 Grid Dataset," https://ec.europa.eu/eurostat/web/gisco/ geodata/reference-data/population-distribution-demography/geostat 2006.

Glaeser, Edward L., "Learning in Cities," *Journal of Urban Economics*, 1999, (46), 254–277.

_ , *Triumph of the City: How Our Greatest Invention Makes Us Richer, Smarter, Greener, Healthier, and Happier*, New York: Penguin Books, 2012.

_ **and David C. Maré**, "Cities and Skills," *Journal of Labor Economics*, April 2001, *19* (2), 316–342.

_ **and Matthew G. Resseger**, "The Complementarity between Cities and Skills," *Journal of Regional Science*, February 2010, *50* (1), 221–244.

Groes, F., P. Kircher, and I. Manovskii, "The U-Shapes of Occupational Mobility," *The Review of Economic Studies*, April 2015, *82* (2), 659–692.

Grujovic, Anja, "Tasks, Cities and Urban Wage Premia," 2020.

Henderson, J.Vernon, "Marshall's Scale Economies," *Journal of Urban Economics*, January 2003, *53* (1), 1–28.

Lazear, Edward, "Age, Experience and Wage Growth," *The American Economic Review*, 1976, *66* (4), 548–558.

Loprest, Pamela J., "Gender Differences in Wage Growth and Job Mobility," *The American Economic Review, Papers and Proceedings of the Hundred and Fourth Annual Meeting of the American Economic Association*, 1992, *82* (2), 526–532.

Lüttge, Julius, "Urban Wage Premia and Heterogeneous Sorting," 2022.

Manning, Alan and Joanna Swaffield, "The Gender Gap in Early-Career Wage Growth," *The Economic Journal*, July 2008, *118* (530), 983–1024.

Moretti, Enrico, "Local Labor Markets," in Orley Ashenfelter and David Card, eds., *Handbook of Labor Economics*, Vol. 4b, Elsevier, 2011, pp. 1237–1313.

Petrongolo, Barbara and Christopher Pissarides, "Scale Effects in Markets with Search," *The Economic Journal*, January 2006, *116* (508), 21–44.

— **and Maddalena Ronchi**, "Gender Gaps and the Structure of Local Labor Markets," *Labour Economics*, June 2020, *64*, 101819.

Rubinstein, Yona and Yoram Weiss, "Post Schooling Wage Growth: Investment, Search and Learning," in Eric A. Hanushek and Finis Welch, eds., *Handbook of the Economics of Education*, Vol. 1, Elsevier, 2006, pp. 1–67.

Topel, Robert H. and Michael P. Ward, "Job Mobility and the Careers of Young Men," *The Quarterly Journal of Economics*, May 1992, *107* (2), 439–479.

Yankow, Jeffrey J., "Why Do Cities Pay More? An Empirical Examination of Some Competing Theories of the Urban Wage Premium," *Journal of Urban Economics*, September 2006, *60* (2), 139–161.

— , "Some Empirical Evidence of the Efficacy of Job Matching in Urban Labor Markets," *International Advances in Economic Research*, May 2009, *15* (2), 233–244.

B Appendix

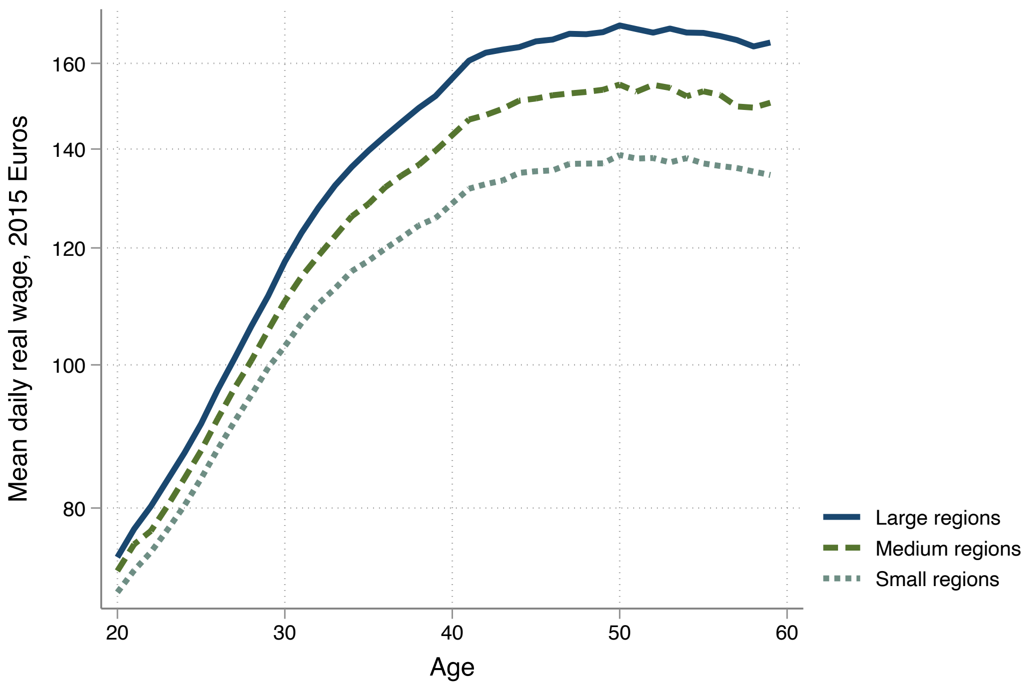

Figure B.1. Average wages by age and region size, composition-adjusted
Notes: Composition-adjusted mean daily wages by age and region size, shown on a log scale. Large regions: densest regions that contain 25% of workers. Medium regions: next densest regions that contain next 25% of workers. Small regions: remaining regions that contain remaining 50% of workers. The share of workers in each education-industry-occupation-gender cell is held constant across regions

Table B.1. Summary statistics: non-region-movers

	Mean
Age	40.72
Education: % vocational training	76.42
Education: % university degree	14.30
% female	28.39
Δ Log wage, year-on-year	1.15
Δ Log wage, annual, within same job	1.06
Δ Log wage, annual, between jobs	0.08
Job mobility rate, quarterly, in %	3.62
Job mobility rate, annual, in %	8.38
Δ Log wage, quarterly	0.23
Δ Log wage, quarterly, conditional on job move	7.03
Observations	4,392,614

Notes: Summary statistics for workers who did not move between regions in the past year. Data are from the 2nd quarter of each year. Wage changes are shown in log points $\times$ 100. That is, a 1.14 log point wage change corresponds to approximately 1.14 per cent wage growth. Mobility rates are shown in per cent.

Table B.2. Summary statistics: workers under 40

	Mean
Age	31.25
Education: % vocational training	76.71
Education: % university degree	14.35
% female	29.34
Δ Log wage, year-on-year	2.32
Δ Log wage, annual, within same job	1.95
Δ Log wage, annual, between jobs	0.37
Job mobility rate, quarterly, in %	6.00
Job mobility rate, annual, in %	12.76
Δ Log wage, quarterly	0.35
Δ Log wage, quarterly, conditional on job move	8.48
Observations	2,203,391

Notes: Summary statistics for workers under 40. Data are from the 2nd quarter of each year. Wage changes are shown in log points $\times$ 100. That is, a 2.32 log point wage change corresponds to approximately 2.3 per cent wage growth. Mobility rates are shown in per cent.

Table B.3. Wage growth components: no controls but with year FEs

	(1)	(2)	(3)	(4)	(5)
	Δ Log wage, year-on -year	Δ Log wage, within job	Δ Log wage, between jobs	Job mobility hazard rate	Δ Log wage, quarterly
Log region size	0.214***	0.156***	0.055***	1.075***	0.009***
	(0.019)	(0.017)	(0.012)	(0.063)	(0.002)
Job move × Log region size					0.441***
					(0.113)
Job move					6.984***
					(0.129)
Year FEs	Yes	Yes	Yes	Yes	Yes
Mean dep. var	1.195	1.093	0.096	8.842	0.244
R^2	0.013	0.019	0.002	0.014	0.034
Observations	3,942,396	3,939,307	3,936,833	4,437,049	4,103,737

Notes: This table shows results from regressions based on specification 1 (columns 1 to 4) and 3 (column 5). All regressions include a constant and a year fixed effect. The sample is restricted to workers in full-time employment on 15 April in each year. Log region size is defined as the number of residents within 10 km of the average resident. Job move is a binary variable indicating whether a worker has changed job in the past quarter. The outcome variable in column 1 is the change in log wage to the previous year. The outcome variable in column 2 is the change in log wage to the previous year that occurred within the same job, computed on quarterly wage growth episodes. The outcome variable in column 3 is the change in log wage to the previous year that occurred between jobs, computed on quarterly wage growth episodes. The outcome variable in column 4 is a binary variable indicating whether a worker has changed their job between 15 January and 15 April of the year. The outcome variable in column 5 is the log wage growth between those two dates. Coefficients are reported with standard errors in parentheses, clustered at the region level. ***, **, and * indicate statistical significance at the 1, 5, and 10% levels.

Table B.4. Wage growth components: no controls but with year FEs, workers under age 40

	(1) Δ Log wage, year-on -year	(2) Δ Log wage, within job	(3) Δ Log wage, between jobs	(4) Job mobility hazard rate	(5) Δ Log wage, quarterly
Log region size	0.397***	0.278***	0.115***	1.409***	0.013***
	(0.028)	(0.024)	(0.016)	(0.081)	(0.003)
Job move × Log region size					0.502***
					(0.143)
Job move					8.301***
					(0.157)
Year FEs	Yes	Yes	Yes	Yes	Yes
Mean dep. var	2.323	1.949	0.367	11.455	0.345
R^2	0.010	0.015	0.002	0.009	0.052
Observations	1,998,107	1,996,804	1,995,362	2,144,282	2,084,598

Notes: This table shows results from regressions based on specification 1 (columns 1 to 4) and 3 (column 5). All regressions include a constant and a year fixed effect. The sample is restricted to workers under age 40 in full-time employment on 15 April in each year. Log region size is defined as the number of residents within 10 km of the average resident. Job move is a binary variable indicating whether a worker has changed job in the past quarter. The outcome variable in column 1 is the change in log wage to the previous year. The outcome variable in column 2 is the change in log wage to the previous year that occurred within the same job, computed on quarterly wage growth episodes. The outcome variable in column 3 is the change in log wage to the previous year that occurred between jobs, computed on quarterly wage growth episodes. The outcome variable in column 4 is a binary variable indicating whether a worker has changed their job between 15 January and 15 April of the year. The outcome variable in column 5 is the log wage growth between those two dates. Coefficients are reported with standard errors in parentheses, clustered at the region level. ***, **, and * indicate statistical significance at the 1, 5, and 10% levels.

Table B.5. Urban wage premia

	Log real wage			
	(1)	(2)	(3)	(4)
Log region size	0.0996***	0.0640***	0.0322***	0.0348***
	(0.0071)	(0.0041)	(0.0027)	(0.0022)
Age		0.0454***		
		(0.0009)		
Age^2		-0.0005***		-0.0004***
		(0.0000)		(0.0000)
Secondary education		0.1745***		-0.0089
		(0.0041)		(0.0060)
University education		0.6173***		0.2196***
		(0.0071)		(0.0106)
Occ: Production		0.1262***		0.0425***
		(0.0049)		(0.0042)
Occ: Cognitive/interactive		0.2915***		0.1082***
		(0.0065)		(0.0038)
Year × Quarter FEs	Yes	Yes	Yes	Yes
Industry FEs		Yes		Yes
Worker FEs			Yes	Yes
Mean Log wage	4.613	4.613	4.613	4.613
R^2	0.089	0.395	0.810	0.821
Observations	3,689,532	3,689,532	3,685,663	3,685,663

Notes: This table shows results from a wage regression including mean-zero region size. All regressions include time fixed effects. Column 1 shows that raw wages are on average 10 per cent higher in a region that is twice as large as a comparison region. Column 2 includes controls, which reduce the urban wage premium to ca. 6.5 per cent. Columns 3 and 4 include workers fixed effects. Coefficients are reported with standard errors in parentheses, clustered at the region level. ***, **, and * indicate statistical significance at the 1, 5, and 10% levels.

Table B.6. Average wage growth by job mobility (linear)

	(1) Mean Δ Log wage, within job	(2) Mean Δ Log wage, between jobs	(3) Mean Δ Log wage, total
Job mobility, 5-year	-0.131***	0.579***	0.048***
	(0.019)	(0.195)	(0.016)
Constant	0.539***	3.462***	0.521***
	(0.009)	(0.397)	(0.009)
R^2	0.001	0.000	0.000
Observations	89,208	17,986	89,208

Notes: The table shows results from a regression of different types of wage growth on a linear job mobility counter and a constant. The sample is restricted to workers who have held a full-time job in the same region for at least five years, starting from 1995, and who moved to another region afterwards. The outcome variable in column 1 is a worker's mean quarterly log wage growth in periods without a job change, computed over a worker's last five years in a region. The outcome variable in column 2 is a worker's mean quarterly log wage growth in periods with a job change, computed over their last five years in a region. The outcome variable in column 3 is a worker's total mean quarterly log wage growth over all periods, computed over their last five years in a region. Log changes are multiplied by 100 so that coefficients are approximately equivalent to percentage point changes. Job mobility is a count of the times a worker has changed their job within the region during the last five years before moving to another region. Coefficients are reported with robust standard errors in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10% levels.

Table B.7. Within-region wage growth and job changes, restricted sample

	Δ Log wage, quarterly	
	(1)	(2)
Job move	3.681***	3.179***
	(0.084)	(0.076)
Region move		0.746***
		(0.080)
Occupation index	8.968***	11.597***
	(0.361)	(0.249)
Industry index	23.449***	28.092***
	(0.836)	(0.410)
Region index		17.184***
		(0.455)
Constant	0.497***	0.469***
	(0.010)	(0.011)
R^2	0.007	0.013
Observations	1,538,031	1,603,871

Notes: The table shows results from a regression of quarterly wage growth a constant and dummies indicating a job move and a region move. The sample is restricted to the workers included in Table 5 (in full-time employment in the same region for five years before a move to a new region). In column 1, the sample includes the five years prior to the region move in which workers did not move between regions. In column 2, the sample also includes the region move each workers undertook following those five years. The outcome variable in column is a worker's quarterly log wage growth. Log changes are multiplied by 100 so that coefficients are approximately equivalent to percentage point changes. The occupation, industry, and region indices capture the expected wage change associated with a move to a new job. These are based on a regression of log wages on personal characteristics, and occupation, industry, and region fixed effects. Coefficients are reported with robust standard errors in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10% levels.