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Cities and assortative matching dynamics over worker careers*

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Abstract

Superior employment matching is considered a key source of agglomeration economies, yet little is known about how urban scale affects matching over workers' careers. Using full-count Norwegian registry data from 1995-2019, we estimate two-way worker and plant fixed effects to construct a worker-level measure of assortative matching. We find that job matches are more assortative in cities and that city workers progress more rapidly toward increasingly better matches over the career. These gains are concentrated among high-ability workers, while low-ability workers become increasingly mismatched in cities. For migrants, assortative matching initially declines following relocation but improves with subsequent job transitions.

Keywords: Assortative matching, agglomeration economies, career progression, wage decomposition, skills, mobility, AKM-estimation

JEL: J24, J31, J61, R23

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1 Introduction

Better employment matching has been promoted as a driver of higher productivity in cities and is considered a source of agglomeration economies. This is an active area of research, with the recent literature providing evidence of superior assortative matching in urban areas (Dauth et al., 2022), particularly for highly educated workers (Leknes et al., 2022). Yet, there is no evidence on the dynamics of assortative matching over worker careers in labor markets of different sizes. Are urban matching advantages fairly distributed across careers, or are they diminished or exacerbated with successive employment matches? And what can such dynamics tell us about the functioning of heterogeneous local labor markets?

This paper provides the first evidence on how assortative matching between heterogeneous workers and firms evolves over the career in thick versus thin labor markets, how these trajectories differ by skill level, and how migration between these markets reshapes career paths. Leveraging recent advances in the measurement of assortative matching and full-count longitudinal register data, we analyze worker-firm matching at a detailed and dynamic level.

Using predicted worker and plant fixed effects estimated through the AKM model, we construct our worker-level measure of assortative matching. We build on the measure proposed by Braunschweig et al. (2024), the absolute rank distance between worker and plant fixed effects, expressed in relative terms to ease interpretation of changes in rank distance over the career. The Norwegian register data allow us to track a large number of workers' career paths and to examine heterogeneity with respect to ability and sorting behavior. Our dynamic estimates exploit within-worker changes in assortative matching across successive job spells to handle sorting and, for the smaller sample of migrants, cross-sectional variation across workers and locations.

Our analysis yields several novel findings. We begin by documenting descriptive patterns in assortative matching over the career. Job mobility is associated with improved alignment between worker and plant quality in both city and non-city areas. However, city workers progress more rapidly to better matches. We then turn to regression-based estimates that control for worker sorting by including worker fixed effects. These estimates reveal an urban advantage in assortative matching that is stable early in the career, around 0.5 percentage points lower rank distance for the first three matches, but widens later on, reaching 2 percentage points by the eighth match. City workers improve their rank distance by 11 percent from the first to the eighth job, compared to a 6 percent improvement among non-city workers.

We also uncover meaningful skill-based heterogeneity in these patterns. High-skilled workers (defined as those in the top quartile of the worker fixed effects distribution) tend to follow an upward matching trajectory and benefit more from thicker labor markets, already from their first transition. In contrast, low-skilled workers (those in the bottom quartile) follow a downward trajectory, which is more pronounced in cities. In a separate analysis of migrating workers, who are found to be positively selected, we observe an initial negative shift in degree of assortative matching following relocation. This drop is subsequently offset by gradual improvements through job transitions, particularly in urban areas. The initial decline resembles the hierarchy effect identified by Card et al. (2025), whereby positively selected migrants move from firms high in the productive hierarchy in the origin area to firms lower in the hierarchy in the destination area. We also find that return migrants, workers that move to cities and subsequently return back (to lower wage areas), are positively selected relative to city movers and exhibit a flatter assortative matching trajectory. Although return decisions may reflect limited gains from assortative matching in cities, the pattern also suggests that non-pecuniary factors may play a role in motivating return migration.

Conceptually, we study dynamic assortative matching between heterogeneous workers and firms in spatially segmented labor markets with search frictions. Our central mechanism is that thicker labor markets reduce search frictions and expand the support of potential firm types, which allows workers, especially high-ability workers, to climb job ladders more rapidly and achieve increasingly assortative matches over time. The modern literature on assortative matching builds on Becker (1973), who introduces sorting driven by complementarities in two-sided markets. Shimer and Smith (2000) extends assignment models with complementarities to a frictional labor market. Subsequent work develops these ideas theoretically and quantitatively, for example in Eeckhout and Kircher (2011) and Lise et al. (2016). From the worker's perspective, match quality is uncertain ex ante and must be experienced to be evaluated (Jovanovic, 1979). Through search and experimentation, workers learn about their own abilities and preferences and gradually converge toward better matches over time (Topel & Ward, 1992). This process is also captured in job-ladder models, in which workers engage in on-the-job search and move to positions offering higher wages (Christensen et al., 2005).

Frictions in the matching process also arise on the employer side. Firms often lack complete information about prospective employees' competencies, particularly in the case of first-time hires. This information asymmetry is underscored by Dustmann et al. (2015), who show that referral-based hires are initially better matched, but that match quality converges with tenure. Supporting this broader narrative, Braunschweig et al. (2024) provide recent empirical evidence of dynamic assortative matching within a single labor market, showing that matches tend to improve over the course of workers' careers. These findings are in line with cross-country evidence linking labor market mobility to life-cycle wage growth (Engbom, 2022). While their analysis is confined to one labor market, we show that dynamic matching patterns differ systematically across labor markets of different sizes and interact with workers' migration decisions. Importantly, access to job opportunities depends on the size of the local labor market. Rural workers face a limited set of potential employers, while urban workers benefit from a richer distribution of potential employers and lower search frictions, which allows them to re-match more frequently, obtain better expected matches, and climb steeper job ladders.[1] Empirical evidence of superior matching in urban labor markets (Dauth et al., 2022; Leknes et al., 2022) reinforces this view and supports the notion of dynamic agglomeration effects, particularly for high-ability workers (Carlsen et al., 2016; De la Roca & Puga, 2017).

Selection of high-performing individuals into thicker labor markets is a well-known empirical observation (Combes et al., 2008), and the standard approach is to introduce worker fixed effects to absorb unobserved

[1] See for instance Helsley and Strange (1990), Berliant et al. (2006), and Sato (2001) for theorethical models addressing matching in cities.

ability. Relocation decisions are shaped by expected costs as well as expected returns. Non-negligible migration costs may affect incidence and timing of relocation, worker sorting, and wages (Diamond, 2016; Kennan & Walker, 2011). These frictions imply that observed migration decisions are highly selective, with implications for post-move matching trajectories, which we examine in our analysis of movers.

The paper is organized as follows. Section 2 describes the data used in the analysis and outlines the estimation strategies, including the AKM estimations. Section 3 presents the main findings on assortative matching throughout the career in city and non-city areas, while heterogeneous effects across skill levels are addressed in Section 4. Section 5 explores the relationship between migration and assortative matching dynamics. Concluding remarks are given in Section 6.

2 Data and Empirical Strategy

2.1 Initial dataset

This section describes the construction of the initial dataset, which forms the first step toward our final analytical sample. We use the employment, tax, and education registers to construct a dataset comprising all Norwegian workers observed from 1995 to 2019. The dataset links workers to plants, allowing us to identify distinct job spells for each worker. It includes a measure of daily wages and a range of worker characteristics, such as age, gender, level of education, immigrant status, years of experience, contract type, industry affiliation, plant affiliation, plant size, and municipality of residence.

Given the lack of more detailed wage data, we restrict the analysis to full-time workers of prime working age, defined as those aged 20-65. We exclude public sector contracts, as the wages of public sector employees are largely determined by national regulations and collective agreements. In addition, public sector compensation often reflects factors beyond productivity, including job security, working conditions, and policies aimed at promoting equality across population groups and regions.[2] Furthermore, we focus on male workers, as full-time female workers in the private sector represent a highly selective group.

To operationalize urban scale, we combine information on economic region classifications, population size, and commuting patterns to construct functional local labor markets. Based on the population size distribution and the standard classification of large cities in Norway, we define the four largest metropolitan areas as cities.[3] Using information on municipality of residence, we classify workers as city residents if they live within these metropolitan areas. Migration between city and non-city areas over the observation period is allowed.

[2]While we exclude spells in the public sector, we retain the original spell sequence, such that private-sector spells reflect their true position in workers' careers.

[3]These metropolitan areas are Oslo, Bergen, Trondheim, and Stavanger. Further details on the construction of functional labor markets and the definition of urban scale are provided in Online Appendix X.

2.2 AKM estimation

As a next step, we estimate the wage components attributable to the worker and plant using the AKM model introduced by Abowd et al. (1999). These estimates provide the foundation for constructing our measures of assortative matching. We assume that the log of daily wages of individual i is generated from a model of the form:

$$y_{it} = \alpha_i + \theta_{j(i,t)} + X_{it}\beta + \epsilon_{it} \tag{1}$$

Here, y_{it} denotes the log daily wage for worker i in year t. The fully portable worker fixed effect, α_i, capture the time-invariant earnings capacity of worker i, while θ_j is a plant fixed effects capturing the wage premium paid by plant j to all its workers.[4] The time-invariant worker and plant heterogeneity serve as our measures of worker and plant quality. The vector of time-variant characteristics X_{it} includes education-specific cubic age profiles (quadratic and cubic age terms interacted with dummies for three levels of education) and year dummies, and β is the corresponding vector of parameters. The error term ϵ_{it} captures all other unobserved wage components.

The validity of Equation (1) rests on the exogenous mobility assumption, which requires that worker mobility is uncorrelated with time-varying factors not captured by the model. To assess the plausibility of this assumption, Card et al. (2013) propose an event-study analysis of wage changes experienced by workers who move between plants of different quality. We follow their diagnostic approach by grouping plants into quartiles based on the average wages of coworkers. Consistent with earlier findings, workers who move to plants with higher-paid coworkers experience a wage increase, while those moving in the opposite direction experience wage declines. In contrast, wage changes are small for workers moving between plants of similar quality. Moreover, wage profiles are relatively stable both before and after the job change, providing suggestive support for the exogenous mobility assumption.

While widely used, the additive formulation of the AKM-model has been questioned, notably by Eeckhout and Kircher (2011), Lise and Robin (2017), and Lopes de Melo (2018). However, Macis and Schivardi (2016), Bonhomme et al. (2019) and Card et al. (2013) provide empirical support for the additive structure of the AKM-model using data from Italy, Sweden and West-Germany, respectively. For Norway, Leknes et al. (2022) show that the AKM-model offers a good approximation of the wage structure. Comparing the AKM-model with a match effect model, they find only modest gains in fit when using the model with match-specific heterogeneity. Following the suggestion of Card et al. (2013), we test the additive specification by studying the mean residuals across 100 cells defined by worker and plant deciles from Equation (1). The plot of mean residuals show no evidence that the AKM model systematically over- or underestimate the daily wages of workers at plants of different qualities.

Abowd et al. (1999) note that plant effects in this two-way fixed effects model are identified only within connected sets formed through worker mobility across plants. In our data, the largest connected set contains 99.8 percent of valid worker-year observations in the initial dataset. Mean worker and plant characteristics are nearly identical between the full sample and the largest connected set, reflecting the

[4] In the analysis, we estimate plant fixed effects, but use the terms *plant* and *firm* interchangeably throughout the paper.

long panel structure of the data and substantial degree of worker mobility over time. Restricting the analysis to the largest connected set yields a sample of about 18.9 million observations, 1.5 million workers, and 260,000 plants.[5]

Andrews et al. (2008) discuss the issue of limited mobility bias and show that low worker mobility can generate a downward bias in the estimated correlation between worker and firm fixed effects. The long panel dimension of our data helps mitigate such concerns. In our sample, the average plant is involved in nearly 23 job switches, suggesting a high degree of worker mobility. Nonetheless, we conduct robustness checks to further assess limited mobility concerns by excluding plants with few workers, as in Leknes et al. (2022).

2.3 Analytical sample

To maintain the highest possible level of worker mobility between plants, we estimate worker and plant fixed effects using the largest connected dataset. However, for the main analysis, we focus on workers whose employment histories are not left-censored, allowing us to observe their career trajectories from their first job onward. To approximate each individual's labor market entry, we apply education-specific cohort thresholds. For workers with primary and secondary education, we include only those born in 1973 or later, ensuring they were no older than 22 years in 1995, the first year of our observation window. For those with short college education (up to four years), the birth year threshold is set to 1969 (maximum age 26 in 1995), and for those with long college education (more than four years), we restrict to those born in 1966 or later (maximum age 29 in 1995).

These restrictions result in an analytical dataset comprising about 7 million worker-year observations. After collapsing the data to unique worker-plant pairs (by spell), and retaining the first eight job matches due to the small sample sizes at the highest job numbers, we obtain just over 2.1 million observations, 709,420 workers, and 189,963 plants.[6] While 22 percent of workers remain with the same employer throughout the period, 24 percent have two job spells, 18 percent have three, and 13 percent have four. The remaining 23 percent of workers have more than four job spells. On average, workers in our analytical sample experience 3.2 job spells. Labor turnover is remarkably similar in city and non-city areas. At each job spell, the probability of transitioning to a new spell is essentially unrelated to the size of the labor market in which the worker is employed. The years of experience accumulated within a spell are also comparable across city and non-city areas, indicating that spell durations are broadly similar.

Table 1 presents the mean worker and plant fixed effects by job number and place of residence. For each job spell, the average quality of workers and plants, measured by their respective fixed effects, is higher in cities than in non-city areas, indicating positive selection into urban labor markets. A second notable pattern is that both workers and plants involved in higher-order job transitions tend to have higher fixed effects than those in lower-order transitions. Additional descriptive statistics are reported in the Online

[5]Online Appendix Y reports descriptive statistics for both the full sample and the largest connected set (Table Y.1), along with other diagnostics of the AKM approach described in the text above (Figures Y.1 - Y.3).

[6]About 12 percent of workers have a gap in their spell sequence. These gaps are due to periods of public sector employment or employment at plants that are not part of the largest connected set.

Appendix.[7] In higher-order transitions, workers are more likely to be college-educated and less likely to be immigrants. The industry composition also shifts along the job ladder, with an increasing share of employment in service sectors and a corresponding decline in manufacturing. The worker heterogeneity across job spells and areas motivates our empirical specifications.

Geographic mobility is common in the sample. City stayers make up 38 percent of workers, while non-city stayers and movers account for 48 percent and 14 percent, respectively. Compared to non-city stayers, both city stayers and movers are more likely to be college-educated and employed in the service sector. On average, city and non-city stayers experience about three job spells, whereas movers have roughly 4.5 job spells. Movers also exhibit higher unobserved ability, as measured by estimated worker fixed effects, than either group of stayers. These patterns motivate a separate analysis of sorting and matching among migrating workers to better understand the spatial and dynamic aspects of assortative matching.

Table 1: Estimated worker and plant FEs by job number and area

Job	Mean worker FE		Mean plant FE	
number	City	Non-city	City	Non-city
1	-0.235	-0.277	-0.018	-0.047
2	-0.093	-0.151	0.017	-0.029
3	0.099	0.029	0.046	-0.013
4	0.262	0.185	0.064	-0.003
5	0.393	0.314	0.075	0.004
6	0.497	0.415	0.079	0.009
7	0.574	0.495	0.083	0.011
8	0.637	0.558	0.079	0.011
Total	0.039	-0.049	0.028	-0.024

Notes: The table reports predicted worker and plant fixed effects from Equation (1) for each job spell, shown separately for city and non-city areas. Individuals are classified as city or non-city workers based on their resident location during the corresponding job spell. Mean plant fixed effects are calculated as the average across workers residing in city or non-city areas in that job spell.

2.4 Measuring assortative matching

We build on a rank-based measure of assortative matching proposed by Braunschweig et al. (2024). The measure is constructed in three steps. First, to ensure comparability of match quality across locations, particularly important in a setting with worker mobility, we rank all workers and plants according to their estimated fixed effects and assign them to 5,000 equally sized bins.[8] In our sample, each bin contains 141-142 workers and 37-38 plants, with the highest-quality workers and plants assigned to bin 5,000. Second, for each worker-plant pair, we compute the absolute rank distance between the worker's and the plant's rank. Finally, to facilitate interpretation, we scale the absolute rank distance by the total number

[7] Figure X.1 illustrates the distribution of workers across job spells, while Table X.1 reports the distribution of workers and plants across city and non-city areas. Table X.2 displays the spell-progress ratios separately for city and non-city areas. Observed characteristics are presented in Table X.3, with additional descriptives for movers and stayers provided in Table X.4.

[8] This avoids mechanical differences in measured matching efficiency that could arise from labor-market-specific dispersion in worker and firm types correlated with market size.

of bins:

$$d_{io} = \frac{|r_i - r_j|}{B} \tag{2}$$

where d_{io} represents the degree of assortative matching for individual i in job spell o. The rank of the worker's fixed effect is r_i, while r_j is the rank of the plant's fixed effect, and B is the number of bins. A smaller rank distance indicates a closer alignment between worker and firm quality, and therefore a more assortative match. The location of each worker-plant pair corresponds to the worker's place of residence.

The rank-based measure provides an estimate of assortative matching at the individual level and enables us to track how matching patterns evolve over successive job transitions for the workers. Relative to measures that rely on the correlation between worker and firm fixed effects in a region (e.g., see applications of Dauth et al. (2022) and Leknes et al. (2022)), the rank-distance measure offers two advantages. First, it is less sensitive to limited mobility bias, as it relies on the relative ranking of worker and firm fixed effects instead of second-moment statistics. Second, because the measure is defined at the individual level, it allows us to account for changes in the composition of workers and plants across job spells and areas.

Our first specification estimates how the city-non-city differences in assortative matching evolve linearly across job spells:

$$d_{io} = \beta_0 + \beta_1 City_{io} + \beta_2 JobSpell_{io} + \beta_3 City_{io} \times JobSpell_{io} + X_{io}\delta + \alpha_i + \epsilon_{io} \tag{3}$$

where $City_{io}$ is a binary indicator for city residency, and $JobSpell_{io}$ is a count variable indexing the job spell (up to the eighth spell). The interaction term ($City_{io} \times JobSpell_{io}$) captures whether the evolution of assortative matching over job spells differs between city and non-city areas. The vector X_{io} contains controls for compositional differences, including education level, plant size, immigrant status, and 2-digit industry fixed effects. The error term is represented by ϵ_{io}. Possible values of the rank distance measure depend on a worker's position in the worker fixed effect distribution. At both ends of the distribution, the maximum rank distance equals the total number of bins. In contrast, for a worker located in the middle of the distribution, the rank distance cannot exceed half the number of bins. To address this heterogeneity, our preferred specification includes worker fixed effects, α_i.

We next relax the linearity assumption and estimate a more flexible specification that allows the trajectory of assortative matching to vary freely across job spells and space:

$$d_{io} = \delta_0 + \gamma_1 \text{City}_{io} + \sum_{k=2}^{8} \delta_k \, \mathbf{1}\{o = k\} + \text{City}_{io} \sum_{k=2}^{8} \gamma_k \, \mathbf{1}\{o = k\} + X_{io}\theta + \alpha_i + \epsilon_{io}. \tag{4}$$

The specification includes a full set of job-spell indicators $\mathbf{1}\{o = k\}$ for spell $k \in \{2, \ldots, 8\}$, where δ_k trace out the match trajectory over workers' careers outside city regions. To allow the trajectory to differ by labor market size, each spell indicator is interacted with the city-indicator. In combination with the general city premium, γ_1, the interaction coefficients γ_k measure how the trajectory in cities differs relative to the corresponding trajectory outside of city areas. The first job spell in non-city areas serves as the reference category. As before, we account for compositional changes by controlling for observable characteristics, captured by X_{io}, along with worker fixed effects α_i. To illustrate general city gaps in assortative matching with confidence intervals, we also estimate a specification in which the city coefficient is replaced with an interaction between city residency and the first job spell.

3 Assortative matching dynamics in city and non-city areas

We begin by documenting clear differences in assortative matching by labor market size. Column (1) of Table 2 shows that workers in cities are, on average, more assortatively matched than workers in non-city areas, consistent with earlier findings by Dauth et al. (2022) and Leknes et al. (2022). In non-city areas, we find that the average rank distance between worker and plant fixed effects is 28.35 percent of the maximum distance, whereas in cities the distance is 0.3 percentage points lower.

Column (2) adds the worker's job spell number and its interaction with the city indicator, revealing that assortative matching improves with job transitions and that this improvement is larger in cities. In non-city areas, each job change reduces the rank distance by 1.3 percentage points, compared with a reduction of two percentage points in cities. At the same time, the estimates indicate that workers in cities are relatively less assortatively matched early in their careers.

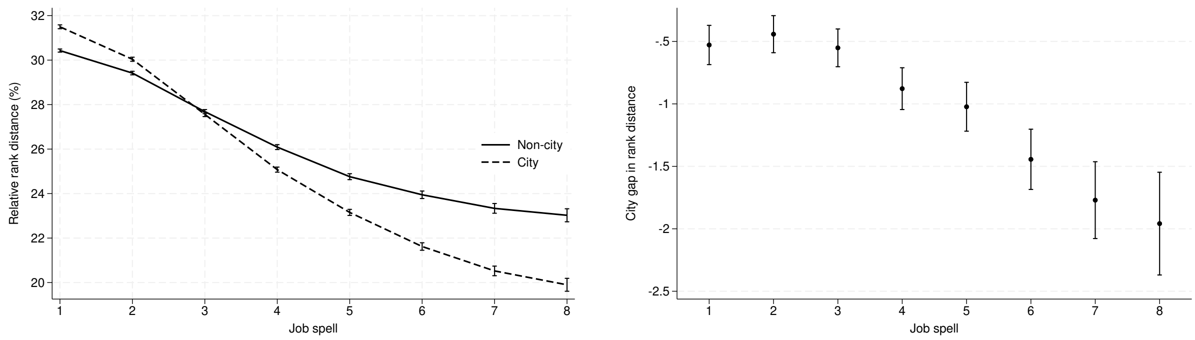
Table 2: Rank distance, city residency, and job spells

	(1)	(2)	(3)	(4)
City	-0.299***	1.812***	1.659***	-0.050
	(0.040)	(0.063)	(0.064)	(0.103)
Job spell		-1.299***	-1.401***	-0.144***
		(0.012)	(0.013)	(0.016)
City x Job spell		-0.671***	-0.693***	-0.198***
		(0.019)	(0.019)	(0.023)
Constant	28.354***	31.736***	32.130***	26.046***
	(0.027)	(0.041)	(0.050)	(0.077)
Controls	No	No	Yes	Yes
Worker FE	No	No	No	Yes
Observations	2,109,860	2,109,860	2,109,860	2,109,860
R-squared	0.00	0.02	0.03	0.01

Notes: The dependent variable is the absolute rank distance between worker and plant fixed effects, scaled by the maximum rank distance of 5,000 and expressed as a percentage. Controls include education level, plant size (number of employees), immigrant status, and 2-digit industry fixed effects. In column (4), the R-squared reported is within workers.
Standard errors, displayed in parentheses, are clustered at the individual level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Adding controls for education level, plant size, immigrant status, and two-digit industry codes in Column (3) leaves the main patterns unchanged, although it somewhat attenuates the initial city disadvantage in assortative matching. Column (4) introduces worker fixed effects to account for unobserved worker heterogeneity and corresponds to Equation (3). Once worker fixed effects are included, the city main effect becomes small and statistically insignificant. The estimated impact of job transitions on assortative matching is also reduced in both city and non-city areas, but dynamic city matching advantages remain and are statistically significant at the 1 percent level. In non-city areas, each job change reduces the rank distance by 0.14 percentage points, compared with 0.34 percentage points in cities.

Including job spell more flexibly, as a series of separate job number indicators, adds further nuance to the analysis of matching dynamics. Panel (a) of Figure 1 provides a descriptive illustration of predicted assortative matching over the career, based on a regression model that includes job spell indicators, a city indicator, and their interactions. Job mobility is associated with improved match quality in both city and non-city areas. However, city workers progress more rapidly to better matches. Although they start out slightly less well matched than their non-city counterparts, from the third job onward, they outperform non-city workers, with the gap widening over subsequent transitions. By the eighth job, the rank distance for city workers is three percentage points lower than that of non-city workers. Over the course of their first eight jobs, city workers improve their rank distance from an initial value of 32 percent to 20 percent, a reduction of 37 percent. In comparison, the corresponding values for non-city workers decrease from 30 percent to 23 percent, representing a 23 percent reduction.[9]



(a) Descriptive illustration

(b) Baseline model. City gaps by spell

Figure 1: Assortative matching over the career by labor market scale

Notes: Panel (a) shows predicted assortative matching over the career for city and non-city areas with a parsimonious model including job spell indicators, a city indicator, and their interactions. Panel (b) shows the estimated city gaps in assortative matching. It corresponds to our baseline model (Column 1 of Table 3), but the specification is amended to include all city-non-city gaps, as documented in Column (3) of Table A.1. Confidence intervals are 95%, with standard errors clustered at the worker level.

Column (1) of Table 3 reports results from our baseline specification with spell-specific indicators, as given by Equation (4). Allowing for a flexible matching trajectory and controlling for worker sorting through worker fixed effects, we find a significant city advantage in assortative matching. Beyond this initial advantage, further improvements in assortative matching become apparent only after the third job spell and thereafter increase more steeply for city workers.

As shown in panel (b) of Figure 1, the difference in assortative matching between city and non-city workers is approximately 0.5 percentage points during the first three job spells and widens to about 2 percentage

[9]These results are supported by differences in full distributions of rank distance in city and non-city areas, shown for selected job spells in the Online Appendix, Figure X.2. Further, as a robustness check, we measure assortative matching using the correlation between worker and plant fixed effects. The correlation is calculated for each job spell, separately in city and non-city areas. The results (reported in Figure Z.1 in the Online Appendix) show that assortative matching improves with job mobility, particularly in cities, consistent with the pattern obtained using our preferred rank-based measure of assortative matching.

points by the eighth job, when controlling for observable characteristics and unobservable time-invariant worker heterogeneity. Over the first eight jobs, rank distance declines by 11 percent in cities and by 6 percent in non-city areas. These magnitudes are comparable to the aggregate results in Braunschweig et al. (2024) with German data, who document a 12 percent decline in rank distance from the first to the eighth job in a single national labor market.

We next assess the robustness of our baseline results to alternative estimation choices, sample restrictions, and an alternative definition of population scale. The degree of labor market attachment may differ between city and non-city workers, potentially biasing estimated differences in assortative matching. Our analysis is centered on full-time workers, but intermittent periods out of full-time employment may occur between job spells, reflecting, for instance, part-time work, unemployment, or education. If city workers exhibit stronger labor-market attachment with shorter or fewer gaps, the estimated city advantage in assortative matching may be overestimated.

Columns (2) and (3) of Table 3 address this concern by adding controls for intermittent spells out of full-time employment and for accumulated years of full-time work experience, respectively. In these specifications, estimates of matching trajectories relative to the first job becomes less reliable, as workers early in their careers naturally have shorter experience and fewer gaps in employment. Our main interest, however, lies in the differences in assortative matching between city and non-city workers within a given job spell, and these estimates are highly robust to the inclusion of these additional controls. The urban gap increases from 0.5 percentage points in the first job to nearly two percentage points by the eighth job, closely mirroring the pattern in our baseline results.[10]

In the baseline specification, plant fixed effects are assumed to be time-invariant. To assess the sensitivity of our results to potential changes in plant quality over time, we re-estimate the AKM model in Equation (1) separately for two sub-periods: 1995-2008 and 2009-2019. Worker fixed effects are assumed to be constant and are therefore identified from the full sample period. The analysis is restricted to the dual-connected set of plants observed in both sub-periods to ensure comparability. Column (4) of Table 3 reports the estimated dynamics of assortative matching under period-specific plant fixed effects. The results are in line with the baseline findings, indicating that our main conclusions are not driven by time variation in plant quality.

We further assess the robustness of our findings using an alternative measure of population scale based on the continuous 1995 population size of 46 economic regions, as defined by Bhuller (2009). The results, reported in Column (5) of Table 3, closely align with our baseline estimates. Workers and plants are initially more assortatively matched in larger labor markets. Following the first job transition, however, this initial advantage narrows, as assortative matching declines in larger labor markets before improving gradually over subsequent job spells. To illustrate the magnitude of these differences, we compare matching trajectories in the largest and smallest labor markets. In the most populous region, the rank distance in the first job spell is 25.1 percent, which is 1.8 percentage points lower than in the smallest region. This

[10] According to Table X.4 in the Online Appendix, gaps in full-time employment are very similar for city and non-city workers. In both groups, 17 percent of workers experience a spell out of full-time employment, and among those who do, the average duration of the gap is approximately 2.5 years.

gap narrows to 1.4 percentage points in the second job spell but then increases gradually, reaching 2.4 percentage points by the sixth job spell and 2.8 percentage points by the eighth job spell.

Table 3: Assortative matching, urban scale, and job number

	(1)	(2)	(3)	(4)	(5)
	Baseline	Sensitivity tests			
		Out of the labor market	Experience	Period-specific plant FEs	Continuous urban scale
City	-0.529***	-0.520***	-0.538***	-0.490***	-0.428***
	(0.098)	(0.098)	(0.098)	(0.136)	(0.039)
Job 2	0.145**	-0.074	0.357***	0.308***	-1.039***
	(0.058)	(0.058)	(0.060)	(0.083)	(0.398)
Job 3	0.226***	0.068	0.659***	0.235**	-0.546
	(0.067)	(0.067)	(0.074)	(0.093)	(0.456)
Job 4	0.055	-0.085	0.709***	-0.243**	-0.357
	(0.079)	(0.079)	(0.093)	(0.110)	(0.536)
Job 5	-0.358***	-0.490***	0.502***	-0.975***	-0.293
	(0.094)	(0.093)	(0.114)	(0.130)	(0.635)
Job 6	-0.642***	-0.769***	0.409***	-1.685***	0.818
	(0.114)	(0.114)	(0.139)	(0.159)	(0.777)
Job 7	-1.061***	-1.184***	0.158	-2.276***	0.316
	(0.144)	(0.144)	(0.171)	(0.200)	(0.978)
Job 8	-1.485***	-1.603***	-0.118	-3.349***	1.057
	(0.189)	(0.188)	(0.215)	(0.263)	(1.295)
City x Job 2	0.087	0.063	0.083	0.046	0.100***
	(0.086)	(0.086)	(0.086)	(0.125)	(0.032)
City x Job 3	-0.023	-0.006	-0.027	-0.121	0.064*
	(0.098)	(0.098)	(0.098)	(0.137)	(0.037)
City x Job 4	-0.349***	-0.321***	-0.353***	-0.519***	0.024
	(0.113)	(0.113)	(0.113)	(0.157)	(0.043)
City x Job 5	-0.495***	-0.460***	-0.494***	-0.770***	-0.019
	(0.132)	(0.132)	(0.132)	(0.183)	(0.051)
City x Job 6	-0.915***	-0.881***	-0.914***	-1.083***	-0.147**
	(0.160)	(0.160)	(0.160)	(0.221)	(0.062)
City x Job 7	-1.242***	-1.209***	-1.231***	-1.416***	-0.152*
	(0.201)	(0.200)	(0.200)	(0.278)	(0.078)
City x Job 8	-1.430***	-1.402***	-1.407***	-1.239***	-0.251**
	(0.264)	(0.264)	(0.264)	(0.368)	(0.103)
Constant	26.018***	26.088***	25.990***	26.834***	31.054***
	(0.075)	(0.075)	(0.075)	(0.104)	(0.476)
Controls	Yes	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes	Yes
Observations	2,109,860	2,109,860	2,109,860	1,506,104	2,109,860
R-squared	0.01	0.01	0.01	0.02	0.01

Notes: The dependent variable is the absolute rank distance between worker and plant fixed effects, scaled by the maximum rank distance of 5,000 and expressed as a percentage. Controls include education level, plant size (number of employees), immigrant status, and 2-digit industry fixed effects. Baseline results are reported in Column (1), while Columns (2) and (3) add controls for intermittent periods out of full-time employment and worker job experience, respectively. In Column (4), the assortative matching static is based on two-period plant fixed effects, and in Column (5) the urban scale variable is the continuous population size (measured in 1995) across 46 local labor markets.

Standard errors, displayed in parentheses, are clustered at the individual level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Limited mobility bias refers to the bias in AKM fixed effects that may arise when inter-firm mobility is low (e.g., Andrews et al., 2008). Although the rank-based measure of assortative matching is expected to be relatively robust to such bias, we assess the results' sensitivity using several approaches. First, following Leknes et al. (2022), we exclude small plants where worker mobility tends to be limited and re-estimate fixed effects using progressively more restrictive plant size thresholds. Specifically, we implement four minimum plant-size cutoffs, ranging from 3 to 11 workers. While these restrictions substantially reduce the number of plants in the estimation sample, the resulting assortative matching patterns remain qualitatively unchanged. Second, addressing that incidental parameter problems may yield extreme values of worker and plant fixed effects, we exclude the top and bottom 1% of the distributions. The results are robust to this trimming. Taken together, these robustness checks suggest that, to the extent limited mobility bias is present, it does not vary systematically with job spell or urban scale.[11]

4 Skill heterogeneity in matching dynamics

The literature on agglomeration economies has emphasized the role of skills in enabling workers to leverage the advantages of urban labor markets (Bacolod et al., 2009; Glaeser & Maré, 2001; Moretti, 2004). In the Norwegian context, prior evidence documents a positive relationship between worker skills, the urban wage premium (Carlsen et al., 2016), and matching opportunities in cities (Leknes et al., 2022). To investigate skill heterogeneity in matching dynamics, we employ a broad measure of skills that captures both observed and unobserved productivity differences across workers, namely the worker fixed effects obtained from the AKM estimation. We divide workers into quartiles based on their estimated worker fixed effects and re-estimate Equation (4) separately for each quartile.

Figure 2 presents results separately for workers in the bottom and top quartiles of the worker fixed effect distribution.[12] The figure reveals sharply contrasting matching dynamics for low- and high-ability workers. For low-ability workers, assortative matching generally deteriorates with successive job transitions. These workers are initially more assortatively matched in non-city areas than in cities, and this gap widens over the career. The divergence becomes statistically significant in job spells three through five. In contrast, high-ability workers experience steadily improving assortative matching over the course of their careers. This pattern is particularly pronounced in cities, where high-ability workers both start out more assortatively matched and benefit more from subsequent job transitions.

How should these findings be interpreted? Because worker fixed effects are time invariant, changes in the rank distance between worker and plant fixed effects necessarily arise through job mobility and changes in the rank of the plants workers move to over their careers. To better understand the sources of the observed matching trajectories, we therefore examine how the quality of plants associated with workers evolves over successive job spells. The results are reported in Table 4. Column (1) shows that both city and

[11] Results from these robustness exercises are reported in the Online Appendix; see Figure Z.2 and Figure Z.3. We also examine the robustness of the results to alternative choices of the number of bins, with no material effect on the findings; see Table Z.1. Results are also robust to an alternative definition of the location of the employment match (see Figure Z.4). In this specification, match location is determined by the residential location of the majority of the firm's workers rather than by the worker's own residence.

[12] Regression results for all skill quartiles are reported in Table A.2 in the appendix. The estimated trajectories vary smoothly across quartiles.

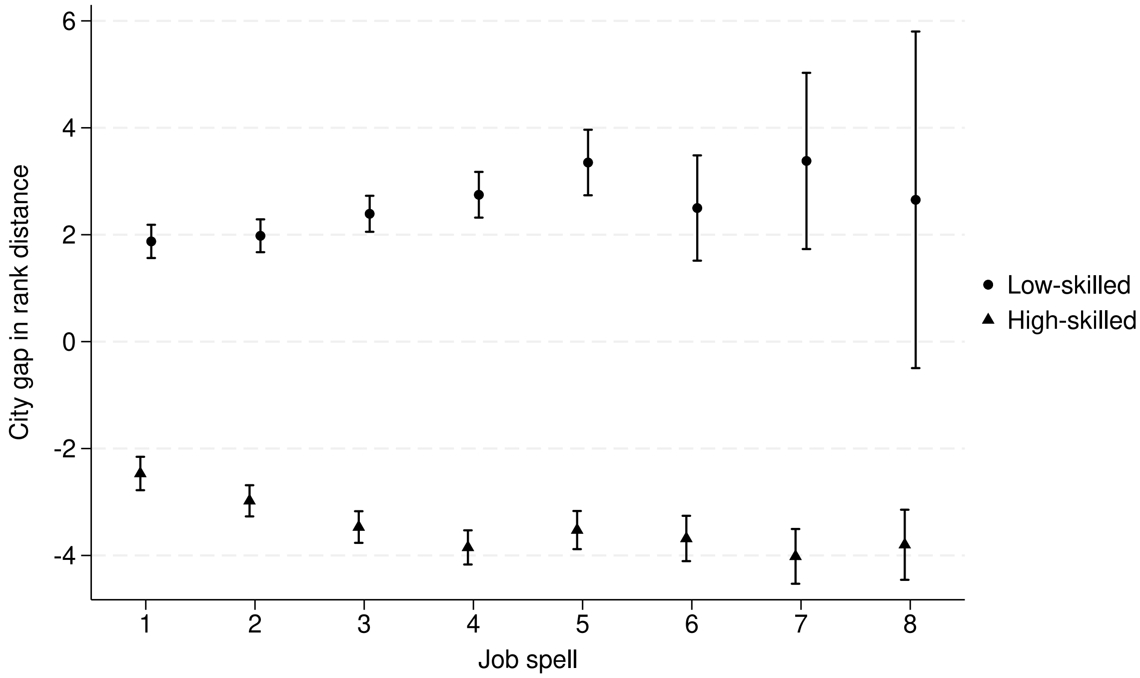


Figure 2: City gaps in assortative matching: low- vs. high-skilled workers

Notes: The figure shows the city-non-city gaps in assortative matching from our baseline model, which includes controls and worker fixed effects, estimated separately for low-skilled and high-skilled workers. Skill groups are defined as the lowest and highest quartile of estimated worker fixed effects, respectively. Confidence intervals are 95%, with standard errors clustered at the worker level.

non-city workers are employed at higher-quality plants as their careers progress. However, city workers are initially matched to higher-quality plants and experience larger subsequent improvements in plant quality following job transitions than workers in non-city areas.

Interestingly, Columns (2) and (3) show that both low- and high-skilled workers are employed at progressively higher-quality plants over the course of their careers, relative to the plant quality in their first job. However, these improvements in plant quality translate into diverging patterns of assortative matching. While assortative matching improves for high-skilled workers, it deteriorates for low-skilled workers. This pattern is present in both city and non-city areas but is more pronounced in cities. These findings contrast with those of Braunschweig et al. (2024), who document improving assortative matching over the career for both low- and high-skilled workers in a single national labor market, although gains for the low-skilled group emerge only after the fourth job transition.

The observed improvement in plant quality following job transitions is consistent with job-ladder models, in which workers engage in on-the-job search and move to employers offering higher wages than their current firm (e.g., Christensen et al., 2005). By contrast, the results are less easily reconciled with employer-side information frictions that diminish over time as firms gradually acquire more precise information about worker ability through observed performance in the labor market. In particular, the continued movement of low-ability workers to higher-quality plants suggests that true ability may not be fully revealed, and that accumulated experience is interpreted as a positive, but noisy, signal of worker productivity. An alternative explanation relates to institutional features of the Norwegian labor market. Strong employment protection

Table 4: Plant quality, city size, and job number

	All workers (1)	Low-skilled (2)	High-skilled (3)
City	0.021***	0.017***	0.024***
	(0.001)	(0.002)	(0.002)
Job 2	0.020***	0.023***	0.020***
	(0.001)	(0.001)	(0.001)
Job 3	0.030***	0.038***	0.027***
	(0.001)	(0.002)	(0.001)
Job 4	0.037***	0.048***	0.032***
	(0.001)	(0.002)	(0.002)
Job 5	0.041***	0.052***	0.038***
	(0.001)	(0.003)	(0.002)
Job 6	0.044***	0.060***	0.041***
	(0.001)	(0.005)	(0.002)
Job 7	0.048***	0.067***	0.045***
	(0.001)	(0.008)	(0.002)
Job 8	0.049***	0.068***	0.049***
	(0.002)	(0.015)	(0.003)
City x Job 2	0.004***	0.002	0.005***
	(0.001)	(0.002)	(0.002)
City x Job 3	0.009***	0.006***	0.010***
	(0.001)	(0.002)	(0.002)
City x Job 4	0.013***	0.008***	0.013***
	(0.001)	(0.003)	(0.002)
City x Job 5	0.014***	0.013***	0.010***
	(0.001)	(0.004)	(0.002)
City x Job 6	0.015***	0.003	0.011***
	(0.002)	(0.007)	(0.003)
City x Job 7	0.018***	0.008	0.015***
	(0.002)	(0.012)	(0.003)
City x Job 8	0.017***	0.026	0.013***
	(0.003)	(0.021)	(0.004)
Constant	-0.051***	-0.064***	-0.022***
	(0.001)	(0.001)	(0.003)
Controls	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes
Observations	2,109,860	534,374	520,048
R-squared	0.19	0.23	0.15

Notes: The dependent variable is plant quality measured as the estimated plant fixed effects. Low-skilled and high-skilled workers are those belonging to the bottom and top quartile of estimated worker fixed effects, respectively. Controls include education level, plant size (number of employees), immigrant status, and 2-digit industry fixed effects.
Standard errors, displayed in parentheses, are clustered at the individual level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

may limit firms' ability to dismiss underperforming workers, thereby weakening the informational content of job separations and slowing the revelation of low ability. Finally, although the results may appear at odds with the notion of more competitive labor markets in cities, it is important to note that we observe only realized employment matches and wages, rather than the full set of offers and rejected matches.

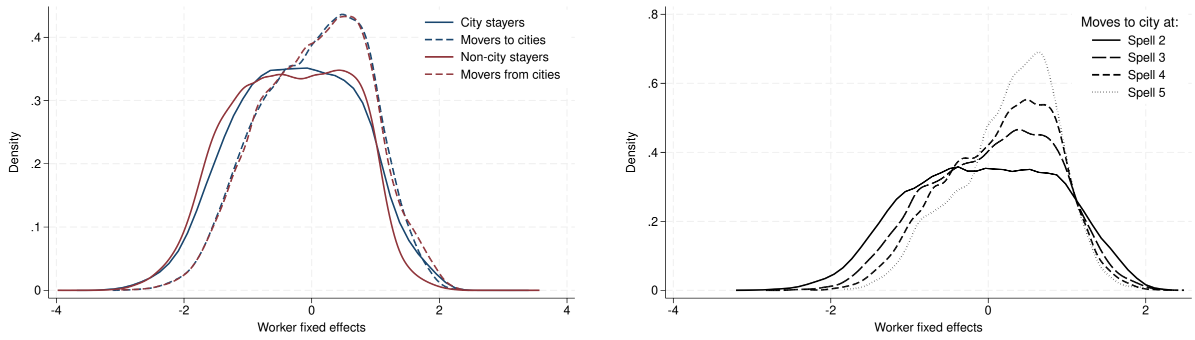
5 Migration and assortative matching dynamics

A central question is how workers' careers are shaped by relocation between labor markets of different sizes. What characterizes movers, including those who relocate early in their careers compared to those who move later, and what can their trajectories reveal about the advantages of labor market scale? A well-established finding in the literature on agglomeration economies is the positive selection of workers into cities (see, e.g., Combes et al. (2008)). However, less is known about workers who leave thicker labor markets. Are such workers negatively selected, unable to thrive in urban labor markets due to lower underlying ability, or do they relocate for other reasons, such as lifestyle preferences or local amenities? Existing evidence suggests that experience acquired in cities is valuable and portable (Carlsen et al., 2016; De la Roca & Puga, 2017). An open question is whether this experience can be leveraged to obtain superior employment matches after relocating to non-city areas. While our data do not allow us to disentangle all underlying motivations, we shed light on selection into and out of cities using estimated worker fixed effects and by examining the matching trajectories of movers.

We impose two sample restrictions to ensure that we can follow individuals consistently throughout their careers. First, we exclude movers who have a gap in their spell sequence prior to their first move, which applies to approximately 16 percent of movers. Second, for individuals who return to their original location, observations following their second move are dropped, accounting for about 9 percent of observations. The resulting sample includes 83,045 movers and 321,060 observations. As a first step, we compare movers and stayers. In the left panel of Figure 3, we plot our measure of worker quality, estimated worker fixed effects, for four groups: movers to cities, movers from cities, city stayers, and non-city stayers. Consistent with prior evidence, city stayers tend to have higher worker fixed effects than non-city stayers, although the distributions overlap substantially. Interestingly, the distributions of worker fixed effects for both mover groups are shifted to the right relative to those of stayers, indicating positive selection into migration. Specifically, the distributions for movers to and from cities are nearly identical, suggesting that workers who leave cities are also positively selected.[13] This pattern provides little support for the notion that migration out of cities is driven primarily by low ability and instead points to alternative explanations, such as lifestyle preferences or local amenities, as potential drivers of urban out-migration.

Experience gained in thicker labor markets has been shown to be more valuable than experience acquired elsewhere, particularly for high-skilled workers. With full information about their own abilities and capabilities, workers who expect to benefit most from acquiring urban experience would find it optimal to relocate to cities early in the careers. In the right-hand panel of Figure 3, we plot the distribution of worker fixed effects for workers who move to cities by job spell. The opposite pattern emerges: workers who relocate later in their careers appear to be more positively selected. This pattern may reflect imperfect information about match quality and about own capabilities, particularly early in the career. If learning about suitability for different jobs requires trial and error in employment matches (Topel & Ward, 1992),

[13] The average city mover ranks at the 62$^{\text{nd}}$ percentile of the non-city ability distribution. As the city distribution is shifted to the right, the average position within the city distribution is slightly lower, at the 59$^{\text{th}}$ percentile. Similarly, movers in the opposite direction go from the 60$^{\text{th}}$ percentile in the city distribution to the 62$^{\text{nd}}$ percentile in the non-city distribution, on average.



(a) WFE distributions across mobility groups **(b)** WFE distributions across spells for city movers

Figure 3: Worker fixed effects (WFE) distributions. Kernel densities

Notes: The figure shows kernel densities of worker fixed effects using a Gaussian kernel with a common bandwidth across groups (within subfigures), chosen using Silverman's rule of thumb on the pooled sample. Panel (a) shows the distributions for city stayers, non-city stayers, movers to cities, and movers to non-cities (categories are mutually exclusive). Individuals are classified as movers to cities or movers to non-cities based on the direction of their first move. Panel (b) displays distributions for movers to cities by the spell of relocation.

and migration entails non-negligible costs, it is plausible that later movers choose to relocate only once they are sufficiently confident that they will succeed in the urban labor market. Alternatively, higher-ability workers may start their careers with better initial matches, which reduces their incentives to relocate. A similar pattern is observed for movers from cities to non-city areas, suggesting that comparable mechanisms may also operate in the opposite direction.[14]

Although movers are positively selected, the relationship between migration and subsequent matching trajectories remains less clear. Relative to the full analytical sample, the number of movers is modest and declines sharply with each job spell, motivating a parsimonious empirical approach in this part of the analysis. An inspection of the data shows that only in job spells two and three do we observe more than 5,000 moves in each direction. We therefore focus on labor market transitions occurring relatively early in workers' careers (spells two through five) and examine how these moves shape subsequent assortative matching dynamics. Results for migrants to cities are presented in Figure 4.[15]

The figure shows that movers tend to experience a deterioration in assortative matching immediately following relocation. Although not directly comparable, this pattern resembles the hierarchy effect documented by Card et al. (2025), whereby movers transition from plants higher in the productive hierarchy in the origin area to plants lower in the hierarchy in the destination area. These initial declines in assortative matching diminish with job spell and are no longer evident for workers relocating in their fifth spell. This pattern may, in part, reflect differences in the selection of migrants relocating at different career stages. Importantly, the initial decline in assortative matching is quickly offset by subsequent improvements through job transitions in cities, highlighting the richer matching opportunities available in thicker labor markets. By contrast, prior to relocation from non-city areas, matching gradients are largely flat. This suggests that high-ability workers in smaller labor markets may face limited scope for further

[14]These results are illustrated in the Online Appendix, Figure Z.5.

[15]The number of movers by job spell is reported in Online Appendix Table X.5. Corresponding assortative matching results for migrants to non-city areas are shown in Online Appendix Figure Z.6. These patterns are similar but noisier due to the smaller number of moves.

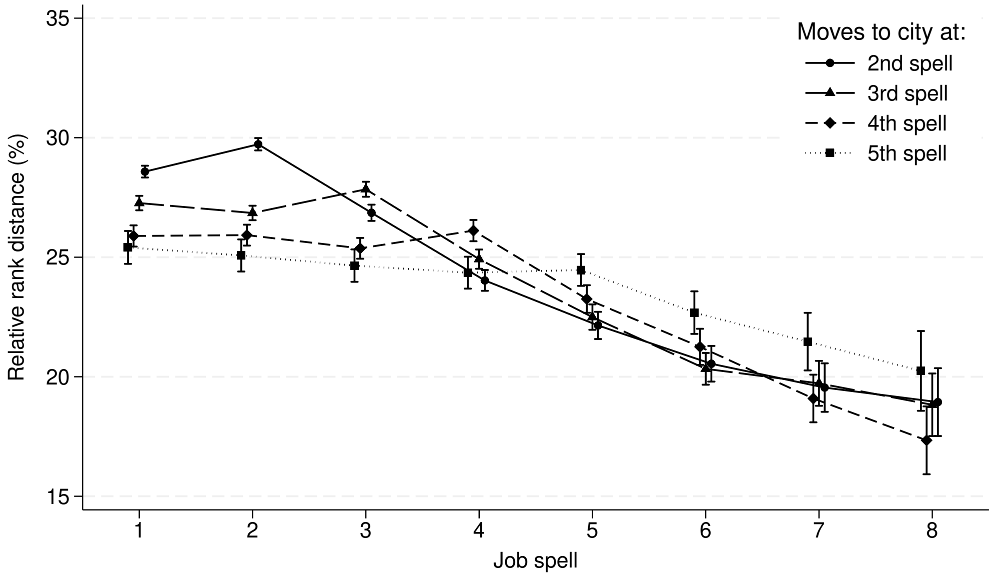


Figure 4: Assortative matching dynamics for workers relocating to cities
Notes: The figure shows assortative matching dynamics for workers who relocate to cities, by the career timing of the move. Each series is estimated from a separate regression of a parsimonious specification including job-spell indicators and no constant term. Confidence intervals are 95 percent, with standard errors clustered at the worker level.

improvements in assortative matching without relocation.[16]

Prior evidence using Spanish data shows that return migrants, workers who move to larger cities and subsequently return, are negatively selected relative to other migrants and benefit less with respect to earnings from their stay (De la Roca, 2017). We therefore extend our analysis to a third group: workers who relocate to a city and later move back to a non-city area. Interestingly, these return migrants are positively selected relative to other city movers.[17] They also exhibit a distinct assortative matching trajectory. Figure 5 compares the trajectories of city movers, return migrants, and non-city stayers. Return migrants display a flatter trajectory than both city movers and non-city stayers. Notably, they are initially more assortatively matched than either group. Late in career, after approximately five job spells, city movers achieve lower relative rank distance than return migrants. The relatively flat trajectory of return migrants aligns with the limited urban gains documented by De la Roca (2017) and with the weaker job-ladder progression observed for this group relative to city movers.[18]

Return migrants move to cities at a similar stage of the career as other city movers, but typically return to non-city areas after about 4.5 job spells. A substantial share returns to their place of origin: 51 percent return to the same municipality and 64 percent to the same economic region. Although the return decisions may reflect limited gains from assortative matching in cities, the pattern also suggests that non-pecuniary factors may play a role in motivating return migration. Potential factors include local amenities (Chen & Rosenthal, 2008; Rappaport, 2009) and place-based social networks, including family ties (Blumenstock

[16]The patterns are highly similar when we include movers with gaps in their spell sequence and return migrants (Figure Z.7 for city-movers and Figure Z.8 for non-city movers).

[17]In Online Appendix Figure Z.9, we plot the distribution of worker fixed effects for non-city stayers, city movers with a single relocation, and city movers who later return migrate.

[18]Online Appendix Figure Z.10 illustrates job-ladder movements, measured by average plant fixed effect by spell number, for return migrants, city movers, and non-city stayers.

et al., 2023; Munshi, 2020).

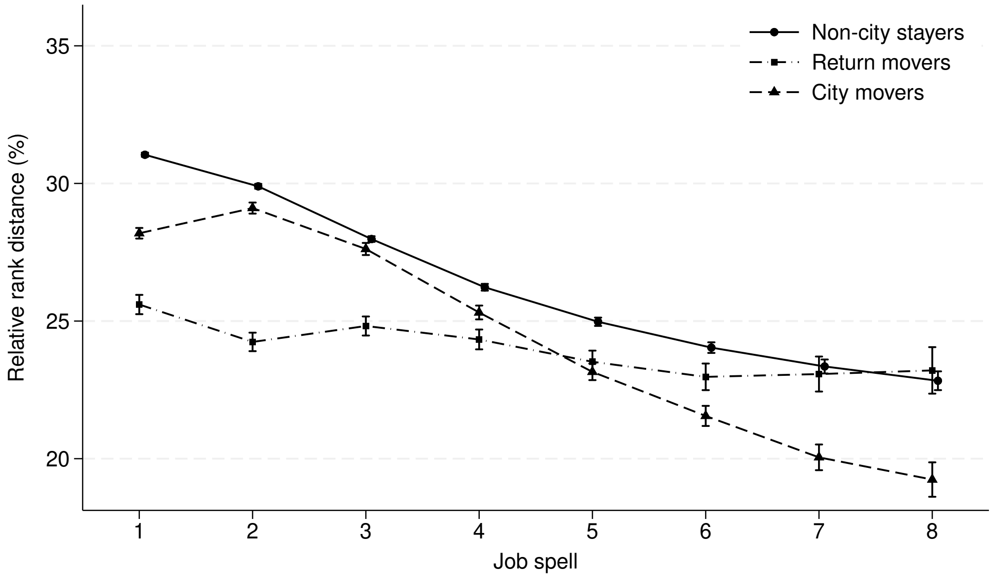


Figure 5: Assortative matching dynamics for city movers, return movers, and non-city stayers
Notes: The figure shows assortative matching dynamics for non-city stayers, workers who move to city-areas with no return-move, and workers who move to city-areas and then return back to non-city areas. Each series is estimated from a separate regression of a parsimonious specification including job-spell indicators and no constant term. Confidence intervals are 95 percent, with standard errors clustered at the worker level.

6 Conclusion

While superior matching in cities is widely viewed as a key source of agglomeration economies, little is known about how matching evolves dynamically over workers' careers across labor markets of different sizes. Using rich longitudinal data and recent advances in the measurement of assortative matching, we provide new evidence that workers in cities are initially more assortatively matched and progress more rapidly toward increasingly assortative matches over the career.

We document substantial skill heterogeneity in these dynamics. High-ability workers experience steadily improving assortative matching, with particularly pronounced gains in cities. In contrast, assortative matching deteriorates for low-ability workers, especially in urban labor markets. An analysis of migrating workers further reveals that relocation is associated with short-run matching disadvantages that are subsequently offset by improvements later in the career. Taken together, these findings are consistent with theoretical frameworks emphasizing search frictions, learning, and job ladder dynamics in shaping matching outcomes in local labor markets, and align with existing empirical evidence on skill-biased urban advantages and hierarchy effects across local labor markets.

Several avenues for future research remain. While our analysis documents robust patterns in matching dynamics, it does not directly identify the mechanisms underlying superior urban matching, such as differences in information flows, vacancy posting behavior, or firm screening. Moreover, local labor market characteristics beyond population scale, including industry composition and coagglomeration forces, may further shape matching trajectories.

From a broader perspective, our findings underscore the efficiency advantages of urban labor markets in allocating workers to plants over time. As urbanization continues globally, understanding how cities shape career trajectories, and for whom, becomes increasingly important for interpreting productivity growth and its distributional consequences.

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Appendices

A Supplemental analysis

Table A.1: Assortative matching, city size, and job number: Adding controls step-wise

	(1)	(2)	(3)
City	1.069***	0.914***	
	(0.057)	(0.057)	
Job 2	-1.011***	-1.191***	0.145**
	(0.045)	(0.046)	(0.058)
Job 3	-2.745***	-3.047***	0.226***
	(0.053)	(0.054)	(0.067)
Job 4	-4.340***	-4.732***	0.055
	(0.063)	(0.064)	(0.079)
Job 5	-5.668***	-6.146***	-0.358***
	(0.075)	(0.076)	(0.094)
Job 6	-6.483***	-7.009***	-0.642***
	(0.091)	(0.093)	(0.114)
Job 7	-7.094***	-7.662***	-1.061***
	(0.116)	(0.118)	(0.144)
Job 8	-7.405***	-7.988***	-1.485***
	(0.153)	(0.155)	(0.189)
City x Job 1			-0.529***
			(0.098)
City x Job 2	-0.448***	-0.491***	-0.442***
	(0.072)	(0.071)	(0.093)
City x Job 3	-1.192***	-1.268***	-0.551***
	(0.083)	(0.082)	(0.095)
City x Job 4	-2.083***	-2.188***	-0.878***
	(0.095)	(0.095)	(0.105)
City x Job 5	-2.677***	-2.788***	-1.023***
	(0.111)	(0.110)	(0.122)
City x Job 6	-3.396***	-3.520***	-1.444***
	(0.133)	(0.133)	(0.151)
City x Job 7	-3.881***	-4.012***	-1.771***
	(0.166)	(0.167)	(0.193)
City x Job 8	-4.195***	-4.323***	-1.959***
	(0.217)	(0.219)	(0.258)
Constant	30.430***	30.762***	26.018***
	(0.036)	(0.045)	(0.075)
Controls	No	Yes	Yes
Worker FE	No	No	Yes
Observations	2,109,860	2,109,860	2,109,860
R-squared	0.02	0.03	0.01

Notes: The dependent variable is the absolute rank distance between worker and plant fixed effects, scaled by the maximum rank distance of 5,000 and expressed as a percentage. In columns (2) and (3), controls include education level, plant size (number of employees), immigrant status, and 2-digit industry fixed effects. The specification in column (3) is reformulated to report city-non-city gaps at each job number, rather than a common city effect and interaction terms.
Standard errors, displayed in parentheses, are clustered at the individual level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Assortative matching, city size, and job number: By skill-categories

	(1) Low-skilled	(2) Medium-skilled Low	(3) Medium-skilled High	(4) High-skilled
City	1.875***	0.904***	-0.931***	-2.467***
	(0.159)	(0.109)	(0.131)	(0.159)
Job 2	2.187***	0.544***	-0.682***	-2.019***
	(0.086)	(0.067)	(0.083)	(0.107)
Job 3	3.405***	0.803***	-0.934***	-2.575***
	(0.112)	(0.078)	(0.093)	(0.119)
Job 4	3.980***	0.691***	-0.970***	-2.784***
	(0.155)	(0.093)	(0.106)	(0.134)
Job 5	4.077***	0.682***	-1.063***	-3.197***
	(0.226)	(0.113)	(0.121)	(0.150)
Job 6	4.696***	0.378***	-1.060***	-3.271***
	(0.365)	(0.145)	(0.141)	(0.175)
Job 7	4.889***	0.401**	-1.588***	-3.523***
	(0.617)	(0.198)	(0.172)	(0.208)
Job 8	5.209***	0.228	-1.596***	-4.066***
	(1.158)	(0.282)	(0.217)	(0.258)
City x Job 2	0.105	0.167*	-0.038	-0.511***
	(0.124)	(0.097)	(0.124)	(0.157)
City x Job 3	0.516***	0.471***	-0.084	-1.002***
	(0.159)	(0.111)	(0.136)	(0.170)
City x Job 4	0.872***	1.007***	-0.280*	-1.383***
	(0.217)	(0.131)	(0.151)	(0.187)
City x Job 5	1.475***	1.177***	-0.425**	-1.058***
	(0.317)	(0.160)	(0.170)	(0.207)
City x Job 6	0.624	1.393***	-0.703***	-1.216***
	(0.506)	(0.205)	(0.197)	(0.239)
City x Job 7	1.505*	1.344***	-0.461*	-1.551***
	(0.845)	(0.280)	(0.240)	(0.281)
City x Job 8	0.778	1.196***	-0.514*	-1.334***
	(1.610)	(0.402)	(0.305)	(0.350)
Constant	37.237***	23.126***	27.782***	39.625***
	(0.387)	(0.234)	(0.316)	(0.515)
Controls	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes
Observations	534,374	531,631	523,807	520,048
R-squared	0.28	0.11	0.12	0.17

Notes: The dependent variable is the absolute rank distance between worker and plant fixed effects, scaled by the maximum rank distance of 5,000 and expressed as a percentage. Columns (1) through (4) present separate regressions for workers grouped into quartiles based on the distribution of worker fixed effects. Controls include education level, plant size (number of employees), and 2-digit industry fixed effects are included.

Standard errors, displayed in parentheses, are clustered at the individual level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Online Appendix

Online Supplementary Material for "Cities and assortative matching dynamics over worker careers."

X Data description and descriptive statistics

The dataset is computed from three administrative registers: employment, tax, and education. The employment register links workers and firms and gives information on work contracts for all employees. It separates between three contract types: full-time contracts with at least 30 hours of work per week, part-time contracts with 20–29 hours of work per week, and part-time contracts with fewer than 20 hours of work per week. Due to lack of data on hourly wages, we restrict the analysis to full-time workers. Based on the length of the contract we calculate the number of days worked per year, which is combined with data on annual wage income to give a measure of daily wages. The tax register gives information on annual earnings for each work contract. For workers with two or three full-time contracts in a year, we only use the main contract, which we define as the contract with the most days or the highest wage (if the number of days is equal across contracts). If the contracts have similar length and identical annual wage, they are excluded (very few cases). Workers with more than three full-time contracts in a year are excluded. We exclude workers whose contract length is one month or less during a year, as well as workers with missing data on annual earnings, level of education, or industry affiliation. We separate between three subgroups of workers according to their level of education: primary, secondary and college. To avoid extreme observations, we exclude the top and bottom one percent of the wage distribution.

The city indicator is constructed in the following manner: Economic regions, as defined by Statistics Norway (2000), are selected based on a population threshold of over 250,000 inhabitants as of 2019. This approach identifies the cities of Oslo, Stavanger/Sandnes, Bergen, and Trondheim. Since these economic regions correspond to NUTS-4 regions, the boundaries are initially limited by county borders. This is particularly problematic for Oslo as it is both a municipality and a county, meaning its economic region boundaries are constrained by administrative borders rather than functional economic areas. To create a region that better reflects a functional local labor market, commuting data is used to incorporate nearby municipalities. A municipality is included if Oslo is the largest commuting destination for its residents and if the number of commuters to Oslo is no less than one-third of the municipality's non-commuting worker population. This adjustment relies on data from 2023, sourced from Statistics Norway's Table 03321: Employed persons (aged 15-74), by municipality of work and municipality of residence. 4th quarter (M) 2000–2023. Based on these criteria, the municipalities grouped with Oslo to form a functional local labor market are Bærum, Asker, Lunner, Nittedal, Gjerdrum, Ullensaker, Eidsvoll, Lillestrøm, Nes, Rælingen, Lørenskog, Enebakk, Nesodden, Nordre Follo, Ås, Vestby, and Frogn.

Table X.1: Number of workers and plants by area and spell

Job number	Number of workers		Number of plants	
	City	Non-city	City	Non-city
1	271,564	387,283	53,144	78,056
2	234,546	285,927	57,133	78,371
3	173,732	189,808	49,025	63,502
4	118,045	122,350	38,615	48,938
5	75,090	77,290	28,661	36,258
6	45,007	47,151	20,435	25,811
7	25,617	27,402	13,659	17,159
8	13,817	15,231	8,671	10,792
Total	368,177	439,752	105,569	139,976

Notes: The table reports the number of workers and plants in both city and non-city areas, separately for each of the first eight job spells. Movers are classified as city or non-city workers based on their location during the corresponding job spell, which explains why the total number of workers in city and non-city areas exceeds the number of unique workers in the sample. Plant location is determined at the individual level from each worker's resident location. As some plants employ workers residing in both city and non-city areas, the total number of plants across the two categories is higher than the total number of distinct plants in the sample.

Table X.2: Progress ratio

Job number	Progress ratio	
	Non-City	City
1	0.737	0.725
2	0.660	0.644
3	0.626	0.620
4	0.597	0.601
5	0.568	0.575
6	0.536	0.551
7	0.513	0.521

Notes: For each job spell from 1 to 7, the table reports the probability that a worker residing in either a city or a non-city area transitions to a new spell, regardless of whether the subsequent spell is located in a city or non-city area.

Table X.3: Descriptive statistics by location and job spell

Spell	Age		Experience		Secondary		College		Immigrant		Manufacturing		Services	
	City	Non-city	City	Non-city	City	Non-city	City	Non-city	City	Non-city	City	Non-city	City	Non-city
1	24.392	22.748	0.097	0.057	0.686	0.831	0.314	0.169	0.295	0.160	0.339	0.529	0.661	0.471
2	27.357	25.871	2.173	2.168	0.602	0.777	0.398	0.223	0.240	0.134	0.287	0.470	0.713	0.530
3	29.742	28.520	4.220	4.278	0.563	0.763	0.437	0.237	0.185	0.102	0.280	0.465	0.720	0.535
4	31.937	30.970	6.195	6.333	0.544	0.758	0.456	0.242	0.144	0.076	0.272	0.458	0.728	0.542
5	33.923	33.152	8.010	8.149	0.534	0.752	0.466	0.248	0.114	0.057	0.262	0.449	0.738	0.551
6	35.675	35.030	9.597	9.738	0.535	0.748	0.465	0.252	0.093	0.043	0.256	0.441	0.744	0.559
7	37.217	36.567	11.020	11.027	0.545	0.751	0.455	0.249	0.080	0.032	0.254	0.435	0.746	0.565
8	38.508	37.929	12.238	12.087	0.563	0.756	0.437	0.244	0.067	0.028	0.249	0.425	0.751	0.575
Total	28.844	27.076	3.640	3.301	0.601	0.787	0.399	0.213	0.210	0.118	0.294	0.484	0.706	0.516

Notes: The table presents descriptive statistics across job spell 1 to 8, and averages across all eight job spells. Manufacturing industries includes manufacturing, construction, water supply, and resource industries. Services capture retail, transport, hotel, restaurants, business services, and cultural services.

Table X.4: Descriptive statistics for stayers and movers

	City stayers	Non-city stayers	Movers to cities	Movers from cities
Age	28.5	26.9	27.9	28.7
Experience	3.301	3.285	3.403	3.705
Secondary Education	0.621	0.822	0.570	0.688
College Education	0.379	0.178	0.430	0.312
Immigrant	0.236	0.121	0.106	0.197
Manufacturing	0.301	0.511	0.309	0.349
Other services	0.699	0.489	0.691	0.651
Gap in full-time employment (share)	0.169	0.167	0.197	0.185
Years out of full-time employment	2.539	2.460	2.503	2.534
Worker FE	-0.014	-0.102	0.160	0.178
Observations	746,778	942,568	234,447	86,613
Number of workers	269,668	341,243	60,375	22,670

Notes: The table presents descriptive statistics for four groups of workers: city stayers, non-city stayers, and movers between cities and non-city areas. For time-varying variables, the descriptive statistics are based on the first yearly observation within each spell. Stayers are defined as those with the same city-category throughout their first 8 job spells. Workers are classified as movers based on the direction of their initial move. Movers with a missing spell number prior to their first move are excluded. Years out of full-time employment is defined as the average number of years spent out of the labor market between consecutive job spells, conditional on experiencing at least one year out of full-time employment.

Table X.5: Observed moves between labor markets by job spell

	Number of workers	
Job number	Non-city to city	City to non-city
2	29,771	10,700
3	17,815	6,027
4	7,905	3,108
5	3,098	1,594
6	1,159	723
7	439	346
8	188	172

Notes: The table shows the number of workers moving between non-city and city areas across job spells 2 to 8. Individuals are classified based on the direction of their first move. This classification is mutually exclusive, meaning that individuals cannot be observed as both city- and non-city migrants regardless of any subsequent relocation. Movers with a missing spell number prior to their first move are excluded.

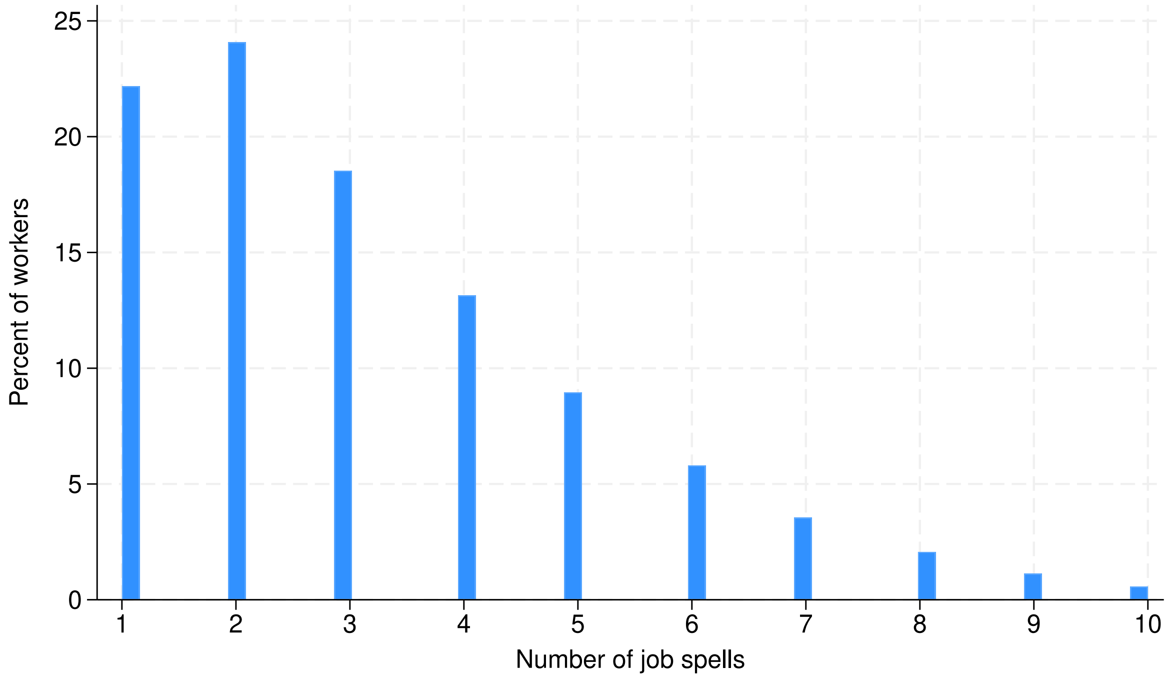
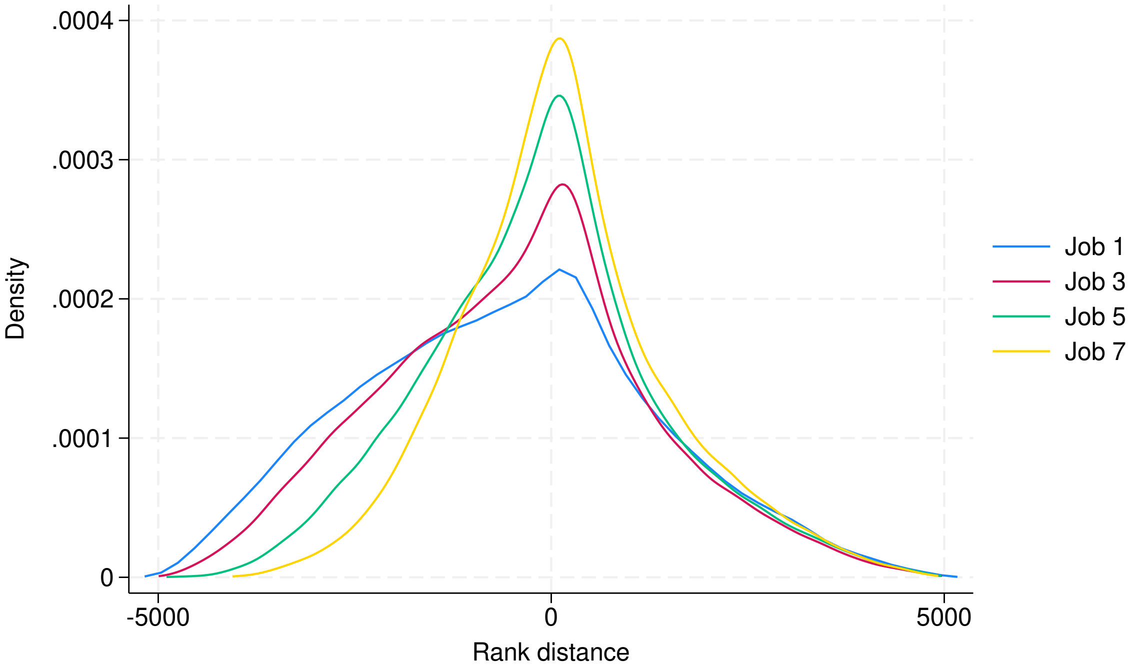
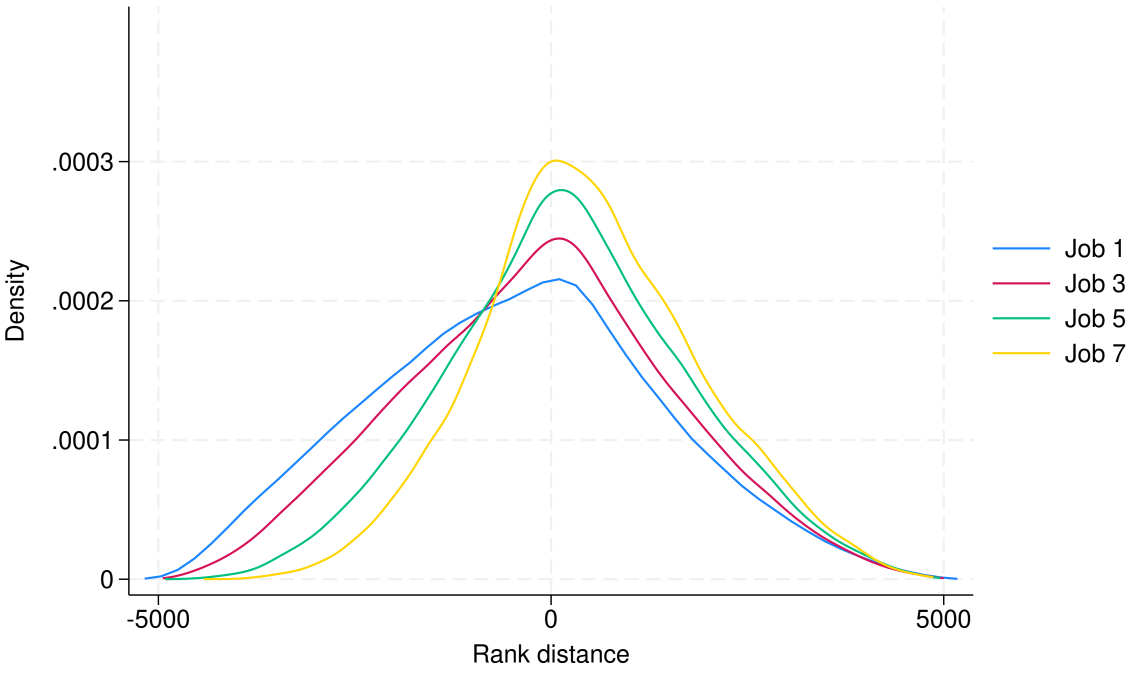


Figure X.1: Distribution of workers across the total number of job spells.
Notes: The figure shows the percentage of workers across number of job spells from 1 to 10 in our analytical sample.



(a) Rank distance in city



(b) Rank distance in non-city

Figure X.2: Distribution of rank distance in city and non-city areas for selected job spells
Notes: A higher density at rank distance zero indicates better assortative matching. A negative rank distance implies a mismatch, where the quality of the plant exceeds the worker's quality.

Y AKM Diagnostics

Table Y.1: Descriptive statistics: original sample vs. largest connected set

	AKM estimation sample	
	Original sample	Largest connected set
Worker characteristics		
Age	41.0	41.0
Mean log daily wages	7.24	7.24
(standard dev.)	(0.48)	(0.48)
Share completed lower secondary	0.21	0.21
Share completed upper secondary	0.55	0.55
Share completed higher education	0.24	0.24
Plant characteristics		
Mean size	150	151
Observations	18,952,140	18,916,562
Individuals	1,537,605	1,533,334
Plants	265,822	261,353

Notes: The table presents descriptive statistics for the AKM estimation sample, comparing the full sample with valid observations and the largest connected set.

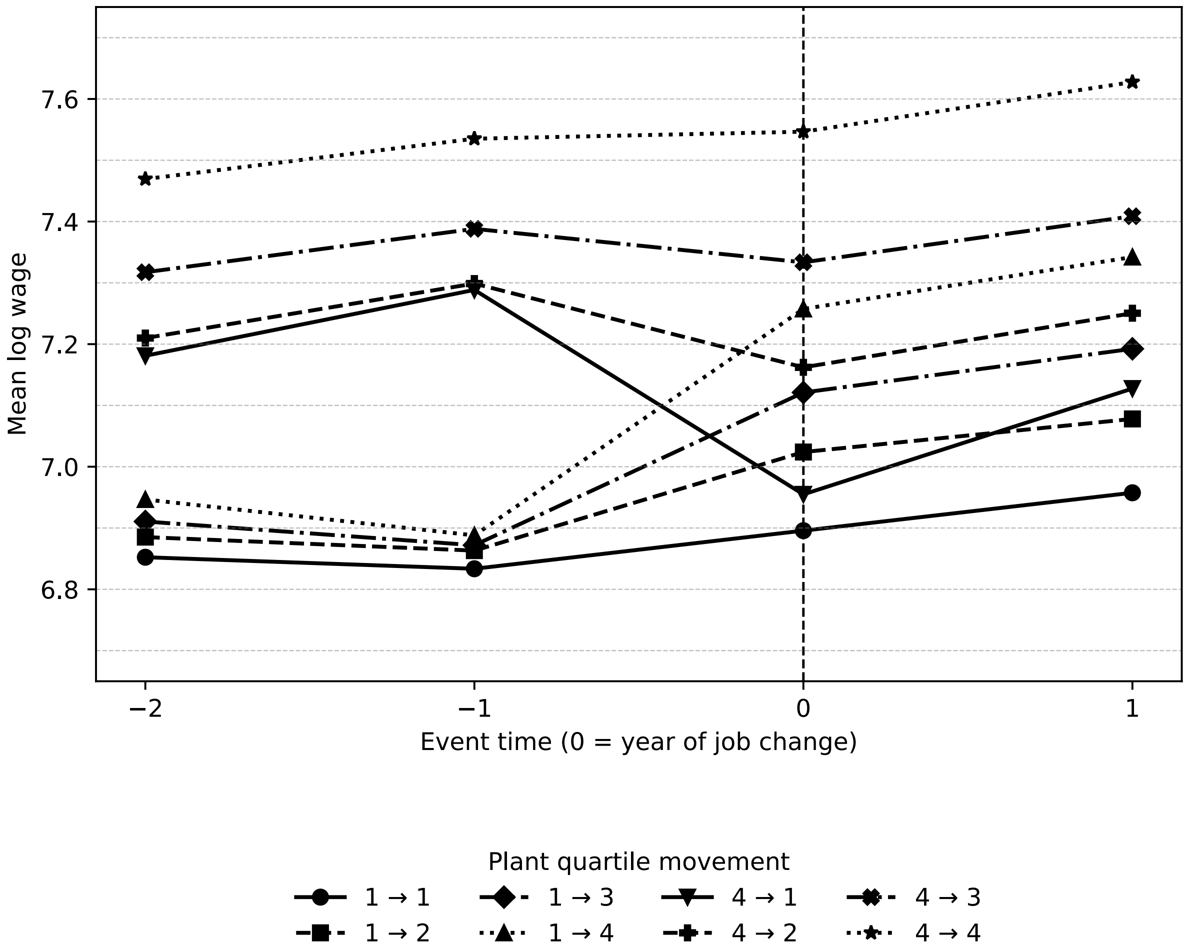


Figure Y.1: Event-study - Exogeneous mobility

Notes: The figure shows the evolution of raw wages for workers who move from an origin plant in the top or bottom quartile group to a destination plant in any of the other quartile groups. Plants are assigned to quartiles based on co-worker daily wages. The sample includes workers in the largest connected set that are continuously observed for at least two years prior to a job switch at the origin plant and two years after the switch at the new destination plant.

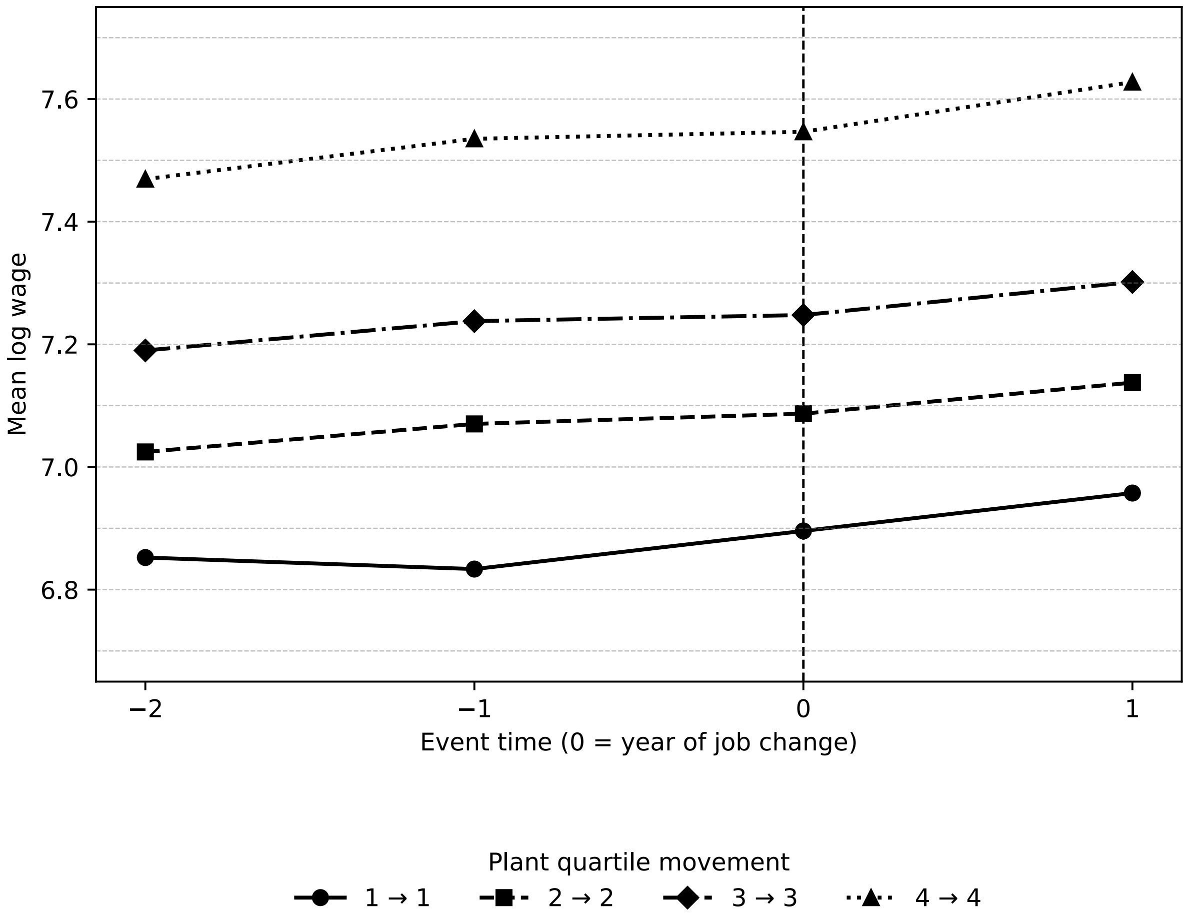


Figure Y.2: Event-study - Exogeneous mobility

Notes: The figure shows the evolution of raw wages for workers who move from an origin plant in either quartile group to a destination plant in the same quartile group. Plants are assigned to quartiles based on co-worker daily wages. The sample includes workers in the largest connected set that are continuously observed for at least two years prior to a job switch at the origin plant and two years after the switch at the new destination plant.

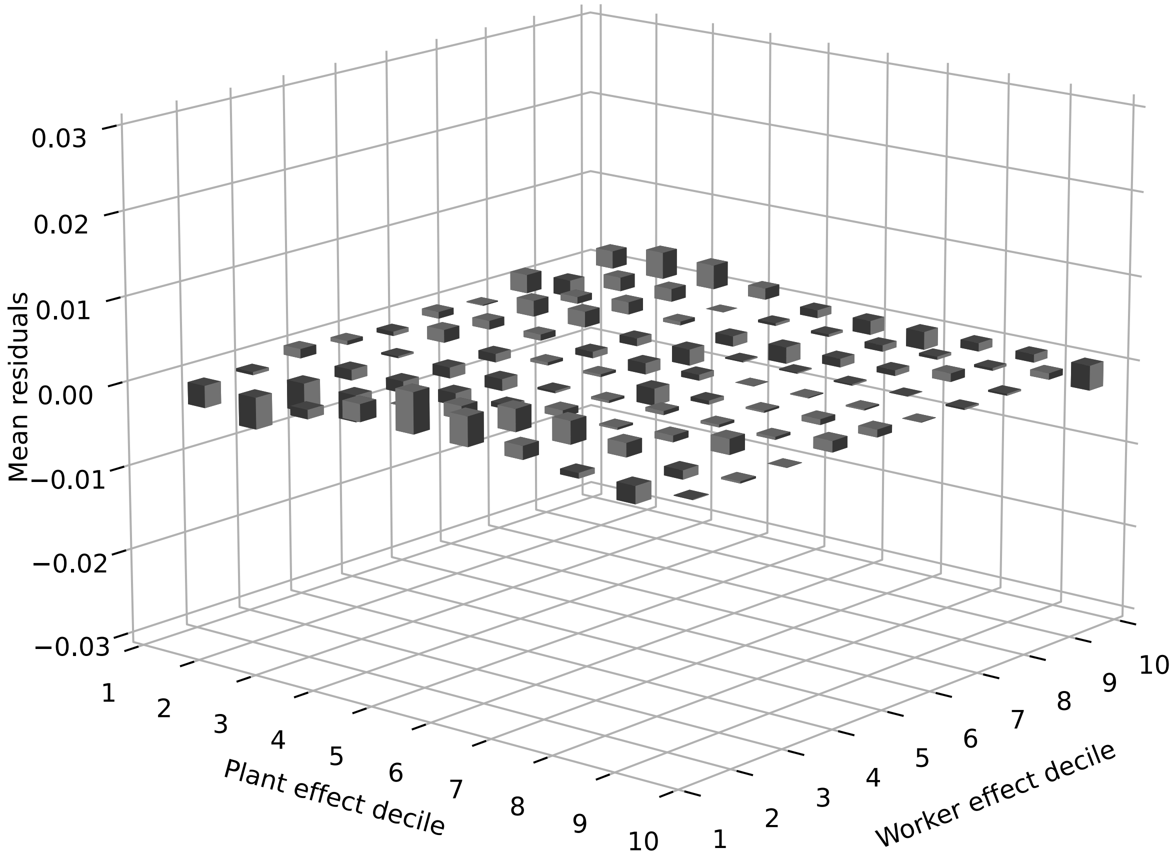


Figure Y.3: Mean Residuals

Notes: The figure shows mean residuals across 100 cells formed by interacting worker-effect deciles with plant-quality deciles from Eq. 1. Workers and plants are first assigned to deciles, then mean residuals are computed within each resulting cell.

Z Supplemental analysis

Table Z.1: Alternative number of quality bins

	(1) 250	(2) 1,000	(3) 2,500	(4) 5,000	(5) 10,000
City	-0.526***	-0.528***	-0.529***	-0.529***	-0.529***
	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)
Job 2	0.145**	0.145**	0.145**	0.145**	0.145**
	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)
Job 3	0.226***	0.226***	0.226***	0.226***	0.226***
	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)
Job 4	0.055	0.055	0.055	0.055	0.055
	(0.079)	(0.079)	(0.079)	(0.079)	(0.079)
Job 5	-0.359***	-0.358***	-0.358***	-0.358***	-0.358***
	(0.094)	(0.094)	(0.094)	(0.094)	(0.094)
Job 6	-0.643***	-0.642***	-0.642***	-0.642***	-0.642***
	(0.114)	(0.114)	(0.114)	(0.114)	(0.114)
Job 7	-1.062***	-1.061***	-1.061***	-1.061***	-1.061***
	(0.144)	(0.144)	(0.144)	(0.144)	(0.144)
Job 8	-1.486***	-1.485***	-1.485***	-1.485***	-1.485***
	(0.189)	(0.189)	(0.189)	(0.189)	(0.189)
City x Job 2	0.086	0.087	0.087	0.087	0.087
	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)
City x Job 3	-0.025	-0.023	-0.023	-0.023	-0.023
	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)
City x Job 4	-0.352***	-0.350***	-0.349***	-0.349***	-0.349***
	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)
City x Job 5	-0.495***	-0.495***	-0.494***	-0.495***	-0.495***
	(0.132)	(0.132)	(0.132)	(0.132)	(0.132)
City x Job 6	-0.915***	-0.916***	-0.915***	-0.915***	-0.915***
	(0.160)	(0.160)	(0.160)	(0.160)	(0.160)
City x Job 7	-1.242***	-1.242***	-1.242***	-1.242***	-1.242***
	(0.201)	(0.201)	(0.201)	(0.201)	(0.201)
City x Job 8	-1.432***	-1.431***	-1.430***	-1.430***	-1.430***
	(0.264)	(0.264)	(0.264)	(0.264)	(0.264)
Constant	26.017***	26.018***	26.018***	26.018***	26.018***
	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)
Controls	Yes	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes	Yes
Observations	2,109,860	2,109,860	2,109,860	2,109,860	2,109,860
R-squared	0.01	0.01	0.01	0.01	0.01

Notes: The dependent variable is the absolute rank distance between workers and plants, scaled by the maximum rank distance and expressed as a percentage. Columns (1) through (5) report estimation results for alternative number of quality bins, ranging from 250 to 10,000. The baseline specification with 5,000 bins is given in column (4). Controls include education level, plant size (number of employees), immigrant status, and 2-digit industry fixed effects.

Standard errors, displayed in parentheses, are clustered at the individual level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

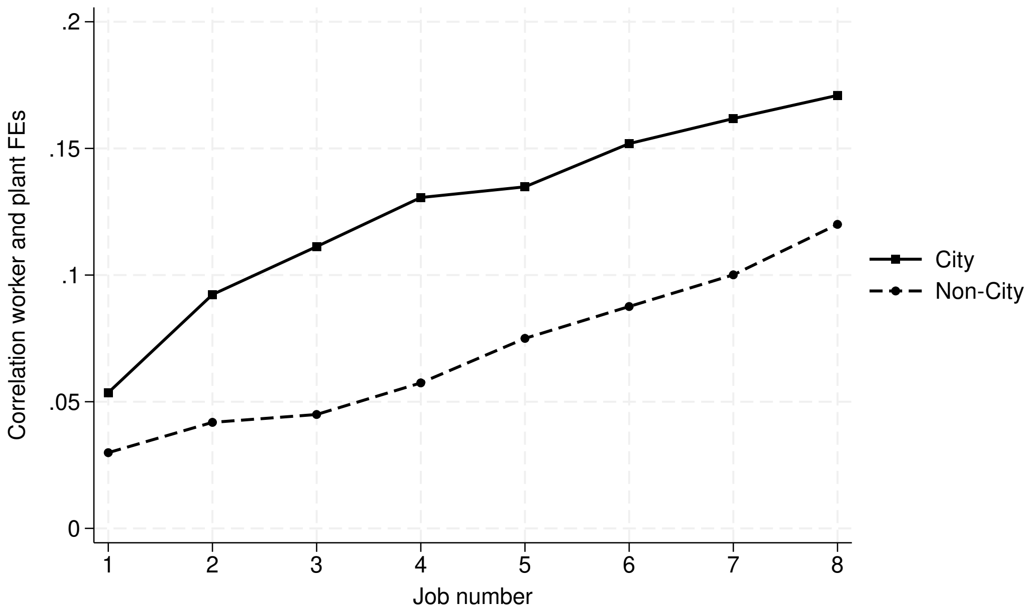
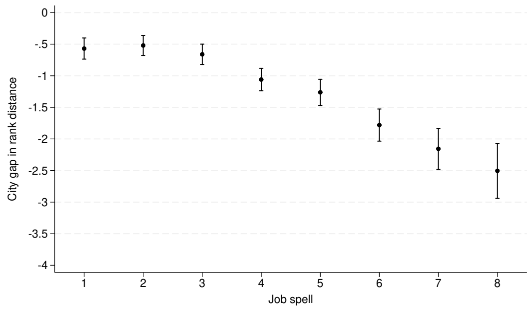
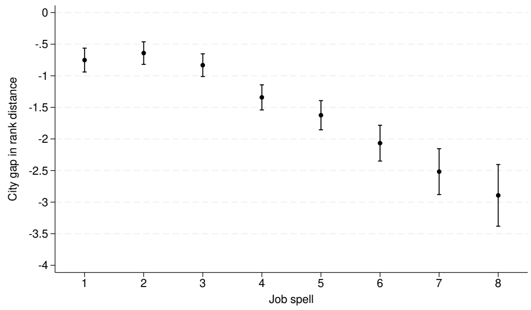


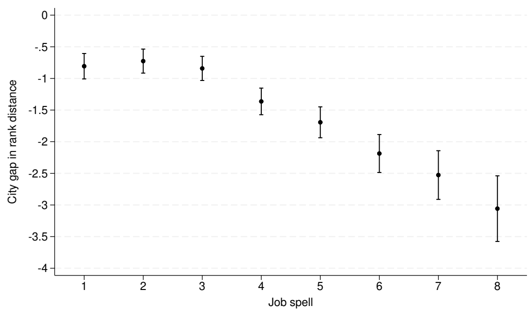
Figure Z.1: Assortative matching in city and non-city areas: Correlation-based measure
Notes: The figure shows results from the correlation of worker and plant fixed effects by job number and labor market size. Higher values indicate better assortative matching.



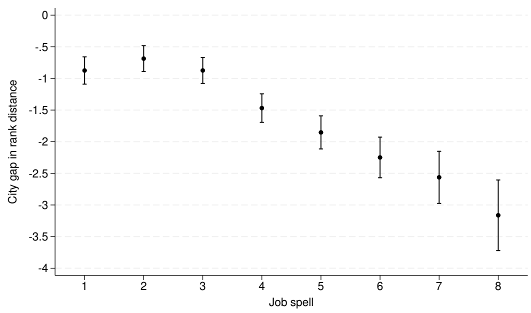
(a) Min. plant size: 3



(b) Min. plant size: 6



(c) Min. plant size: 8



(d) Min. plant size: 11

Figure Z.2: Excluding small plants

Notes: Panels (a) through (d) show the estimated city gaps in assortative matching for alternative cutoff levels with respect to minimum plant size. In each panel, worker and plant fixed effects are re-estimated given the new sample.

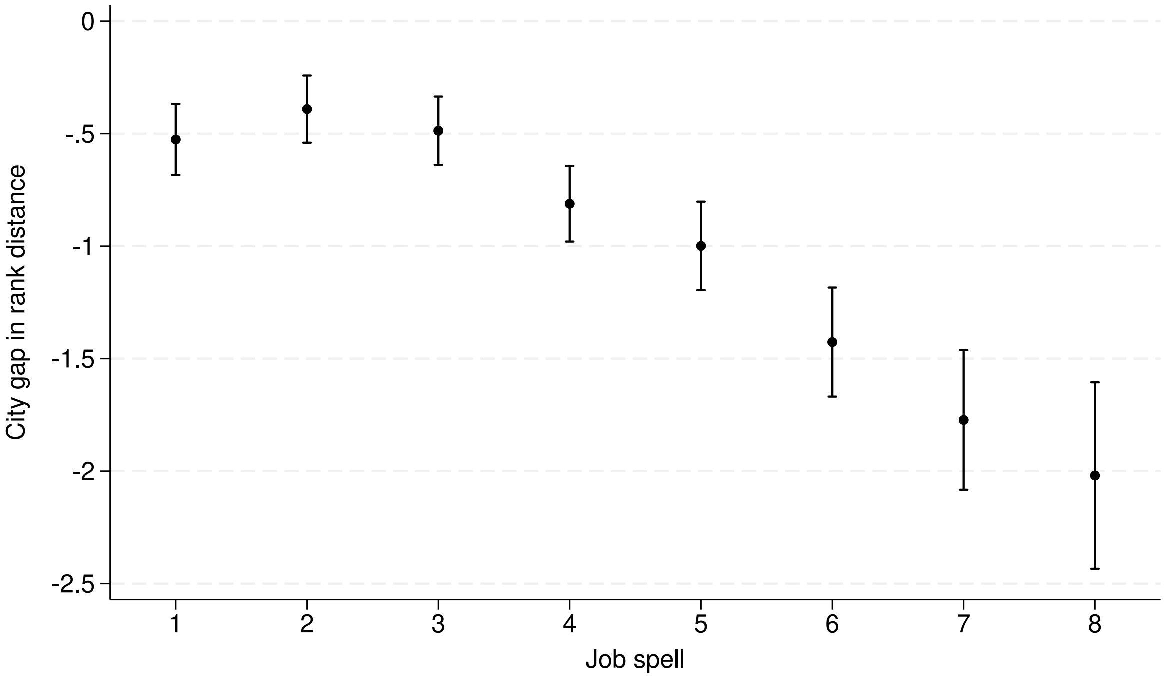


Figure Z.3: Excluding top and bottom 1% of fixed effect distributions

Notes: The figure shows the estimated city gaps in assortative matching when workers and plants in the top and bottom one percent of their respective fixed-effects distributions are excluded.

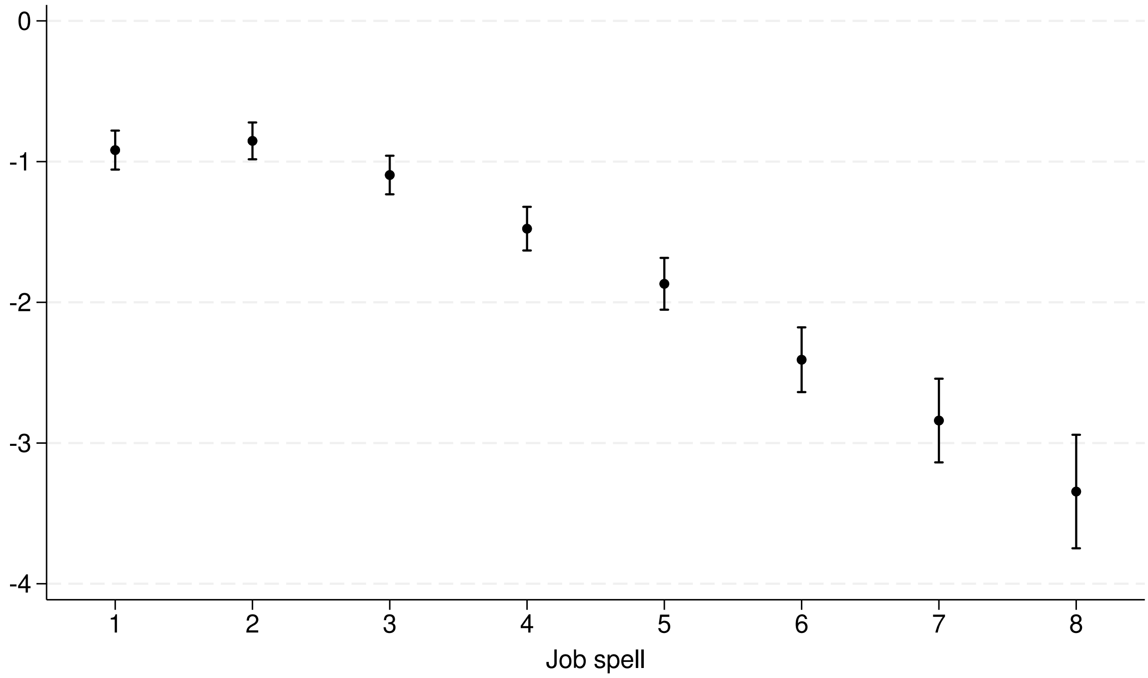


Figure Z.4: Alternative definition of employment match location

Notes: The figure shows the city-non-city gaps in assortative matching from our baseline model, which includes controls and worker fixed effects, where worker-plant pairs are assigned to a plant-level location. Plants are classified as either city or non-city based on the residential distribution of their employees: if more than 50 percent reside in a city area, the plant is classified as a city plant. Confidence intervals are 95%, with standard errors clustered at the worker level.

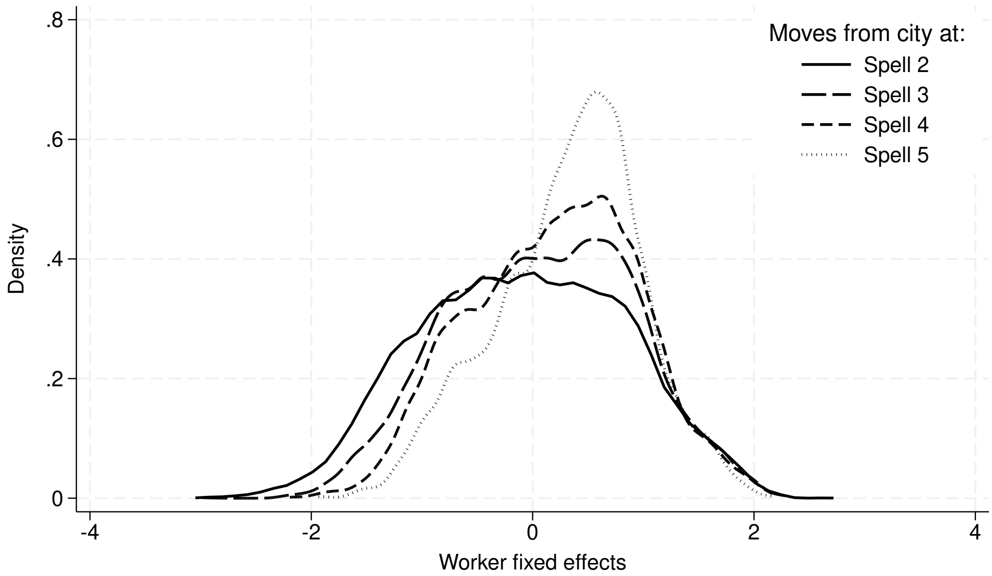


Figure Z.5: Worker fixed effects distributions by spell for movers from cities

Notes: The figure displays distributions for movers from cities by the spell of relocation.

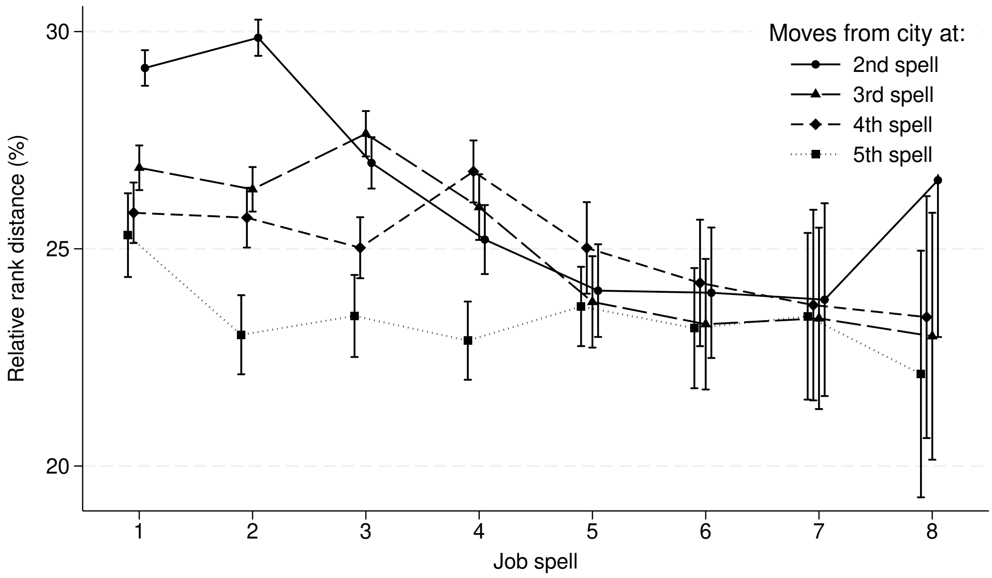


Figure Z.6: Assortative matching dynamics for workers relocating from cities
Notes: The figure shows assortative matching dynamics for workers who relocate from cities to non-cities, by the career timing of the move. Each series is estimated from a separate regression of a parsimonious specification including job-spell indicators and no constant term.. Confidence intervals are 95 percent, with standard errors clustered at the worker level.

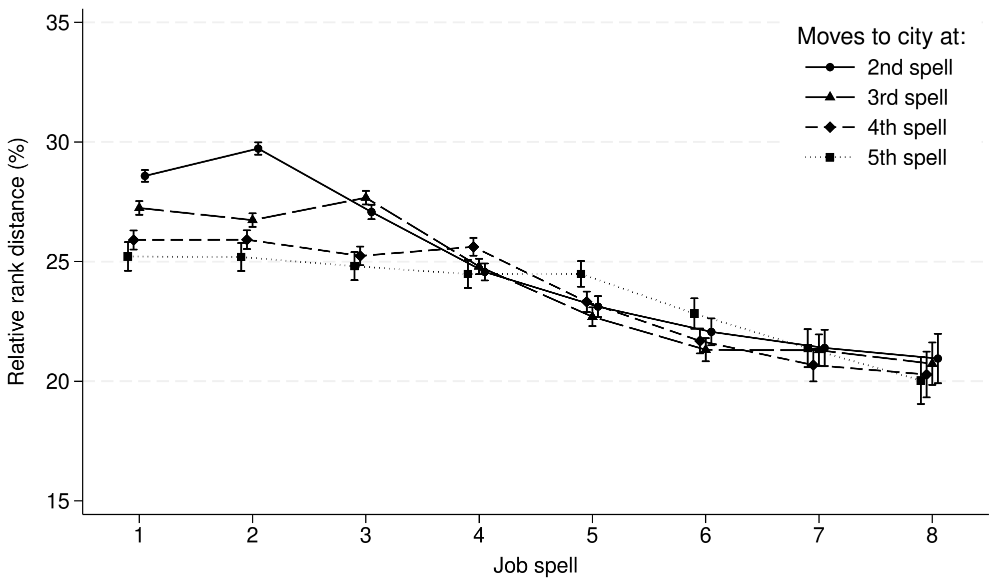


Figure Z.7: Assortative matching dynamics for workers relocating to cities with no sample restrictions
Notes: The figure shows assortative matching dynamics for workers who relocate to cities. Workers are defined as city or non-city movers based on the direction of their first move. The sample includes workers with missing spell observations prior to their first move, as well as spells observed after return migration. Each series is estimated from a separate regression of a parsimonious specification including job-spell indicators and no constant term. Confidence intervals are 95 percent, with standard errors clustered at the worker level.

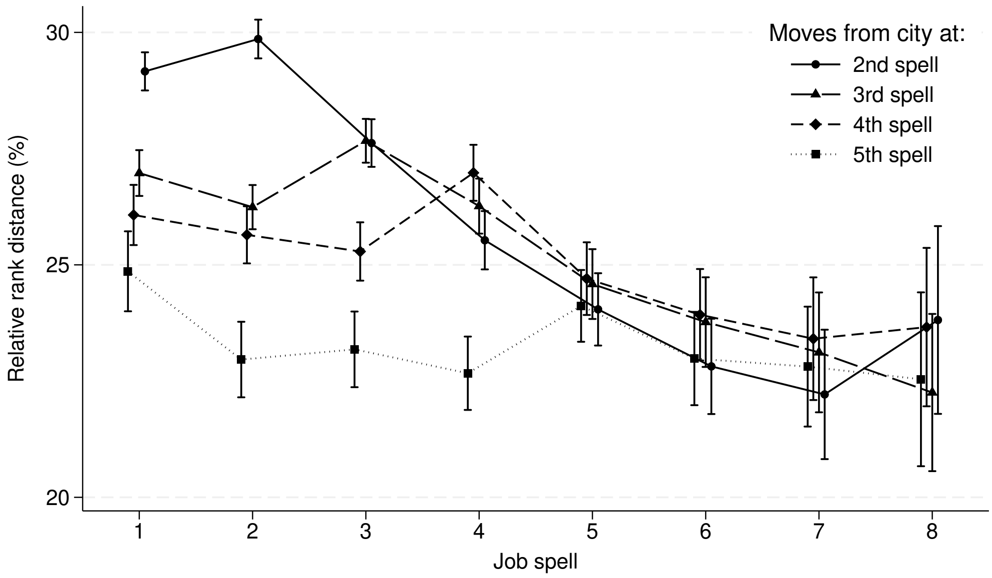


Figure Z.8: Assortative matching dynamics for workers relocating from cities with no sample restrictions
Notes: The figure shows assortative matching dynamics for workers who relocate from cities to non-cities. Workers are defined as city or non-city movers based on the direction of their first move. The sample includes workers with missing spell observations prior to their first move, as well as spells observed after return migration. Each series is estimated from a separate regression of a parsimonious specification including job-spell indicators and no constant term. Confidence intervals are 95 percent, with standard errors clustered at the worker level.

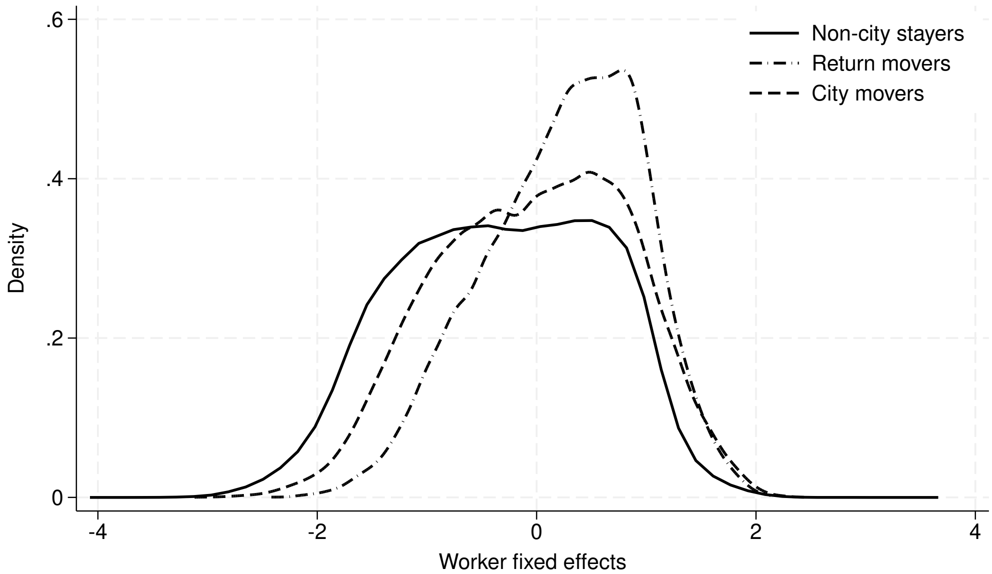


Figure Z.9: Worker fixed effects distribution of city movers, return movers, and non-city stayers
Notes: The figure shows kernel densities of worker fixed effects using a Gaussian kernel with a common bandwidth across groups, chosen using Silverman's rule of thumb on the pooled sample. The figure displays distributions for city movers with a single move, city movers with a return move, and non-city stayers.

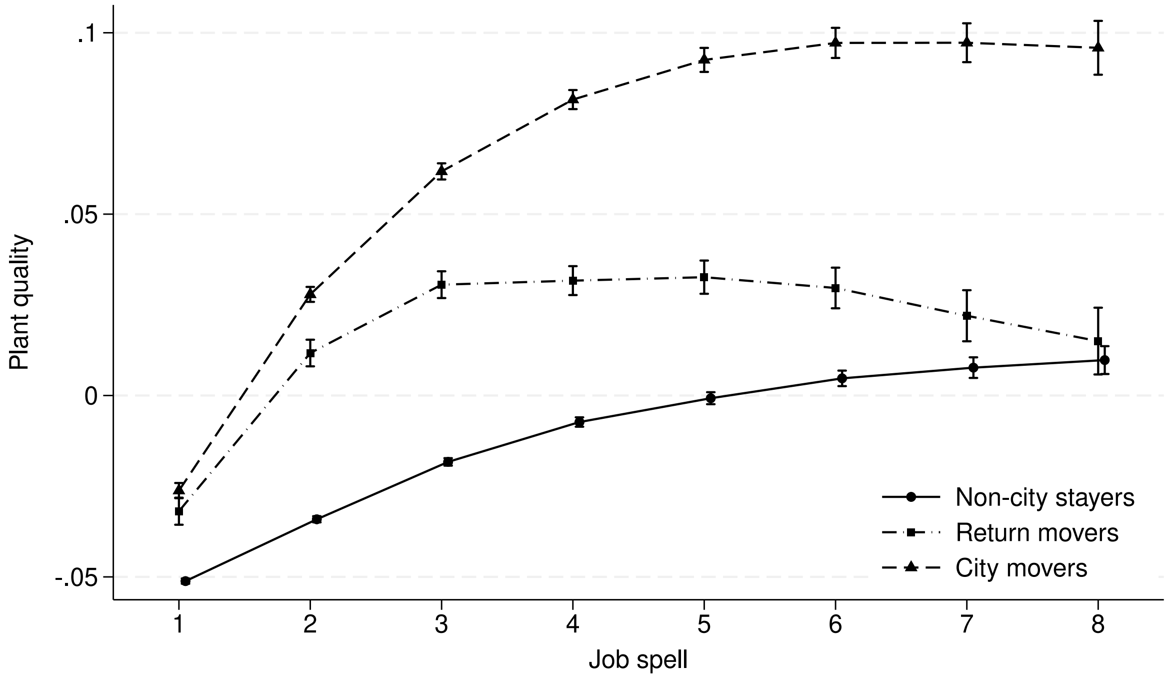


Figure Z.10: Job-ladder progression for city movers, return movers, and non-city stayers
Notes: The figure shows job ladder trajectories for city movers with a single relocation, city movers who return migrate, and non-city stayers. Each series is estimated from a separate regression of a parsimonious specification including job-spell indicators and no constant term. Confidence intervals are 95 percent, with standard errors clustered at the worker level.