The Local Root of Wage Inequality

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Abstract

Wages are on average higher in larger cities, yet the real earnings of low-wage workers are lower. Using French administrative data, I document two novel facts. Large cities concentrate high-paying jobs, while low-paying jobs are everywhere. The reallocation of workers across jobs spurs faster wage growth in larger cities. I propose a framework that rationalizes these facts. Productive employers agglomerate in large cities to maximize their size. Fiercer competition steepens the local ladder, and workers accept lower real earnings anticipating future wage growth. After estimating the model, I find that housing-adjusted unemployment benefits amplify spatial disparities but raise aggregate welfare.

JEL Codes: E24, E25, E64, J31, J38, J42, R12, R13, R23, R32.

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[M]any urban dwellers suffer from extreme inequality. In a world with high and growing levels of urbanization, the future of inequality largely depends on what happens in cities [...].

United Nations, *World Social Report 2020*

Wages vary substantially across cities, though not uniformly. In urban hubs, wages are high, but so is inequality. There, high-income earners live alongside low-wage workers who also face high costs of living. In Paris for instance, the average wage is 57% higher than in Le Mans, a mid-size city at the median of the wage distribution (Figure 1(a)). However, low-income earners — those in the bottom 10% of the local wage distribution — earn 15% *less* than their counterparts in Le Mans after accounting for housing prices (Figure 1(b)). Policymakers frequently debate whether policies aimed at low-wage workers should factor in local prices. Yet, little is known as to why low wages persist in large cities. Why are wages both higher and more dispersed in larger cities? How come many workers earn lower real wages there? And should labor policies be place-based?

This paper offers answers to these questions in four parts. First, I use administrative data to decompose the drivers behind spatial wage inequality. Second, I provide a framework that endogenously generates higher wages and greater wage dispersion in larger cities, which I estimate in the third part of the paper. Fourth, I quantify the consequences of indexing unemployment benefits to housing prices on aggregate efficiency and spatial inequality.

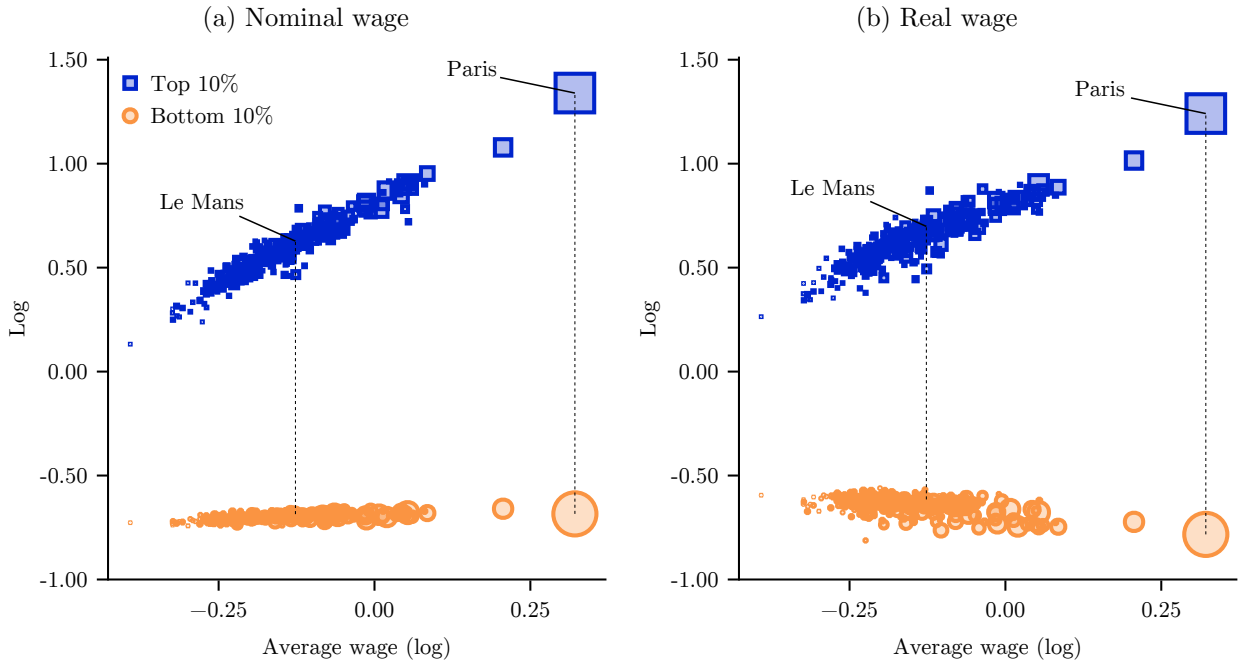
Specifically, in the first part of the paper, I leverage French matched employer-employee data to document two new facts about the importance of employers for spatial wage disparities. First, I show that high-paying jobs are concentrated in large cities while low-paying jobs are everywhere.

I quantify the relative importance of jobs and worker heterogeneity by estimating a mover design à la Abowd et al. (1999) — AKM henceforth. I project wages on worker and job fixed effects. I extend the standard framework to allow for city-specific returns to experience. I define workers' contribution to wages as the sum of the worker fixed effects — which capture time-invariant characteristics — and the local returns to experience. Assuming conditional random mobility of workers across jobs, the job fixed effects identify wage premia: the extra wage a worker earns when employed at a particular job above and beyond their time-invariant skills and city experience.

The average wage premia is 3.1% higher in commuting zones (CZ) twice as large, or 31% of the between-city wage variance. However, low-paying jobs persist in large cities: the premium offered by jobs in the bottom 10% of Paris's distribution is 27% lower than the average French job. Wage premia are thus more dispersed in larger cities, accounting for 33% of the spatial variation in within-city inequality. The cohabitation of low- and high-skill workers in large cities drives 69% of the between-city and 57% of the within-city variance. The industrial and occupational composition of cities explain little of the persistence of low-paying jobs in large cities.

Second, I document that workers are not stuck at low-paying jobs; rather, the reallocation of workers from low- to high-paying jobs is a key force behind the city-size wage premium. On average, 3.9% of workers switch jobs every quarter. The job switching rates are homogeneous across space

Figure 1: Gross hourly wage by commuting zone



Data source: *Déclaration Annuelle de Données Sociales*. Each dot is a commuting zone. Panel (a) displays the average wage in the bottom 10% (orange circle) and top 10% (blue rectangle) of the CZ wage distribution. Panel (b) displays the statistics for wages deflated by a citywide Cobb-Douglas price index with a housing expenditure share of 0.2. Both statistics are projected against the unconditional CZ average wage. The size of the markers is proportional to the number of workers per CZ.

once controlling for observed and unobserved workers' characteristics.

However, the job ladder is steeper in larger cities. I estimate the ladder steepness via the increase in wage premia upon a switch, i.e., the extra wage growth of job switchers relative to that of job stayers conditional on worker and job fixed effects. Wage premia increase by 10.1% when workers switch jobs in Paris. This is 7.6% nationally. As a result, wages diverge over time: it takes 17 years — half of a worker's career — for the gap in wage premia induced by reallocation to reach their between-city level. Large cities offer steeper ladders for every occupation and quartile of the wage distribution. The bulk of the local returns to job switching materialize for workers staying within the same occupation, strengthening the case that they do not capture human capital accumulation.

The two facts highlight the importance of employers for spatial wage inequality and challenge existing theories. The spatial distribution of skills cannot explain why wage premia are higher in larger cities. Hicks-neutral local TFPs can generate wage-premia gaps across space but not the dispersion of premia within cities. Finally, idiosyncratic productivity shocks at the worker–location level produce within-city inequality but not the reallocation of workers from low- to high-paying jobs. In the rest of the paper, I focus on the portion of spatial wage inequality driven by employers, and I develop a new framework that ties the two facts together.

Workers are ex-ante homogeneous. They choose where to live to maximize their lifetime utility, which depends on their expected lifetime income, housing prices, and local amenities. Workers enter a city as unemployed, and progressively experience wage growth by climbing the local job ladder. Employers differ in productivity and decide where to produce and hire workers. Search

frictions constrain their size. As in Burdett and Mortensen (1998), wages serve as a hiring tool: offering higher wages allows employers to attract and retain more workers from local competitors.

I characterize the model analytically, which delivers two new insights as to the possible drivers of spatial wage inequality. First, productive employers agglomerate in large cities to access a slack labor market. The location decision of employers depends on three considerations: how many workers they can hire, and how expensive labor and commercial housing are. The higher vacancy contact rate in slack markets lets firms hire more workers. Complementarity in production between productivity and size implies that productive employers are more willing to pay to produce there. In equilibrium, markets are slacker in large cities as housing prices price out unproductive employers. Local competition intensifies, and firms offer higher wages to attain their target size. Hiring frictions therefore generate a positive correlation between city size, employer productivity, and wages.

Second, low-paying jobs persist in large cities because workers hired from unemployment cannot bargain their way into higher wages. Under monopsony power, wages depend on how much competition employers face. In large cities, firms that hire most of their workforce by poaching local competitors offer the highest wages nationwide as all their competitors are more willing to pay their workers. However, employers drawing primarily from unemployment do not compete directly with other firms in the city. Wages at the bottom of the ladders therefore primarily reflect the outside option of unemployed workers, and low-paying jobs exist everywhere. In particular, unemployed workers accept jobs with lower real wages in larger cities as they anticipate fast wage growth.

To quantify the importance of these forces, in the third part of the paper, I estimate a quantitative version of the model. I extend the model in three ways. Cities also differ in TFP, which captures exogenous fundamentals and productivity spillovers. Second, I allow firms to grow by posting many vacancies instead of locating in a slack labor market. They also face idiosyncratic local costs capturing unobserved heterogeneity in location choice. Third, I add two reasons frequently mentioned to explain the low real wages in large cities: idiosyncratic preferences and migration costs. The model is estimated on the AKM job fixed effects to abstract from worker heterogeneity.

I prove identification for 18 of the 23 parameters by combining strategies from quantitative spatial and wage-posting models. The key part of the estimation is to separately identify the four margins driving firms' location decisions. Worker flows in and out of employment and across firms identify search frictions. Labor market slackness is inferred from firm size and search frictions. The correlation between firm locations and local profitability pins down the dispersion in local costs, where profits are computed using firm size, wage premia, and identified productivity and vacancy postings. Finally, TFPs are residuals matching each location's average wage premia.

I find that productive employers concentrate in large cities to access slacker labor markets rather than high productivity. In the data, firms are larger in bigger locations, and vacancy postings fall short of rationalizing the size gaps. Large cities therefore offer a higher vacancy filling rate. All else equal, an employer moving from Le Mans to Paris increases its size by 45%. Productive employers agglomerate there, and between-city wage gaps arise endogenously. As a result, local TFPs are relatively homogeneous: a reallocation from Le Mans to Paris raises productivity by 3%, and local TFPs account for 15% of the between-city productivity variance.

The estimation procedure targets neither how within-city inequality varies across space nor how steep the local job ladders are. I use the two facts as over-identification tests. The model explains 103% of the spatial variation in within-city wage premia variance. Larger cities are more unequal because the fiercer competition has heterogeneous incidence across firms. Employers in the top 10% of Paris's wage distribution charge markdowns 12 percentage points (p.p.) lower than employers with similar productivity in other, less competitive cities. However, the markdowns of employers in the bottom 10% in Paris are 6 p.p. higher than those of similar firms elsewhere since they rely relatively more on unemployed workers. The job ladder is steeper in larger cities, and the model rationalizes 108% of the spatial variation in returns to job switching.

Altogether, I find that every worker in larger cities earns higher expected lifetime real earnings. Unemployed workers in Paris earn present real earnings 7.5% lower than in Le Mans as they face higher housing prices. However, their expected lifetime real income is 2.5% higher after accounting for the future high-paying opportunities. The reallocation of workers across jobs, and the option value it begets, are thus key to the location decision of workers.

Having validated the model, the fourth part of the paper uses it to evaluate a policy that indexes unemployment benefits to local housing prices. Policies designed to help low-wage workers face the high costs of living in large cities have been adopted in several countries (e.g., Germany and Japan) and are frequently debated in many others. Their consequences, both on spatial disparities and the aggregate economy, remain elusive. The model is unique to assess the policy as it features unemployment, the option value offered by large cities, and the long-term reallocation of jobs through space. I design the policy so that unemployed workers earn the same real wage everywhere. Higher benefits in expensive locations are funded by lower benefits in cheaper cities, and the transfers induced by the policy amount to 0.17% of the laissez-faire GDP.

Housing-adjusted unemployment benefits amplify spatial disparities but yield significant efficiency gains. The policy is spatially regressive: unemployed workers in high-cost cities receive a net transfer despite being better off originally. The welfare of workers born in Paris rises by 2.2% in lifetime earnings equivalence, whereas it declines by 0.7% for those born in Le Mans. Welfare disparities grow as the policy amplifies between-city wage gaps.

The reallocation of employers across space explains the bulk of the widened between-city wage inequality. The policy increases the outside option of workers in large locations. Holding constant the spatial allocation of jobs, the higher outside option fades out throughout the ladder, and the pass-through to average wages is relatively small. In general equilibrium, the policy spurs agglomeration: a greater fraction of workers locate in large cities, thus slackening the local labor market and amplifying the concentration of productive employers there. The general equilibrium response explains 65% of the increase in between-city wage variance.

At the same time, the policy yields sizable aggregate gains. TFP increases by 0.8%, and aggregate consumer surplus rises by 1.7%. Two inefficiencies create misallocation in the laissez-faire equilibrium. The first is a market power externality: markdowns are too high in large cities as productive employers do not internalize how their wages shape the spatial allocation of workers. The second is a pooling externality: unproductive employers tighten the labor market of large cities.

Both forces reduce the aggregate employment share of productive employers. Housing-adjusted unemployment benefits are a unique second-best policy that acts on both margins. It reduces markdowns in large locations by increasing workers' outside option. It also prices out unproductive employers by increasing labor costs. I quantify the relative strength of both externalities, and find that 74% of the TFP gains are due to the novel market power externality.

Related literature. This paper relates to several strands of literature. The first studies spatial wage inequality. A vast body of research, started by Marshall (1890), and then followed — among many others — by Rosen (1979), Roback (1982), Combes et al. (2008), and Moretti (2011), analyzes wage gaps *across* locations. Particularly related are Card et al. (2025) and Carry et al. (2025) who document the importance of employers for between-city inequality. Motivated by the evidence that between-city wage variation explains less than 20% of the aggregate wage variance, Glaeser et al. (2009), Baum-Snow and Pavan (2013), Eeckhout et al. (2014), Baum-Snow et al. (2018), Davis and Dingel (2019), and Papageorgiou (2022) analyze wage inequality *within* cities, primarily focusing on worker heterogeneity. I link the two literatures by showing that the spatial allocation of employers explains a sizeable portion of why wages are higher and more dispersed in larger cities.[1]

Second, this paper contributes to the literature on the dynamic wage effects of cities (Glaeser and Maré, 2001; Baum-Snow and Pavan, 2012; De la Roca and Puga, 2017; Bilal and Rossi-Hansberg, 2021; Eckert et al., 2022; Porcher et al., 2023; Lhuillier, 2023). Whereas previous studies emphasize human capital accumulation, I estimate that differences in local job ladders — as measured by the growth in wage premia — account for 29% of the between-city differences in wage growth.

I microfound the differences in local job ladders through a model of firm sorting in which employers compete locally for workers by poaching each other. Schmutz and Sidibé (2019), Martellini (2022), and Heise and Porzio (2022) integrate on-the-job search in quantitative spatial models. I contribute to these papers by endogenizing employers' location choice, which I show drives the impacts of housing-adjusted unemployment benefits on spatial disparities.

Most closely related are Bilal (2023) and Lindenlaub et al. (2025) who both study firm sorting across frictional local labor markets.[2] Relative to the former, I introduce job-to-job mobility and show that it generates a quantitatively important labor market power externality new to the place-based policy literature (e.g., Kline and Moretti, 2014; Fajgelbaum and Gaubert, 2025). Lindenlaub et al. (2025) also develop a framework where firms' locations shape local ladders. The two papers mainly differ in how they model space. Their analysis focuses on the pure sorting, measure-preserving allocation along a continuous line, which allows for elegant analytical results. The number of employers per location is set by the exogenous housing supply, and within-city productivity dispersion follows from ex-post parametric productivity shocks. I let the labor market

[1] Local wage dispersion arises in models where labor markets are segmented by neighborhoods (e.g., Ahlfeldt et al., 2015; Hoelzlein, 2020; Almagro and Domínguez-Iino, 2025). These frameworks are silent on cross-city differences.

[2] Other papers emphasize the importance of firm sorting for spatial disparities, including Behrens et al. (2014), Gaubert (2018), Hong (2024), Franco (2024), and Kleinman (2024). Absent frictional labor markets, productive firms necessarily concentrate in high productivity cities as they do not value market slackness. By contrast, I find that TFP gaps are small, and that productive employers agglomerate in large cities to mitigate search frictions.

tightness vary freely across cities, which I quantify as the main driver of firm sorting and the origins of the model's inefficiencies. In addition, I fully endogenize the local productivity distributions.

The rest of this paper is organized as follows. Section 1 presents the data and novel facts. Section 2 develops and characterizes the theoretical framework. Section 3 lays out the quantitative extensions of the model and its estimation. Section 4 presents the estimation results, and Section 5 concludes with the policy analysis.

1 Two facts about spatial wage inequality

1.1 Data

I use employer tax records from France (*Déclaration Annuelle de Données Sociales*, DADS) between 2008 and 2019. The dataset is a 4% representative panel that tracks the entire history of individuals in the labor market (*DADS panel*). It provides information on workers' earnings, hours worked, the establishment where they are employed and their occupation, the location where they work and live, along with demographic information. The dataset has two advantages. First, its panel structure allows to track workers across jobs and locations. Second, its large sample guarantees sufficient statistical power to precisely estimate statistics at granular geographical units.

I focus my analysis on full-time employees between 25 and 55 years old. Workers in the public sector have their wages determined nationally by tenure rather than the market. I therefore keep workers employed in the private sector, and I exclude the education and health industries due to their large fraction of public servants. I define gross hourly wages as earnings and bonuses divided by hours worked. I deflate wages by the aggregate consumption price index and express them in 2018 euros. Appendix D provides more details on the sample construction.

I define a job as an establishment $\times$ 4-digit occupation, and a city as a CZ. A CZ is a statistical area defined by the French statistical agency (INSEE). It consists of a collection of neighboring municipalities clustered to reduce commuting flows across them. CZs are thus the natural geographical unit for local labor markets. There are 297 such areas in metropolitan France, with an average size of 31,823 employed workers. I use the terms CZs, cities, and locations interchangeably.

For computational feasibility and statistical accuracy, I group cities according to their average wage. I construct ten population-weighted deciles of average wages. The first decile contains 100 cities, Le Mans is in the fourth group, and the tenth decile is composed of Paris and Saclay, the South-West suburb of Paris. Table C.3 provides summary statistics on each of the city clusters. This clustering accounts for 97% of the variation in average wages and wage variance across CZs.

1.2 Spatial wage inequality in France

Figure 1 displays the extent to which wages vary across and within cities in France. Panel (a) plots the average wage in the bottom 10% (orange circles) and top 10% (blue rectangles) of the cities' wage distribution against the unconditional average wage.

Two patterns stand out. First, there are large average wage differences across CZs. The average wage in Paris is 57% higher than in Le Mans, the median city in the wage distribution. High-wage cities tend to be larger: workers in cities twice as large earn on average wages 5.7% higher. Decomposing the aggregate wage variance into a between- and within-city component,

$$\mathbb{V}\text{ar}[\log w] = \underbrace{\mathbb{V}\text{ar}[\mathbb{E}(\log w)]}_{\text{Between-city}} + \underbrace{\mathbb{E}[\mathbb{V}\text{ar}(\log w)]}_{\text{Within-city}},$$

the spatial variation in average wages accounts for 9.5% of the total wage variance.

Second, cities vary substantially in how unequal they are. For instance, the standard deviation of log wages in Paris is 0.56, 53% higher than in Le Mans. For comparison, this is 0.64 in the United States and 0.44 in France, countries often associated with high and low inequality. Larger cities are more unequal as they host both low- and very-high wages. Workers in the top 10% of the wage distribution in Paris are in the top 1% nationwide. By contrast, low-wage workers earn similar wages throughout France. While Figure 1(a) may be mechanically driven by a binding minimum wage, the pattern extends beyond the bottom 10% of wages (Figure C.2(a)).

Figure 1(b) repeats the exercise with real wages, computed as wages deflated by a citywide Cobb-Douglas price index with a housing expenditure share of 0.2. Low-wage workers earn lower real earnings in larger cities. For instance, workers in the bottom 10% in Paris are in the bottom 1% of the national real wage distribution. The pattern is robust to computing the price index at the municipality level to account for the sorting of workers across neighborhoods. It also holds among domestic migrants, i.e., those who explicitly choose to live there (Figure C.2(b)).

I now quantify the role of workers and employers in between- and within-city wage inequality.

1.3 Empirical design

I estimate the importance of workers and employers for wages via a two-way fixed effect model à la AKM. Specifically, I estimate

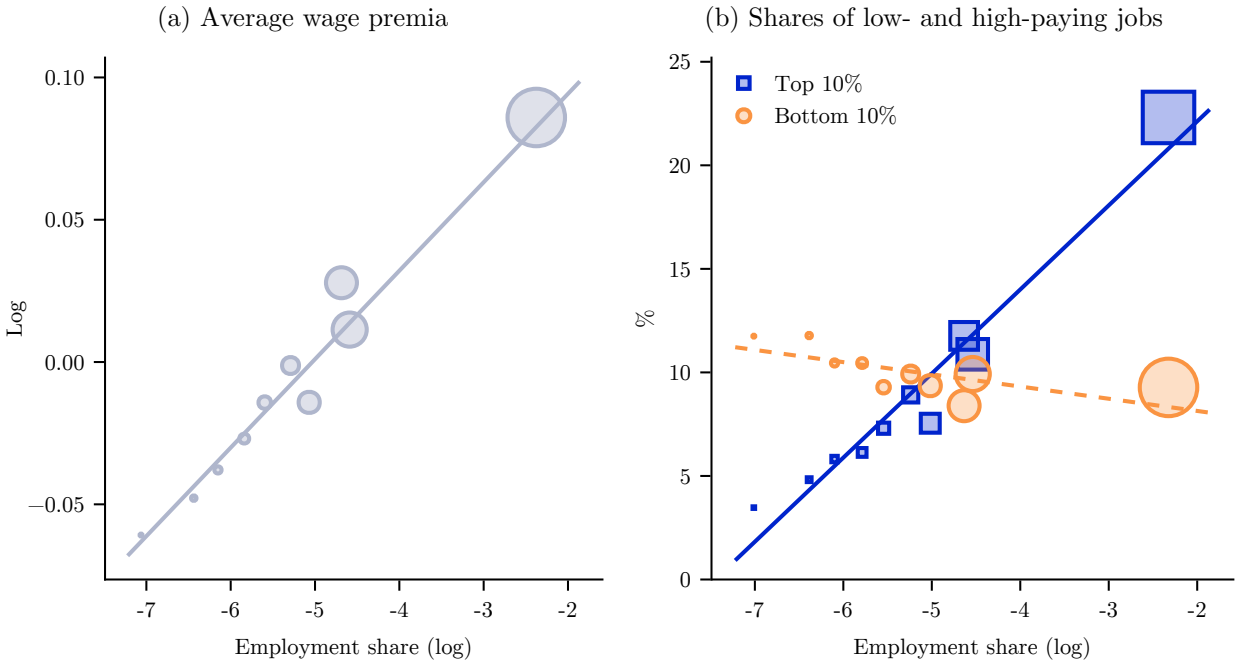
$$\log w_{it} = \alpha_i + \beta_{\ell(i,t)} x_{it} + \gamma_{j(i,t)} + \varepsilon_{it}, \tag{1}$$

where i is a worker, t is a quarter-year, x_{it} denotes the number of years worked, and $\ell(i,t)$ and $j(i,t)$ are indices for the city group and job where i is employed at time t. The worker fixed effects α_i control for time-invariant worker characteristics (e.g., education, gender) and other unobserved abilities. The parameters $\{\beta_\ell\}_{\ell=1}^{L}$ summarize the impact of experience on wages, allowing cities to offer differential returns to experience. I define the contribution of workers to wages as the sum of the static and dynamic components: $\psi_{it} \equiv \alpha_i + \beta_{\ell(i,t)} x_{it}$. Finally, γ_j are job fixed effects.

Workers who move between jobs identify the job fixed effects if the mobility of workers is random conditionally on these workers and their jobs. In this case, the fixed effects measure the extra wage offered by a particular job — a job wage premium. Across space, the levels of the fixed effects are identified from workers switching jobs across locations.

The random mobility assumption behind (1) is weaker than traditionally used in the urban and labor literature (e.g., Combes et al., 2008). First, as in Card et al. (2025), the mobility patterns

Figure 2: The spatial distribution of wage premia



Left panel displays the average job FE per city group against the average employment share of CZs in each group. Right panel displays the employment share of low-paying (orange circles) and high-paying (blue rectangles) jobs in each city group. Low-paying (high-paying) jobs are defined as jobs with a fixed effect in the bottom 10% (top 10%) of the national fixed effects distribution. In both panels, the fixed effects are obtained from (1).

are allowed to vary by establishments, for instance, if workers systematically move from low- to high-paying firms. Second, the mobility patterns can also vary by occupations, for instance, if past occupations affect the jobs and cities workers have access to. If the random mobility assumption fails, the job fixed effects and the residuals quantify the wage variations not explained by time-invariant worker characteristics and their experience, i.e., residual wage inequality.[3]

To limit well-known econometric difficulties linked to limited mobility bias, I follow Bonhomme et al. (2019) and group workers and jobs into 100 equally populated clusters based on their unconditional average wage.[4] I then estimate equation (1) by OLS at the group level, and use the AKM fixed effects to establish two novel facts on the importance of employers for spatial wage inequality.

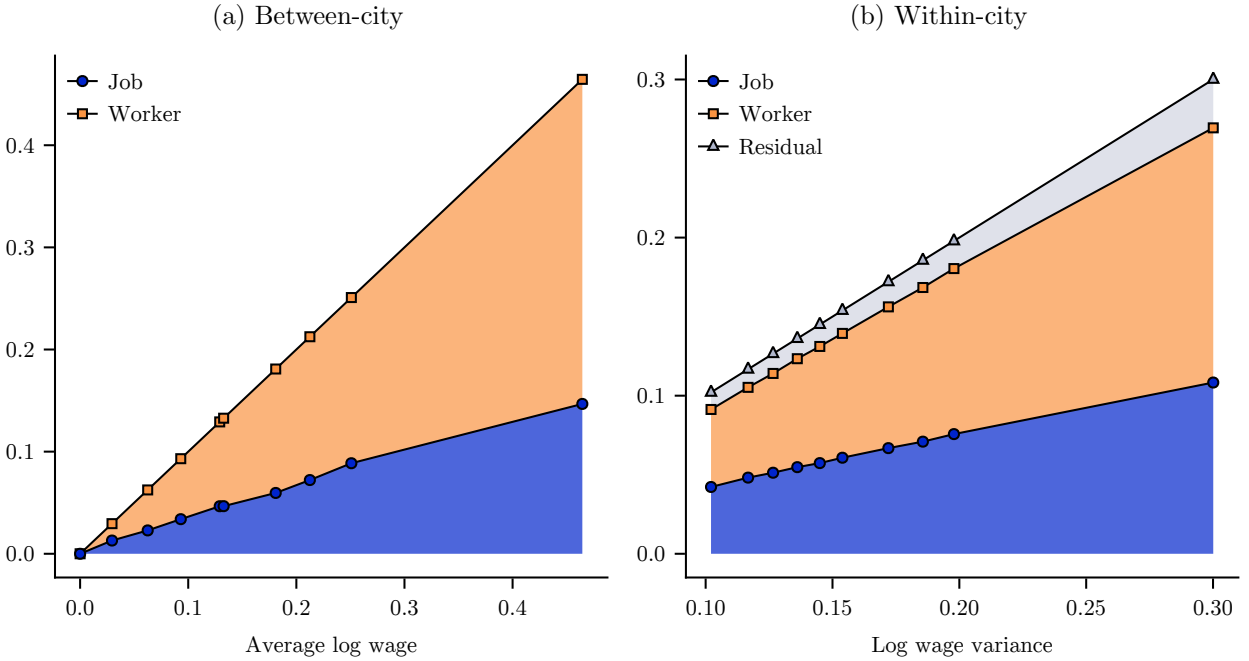
1.4 High-paying jobs cluster in large cities, low-paying jobs are everywhere

Jobs pay higher wage premia on average in larger locations. Figure 2(a) plots the average job fixed effect within each city group against the average employment share of cities in each group. On average, workers earn a wage premium 3.1% higher in cities twice as large. The magnitude is similar to Combes et al. (2008) in France and Card et al. (2025) in the United States, and aligns with estimates of agglomeration benefits (e.g., Combes and Gobillon, 2015). However, the city-size wage premium is here tied to jobs, and it is possible to assess whether all jobs pay higher wages.

[3]The conditional random mobility assumption is satisfied in the model I develop in Section 2.

[4]The grouping for jobs is done within city groups to preserve the local nature of an establishment. The results are virtually identical when varying the number of clusters between 10 and 200.

Figure 3: The role of workers and employers on spatial wage inequality



Left panel displays the between-city wage decomposition (2). The blue and orange areas plot the average job (γ_j) and worker (ψ_i) fixed effects. Average wages, worker fixed effects, and job fixed effects normalized to zero in the lowest wage location. Right panel displays the within-city wage decomposition (3). The blue area plots the contribution of jobs, $\mathbb{V}\text{ar}_\ell[\gamma_j] + \mathbb{C}\text{ov}_\ell[\psi_i, \gamma_j]$. The orange area plots the contribution of workers, $\mathbb{V}\text{ar}_\ell[\psi_i] + \mathbb{C}\text{ov}_\ell[\psi_i, \gamma_j]$. The grey area plots the residuals, $\mathbb{V}\text{ar}_\ell[\varepsilon_{it}]$. In both panels, the fixed effects are obtained from (1).

To do so, Figure 2(b) displays where low- and high-paying jobs are located. I identify jobs whose fixed effect is in the bottom 10% (low-paying) and top 10% (high-paying) of the national job fixed effect distribution. I then compute the fraction of workers in each city that are employed at either jobs. Figure C.3(a) extends the analysis to all the deciles, and Figure C.3(b) repeats the analysis for job shares instead of employment shares.

The spatial allocation of jobs is strikingly different for low- and high-paying jobs. While every location has low-paying jobs, high-paying jobs are disproportionally present in the largest cities. For instance, 22.3% of workers are employed at high-paying jobs in Paris; this is 5.8% of them in Le Mans. By contrast, 9.3% and 10.5% of workers work at low-paying jobs in Paris and Le Mans.

The location of jobs thus matters for both between- and within-city inequality. The spatial concentration of high-paying jobs drives wages upwards in large cities. At the same time, it also implies greater within-city inequality as low-paying jobs persist there.

I quantify the importance of jobs for both dimensions through two decompositions. According to (1), between-city wage gaps arise from differences in worker and job composition:

$$\mathbb{E}_\ell[\log w_{it}] = \underbrace{\mathbb{E}_\ell[\psi_{it}]}_{\text{Worker}} + \underbrace{\mathbb{E}_\ell[\gamma_{j(i,t)}]}_{\text{Job}}. \tag{2}$$

Meanwhile, inequality may be high in large cities because workers are very heterogeneous, pay

premia are dispersed, or residuals are large:

$$\mathbb{V}\text{ar}_\ell[\log w_{it}] = \underbrace{\mathbb{V}\text{ar}_\ell[\psi_{it}] + \mathbb{C}\text{ov}_\ell[\psi_{it}, \gamma_{j(i,t)}]}_{\text{Worker}} + \underbrace{\mathbb{V}\text{ar}_\ell[\gamma_{j(i,t)}] + \mathbb{C}\text{ov}_\ell[\psi_{it}, \gamma_{j(i,t)}]}_{\text{Jobs}} + \underbrace{\mathbb{V}\text{ar}_\ell[\varepsilon_{it}]}_{\text{Residuals}}. \quad (3)$$

Figure 3 implements the between- and within-city decomposition. Each marker represents a city group. In panel (a), the blue and orange areas are the average job and worker fixed effects, projected against the local average wage. Each component is expressed relative to the smallest location. In panel (b), the blue, orange, and grey area depict the location-specific dispersion in job fixed effects, workers fixed effects, and residuals, projected against the city wage variance.

Figure 3 documents the importance of employers for spatial wage inequality. The higher wage premia in larger cities explains 31% of the between-city wage variance. Worker fixed effects contribute 69%. Within cities, the greater dispersion in premia accounts for 33% of why large cities are more unequal. Worker heterogeneity adds 57%, and the remaining 10% reflect residual variation.

Figure B.1 further examines why wage premia are more dispersed in larger locations through two exercises. First, I quantify whether the presence of low-paying industries or occupations explains the persistence of low-paying jobs in large cities. I separate the role of occupations and industries from that of establishments by projecting the job fixed effects onto occupation, industry and establishment fixed effects:

$$\gamma_j = \delta_{o(j)} + \phi_{\iota(j)} + \kappa_{f(j)} + \nu_j. \quad (4)$$

In the above, $o(j)$, $\iota(j)$, and $f(j)$ refer to the occupation, industry and establishment of job j. I estimate (4) by weighted OLS where the weights are the employment shares of each job.

Figure B.1(a) uses (4) to decompose the relative importance of establishment, industry, and occupation for the within-city wage variance. Industries explain very little of within-city inequality. Occupations matter, but relatively less than establishments: they account for 28.3% of the spatial differences in within-city wage premia dispersion. Said differently: comparing seemingly identical workers employed in the same occupation, the identity of their employers explains 26.2% of why total wages are more unequal in larger cities.

The second exercise shows that the greater sorting of high-wage workers into high-wage jobs in large cities does not explain why they are more unequal. The baseline within-city decomposition (3) bundles the job and worker fixed effects variances with half of their covariance. I do so because, everything else equal, the covariance is an increasing function of worker and job heterogeneity. Instead, sorting is best captured by the correlation between the worker and job fixed effects. While there does not exist an exact statistical decomposition that isolates the role of sorting, Figure B.1(b) shows that the correlation is weaker in larger cities.

The spatial allocation of jobs thus matters substantially for between- and within-city wage inequality. I now show that workers are not stuck at low-paying jobs; instead, the reallocation from low- to high-paying jobs is a key driver of the city-size wage premium.

1.5 The job ladder is steeper in larger cities

I define a job switch as a transition across establishments or occupations.[5] Matched employer-employee datasets do not record phases of non-employment, and I impose two restrictions to focus on job-to-job transitions. First, the switch takes place within 90 days of the previous employment spell (79% of switches). Second, it is associated with non-negative wage growth (61% of switches). I reproduce the results in Table C.5 when all switches are considered. Finally, to capture local job ladders, I restrict my attention to switches within CZs (87% of switches).

In the aggregate, 3.9% of workers switch jobs every quarter. The orange circles in Figure 4(a) depict the job switching rate by location. Workers switch jobs more often in larger locations: the job switching rate in Paris is 4.9%, 1.5 p.p. higher than in Le Mans. However, workers in larger cities are younger and more skilled, two characteristics known to influence job switching (e.g., Topel and Ward, 1992; Haltiwanger et al., 2018). To address this possible compositional bias, I estimate the causal effect of cities on job switching through a mover design:

$$\text{J2J}_{it} = \eta_i + \theta x_{it} + \lambda_{\ell(i,t)} + \varepsilon_{it}. \tag{5}$$

In the above, $\text{J2J}_{it} = 1$ if worker i switches job during quarter t. η_i are worker fixed effects, which capture, amongst other things, the skill of worker i, and θx_{it} controls for the experience of i. The location fixed effects $\{\lambda_\ell\}_{\ell=1}^{L}$ are identified off workers moving across cities. They identify the causal effect of location ℓ on the job switching rate if workers' migration decisions are orthogonal to their idiosyncratic abilities to switch jobs in a particular location.

Locations have little to no causal impact on how frequently workers switch jobs. The blue rectangles in Figure 4(a) show the location fixed effects estimated by (5). The conditional job switching rates are uniform throughout space except in Paris, which stands as an outlier.

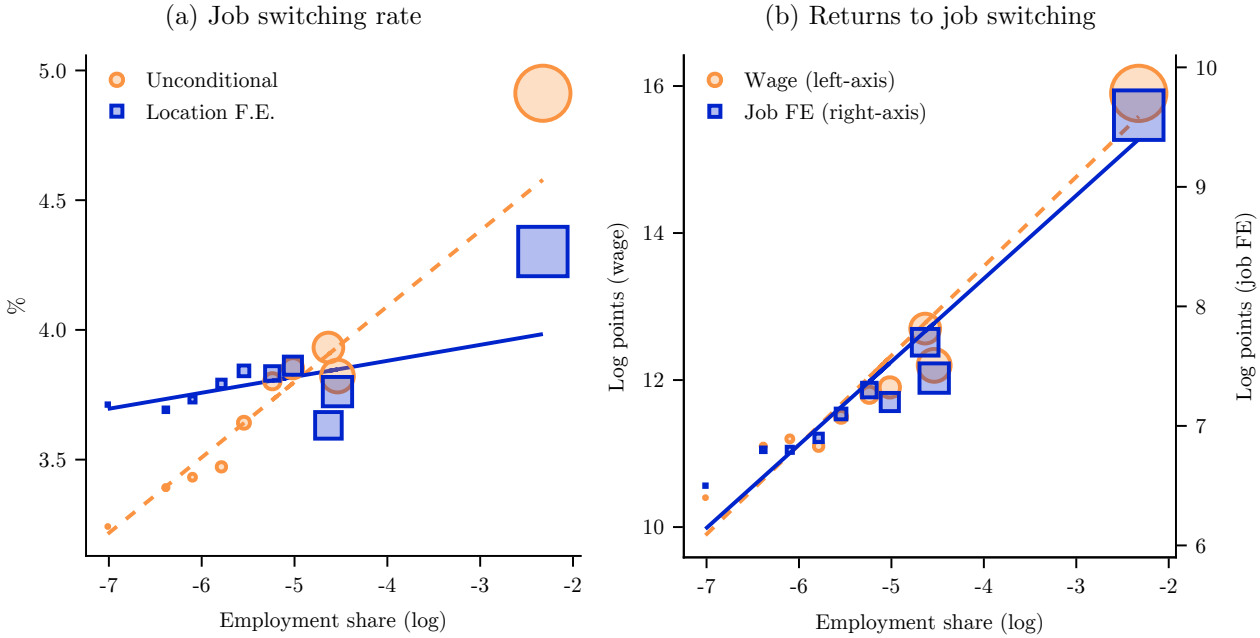
While cities do not affect how often workers switch jobs, they shape wage growth through the steepness of the local job ladder. The orange circles in Figure 4(b) plot the average wage growth conditional on a job switch. On average, a job switch is associated with a 12.4% wage increase. In Paris, these wage gains are 16.8%, whereas they are 10.4% in Le Mans. Generalizing to all cities, workers gain an additional 1.2 p.p. upon switching jobs in cities twice as large.

Job switching may be associated with faster wage growth in larger cities for several reasons. Workers may accumulate more knowledge in larger, skill-dense locations (e.g., Crews, 2023; Lhuillier, 2023). Which jobs workers switch to may also not be random; in particular, skilled workers, or workers employed at high-paying employers, may have access to a specific network.

I return to the AKM premia to test whether learning or selective job mobility drive the local returns to job switching. The job fixed effects are estimated controlling for the local returns to experience; the growth in wage premia thus measures the extra wage growth of job switchers relative to the average wage growth of job stayers in each location, which serves as a baseline control for learning. Furthermore, AKM allows for mobility patterns to vary across workers and jobs.

[5] To maintain consistency throughout and use the AKM fixed effects, I compute switches across the job clusters constructed in Section 1.3. The switching rate across jobs is 4.1%, close to that across job clusters (3.9%).

Figure 4: Job switching across space



Panel (a) plots the average switching rate by location (orange circle) and the location fixed effects estimated in (5) (blue rectangles). A worker switches jobs if they switch establishments or occupations within 90 days of their previous employment spell and the wage growth is non-negative. Panel (b) plots the average wage growth (orange circle, left axis) and job fixed effects growth (blue rectangles, right axis) upon a job switch. Job fixed effects estimated in (1). All statistics are projected against the average employment share of CZs in each group.

The blue rectangles in Figure 4(b) present the average growth in wage premia by location. Controlling for experience and selective job mobility decreases the aggregate returns to job switching: the nationwide, average growth in wage premia is 7.6%. However, the between-city differences remain large: workers experience an additional 0.7 p.p. increase in their wage premia upon switching jobs in cities twice as large.

I provide two robustness exercises to assess whether human capital accumulation drives the higher returns to job switching in large cities. The growth in wage premia may indeed partly reflect learning to the extent that it is not fully captured by on-the-job wage growth. To test whether that is the case, I estimate the reduced-form specification

$$\log\left(\frac{\gamma_{j(i,t+1)}}{\gamma_{j(i,t)}}\right) = \xi \text{J2J}_{it} + \zeta \text{J2J}_{it} \times \log \text{city size}_{\ell(i,t)} + \boldsymbol{\Gamma}' \boldsymbol{X}_{it} + \varepsilon_{it}, \tag{6}$$

where city size$_\ell$ is the number of workers in location ℓ, and $\boldsymbol{X}_{it}$ are controls for human capital accumulation. I use two separate designs. First, learning is often associated with occupation upgrading (e.g., Gathmann and Schönberg, 2010). I therefore include in (6) origin-occupation $\times$ destination-occupation fixed effects at the 3-digit level. The spatial differences in returns to job switching are then estimated off workers who switch establishments within the same occupation. Second, individuals particularly able to harness learning opportunities may agglomerate in large, fast-learning cities. I re-estimate the job fixed effects by including worker-specific returns to experience in (1). The growth in the job fixed effects is then estimated net of the long-term wage growth of the workers at these jobs. I then estimate (6) with the newly estimated fixed effects.

Table B.1 presents the results. Columns (1) and (2) report the baseline estimates using wage and wage premia growth as dependent variables. Columns (3) and (4) implement the occupation and heterogeneous learning robustness exercises. In all cases, job switching brings faster growth in larger places, and the point estimates are fairly stable across specifications.

Do larger cities offer a steeper ladder for everyone? Columns 5 and 6 of Table B.1 conduct two heterogeneity analyses. In the first, I estimate (6) separately for each one-digit occupation. In the second, I estimate (6) separately by quartile of the local job fixed effect distribution. In both cases, I find that the job ladder is steeper in larger cities for everyone. In particular, the size elasticity for low-skill workers (blue-collar and low-skill service occupations) and workers at the bottom of the ladder tracks closely the average estimate.

The spatial differences in job ladder steepness have sizable consequences on lifetime earnings. I quantify the importance of local job switching on wages through two exercises. The first quantifies how much of the spatial differences in wage growth comes from the local job ladder. Combining the two panels of Figure 4, the wage growth in location ℓ spurred by job switching is $g_\ell = \lambda_\ell \mathbb{E}_\ell \left[\log \left(\frac{\gamma_{j(i,t+1)}}{\gamma_{j(i,t)}} \right) \right]$.[6] This predicted growth accounts for 29% of the between-city wage growth variance. The second exercise relates the local job ladder to the between-city gap in wage premia documented in Section 1.4. Consider two workers located in ℓ and ℓ' who start their careers with identical wages. After x years, their wage gap grows by $x(g_\ell - g_{\ell'})$. Using this back-of-the-envelope expression, I quantify that it takes 17 years — about half of a worker's career — for the wage premia gap induced by reallocation to reach their between-city level.

1.6 Summary of testable implications

Sections 1.4 and 1.5 document the importance of employers for spatial wage inequality through two novel facts. First, jobs paying the highest wage premia are concentrated in the largest cities, whereas low-paying jobs are everywhere. Second, the returns to job switching are higher in larger cities. Together, the spatial distribution of employers accounts for a substantial fraction of the higher, more unequal, and faster-growing wages in larger cities.

These facts are inconsistent with existing theories of spatial wage disparities. First, all the facts control for unobserved worker heterogeneity and local returns to experience; worker sorting à la Eeckhout et al. (2014) cannot therefore account for them. Second, Hicks-neutral TFP gaps, which are standard in quantitative spatial models, do not intrinsically generate within-city wage premia dispersion. Third, *ex-post* productivity or amenity shocks, as in Fajgelbaum et al. (2019), do not explain why workers consistently reallocate from low- to high-paying jobs.

Accordingly, I develop a new theory that ties the two facts together. The framework focuses on the wage variation attributed to employers, leaving aside worker heterogeneity as it has been extensively studied. The framework serves two purposes. First, it provides an internally consistent explanation for the spatial distribution of wage premia. Second, I use it to assess the general equilibrium implications of labor place-based policies such as housing-indexed unemployment benefits.

[6] The location fixed effects estimated in (5) are normalized by the unconditional, aggregate job switching rate.

2 A spatial theory of wage premia

The framework combines a general equilibrium job ladder model à la Burdett and Mortensen (1998) with a standard quantitative spatial model (Redding and Rossi-Hansberg, 2017). I concentrate here on the model's core features and characterize the equilibrium analytically.

2.1 Setup

The economy has two types of agents. There is a unit mass of *ex-ante* homogeneous workers and a mass $M \leq 1$ of heterogeneous employers. Workers and employers meet within L locations. Time is continuous. There is no aggregate shock, and I focus on the steady state equilibrium.

Cities. Cities are indexed by ℓ with $\ell \in \{1, 2, \ldots, L\}$. They offer amenities A_ℓ to the workers that reside there. Cities differ in no other way *ex-ante*. I therefore order cities by their amenities: $A_1 < A_2 < \cdots < A_L$. I later allow for TFP differentials. Focusing initially on amenities highlights how employer sorting endogenously creates wage differences across cities.

Workers. Workers are risk neutral, infinitely lived, and discount the future at rate ρ. They consume a freely traded good taken as the numéraire and local housing according to Cobb-Douglas preferences. Their lifetime utility is

$$\mathbb{E}_0 \left[\int_0^\infty \mathrm{e}^{-\rho t} \left(\frac{h_t}{\alpha} \right)^\alpha \left(\frac{c_t}{1-\alpha} \right)^{1-\alpha} dt \right],$$

where α is the expenditure share on housing. The expectation is taken over future income. Workers do not have access to a savings device: if they reside in location ℓ and earn labor income y_t, they face the per-period budget constraint $p_\ell^r h_t + c_t \leq y_t$, where p_ℓ^r is the price of residential housing.

Unemployed workers produce the numéraire with productivity b. They receive job offers at Poisson rate $\zeta \lambda_\ell$, where λ_ℓ is the contact rate in market ℓ and $\zeta \geq 1$ is the relative search efficiency of unemployed workers. Employed workers supply inelastically one unit of labor, so their income equals their wage. They receive offers at rate λ_ℓ and fall back into unemployment at rate δ.

Offers are drawn from the local job offer distribution F_ℓ. That is, workers only search for jobs in the city where they live.[7] Workers are free to migrate across cities, but jobs are tied to a location. Accordingly, if a worker wants to switch locations, they must quit their job. These assumptions, while strong, are broadly consistent with the data: most job switches occur within cities, and workers who move between them experience longer non-employment spells (Table C.4).

The spatial allocation of workers is characterized by the triplet $\{m_\ell, e_\ell, u_\ell\}_{\ell=1}^L$, which denotes the measures of total, employed, and unemployed workers. Feasibility demands $\sum_{\ell=1}^L m_\ell = 1$.

Employers. Employers are infinitely lived. They produce the numéraire of the economy. Their time-invariant productivity is z, with aggregate distribution Γ over the support $[\underline{z}, \bar{z}]$, $\bar{z} \leq \infty$. I

[7] For a quantitative spatial model with wage posting and between-city search, see Heise and Porzio (2022).

assume that Γ admits a finite and continuous density. The production and revenues generated by an employer with productivity z when they hire n workers is $R(z,n) = zn$. Given constant returns to scale, z is also the marginal product of labor (MPL) of a job at this employer. As such, I use employers and jobs interchangeably.[8] Productivity and size are complements in production: productive employers are more willing to pay for an additional worker. I assume that $\underline{z}$ is high enough relative to b so that all jobs are profitable in at least one city.

Employers hire workers in frictional local labor markets. The hiring process follows Burdett and Mortensen (1998). Employers have monopsony power over workers and are atomistic. They post a unit measure of job offers in the city where they produce, so that aggregate vacancies in ℓ equate the measure of firms there, M_ℓ. Employers commit to a wage, specified on the offer, that cannot be renegotiated throughout the employment spell. In particular, employers cannot make counteroffers when their workers receive alternative job opportunities. Rather, they optimally set their wage *ex ante* to maximize profits.

Employers freely choose the city where they produce and hire workers. They pay unit housing cost p^c_ℓ to locate in city ℓ. The endogenous distribution of jobs across space is summarized by the mass of employers in each city, M_ℓ, and the local productivity distribution, $d\Gamma_\ell$. The allocation $M_\ell, d\Gamma_\ell{}_{\ell=1}^{L}$ is feasible if the number of jobs across space is no greater than the total number available:

$$\sum_{\ell=1}^{L} M_\ell d\Gamma_\ell(z) \leq M d\Gamma(z). \tag{7}$$

Matching. How often workers and firms meet in a city depends on the number of job seekers, $\zeta u_\ell + e_\ell$, and the number of vacancies, M_ℓ. The number of matches is $\mathcal{M}_\ell = \mathcal{M}(M_\ell, u_\ell + \zeta e_\ell)$, where the matching function has constant returns to scale and is weakly increasing in both arguments. Accordingly, the local labor market tightness $\theta_\ell = \frac{M_\ell}{\zeta u_\ell + e_\ell}$ pins down how often workers receive job offers, $\lambda_\ell = \frac{\mathcal{M}_\ell}{\zeta u_\ell + e_\ell} = \mathcal{M}(\theta_\ell, 1)$, and how often vacancies reach workers, $q_\ell = \frac{\mathcal{M}_\ell}{M_\ell} = \frac{\lambda_\ell}{\theta_\ell}$. In a tighter market, the job finding rate is higher and the vacancy contact rate is lower.

I assume for now that the job finding rates are constant across locations, $\frac{\partial \mathcal{M}}{\partial M_\ell} = 0$. In addition to being broadly consistent with Figure 4(a), this assumption offers analytical tractability. I set $\lambda = \lambda_\ell$ in this section, and I relax this assumption when I estimate the model.

Housing markets. The residential (r) and commercial (c) housing markets are segmented. In each sector $s \in \{c, r\}$, landlords produce housing with a Cobb-Douglas technology, $H^s_\ell = (K^s_\ell)^{\beta^s}(L^s)^{1-\beta^s}$, where K^s_ℓ is a numéraire input and L^s is a fixed factor (e.g., land). Housing units are sold at price p^s_ℓ, and landlords consume the numéraire with their profits.[9]

[8] The framework does not explicitly model occupation. Occupations can be incorporated under a perfect substitutability assumption: $R(z_f, \{n_s\}_s) = \int p(z_f, s) n_s ds$, where z_f and s are the establishment and occupation productivity. As in Engbom and Moser (2022), the model can then be solved separately for each occupation, and is therefore isomorphic to the original model with $z = p(z_f, s)$ capturing the productivity of the pair occupation $\times$ establishment. I abstract from complementarity in production given that establishments are the main driver of the empirical results.

[9] Whether the fixed factor is owned by immobile landlords or collectively by workers is without loss of generality. Likewise, the positive analysis of the paper holds assuming a reduced-form housing supply function. This

I characterize the steady state in three steps. First, I derive the spatial allocation of workers. I then solve for the local wage distributions. Finally, I characterize the location choice of employers.

2.2 Job search

The expected lifetime utility of an unemployed worker in location ℓ, U_ℓ, satisfies the HJB equation

$$\rho U_\ell = \frac{A_\ell b}{P_\ell} + \zeta\lambda \int \max\{V_\ell(w) - U_\ell, 0\} dF_\ell(w), \tag{8}$$

where $P_\ell \equiv (p_\ell^r)^\alpha$ is the price index. The lifetime utility depends on contemporaneous real earnings adjusted for local amenities, and the expected value from future job opportunities, where $V_\ell(w)$ is the expected lifetime utility of a worker employed at wage w in location ℓ:

$$\rho V_\ell(w) = \frac{A_\ell w}{P_\ell} + \lambda \int \max\{V_\ell(w') - V_\ell(w), 0\} dF_\ell(w') + \delta[U_\ell - V_\ell(w)], \tag{9}$$

Employed workers internalize that they may fall back into unemployment at rate δ.

Unemployed workers choose where to live to maximize their expected lifetime utility:

$$\bar{U} = \max_\ell U_\ell. \tag{10}$$

In equilibrium, they are indifferent between all the populated locations. Appendix E.1 shows that expected lifetime utility can be written more compactly as

$$U_\ell = \frac{A_\ell \mathcal{W}_\ell}{P_\ell}, \tag{11}$$

where $\mathcal{W}_\ell$ is the net present value of expected lifetime income. Combined with (10), the location choice of unemployed workers satisfies a standard Rosen (1979) and Roback (1982) indifference condition. The novelty is that workers value expected lifetime income rather than present earnings.

Once settled in a location, unemployed workers trade off a higher search efficiency against lower present earnings. They accept wage offers greater than the local reservation wage $\underline{w}_\ell$ given by

$$\underline{w}_\ell = b + \lambda(\zeta - 1) \int_{\underline{w}_\ell}^{\infty} \frac{1 - F_\ell(w)}{\rho + \delta + \lambda(1 - F_\ell(w))} dw. \tag{12}$$

The relative search efficiency of unemployed workers controls the sensitivity of the reservation wage to the search option value. The tradeoff disappears when there is no loss in search efficiency, in which case the reservation wage equates workers' outside option: $\underline{w}_\ell = b$. Either way, the reservation wage is independent of local amenities and housing prices since these affect all workers equally.

Employed workers must quit their job to change location. In steady state, no workers choose to do so. They then behave as income maximizers as long as they are employed. Their utility is increasing with their wage, and they climb the local ladder by accepting better-paying job offers.

Equations (11) and (12) deliver sharp predictions on the wages that workers accept throughout space. In locations with better jobs, the option value of search is higher, and so is the reservation wage. At the same time, workers employed on low rungs of the ladder anticipate faster wage growth.

microfoundation ensures that Walras' law holds which is useful for welfare accounting.

As a result, they accept jobs with lower real wages. Proposition 1 summarizes these results.[10]

Proposition 1 (Reservation wage)**.**
Consider two locations, ℓ and ℓ', and suppose ℓ has a higher wage offer distribution, $F_\ell \succ F_{\ell'}$. Then, the nominal reservation wage is higher in ℓ, $\underline{w}_\ell \geq \underline{w}_{\ell'}$, strictly so if $\zeta > 1$. Meanwhile, the real reservation wage gross of amenities is strictly lower, $\frac{A_\ell \underline{w}_\ell}{P_\ell} < \frac{A_{\ell'} \underline{w}_{\ell'}}{P_{\ell'}}$.

Proof. See Appendix E.2. □

The job offer distributions depend on where firms are and the wage they offer.

2.3 Local wage distributions

Employers decide where to produce, how many workers to hire, and at which wage to pay them. Assuming a low discount rate as in Burdett and Mortensen (1998), their expected profits are[11]

$$\pi(z) = \max_\ell \pi_\ell(z) = \max_\ell \left\{ \max_{w,n} R(z,n) - wn - p_\ell^c \quad \text{s.t.} \quad n \leq n_\ell(w) \right\}. \tag{13}$$

Firm size is constrained by the local labor supply curves

$$n_\ell(w) = \frac{1}{\theta_\ell} \frac{k}{[1 + k(1 - F_\ell(w))]^2}, \tag{14}$$

where $k \equiv \lambda/\delta$ summarizes the speed at which workers climb the job ladder. The labor supply curves slope upward: when a firm offers a higher wage, it hires more workers from local competitors, and it reduces how many of its own workers are poached by the competition.

The labor supply varies across space in two ways. First, the vacancy contact rate is lower in tighter markets, and firms are smaller for any given wage. Second, the competition for workers may be fiercer. In locations where F_ℓ is higher, the hiring rate for any given wage is lower while the separation rate is higher as workers face more better-paying opportunities. The frequency at which workers switch jobs determines the sensitivity of the supply curves to local competition. When switches are rare ($k \approx 0$), the number of workers per offer is given by the vacancy contact rate.

Firms thus have two ways to minimize search frictions: wages are an effective hiring tool, and so is their location choice. Accordingly, the solution to (13) consists of two joint fixed points. First, the wage posted by an employer depends on the wage-setting strategies of its local competitors. Second, firms factor in prices when choosing locations. I derive optimal wages given a spatial allocation of employers and then characterize employers' location decision.

Within cities, the results from Burdett and Mortensen (1998) apply. Employers are on their labor supply curve, $n = n_\ell(w)$. The wage offer distributions are continuous over the interval $[\underline{w}_\ell, \bar{w}_\ell]$ for any productivity distribution Γ_ℓ (Appendix E.4). The complementarity in the revenue function between productivity and size implies that wages are strictly increasing in z within cities: more productive employers have a larger target size, and for that, offer higher wages. As a result, the

[10] Throughout, I use $\succ$ to denote first order stochastic dominance.
[11] Appendix E.3 derives the employer problem and the local labor supply curves for any discount rate.

rank of a job in the local wage offer distribution corresponds to that of the employer in the local employer distribution: $F_\ell[w_\ell(z)] = \Gamma_\ell(z)$, where $w_\ell(z)$ is the optimal wage strategy.

The wage distribution of city ℓ is determined by two functions. First, the number of workers employed at a job with productivity $z \in \operatorname{supp} \Gamma_\ell$ is

$$n_\ell(z) \equiv n_\ell[w_\ell(z)] = \frac{1}{\theta_\ell} \frac{k}{[1 + k(1 - \Gamma_\ell(z))]^2}. \tag{15}$$

Employer size directly follows from the labor supply curves (14) and the rank-preserving condition $F_\ell[w_\ell(z)] = \Gamma_\ell(z)$. Second, the wage offered by an employer with productivity $z \in \operatorname{supp} \Gamma_\ell$ is

$$w_\ell(z) = \underbrace{\left(\frac{n_\ell(\underline{w}_\ell)}{n_\ell(z)}\right)}_{\substack{\text{Emp. share} \\ \text{from unemp.}}} \times \underbrace{\underline{w}_\ell}_{\substack{\text{Outside} \\ \text{option}}} + \underbrace{\left(1 - \frac{n_\ell(\underline{w}_\ell)}{n_\ell(z)}\right)}_{\substack{\text{Emp. share} \\ \text{from poaching}}} \times \underbrace{\int_{\underline{z}_\ell}^{z} t \left(\frac{dn_\ell(x)}{\int_{\underline{z}_\ell}^{z} dn_\ell(x')}\right)}_{\substack{\text{Competitors'} \\ \text{avg. productivity}}}. \tag{16}$$

Monopsony power implies that wages depend on the local competition employers face. How fierce is this competition depends on two factors: how many workers are poached from the local competition, and how willing these competitors are to retain their workers. Cities shape the second dimension, but the effects are heterogeneous across employers depending on their poaching rate.

The least productive employers in a city only hire workers from unemployment as they are the least willing to pay for them. The only bargaining position of unemployed workers is their reservation wage, $\underline{w}_\ell \approx b$, where the approximation is exact when $\zeta = 1$. As a result, workers at the bottom of the ladders earn similar wages, and low-paying jobs are present everywhere.

More productive employers offer higher wages to poach workers from their lower-paying competitors. The higher their relative productivity, the more they compete with the other firms, and the more sensitive their wages are to the local productivity distribution. When all employers are relatively more productive, the competition intensifies. The wage distribution shifts up, and the wage gains are concentrated at the top of the ladder where employers face off all the local competition.

Combined, the local concentration of productive employers steepens the job ladder. Workers experience faster wage growth when switching jobs as they have access to a relatively greater number of high-paying jobs. Proposition 2 summarizes these results.

Proposition 2 (Spatial wage inequality)**.**
Consider locations ℓ and ℓ' such that the productivity distribution is higher in ℓ, $\Gamma_\ell \succ \Gamma_{\ell'}$. Then,

1. *The wage offer distribution in ℓ first order stochastically dominates, $F_\ell \succ F_{\ell'}$. As a consequence, the average wage is higher, wage gains upon a job switch are larger, $\mathbb{E}_\ell[\frac{W}{w} \mid W > w, w] > \mathbb{E}_{\ell'}[\frac{W}{w} \mid W > w, w]$, and the real reservation wage is lower;*
2. *The mean-to-min ratio is larger in ℓ: $\frac{\mathbb{E}_\ell[W]}{\underline{w}_\ell} > \frac{\mathbb{E}_{\ell'}[W]}{\underline{w}_{\ell'}}$.*

Proof. See Appendix E.5. □

Proposition 2 replicates the two facts that called for a new theory of spatial wage inequality. It holds if productive employers are spatially concentrated. I now show this is the case in equilibrium.

2.4 The spatial allocation of employers

Employers produce in the location(s) that maximize their profits:

$$\pi_\ell(z) \geq \pi_{\ell'}(z) \text{ for all } \ell' \neq \ell \iff z \in \text{supp } \Gamma_\ell. \tag{17}$$

An equilibrium spatial allocation of employers is a tuple $\{M_\ell, d\Gamma_\ell\}_{\ell=1}^L$ that satisfies feasibility (7) and profit maximization (17), given (13), (15), (16), and an allocation of workers $\{m_\ell\}_{\ell=1}^L$.

The labor supply curves are equilibrium objects. Market tightness determines the level of the curves. Local competition shapes relative size. The profitability of each location thus depends on the spatial allocation of employers, and standard optimal transport techniques cannot be used to solve (17) (Chade and Eeckhout, 2020). Nevertheless, a sharp characterization exists thanks to the complementarity between productivity and size. I first show that productive employers concentrate in cities with slacker labor markets, and then establish that these are the larger cities.

Consider a given distribution of market tightness. Productive employers are more willing to pay to maximize their size, and all else equal, they have the strongest incentives to be where the vacancy filling rate is high. In equilibrium, a tension arises between tightness and competition: when productive employers agglomerate in the slackest market, most firms slide down the job ladder as they struggle to keep their workers. As a result, mid-productivity employers attain the same size in slack and tight markets as the endogenous competition offsets the size advantage of the former. The technological complementarity ensures that sorting prevails, but productivity distributions may overlap across locations. Weak search frictions increase how substitutable locations are by accelerating the reallocation of workers to high-paying firms.

Proposition 3 (Local productivity distributions)**.**
Locations with a slacker labor market attract relatively more productive employers: $\theta_\ell < \theta_{\ell'}$ if and only if $\Gamma_\ell \succ \Gamma_{\ell'}$. If search frictions are small relative to the difference in tightness, $\sqrt{\frac{\theta_{\ell'}}{\theta_\ell}} < 1 + k$, productivity distributions overlap, $d\Gamma(supp\,\Gamma_\ell \cap supp\,\Gamma_{\ell'}) > 0$.

Proof. See Appendix A.1. □

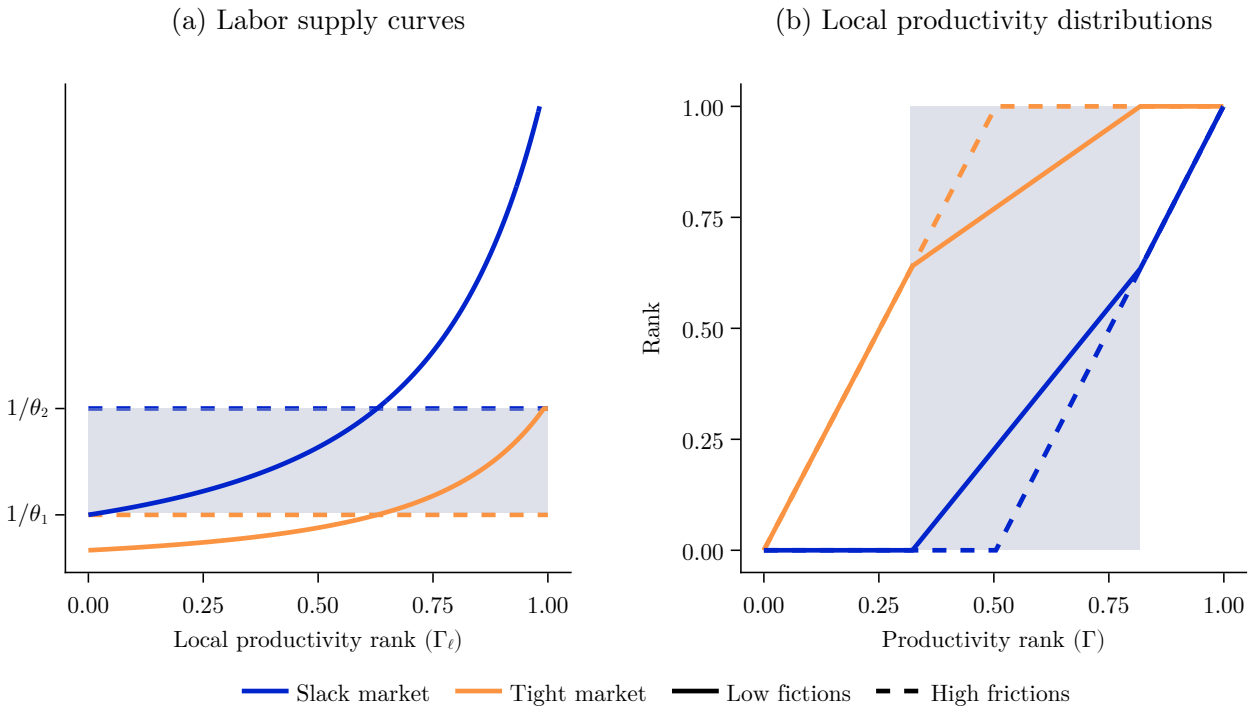
Which locations have slacker markets? Given a uniform allocation of employers, markets with many workers are slacker; a greater number of employers thus locate there. Commercial housing prices rise, and not every employer finds it profitable to produce there. In particular, this congestion force implies that larger locations have more jobs *and* a slacker market.

Proposition 4 (Labor market slackness)**.**
Suppose that $\zeta \approx 1$. Then, in equilibrium, large cities attract more employers and have a slacker labor market: $m_\ell > m_{\ell'} \iff M_\ell > M_{\ell'} \iff \theta_\ell < \theta_{\ell'}$.

Proof. See Appendix A.2. □

Figure 5 helps visualize the two propositions. The left panel depicts the local labor supply curves against firms' rank in the local productivity distribution. The right panel displays the

Figure 5: The spatial allocation of employers



Left panel shows the local labor supply curves (n_ℓ) against firms' rank in the local productivity distribution. The supply curves are given by (14). Right panel plots the productivity rank in the local distributions (Γ_ℓ) as a function of the productivity rank in the national distribution (Γ). Blue and orange curves refer to locations with a slack and tight market. The solid and dashed lines show equilibria under weak ($k > 0$) and infinite ($k \to 0$) search frictions. The grey area represents the range of productivities for which firms are present in both locations under weak frictions.

spatial allocation of employers: it shows how the national productivity rank of a firm maps into their local rank. The blue and orange curves refer to cities with a slack and a tight labor market. The solid and dashed lines depict allocations under weak ($k > 0$) and infinite ($k \to 0$) frictions.

When search frictions are large, the sorting of firms across space is "perfect". Absent job-to-job mobility, employers hire only from unemployment. Vacancies have a higher contact rate in slacker markets, and firms are uniformly larger. The complementarity between productivity and size guarantees that if an unproductive employer finds it profitable to produce there, so must a productive one. High commercial housing prices in the larger, slacker market prevent low productivity firms from producing there. Finally, as in standard matching models, the uniformly greater size ensures that no positive measure of employers is indifferent between a slack and a tight market.

In the presence of job-to-job mobility, the productivity distributions may overlap across locations. In that case, firms' willingness to pay relative to their local competitors also shapes their size. Sorting must still prevail: a productive employer has more incentives to locate in a slack market since, in any city, they can attain a larger size than their unproductive competitors. However, firms at the bottom of the ladder there do not benefit equally from the higher vacancy contact rate as most of their workers are poached by productive competitors. Instead, they can attain the same size in a tighter market where they can poach most of the other firms. Indifference follows for mid-productivity employers.

Together, Propositions 1 to 4 show how the sorting of employers across space generates between- and within-city inequality as in the data. Productive employers concentrate in large, slack cities to maximize their size. The local labor market competition intensifies. The higher productivity spills over into wages for workers at the top of the ladder without materializing for workers at the bottom. As a result, larger cities offer higher wages, greater within-city inequality, and faster wage growth as workers reallocate from low- to high-paying employers. In particular, unemployed workers accept jobs with lower real wages anticipating future wage growth.[12]

It is worth emphasizing the unique prediction of the model: spatial wage inequality arises without *ex-ante* TFP gaps. Search frictions are essential to reach this conclusion. I write down in Appendix E.6 a general model of employer sorting with competitive labor markets. In this environment, locations differ in their revenue TFP and input costs. If TFPs are homogeneous, employers sort according to input prices, and productive employers produce in large cities because wages are lower there. A positive correlation between size and TFP is thus needed to generate a city-size wage premium — even in the presence of firm sorting. Search frictions break this necessity because employers sort to access slacker markets, and they are willing to pay higher wages for it.

Propositions 1 to 4 are qualitative predictions. I now develop and estimate a quantitative version of the model to test if it can explain the spatial distribution of wage premia in the data.

3 Extended model and estimation

3.1 Quantitative model

Extensions. I relax the strong assumptions imposed until now. I allow cities to differ in their TFP, T_ℓ. Local TFP complements employers' productivity: the MPL of a worker hired by employer z in location ℓ is zT_ℓ. Local TFP results from fundamentals and reduced-form productivity spillovers, $T_\ell = \mathcal{T}_\ell m_\ell^\nu$, where ν is the spillover elasticity.[13] Between-city wage gaps can arise from differences in local competition or TFP.

On the employer side, I make three extensions. First, employers face idiosyncratic housing or local costs, $\{\varepsilon_\ell\}_{\ell=1}^L$, with mean B_ℓ. A negative B_ℓ reflects that establishing a business in location ℓ is relatively easier (e.g., due to lighter regulations or higher local human capital). These costs, which will let the model match the local market tightness in the data, are taken as exogenous.

Second, I allow employers to hire many workers by posting multiple vacancies, so they can expand without having to raise wages too quickly or move to slack markets. Vacancies are costly

[12] Propositions 1 to 4 hold in any equilibrium. Whether the equilibrium is unique depends on the relative strengths of the agglomeration and congestion forces. As workers agglomerate in a location, residential housing prices rise. At the same time, the slacker market attracts more productive employers and raises wages. Local amenities partially anchor the spatial allocation of workers, but multiple equilibria may arise. I introduce idiosyncratic location preferences in the quantitative model to ensure uniqueness of the equilibrium.

[13] I assume the productivity spillovers are a function of the number of workers as standard in quantitative spatial models. I estimate $\mathbb{V}\text{ar}[T_\ell] \approx 0$, such that the functional form assumed for the spillovers is inconsequential.

and come at a convex cost

$$c(v) = \frac{v^{1+\gamma}}{1+\gamma},$$

where $\gamma > 0$ denotes the vacancy cost elasticity. Employers size reflect their position in the local job ladder together with how many offers they post:

$$n_\ell(w, v) = \frac{k_\ell}{[1 + k_\ell(1 - F_\ell(w))]^2} \frac{v}{\theta_\ell}, \tag{18}$$

where the tightness is now

$$\theta_\ell = \frac{V_\ell}{\zeta u_\ell + e_\ell} \quad \text{for} \quad V_\ell = M_\ell \int v_\ell(z) d\Gamma_\ell(z). \tag{19}$$

Third, I endogenize the mass of employers and therefore aggregate employment. As in Melitz (2003), firms pay a cost f to enter the economy. Upon entering, they draw their productivity z and idiosyncratic local costs $\{\varepsilon_\ell\}_{\ell=1}^L$. Free entry implies $\mathbb{E}[\pi(z, \{\varepsilon_\ell\}_{\ell=1}^L)] = f$.

With these three ingredients, an employer with productivity z and local costs $\{\varepsilon_\ell\}_{\ell=1}^L$ solves

$$\pi(z, \{\varepsilon_\ell\}_{\ell=1}^L) = \max_{\ell,w,n,v} R(zT_\ell, n) - wn - c(v) - p_\ell^c - \varepsilon_\ell \quad \text{s.t.} \quad n \leq n_\ell(w, v). \tag{20}$$

Finally, I introduce two additional reasons why workers may accept lower real earnings in large cities. First, I add migration costs. Workers permanently exit the labor force at Poisson rate ξ, upon which they are replaced by their descendants. New entrants enter the labor force in the same location as their parent, and pay a pecuniary flow migration cost κ to relocate elsewhere.[14] Migration costs imply that the welfare of unemployed workers varies by birthplaces, thus generating *ex-ante* spatial inequality. Second, individuals have idiosyncratic preferences for each location. These preferences, which also ensure uniqueness of the equilibrium when they are sufficiently dispersed, are drawn upon entry in the labor force and remain constant thereafter.

Appendix F.1 presents in detail the quantitative model and the equilibrium.

Parametric assumptions. I impose the following parametric assumptions. The aggregate productivity distribution is Pareto with shape σ. Its scale is normalized to ensure a mean productivity of one. The idiosyncratic entry costs of employers are i.i.d. across space. They are drawn from Gumbel distribution with inverse dispersion ϑ and location $\{B_\ell\}_{\ell=1}^L$. Workers' idiosyncratic preferences are i.i.d. Fréchet distributed with shape χ. Finally, the matching function is Cobb-Douglas with matching efficiency μ and elasticity ψ: $\mathcal{M}_\ell = \mu V_\ell^\psi (u_\ell + \zeta e_\ell)^{1-\psi}$. In particular, I allow for spatial differences in job finding rates, $\psi > 0$.

3.2 Identification

Model inversion. The estimation of the model is organized in two blocks. Its core is contained in the first block, which leverages the structure of the model to estimate the bulk of the parameters without the need for simulation. Proposition 5 proves identification of 18 of the 23 parameters.

[14] I abstract from heterogeneity in migration costs because the city clusters do not contain geographic information.

Proposition 5 (Identification)**.**
Given aggregate data on the EU and job switching rate, location-specific data on the UE rate and housing prices, and firm-level employment and wage data, the parameters α, b, δ, ζ, ξ, μ, ψ, M, γ, L^r, β^r, L^c, β^c, and f are identified. The dispersion and scale of employers' idiosyncratic costs ϑ and $\{B_\ell\}_{\ell=1}^L$ are identified conditional on small TFP differentials. Amenities $\{A_\ell\}_{\ell=1}^L$ and the migration cost κ are identified given workers' discount factor ρ and idiosyncratic location preferences χ.

Proof. See Appendix G.1. □

I present here the intuition behind the proof, focusing on the parameters that govern employer sorting. The location choice of employers is pinned down by four sets of parameters: search frictions, the dispersion and scale of the idiosyncratic costs, the local labor market tightness, and TFPs. Three of these four parameters are identified by Proposition 5.

First, the spatial allocation of workers $\{e_\ell\}_{\ell=1}^L$ is observed and rationalized by the appropriate vector of amenities. Second, search frictions are identified from worker flows. The aggregate employment-to-unemployment (EU) rate is equal to δ. The labor force exit rate ξ is identified from the average career duration: $\xi = 1/\mathbb{E}[\text{career length}]$. The location-specific unemployment-to-employment (UE) rates identify the contact rates of unemployed workers: $\zeta\lambda_\ell = \text{UE}_\ell$. Conditional on the UE rates, the job switching rate pins down the search efficiency of unemployed workers ζ.

Third, the dispersion and scale of the entry costs are identified from the correlation between local profit opportunities and employers' location choice. Given the Gumbel parametric assumption, the log-likelihood that an employer j with productivity z_j locates in ℓ is

$$\log \Omega_\ell(z_j) = \text{FE}_\ell + \text{FE}_{z_j} + \vartheta\tilde{\pi}_\ell(z_j), \tag{21}$$

where $\text{FE}_\ell \propto B_\ell$, $\mathrm{e}^{-\text{FE}_z} = \sum_\ell \mathrm{e}^{\vartheta\pi_\ell(z)}$, and $\tilde{\pi}_\ell(z_j) = (z_j T_\ell - w_j)n_j - c(v_j) - p_\ell^c$ are measurable profits.

To recover model-consistent profits, I extend the insights of Bontemps et al. (2000) to a setting with local labor markets. The wage bill is obtained from employer size and wages. Employer productivity is identified using the wage optimality condition,

$$z_j T_{\ell_j} \equiv \zeta_j = w_j + \left(\frac{1 + k_{\ell_j}(1 - F_j)}{2k_{\ell_j}}\right) \frac{\partial w_{\ell_j}(F_j)}{\partial F}, \tag{22}$$

where ℓ_j denotes the production location of j, F_j their rank in the local wage offer distribution, and $w_\ell(F)$ is the inverse function of $F_\ell(w)$. ζ_j refers to the total productivity of j gross of TFP.

Finally, vacancy costs and labor market tightness are identified from employer size. Employers' rank, together with the search frictions they face, determines the number of workers they hire per vacancy. Their vacancy share v_j/V_{ℓ_j} is then recovered from their size using (18). The vacancy optimality condition identifies the vacancy cost elasticity γ and the measure of vacancies in each location V_ℓ. From there, I obtain the local labor market tightness $\frac{V_\ell}{\zeta u_\ell + e_\ell}$ and the vacancy cost $c(v_j)$.

Combining these steps, I compute realized measurable profits $\tilde{\pi}_{\ell_j}(\zeta_j) = (\zeta_j - w_j)n_j - c_j - p_{\ell_j}^c$. If TFPs are relatively similar across locations, the productivity of employers closely tracks their MPL. Then, realized profits can be used to infer potential profits in other locations, $\pi_\ell(\zeta_j) \approx \pi_\ell(z_j)$,

and (21) identifies ϑ and $\{B_\ell\}_{\ell=1}^L$. In practice, TFP gaps may be large. To address this concern, I estimate ϑ and $\{B_\ell\}_{\ell=1}^L$ jointly with TFPs within the second block of the estimation.

Indirect inference. The second step of the estimation calibrates jointly the remaining parameters by indirect inference. Given the parameters identified by Proposition 5, I simulate the model and minimize the distance between a vector of empirical statistics and the same statistics in the model. First, I calibrate local TFPs as residuals to match the average wage of each city net of the employer sorting predicted by the model. Second, I calibrate the Pareto shape σ to match the aggregate wage variance. Third, I estimate (21) in the model and set the entry cost dispersion to match the empirical conditional correlation in the data. Fourth, I set the scale of the idiosyncratic housing costs to match the local labor market tightness.

Knowledge of the last two parameters — the productivity spillovers and the taste-shock dispersion — is not required for this calibration exercise. I therefore estimate them once all the other parameters have been identified. Given the TFP vector $\{T_\ell\}_{\ell=1}^L$ and the functional form $T_\ell = \mathcal{T}_\ell m_\ell^\nu$, the productivity spillovers are obtained by projecting T_ℓ onto city size.

The taste shock dispersion χ is calibrated to match reduced-form estimates of the local labor supply elasticity. Standard estimates, obtained by projecting population onto average real wages, do not map into χ in the model for two reasons. First, workers value expected lifetime real earnings. Second, migration costs impede the reallocation of workers across locations. The first force implies that the reduced-form elasticity lies below the taste shock dispersion, while the second implies the opposite. Instead, I reproduce the most common empirical design used in the literature within the model: I implement local income tax reforms, and compute the new equilibrium under each reform (e.g., Fajgelbaum et al., 2019). I compare the new and baseline equilibria, and select χ to match the reduced-form labor supply elasticity. Appendix G.2 provides further details.[15]

3.3 Data

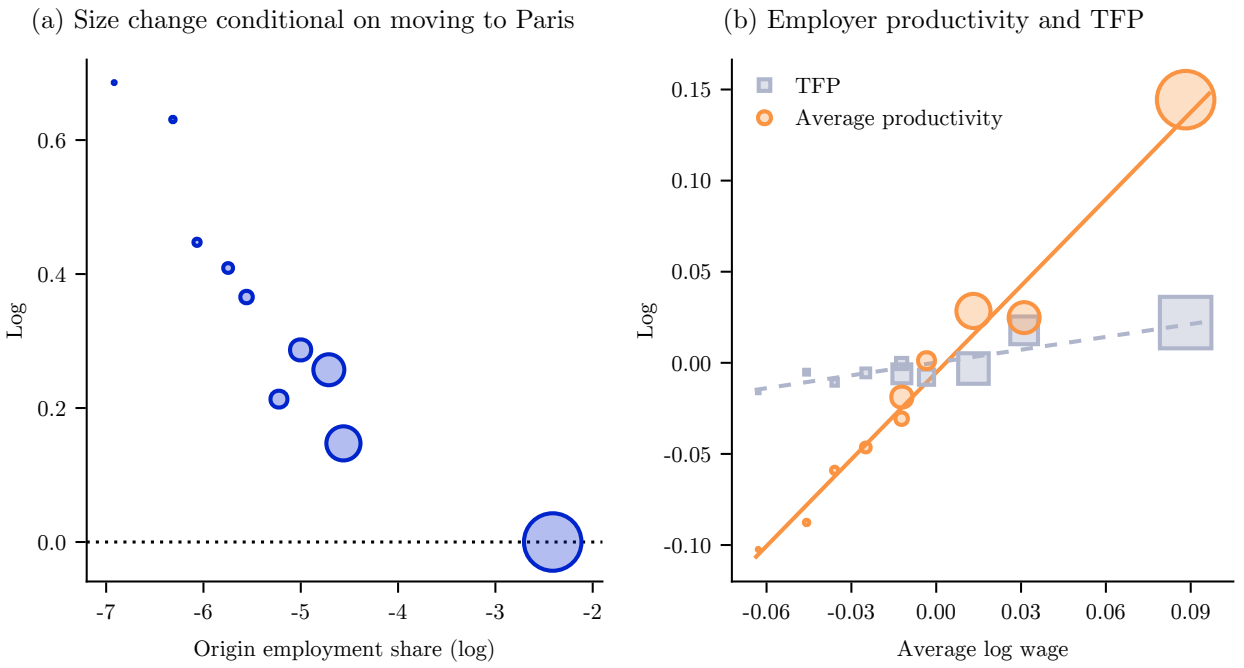
I briefly describe the data used for the estimation. Further details are included in Appendix D. I set a quarterly frequency. I solve the model for the 10 city groups defined in Section 1.1. There remains 297 labor markets, but each market within a group is homogeneous.[16] I abstract from worker heterogeneity and measure wages by the job fixed effects estimated in Section 1.3. I extend the model to allow for skill heterogeneity in Section F.3. I use the extended model to show that the AKM model is well specified when the job switching rates are uniform across skills. I further show quantitatively that the mis-specification bias is small when this condition is not met.

I obtain residential housing prices from the *Carte des Loyers* (Rental Map) dataset. I do not have access to city-level commercial rental rates. Instead, I define commercial housing prices as residential housing prices adjusted for the aggregate relative price of commercial housing. I scale up commercial prices by the average surface of commercial units since employers do not face an

[15] As shown in Proposition 5, the taste shock dispersion and the discount factor are relevant only for the estimation of the amenities and migration costs, and thus matter only for the policy counterfactual.

[16] Increasing the number of groups would increase measurement error in the job fixed effects.

Figure 6: The drivers of employer sorting



Left panel shows the average change in log firm size conditional on a reallocation to Paris as computed in (23). Size change plotted against the employment share of the origin location. Right panel shows the employment-weighted average log employer productivity (orange circles) and log TFP (grey rectangles) against the average log wage in the model. All variables are expressed in deviations from aggregate means.

intensive margin in the model. I obtain the average commercial housing price and surface from the *Demande de Valeurs Foncières* (French Real Estate Transaction Values) dataset. Finally, I read the housing expenditure share from the aggregate national accounts (INSEE, 2020).

The flows in and out of employment are obtained from the *Enquête emploi en continu* (Labor Force Survey) dataset. The aggregate job switching rate is computed from the panel matched employer-employee data. Consistently with the model, I define a job switch as a transition between jobs within a location that leads to a wage increase.

Finally, I target a reduced-form local labor supply elasticity of 2.5, in the middle of the range of empirical estimates (Table A.17 of Fajgelbaum et al., 2019). I externally calibrate the discount factor and set $\rho = 0.005$ to match an annual real interest rate of 2%.

4 Estimation results

I present the estimation results around three quantitative takeaways. Table B.2 contains the parameter estimates, and I discuss below how standard parameters relate to benchmark estimates.

4.1 Productive employers agglomerate in slack markets

First, productive employers concentrate in large cities to exploit a slack labor market rather than high local productivity. Figure 6 presents the drivers of employer sorting in the model. Panel (a) shows the causal effect of cities on firm size. Specifically, I compute the average change in size

if firms relocated to Paris, keeping their wage and vacancy postings constant. Given an origin location ℓ, this size growth is given by

$$\mathbb{E}\left[\log\left(\frac{n_{\text{Paris}}}{n_\ell}\right) \mid \ell\right] = \frac{\int \log\left(\frac{n_{\ell'}[w_\ell(z),v_\ell(z)]}{n_\ell[w_\ell(z),v_\ell(z)]}\right)\Omega_{\text{Paris}}(z)d\Gamma_\ell(z)}{\int \Omega_{\text{Paris}}(z)d\Gamma_\ell(z)}, \tag{23}$$

where $\Omega_{\ell'}(z)$ refers to the probability that a firm with productivity z locates in ℓ'.[17] Where firms are is crucial to their size: a firm who moves from Le Mans to Paris increases its size by 45% on average. Firms in large cities are bigger because the labor market there is slacker, and therefore the vacancy filling rate is higher (Figure C.6(b)).[18] Panel (b) shows the causal effect of cities on firms' productivity, i.e., local TFPs (grey rectangles), along with the average employment-weighted firm productivity (orange circles). While there are substantial spatial gaps in productivity, local TFPs are relatively homogeneous: a firm moving from Le Mans to Paris sees its productivity rise by 3%. In total, local TFPs explain 15% of the between-city productivity variance.

A priori, labor market tightness, TFP, and idiosyncratic housing costs jointly determine the spatial sorting of employers. In the data, search frictions are relatively uniform across locations, with slightly lower UE rates in larger cities (Figure C.7). Meanwhile, the average employer has more workers there. Through the lens of the model, the higher size arises either from a slacker market or many vacancy postings driven by high revenues per worker. The between-city differences in revenues per worker, inferred from the wage gaps, are too small to explain the size differences, leading to a strong negative correlation between city size and labor market tightness. The small dispersion in UE rates also points to a relatively low matching function elasticity, estimated at 0.2, within but toward the lower end of the range reported by Petrongolo and Pissarides (2001).

My estimate of the idiosyncratic housing costs dispersion broadly lines up with recent papers that study firms' location choice. I find $\vartheta = 5.3$. Converted to a Fréchet elasticity, this corresponds to 4, slightly above the value obtained by Fajgelbaum et al. (2019) in the United States.

Lastly, TFPs are estimated as wage residuals. A slacker labor market gives productive employers incentives to locate there, even absent TFP gaps. Competition intensifies, and wages rise endogenously.[19] Little extra productivity is required to rationalize the between-city variation in wage premia. As a result, I estimate a productivity spillover elasticity of 0.008.[20] While this is one order of magnitude smaller than benchmark estimates, it is consistent with Carry et al. (2025) who exploit establishment reallocation to separately identify employer sorting from local TFP.

4.2 Low-paying jobs persist in productive locations

The second quantitative takeaway is that low-paying jobs persist in large cities although employers are relatively more productive. As a result, these locations are more unequal.

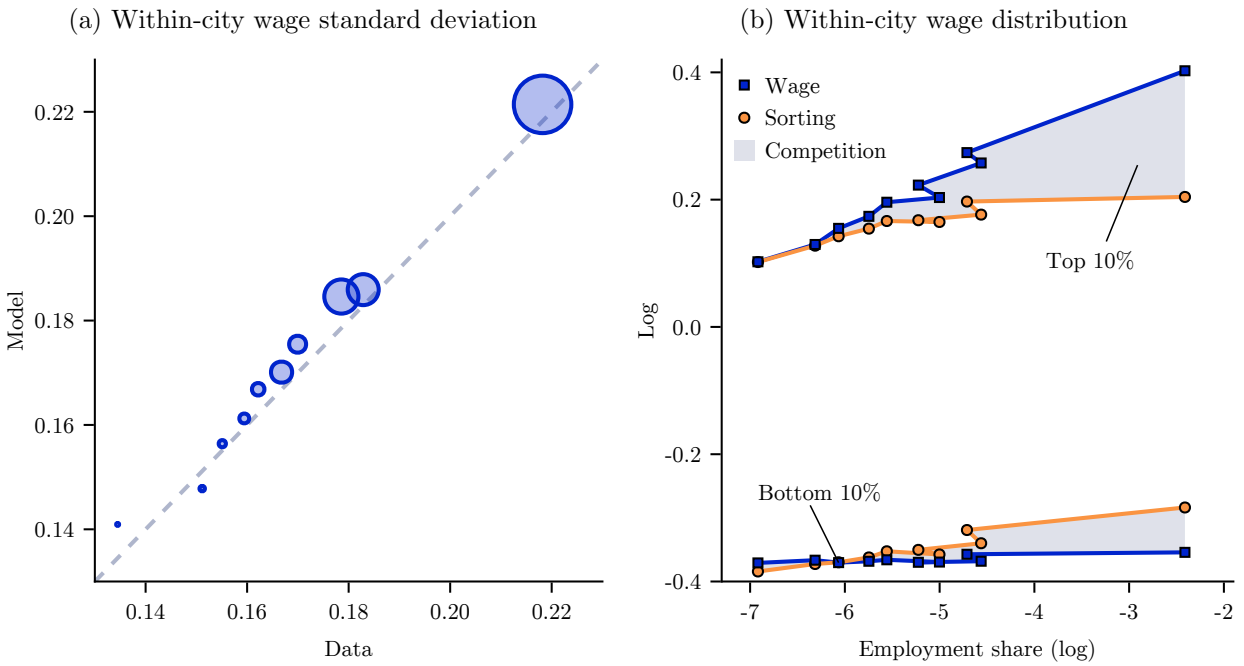
[17] Figure C.6(a) repeats the exercise for every origin and destination locations.

[18] Under competitive markets, firms would be the same size everywhere given wages and TFPs (Appendix E.6).

[19] Productivity is not fully passed through to wages. The labor supply elasticity shapes markdowns. This elasticity jointly depends on search frictions and the elasticity of the vacancy cost. Together, the model features an average labor supply elasticity of 5, as in Berger et al. (2022) and Lamadon et al. (2022).

[20] The model speaks to labor TFP. Other sources of local productivity, if present, are not passed through to wages.

Figure 7: Local wage inequality in the model and the data



Left panel plots the within-city log wage variance in the model against the within-city variance in job fixed effects in the data. Job fixed effects are estimated in (1). The dashed line is the 45-degree line. Right panel implements (24) separately for wages in the bottom and top 10% of the local wage distribution. The blue rectangles show the average wage. The orange circles show the TFP and composition effect (first two terms). The grey area plots the competition effect (third term). All variables plotted against the average employment share of CZs in each group.

Figure 7(a) shows the within-city wage standard deviation in the model against the wage premia standard deviation in the data. The dashed line is the 45-degree line. The model explains 103% of the spatial variation in within-city wage inequality. Importantly, within-city inequality is not targeted in the estimation and thus acts as a proper over-identification test. The blue rectangles in Figure 7(b) display the average wage in the bottom and top 10% of the local wage distributions. As in the data, large cities are more unequal because they host high- and low-paying jobs.[21]

Large cities may be more unequal for two reasons. They may host unproductive and productive employers. Or, the competition that takes place there may inherently foster inequality. I decompose the relative importance of employer composition and local competition on wages through

$$\mathbb{E}_\ell[\log w \mid \mathcal{W}] = \log T_\ell + \mathbb{E}_\ell\left[\log \frac{z}{\bar{\mu}(z)} \mid \mathcal{W}\right] + \mathbb{E}_\ell\left[\log \frac{\bar{\mu}(z)}{\mu_\ell(z)} \mid \mathcal{W}\right]. \tag{24}$$

In (24), $\mathcal{W}$ refers to a wage partition. $\mu_\ell(z) \equiv zT_\ell/w_\ell(z)$ is the markdown charged by employer z in location ℓ, and $\bar{\mu}(z) = L^{-1}\sum_\ell \mu_\ell(z)$ is the unweighted average markdown for z. With this convention, the higher the markdown, the greater the market power of employers.

The first term in (24) captures the direct effect of local TFP. The second term is the partial equilibrium effect of employer sorting on wages. As productive employers concentrate in large cities, MPLs rise. However, the most productive firms also charge higher markdowns because very few

[21] In Figure C.8(a), I estimate the city-size elasticity of wage premia by decile, $\log w_{q\ell} = \alpha_q + \beta_q \log m_\ell + u_{q\ell}$, where $w_{q\ell}$ is the average wage in the qth decile of ℓ's premia distribution. The orange circles and blue rectangles display the elasticities in the data and in the model. The two align closely.

firms can compete with them (Figure C.9, see also Gouin-Bonenfant, 2022). The second term thus summarizes how the employer composition affects wages holding constant competition. The third term represents the general equilibrium impact of cities on wages through local competition.[22]

Figure 7(b) applies this decomposition separately for wages in the bottom and top 10% of the local wage distribution. The orange circles plot the TFP and composition effects. The difference between the two, summarized by the grey shaded areas, is the competition effect.

The fierce competition in large cities forces productive employers to offer very high wages. Employers in the top 10% of the wage distribution in Paris are substantially more productive than employers at the top in Le Mans (46%). However, they also charge higher markdowns, and were they not subject to the local labor market competition, the wage gap would be 6%. In equilibrium, they compete locally with employers who are relatively more willing to pay their workers, which reduces their markdown by 12 p.p. and brings the wage gap to 25%.

Despite the fiercer competition, low-paying jobs persist in large cities because unemployed workers lack the bargaining power to extract rents. Employers in the bottom 10% of wages in Paris are 9% more productive than employers at the bottom in Le Mans. However, these employers hire most of their workforce from unemployment. They face similar competitive pressure, offer a wage close to the reservation wage, and the higher productivity in Paris does not spill over onto wages.

Large cities are therefore more unequal because the fiercer competition has heterogeneous incidence across firms. Figure C.8(c) computes the counterfactual wage standard deviation were markdowns uniform across locations. In that case, there are barely any spatial differences in wage inequality. This heterogeneous competition effect is unique to this framework as it arises from the interaction between employer sorting and the competition for workers along local job ladders.

4.3 Every worker earns higher lifetime real earnings in larger cities

I conclude this section with the third takeaway: every worker earns higher lifetime real earnings in larger cities. Figure 8(a) plots the local returns to job switching, in the model on the y-axis and in the data on the x-axis. In the data, I use the estimates computed with the job fixed effects (Figure 4(b), blue rectangles). In the model, the local returns are computed as the average wage growth conditional on a job switch:

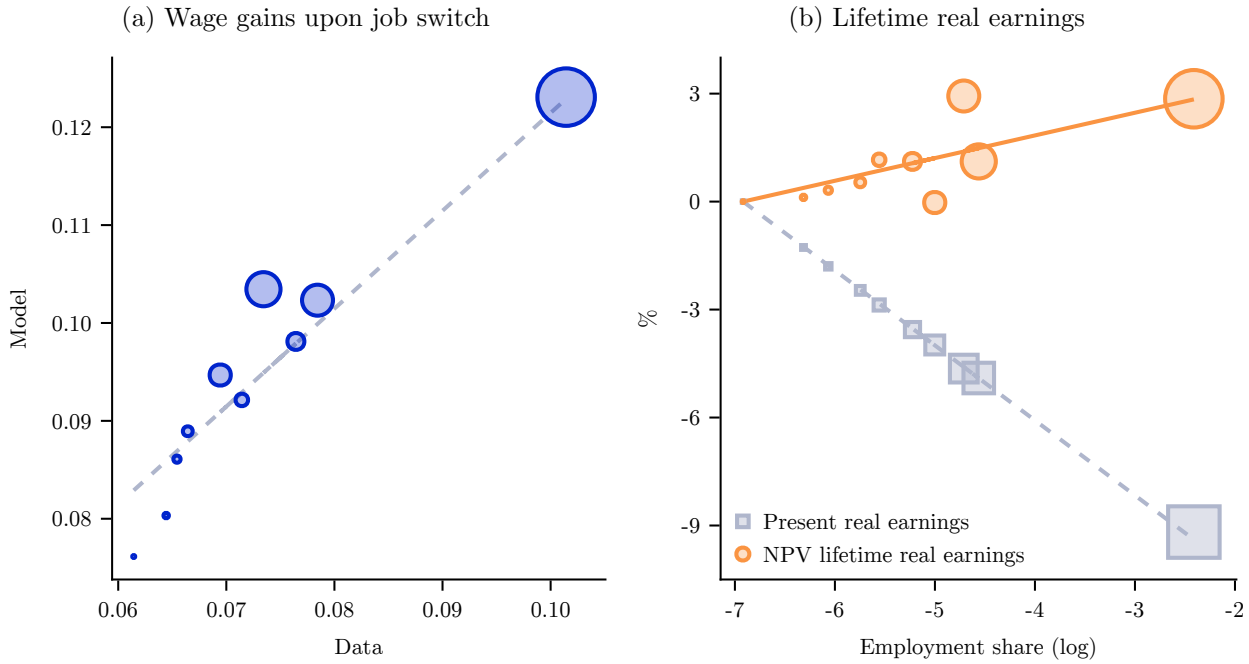
$$\mathbb{E}_\ell \left[\log \frac{W'}{W} \mid \text{switch} \right] = \int \frac{1}{1 - F_\ell(w)} \int_w \log \left(\frac{w'}{w} \right) dF_\ell(w') dG_\ell(w).$$

As for within-city wage inequality, the local returns to job switching serve as an over-identification test as they are not targeted in the estimation.

The model slightly overpredicts the aggregate gains of job switching. On average, job switchers experience a wage increase of 9.7% in the model; this is 7.5% in the data. Likewise, it slightly over-estimates how steep the job ladder is in large cities. Switching jobs in cities twice as large

[22] The within-firm effect of cities on wages (i.e., what happens to wages when an employer changes location) is thus captured by the first and third terms. Carry et al. (2025) estimate little wage change on average upon reallocation. Figure C.8(b) shows this result is consistent with my model: between-city wage gaps closely track average employer productivity gross of their nationwide markdowns.

Figure 8: Local job ladders, wage growth, and lifetime earnings



Left panel plots the average growth in wage premia upon a job switch, in the model (left-axis) and the data (right-axis). In the data, statistics computed as wage growth in job fixed effects upon a job switch as in Figure 4(b). In the model, statistics computed as $\mathbb{E}_\ell[\log(w'/w) \mid w' \geq w]$. Right panel shows the present real earnings of unemployed workers in grey rectangles, and the net present value of expected lifetime real earnings in orange circles. Lifetime earnings $\mathcal{W}_\ell$ given by (28). Both statistics are projected against the average employment share of CZs in each group.

brings an extra wage growth of 0.8 p.p. in the model, compared to 0.7 p.p. in the data.

Figure 8(b) quantifies the implications of the local job ladders for lifetime consumption. The grey rectangles show the present real earnings of unemployed workers in each location, b/P_ℓ. The orange circles are the net present value (NPV) of their expected real lifetime earnings, $\mathcal{W}_\ell/P_\ell$.

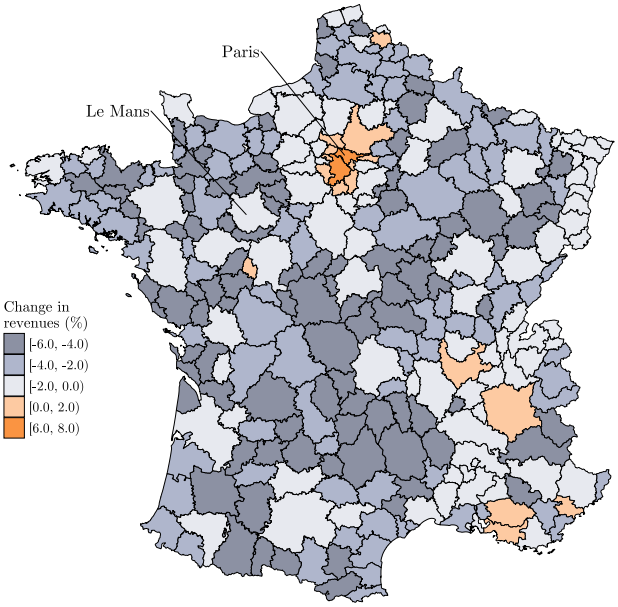
Unemployed workers in larger cities enjoy higher expected lifetime consumption thanks to the future high-paying opportunities. As in the data, their present real earnings are lower as housing is more expensive and their revenues are constant across locations. For instance, the present real earnings of unemployed workers in Paris are 7.5% lower than in Le Mans. However, workers in Paris benefit from the steeper local job ladder, and their expected lifetime real earnings are 2.5% higher. Generalizing to all locations, the NPV of expected lifetime real earnings for unemployed workers is 0.6% higher in cities twice as large.[23] The search option value offered by large cities — and the wage growth it begets — is thus a central component to workers' choice of location.

In summary, productive employers concentrate in large cities to access a slack labor market. Higher wages, greater inequality, and faster wage growth follow from intensified local competition for workers, and the model quantitatively rationalizes the spatial distribution of wage premia observed in the data. In particular, all workers in large cities enjoy higher lifetime real earnings, even those whose current real wages are lower. Having validated the model, I conclude the paper by evaluating

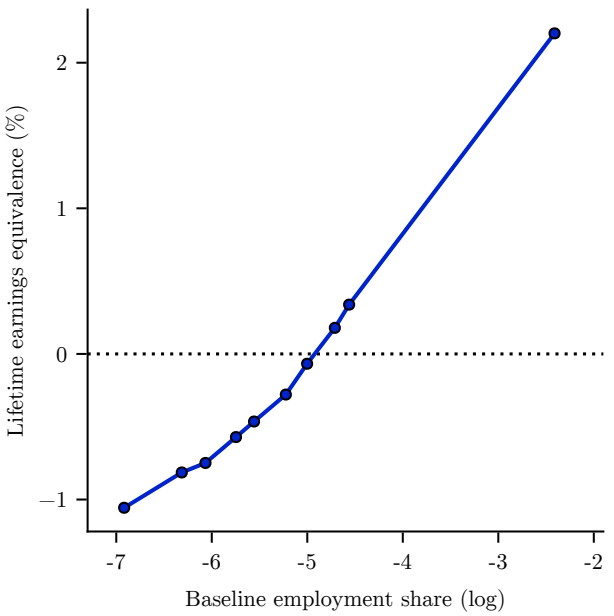
[23] There are also differences in lifetime earnings across workers within cities. When the discount rate is low, these differences vanish. As a result, the city-size elasticity of expected lifetime real earnings for the average worker is close to that of the unemployed (0.008).

Figure 9: Housing-adjusted unemployment benefits

(a) Unemployment benefits



(b) Change in welfare by birthplace



Left panel shows the change in revenues for unemployed workers by CZ. Right panel shows the change in welfare by birthplace. Welfare change computed as lifetime earnings compensating equivalence: the percent increase in lifetime earnings that render workers indifferent between the baseline and the policy equilibria. The statistics is plotted against the employment share of CZs in each group in the laissez-faire equilibrium.

the consequences of indexing unemployment insurance benefits to local costs of living.

5 The consequences of place-based unemployment benefits

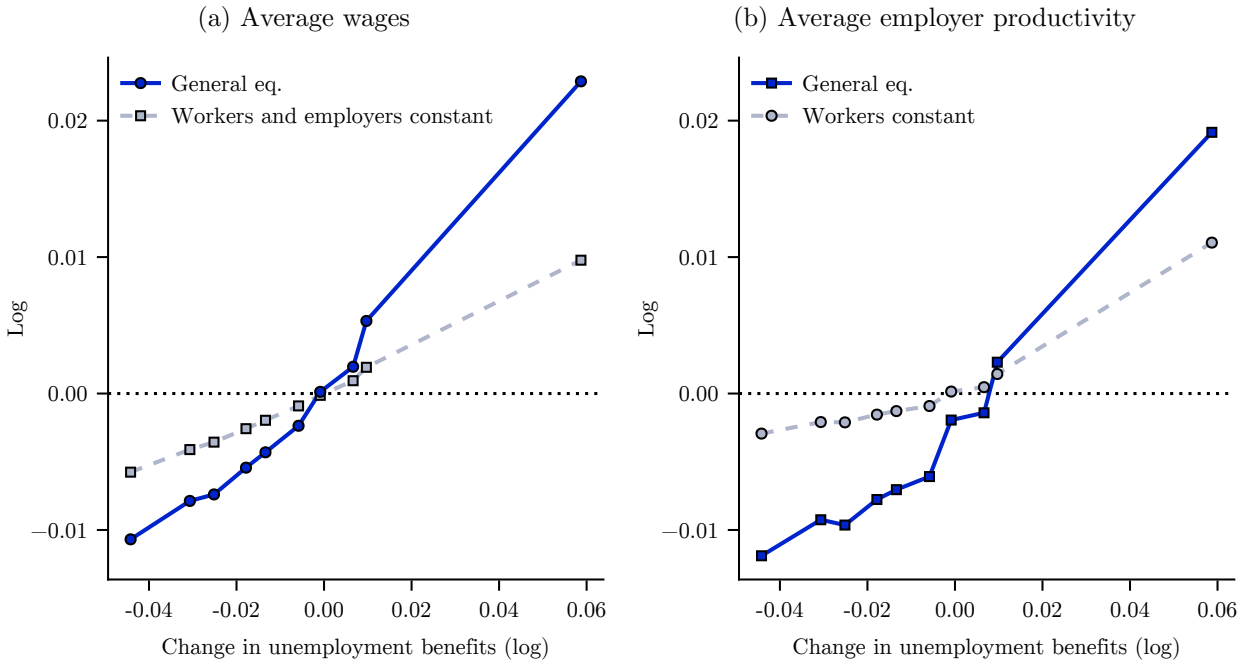
Several countries adjust unemployment benefits (UB) to the local costs of living (e.g., *Bürgergeld* in Germany, *Housing Security Benefit* in Japan). Many others frequently debate related policy proposals. The framework developed in this paper is a unique laboratory to quantify the consequences of such policies. At the micro level, it features unemployment and the option value offered by large locations. At the macro level, it allows for the long-term spatial reallocation of jobs.

I study a policy that indexes UB to housing prices. Let τ_ℓ denote the location-specific UB rate. The policy is such that the present consumption of unemployed workers is equated across space, $\frac{b\tau_\ell + T}{P_\ell} = \bar{c}$, where T is a lump-sum transfer that finances the policy, and $\bar{c}$ is the average consumption of unemployed workers under the policy equilibrium.[24]

The policy is consequential. Figure 9(a) shows the change in revenues induced by the policy for unemployed workers. Nine cities out of ten experience a decrease in their unemployment benefits, with an average drop of 1.9%. The remaining locations see their unemployment benefits increase by an average 3.8%; most of the increase is concentrated in Paris and its suburbs. In the aggregate, the total transfers induced by the policy amount to 0.17% of GDP under the laissez-faire equilibrium. I first assess the policy's impact across space and then quantify its aggregate effects.

[24] The lump-sum transfer applies to all workers and ensures a balanced budget: $\sum_\ell u_\ell b(\tau_\ell - 1) + T = 0$.

Figure 10: The spatial consequences of housing-adjusted unemployment benefits



Left panel shows the change in average wage by location, in grey when the spatial allocation of workers and employers is held constant at the laissez-faire equilibrium, and in blue in general equilibrium. Right panel shows the change in employment-weighted employer productivity, in grey when the spatial allocation of workers is held constant, and in blue in general equilibrium. All variables plotted against the change in UB.

5.1 Spatial inequality

Housing-adjusted UB are spatially regressive: they improve the welfare of workers in large locations at the expense of those in small cities, thereby accentuating pre-existing spatial disparities. Figure 9(b) displays the change in welfare by birthplace. I measure welfare changes in terms of lifetime earnings equivalence: by how much lifetime earnings have to increase for workers to be indifferent between the laissez-faire and policy equilibria Appendix F.2 details the welfare computation further. The policy is equivalent to a 2.2% increase in lifetime earnings for workers born in Paris; it amounts to a 0.7% decrease in lifetime earnings for those born in Le Mans.

Welfare disparities rise as the policy significantly amplifies spatial wage inequality. The blue rectangles in Figure 10(a) show the change in average wages. The wage gap between Paris and Le Mans increases from 12% to 16%. Within-city inequality deepens in small locations, whereas the policy has moderate success at reducing how unequal large cities are (Figure C.10(a)).

To understand why the policy has such a pronounced impact on wages, I unpack its consequences into partial and general equilibrium effects. The partial equilibrium is computed holding workers and firms locations fixed and letting employers adjust their wages. The grey rectangles in Figure 10(a) show the average wage under this partial equilibrium counterfactual.

In partial equilibrium, housing-adjusted unemployment benefits reduce the inequality of large cities with moderate impacts on spatial wage gaps. The higher benefits in large cities increase the outside option of unemployed workers there. Employers who rely mostly on unemployed workers reduce their markdown, and the policy has a large pass-through onto low-paying jobs (Fig-

ure C.10(b)). However, the higher outside option fades out throughout the job ladder as the distribution of willingness to pay remains unchanged, and the average wage only rises mildly.

In general equilibrium, the policy reallocates productive employers towards large cities. The blue circles in Figure 10(b) depict the change in average employer productivity. The policy spurs agglomeration: large cities become more attractive for workers thanks to the higher expected lifetime earnings. The local labor market slackens, and marginal productive employers locate there. The employment share of Paris increases by 1.6 p.p., and the average employer productivity by 1.1%. The lower productivity in small locations depresses wages. The fiercer competition in large cities shifts up the entire wage distribution, and within-city inequality remains fairly stable. The spatial reallocation of jobs explains 65% of the increase in between-city wage variance.

Employers' location choices are key for the consequences of place-based unemployment benefits on spatial disparities. They also drive the policies' aggregate consequences.

5.2 Efficiency

Place-based unemployment benefits substantially raise output and welfare by dampening spatial misallocation. GDP grows by 0.7% and consumer surplus increases by 1.7% (Table 11(a), column 1). Most of the GDP increase occurs in the tradable sector (77%). In this sector, aggregate output is a function of aggregate employment and Total Factor Productivity (TFP):

$$\log Y = \underbrace{\log E}_{\text{Employment}} + \underbrace{\log\left(\sum_{\ell} \frac{e_\ell}{E} \times \mathbb{E}_\ell^{n_\ell}[T_\ell Z]\right)}_{\text{TFP}},$$

where $E = \sum_\ell e_\ell$ is the aggregate employment rate, and average productivity is employment-weighted. Employment is fairly stable, and all of the tradable output gains arises from TFP growth (110%). Two forces may *a priori* drive the productivity gains. First, the policy reallocates workers to high productivity locations: $\Delta\text{TFP} \approx \sum_\ell \mathbb{E}_\ell^{n_\ell}[T_\ell Z]\Delta e_\ell/E$. Second, the policy improves the allocation of workers to firms within locations: $\Delta\text{TFP} \approx \sum_\ell (e_\ell/E)\Delta\mathbb{E}_\ell^{n_\ell}[T_\ell Z]$. Using this decomposition, I find that the spatial reallocation of workers drives TFP growth (111%).

Housing-adjusted UB yields efficiency gains by correcting two inefficiencies that arise through the local labor market tightness. The first externality is a market power externality. Employers do not internalize how their wage shapes workers' location choice. In particular, markdowns are too high in large cities as they concentrate the most productive employers who charge the highest markdowns. Too few workers locate there, and the labor market is too tight. This depresses aggregate TFP by reducing the employment share of productive employers. It also prevents inframarginal workers of accessing high wage, high amenity locations, thereby lowering consumer surplus.[25]

The second externality is a pooling externality as in Bilal (2023). At the margin, too many unproductive employers locate in large locations to benefit from the slack labor market. This lowers

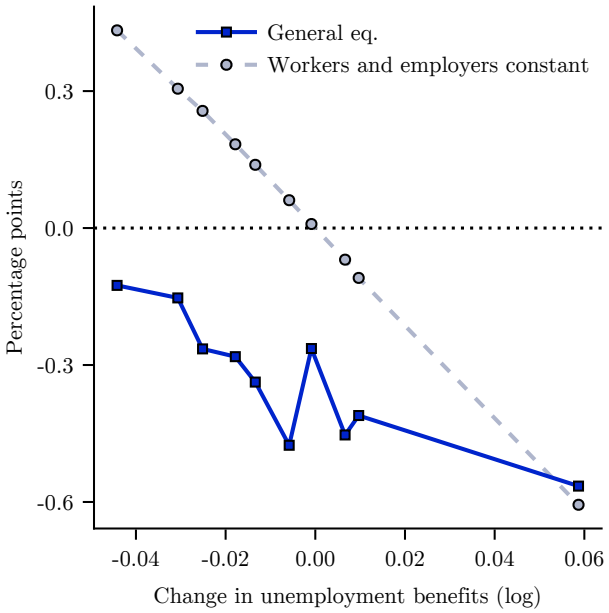
[25] Markdowns do not induce misallocation in standard wage setting models because wages and productivity are monotonically related. By contrast, it leads here to input misallocation across space, similar to the misallocation induced by markups.

Figure 11: The aggregate consequences of housing-adjusted unemployment benefits

(a) Average markdown

	Benefits	Subsidies
Output (%)	0.69	0.54
Tradable	0.53	0.40
Non-tradable	0.16	0.14
Employment rate (p.p.)	-0.06	-0.04
TFP (%)	0.78	0.57
Between	0.86	0.87
Within	-0.09	-0.30
Average wage (%)	0.75	0.53
Markdown (p.p.)	0.01	0.05
Consumer surplus (%)	1.66	1.42
Between	1.34	1.34
Within	0.32	0.08

(b) Average markdown



Left panel shows the change in aggregate variables in response to the housing-adjusted unemployment benefits policy (column 1) and lump-sum place-based subsidies (column 2). Indented rows (e.g., tradable) correspond to the change in the non-indented variable (e.g., output) caused by that indented variable. Right panel plots the change in average markdown by location, in grey when the spatial allocation of workers and employers is held constant at the laissez-faire equilibrium, and in blue in general equilibrium. Both variables plotted against the change in UB.

wages, tightens the market, and further reduces the employment share of productive firms.

Place-based unemployment benefits are a unique second-best policy that acts on both externalities. First, the policy lowers markdowns, and particularly so in high productivity cities. Figure 11(b) plots the change in average markdowns. Holding constant the spatial allocation of workers and employers, the policy increases workers' outside option in expensive cities and lowers it in cheap places. The markdowns adjust accordingly. In general equilibrium, the policy homogenizes cities: it reallocates low productivity employers to low productivity cities, and vice versa for large cities. The median employer faces accrued competition, and markdowns shrink even in small locations.[26]

Second, the policy increases the cost of labor in expensive locations, which prices out a fraction of unproductive employers. The grey rectangles in Figure 10(b) display the change in average employer productivity when the policy is in place but the worker allocation is kept fixed at the laissez-faire equilibrium. Figure C.11(a) shows how the number of jobs responds. Holding constant workers' location choice, the number of jobs in Paris decreases by 4.8%, and the average employer productivity rises by 1.9%. In general equilibrium, the number of jobs rises but significantly less than the number of workers, allowing the labor market to slacken (Figure C.11(b) and C.11(c)).

I quantify the relative importance of both externalities by studying the consequences of standard, lump-sum subsidies. I design the subsidies to reproduce the same allocation of workers as under the place-based unemployment benefits policy. Unemployed and employed workers receive

[26] While the policy reduces markdowns throughout space, it also reallocates more workers to high-markdown locations. The aggregate markdown is constant as a result (Table 11(a)).

the transfers. Their outside option thus stays constant, so do labor costs, and this policy only corrects the market power externality. The second column of Table 11(a) presents the consequences of the subsidies.

Lump-sum subsidies are costlier and less effective than housing-adjusted unemployment benefits. The total amount of transfer induced by the policy is about three times larger than the UB policy. Aggregate consumer surplus increases by 1.4%, and TFP in the tradable sector rises by 0.57%. TFP gains are lower because the subsidies do not dampen the pooling externality. The reallocation of workers to high-production location induces the same TFP gains as in baseline policy; however, the allocation of workers to firms worsens in those cities, which reduces the TFP gains by 0.3 p.p. Nevertheless, comparing the two policies, the bulk of the productivity gains (74%) occurs as the UB policy corrects the markdown externality. This externality, which arises from the sorting of employers and the local poaching competition, is unique to this framework.

6 Conclusion

This paper documents the importance of employers for spatial wage inequality. Wages are high in large cities to a great extent because high-paying jobs are concentrated there. Yet, low-paying jobs persist there, and large cities are more unequal. The reallocation of workers from low- to high-paying jobs is a focal component of the city-size wage premium.

I rationalize the facts through a model of employer sorting and competition for workers along local job ladders. Productive employers concentrate in large cities to access a slack labor market and hire many workers. The competition for workers intensifies and puts upward pressure on wages. Low-paying jobs remain as employers who hire most of their workforce from unemployment are not affected by the poaching competition. The steeper local job ladder implies that every worker earns higher lifetime real earnings, including those whose present real wages are lower.

While the fierce competition in large locations reduces productive employers' markdowns, markdowns are still too high in the laissez-faire equilibrium as employers do not internalize how their wage-setting strategy shapes workers' location choice. Indexing unemployment benefits to housing prices partially corrects this novel inefficiency by raising workers' outside options in large cities.

There are several directions along which to expand this research agenda. First, the framework can easily be integrated into a full quantitative spatial model with heterogeneous skills, congestion externalities, and costly trade, to study optimal spatial policies. Second, the paper focuses on steady states, leaving open how local shocks or policies shape the transitional dynamics of wages. Lastly, the framework extends beyond spatial economics to any environment where employers self-select into markets, such as across industries.

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A Proofs

A.1 Proof of Proposition 3

Lemma 1 (Envelope theorem)**.**
The profit function $\pi_\ell(z)$ is continuously differentiable with $\frac{d\pi_\ell(z)}{dz} = n_\ell(z)$

Proof. Differentiability follows from the Envelope theorem. □

Lemma 2 (Convex support)**.**
The support of the productivity distribution in each city is an interval.

Proof. Suppose not. That is, for some city ℓ, Γ_ℓ has a hole. Wlog, suppose there is a unique hole, such that $\operatorname{supp}\Gamma_\ell = [\underline{z}_\ell, z] \cup [z+\varepsilon, \bar{z}_\ell]$, $\varepsilon > 0$. The profit maximization condition (17) then requires

1. $\pi_\ell(z') \geq \pi_{\ell'}(z')$ for all $z' \in \operatorname{supp}\Gamma_\ell$ and all cities ℓ',
2. $\pi_\ell(z') < \pi_{\ell^\star}(z')$ for all $z' \in (z, z+\varepsilon)$ and at least one city $\ell^\star$.

By continuity, these imply (i) $\pi_\ell(z) = \pi_{\ell^\star}(z)$ and (ii) $\frac{d\pi_\ell(z)}{dz} < \frac{d\pi_{\ell^\star}(z)}{dz}$. Since $n_\ell(z)$ is constant outside the support of Γ_ℓ and strictly increasing in it, Lemma 1 and (ii) imply $n_\ell(z') = \frac{d\pi_\ell(z')}{dz} < \frac{d\pi_{\ell^\star}(z')}{dz} = n_{\ell^\star}(z')$ for all $z' \in (z, z+\varepsilon)$. By continuity, $\pi_\ell(z+\varepsilon) < \pi_{\ell^\star}(z+\varepsilon)$, a contradiction. □

Lemma 3 (First order stochastic dominance ordering)**.**
For two cities ℓ and ℓ', $\theta_\ell < \theta_{\ell'}$ if and only if $\Gamma_\ell \succ \Gamma_{\ell'}$.

Proof. I start by showing that $\theta_\ell < \theta_{\ell'} \Rightarrow \Gamma_\ell \succ \Gamma_{\ell'}$. For the sake of contradiction, suppose that there exists a set $\mathcal{Z} \subseteq [\underline{z}, \bar{z}]$ of positive measure satisfying the three following conditions:

1. $\min \mathcal{Z} \geq \min(\underline{z}_\ell, \underline{z}_{\ell'})$;

2. $\max \mathcal{Z} \leq \max(\bar{z}_\ell, \bar{z}_{\ell'})$;

3. $\bar{\Gamma}_{\ell'}(z) \geq \bar{\Gamma}_\ell(z)$ for all $z \in \mathcal{Z}$.

The third condition implies $\Gamma_\ell \not\succ \Gamma_{\ell'}$. The first two are needed since, trivially, $\Gamma_\ell(z) = \Gamma_{\ell'}(z) = 0$ for $z < \min(\underline{z}_\ell, \underline{z}_{\ell'})$ and $\bar{\Gamma}_\ell(z) = \bar{\Gamma}_{\ell'}(z) = 0$ for $z > \max(\bar{z}_\ell, \bar{z}_{\ell'})$.

The third condition implies $\max \mathcal{Z} \leq \bar{z}_{\ell'}$. Lemma 1 and (15) imply

$$\frac{d\pi_\ell(z)}{dz} = \frac{1}{\theta_\ell} \frac{k}{[1 + k\bar{\Gamma}_\ell(z)]^2} \geq \frac{1}{\theta_\ell} \frac{k}{[1 + k\bar{\Gamma}_{\ell'}(z)]^2} > \frac{1}{\theta_{\ell'}} \frac{k}{[1 + k\bar{\Gamma}_{\ell'}(z)]^2} = \frac{d\pi_{\ell'}(z)}{dz}, \quad \forall z \in \mathcal{Z}. \tag{25}$$

Suppose first that $\min \mathcal{Z} \geq \underline{z}_{\ell'}$, such that $\mathcal{Z} \subseteq \text{supp } \Gamma_{\ell'}$. In that case, profit maximization (17) demands $\pi_{\ell'}(z) \geq \pi_\ell(z)$ for all $z \in \mathcal{Z}$. If $\pi_{\ell'}(z) = \pi_\ell(z)$ for any $z \in \mathcal{Z}$, then (25) implies $\pi_{\ell'}(z') < \pi_\ell(z')$ for $z' \in B^+(z) \subset \mathcal{Z}$, a contradiction.[27] Hence, it must be that $\pi_{\ell'}(z) > \pi_\ell(z)$ for all $z \in \mathcal{Z}$, and $\min \mathcal{Z} \geq \bar{z}_\ell$. The inequality (25) thus simplifies to

$$\frac{d\pi_\ell(z)}{dz} = \frac{k}{\theta_\ell} > \frac{1}{\theta_{\ell'}} \frac{k}{[1 + k\bar{\Gamma}_{\ell'}(z)]^2} = \frac{d\pi_{\ell'}(z)}{dz}, \quad \forall z \in [\bar{z}_\ell, \max \mathcal{Z}].$$

Meanwhile, profit maximization (17) requires $\pi_{\ell'}(\bar{z}_\ell) \leq \pi_\ell(\bar{z}_\ell)$. Together, these two inequalities imply $\pi_{\ell'}(z) < \pi_\ell(z)$ for all $z \in [\bar{z}_\ell, \max \mathcal{Z}]$, which contradicts $\mathcal{Z} \subseteq \text{supp } \Gamma_{\ell'}$ by profit maximization.

Suppose instead $\min \mathcal{Z} < \underline{z}_{\ell'}$, and therefore, $\min \mathcal{Z} \geq \underline{z}_\ell$. For all $z \in [\min \mathcal{Z}, \underline{z}_{\ell'}]$, (25) becomes

$$\frac{d\pi_\ell(z)}{dz} = \frac{1}{\theta_\ell} \frac{k}{[1 + k\bar{\Gamma}_\ell(z)]^2} > \frac{1}{\theta_{\ell'}} \frac{k}{(1+k)^2} = \frac{d\pi_{\ell'}(z)}{dz}. \tag{26}$$

In addition, profit maximization (17) demands $\pi_\ell(z) \geq \pi_{\ell'}(z)$ for all $z \in [\min \mathcal{Z}, \underline{z}_{\ell'}]$. Together, these inequalities imply $\pi_\ell(\underline{z}_{\ell'}) > \pi_{\ell'}(\underline{z}_{\ell'})$, a contradiction with profit maximization.

$\theta_\ell < \theta_{\ell'} \Leftarrow \Gamma_\ell \succ \Gamma_{\ell'}$ automatically follows. Suppose not $\theta_\ell < \theta_{\ell'}$, i.e., $\theta_\ell \geq \theta_{\ell'}$. I show that $\Gamma_\ell \not\succ \Gamma_{\ell'}$. If $\theta_\ell > \theta_{\ell'}$, I have already shown that $\Gamma_{\ell'} \succ \Gamma_\ell$. If $\theta_{\ell'} = \theta_\ell$, it must be that $\Gamma_{\ell'} = \Gamma_\ell$ almost everywhere for otherwise similar contradictions as above can be constructed. □

Lemma 4 (Overlapping supports)**.**
Take two cities ℓ and ℓ' so that $\theta_\ell < \theta_{\ell'}$. Then, supp $\Gamma_\ell \cap$ supp $\Gamma_{\ell'}$ has positive measure if and only if $\theta_{\ell'} < (1+k)^2 \theta_\ell$.

Proof. I first prove $\Leftarrow$. Suppose $\theta_{\ell'} < (1+k)^2 \theta_\ell$. For the sake of contradiction, suppose also that there is no overlap. Since $\theta_\ell < \theta_{\ell'}$, Lemma 3 implies $\bar{z}_{\ell'} \leq \underline{z}_\ell$. Furthermore, profit maximization (17) requires $\pi_{\ell'}(\underline{z}_\ell) \leq \pi_\ell(\underline{z}_\ell)$ and $\pi_{\ell'}(z) > \pi_\ell(z)$ for $z \in B^-(\bar{z}_{\ell'})$. Hence, π_ℓ and $\pi_{\ell'}$ must cross at least once in $[\bar{z}_{\ell'}, \underline{z}_\ell]$ and π_ℓ crosses $\pi_{\ell'}$ from below; that is, there exists $z^\star \in [\bar{z}_{\ell'}, \underline{z}_\ell]$ so that $\pi_\ell(z^\star) = \pi_{\ell'}(z^\star)$ and $\pi'_\ell(z) > \pi'_{\ell'}(z)$ for $z \in B^-(z^\star)$. By continuity, this implies $\pi'_\ell(z^\star) \geq \pi'_{\ell'}(z^\star)$. Furthermore, it must be that $\Gamma_{\ell'}(z^\star) = 1$. These, together with Lemma 1, imply

$$\frac{1}{\theta_\ell} \frac{k}{(1+k)^2} = n_\ell(\underline{z}_\ell) = \frac{d\pi_\ell(z^\star)}{dz} \geq \frac{d\pi_{\ell'}(z^\star)}{dz} = n_{\ell'}(\bar{z}_{\ell'}) = \frac{k}{\theta_{\ell'}},$$

[27] $B(x)$ refers to an open ball around x, and $B^+(x)$ and $B^-(x)$ an open ball to the right and left of x.

where the first and last equalities follow from n_ℓ and $n_{\ell'}$ being constant outside of their respective support. However, $\theta_{\ell'} < (1+k)^2\theta_\ell$, a contradiction.

I now prove the other direction. For this, suppose not $\theta_{\ell'} < (1+k)^2\theta_\ell$, or $\theta_{\ell'} \geq (1+k)^2\theta_\ell$. I want to show that this implies no overlap. Hence, for the sake of contradiction, suppose that there is overlap in the job distribution. Lemma 2 then implies supp $\Gamma_\ell \cap$ supp $\Gamma_{\ell'} = [\underline{z}_\ell, \bar{z}_{\ell'}]$ with $\underline{z}_\ell < \bar{z}_{\ell'}$. Employers in $[\underline{z}_\ell, \bar{z}_{\ell'}]$ must be indifferent between the two cities, $\pi_\ell(z) = \pi_{\ell'}(z)$ for all $z \in [\underline{z}_\ell, \bar{z}_{\ell'}]$, and therefore $\pi'_\ell(z) = \pi'_{\ell'}(z)$. By Lemma 1, this must hold at $\underline{z}_\ell$, and therefore

$$\frac{1}{\theta_\ell}\frac{k}{(1+k)^2} = n_\ell(\underline{z}_\ell) = \frac{d\pi_\ell(\underline{z}_\ell)}{dz} = \frac{d\pi_{\ell'}(\underline{z}_\ell)}{dz} = n_{\ell'}(\underline{z}_\ell) = \frac{1}{\theta_{\ell'}}\frac{k}{(1+k\bar{\Gamma}_{\ell'}(\underline{z}_\ell))^2}.$$

However, $\theta_{\ell'} \geq (1+k)^2\theta_\ell$, and this equality cannot hold for any $\Gamma_{\ell'}(\underline{z}_\ell) \in (0,1)$, a contradiction. □

A.2 Proof of Proposition 4

Lemma 5 (Housing prices)**.**
Fix $\boldsymbol{\theta}$ and re-arrange cities so that θ_ℓ is decreasing in ℓ. Then, the spatial job allocation is sustained by a vector of housing prices $\{p^c_\ell\}_{\ell=1}^L$ that satisfies the difference equation

$$p^c_{\ell+1} = p^c_\ell + \left(\underline{z}_{\ell+1} - \underline{w}_{\ell+1}\right) n_{\ell+1}(\underline{z}_{\ell+1}) - \left(\underline{z}_\ell - \underline{w}_\ell\right) n_\ell(\underline{z}_\ell) - \int_{\underline{z}_\ell}^{\underline{z}_{\ell+1}} n_\ell(\zeta)\mathrm{d}\zeta, \tag{27}$$

subject to the boundary condition $p^c_1 = \left(\frac{M - \sum_{\ell>1} M_\ell}{L^c}\right)^{\frac{1-\beta^c}{\beta^c}} \frac{1}{\beta^c}$.

Proof. Fix city ℓ. Take the city ℓ' such that $\theta_{\ell'} > \theta_\ell$ and there is no other third city l so that $\theta_{\ell'} > \theta_l > \theta_\ell$. If the locations are inversely ordered by θ_ℓ, such ℓ' exists for all $\ell \in \{2, \ldots, L\}$. Lemma 2, Lemma 3, and feasibility (7) together imply that $\underline{z}_\ell \in$ supp $\Gamma_{\ell'}$. Profit maximization (17) then requires $\pi_\ell(\underline{z}_\ell) = \pi_{\ell'}(\underline{z}_\ell)$. Re-arranging: $p^c_\ell = (\underline{z}_\ell - \underline{w}_\ell)n_\ell(\underline{z}_\ell) - \pi_{\ell'}(\underline{z}_\ell)$. Meanwhile, the fundamental theorem of calculus implies $\pi_{\ell'}(\underline{z}_\ell) = \pi_{\ell'}(\underline{z}_{\ell'}) + \int_{\underline{z}_{\ell'}}^{\underline{z}_\ell} \pi'_{\ell'}(\zeta)d\zeta = \pi_{\ell'}(\underline{z}_{\ell'}) + \int_{\underline{z}_{\ell'}}^{\underline{z}_\ell} n_{\ell'}(\zeta)d\zeta$ where the second equality follows from Lemma 1. Using $\pi_{\ell'}(\underline{z}_{\ell'}) = (\underline{z}_{\ell'} - \underline{w}_{\ell'})n_{\ell'}(\underline{z}_{\ell'}) - p^c_{\ell'}$ and combining with the original expression yields (27). The boundary condition follows from the commercial housing market clearing condition in location 1 and $M_1 = M - \sum_{\ell>1} M_\ell$.[28] □

Lemma 6 (Slackness)**.**
Suppose $\zeta = 1$. Then, $e_\ell > e_{\ell'} \iff \theta_\ell < \theta_{\ell'} \iff p^c_\ell > p^c_{\ell'} \iff M_\ell > M_{\ell'}$.[29]

Proof. $p^c_\ell > p^c_{\ell'} \iff M_\ell > M_{\ell'}$ follows from the commercial housing market clearing condition. Turning to $\theta_\ell < \theta_{\ell'} \iff p^c_\ell > p^c_{\ell'}$, I start by proving $\theta_\ell < \theta_{\ell'} \Rightarrow p^c_\ell > p^c_{\ell'}$. Take two cities ℓ and ℓ' that are adjacent in the $\boldsymbol{\theta}$-space with $\theta_\ell < \theta_{\ell'}$. Lemma 3 implies $\underline{z}_\ell > \underline{z}_{\ell'}$. Since $n_{\ell'}$ is strictly increasing, equation (27) implies

$$p^c_\ell - p^c_{\ell'} > (\underline{z}_\ell - b)\left[n_\ell(\underline{z}_\ell) - n_{\ell'}(\underline{z}_\ell)\right] + (\underline{z}_{\ell'} - b)\left[n_{\ell'}(\underline{z}_\ell) - n_{\ell'}(\underline{z}_{\ell'})\right].$$

[28] The equilibrium commercial housing market clearing condition is $p^c_\ell = (M_\ell/L^c)^{\frac{1-\beta^c}{\beta^c}}/\beta^c$.

[29] Lemma 6 assumes $\zeta = 1$. Since these are strict inequalities and the model is continuous in ζ, they hold for $\zeta \approx 1$.

The second term is strictly positive since $n_{\ell'}$ is increasing in z. For the first term, there are two cases. If there is overlap between the two locations, it must be that $n_\ell(z) = \frac{d\pi_\ell(z)}{dz} = \frac{d\pi_{\ell'}(z)}{dz} = n_{\ell'}(z)$ for $z \in B^+(\underline{z}_\ell)$, which must hold at $\underline{z}_\ell$. If there is no overlap, $\pi_\ell(z)$ crosses $\pi_{\ell'}(z)$ from below at $\underline{z}_\ell$, and $n_\ell(\underline{z}_\ell) = \pi'_\ell(\underline{z}_\ell) > \pi'_{\ell'}(\underline{z}_\ell) = n_{\ell'}(\underline{z}_\ell)$. In both cases, I obtain $p^c_\ell - p^c_{\ell'} > 0$.

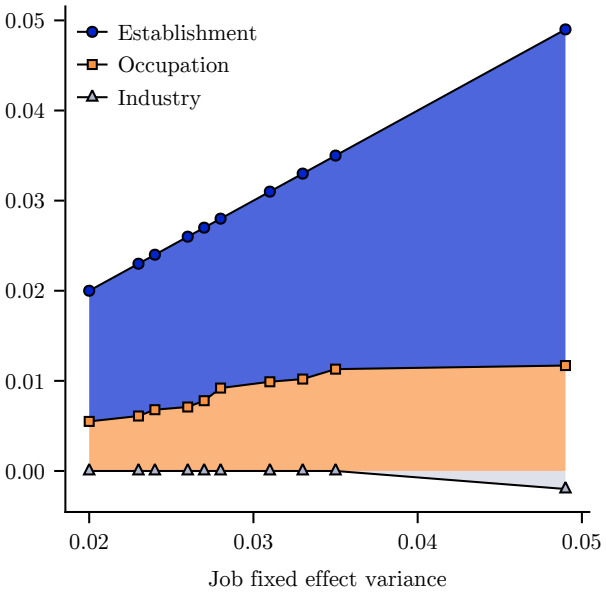
I now prove $\theta_\ell < \theta_{\ell'} \Leftarrow p^c_\ell > p^c_{\ell'}$. Suppose not $\theta_\ell < \theta_{\ell'}$, i.e., $\theta_\ell \geq \theta_{\ell'}$. If $\theta_\ell > \theta_{\ell'}$, the previous argument yields $p^c_\ell < p^c_{\ell'}$. If $\theta_\ell = \theta_{\ell'}$, then Lemma 3 implies $\Gamma_\ell = \Gamma_{\ell'}$, and equation (27) yields $p^c_\ell = p^c_{\ell'}$. Together, I have $p^c_\ell \leq p^c_{\ell'}$, i.e., not $p^c_\ell > p^c_{\ell'}$.

I conclude with $e_\ell > e_{\ell'} \iff \theta_\ell < \theta_{\ell'}$, starting with $e_\ell > e_{\ell'} \Rightarrow \theta_\ell < \theta_{\ell'}$. For the sake of contradiction, suppose that $\theta_\ell \geq \theta_{\ell'}$. Since $e_\ell > e_{\ell'}$, it must be that $M_\ell > M_{\ell'}$, and therefore $\theta_\ell < \theta_{\ell'}$, a contradiction. Turning to $e_\ell > e_{\ell'} \Leftarrow \theta_\ell < \theta_{\ell'}$, suppose not $e_\ell > e_{\ell'}$, i.e. $e_\ell \leq e_{\ell'}$. If $e_\ell < e_{\ell'}$, the previous argument implies $\theta_\ell > \theta_{\ell'}$. So suppose $e_\ell = e_{\ell'}$. Then, $\theta_\ell/\theta_{\ell'} = M_\ell/M_{\ell'} > 1 \iff M_\ell > M_{\ell'}$, also a contradiction of $\theta_\ell < \theta_{\ell'} \iff M_\ell > M_{\ell'}$. □

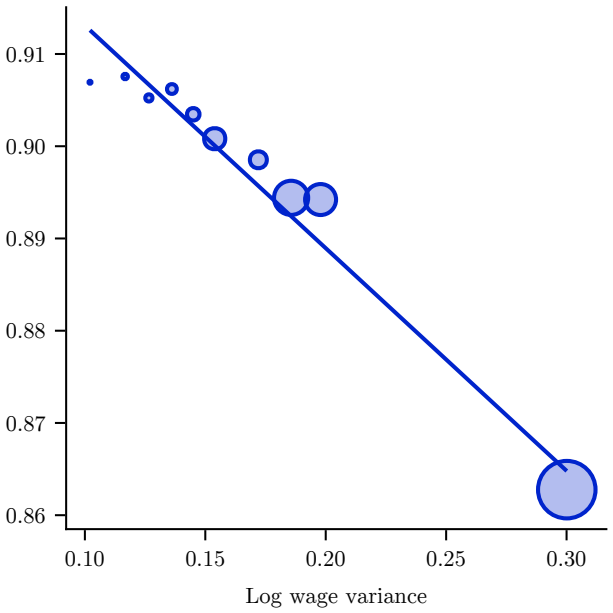
B Tables and figures

Figure B.1: The drivers of within-city wage premia dispersion

(a) Industries, occupations, and establishments



(b) Correlation between worker and job F.E.



Panel (a) displays the decomposition of the within-city job FE variance. The grey area plots the dispersion in industry FE, $\mathbb{V}\text{ar}_\ell[\phi_{\iota(j)}] + \mathbb{C}\text{ov}[\delta_{o(j)}, \phi_{\iota(j)}] + \mathbb{C}\text{ov}[\phi_{\iota(j)}, \kappa_f(j)]$, the orange area the dispersion in occupation FE, $\mathbb{V}\text{ar}_\ell[\delta_{o(j)}] + \mathbb{C}\text{ov}[\delta_{o(j)}, \phi_{\iota(j)}] + \mathbb{C}\text{ov}[\delta_{o(j)}, \kappa_f(j)]$, and the blue area the remainder, $\mathbb{V}\text{ar}_\ell[\kappa_{f(j)}] + \mathbb{V}\text{ar}_\ell[\nu_j] + \mathbb{C}\text{ov}[\kappa_{f(j)}, \phi_{\iota(j)}] + \mathbb{C}\text{ov}[\delta_{o(j)}, \kappa_f(j)]$. Panel (b) displays the correlation between the worker and job FEs. The job FEs are obtained from (1), and the occupation, industry, and establishment FEs from (4).

Table B.1: The local returns to job switching

	(1)	(2)	(3)	(4)	(5)	(6)
Aggregate	1.25	0.70	0.50	0.70		
	(0.090)	(0.054)	(0.048)	(0.054)		
By occupation						
Blue-collar					0.47	
					(0.038)	
Low-skill service					0.91	
					(0.062)	
Intermediary					0.63	
					(0.059)	
White-collar					0.69	
					(0.055)	
By rank						
1st quartile						1.04
						(0.094)
2nd quartile						0.59
						(0.010)
3rd quartile						0.29
						(0.019)
4th quartile						1.01
						(0.198)
Dep. variable	Wage	Job F.E.	Job F.E.	Job F.E.	Job F.E.	Job F.E.
W/in occupation	·	·	✓	·	·	·
Worker slope	·	·	·	✓	·	·
Occupation F.E.	·	·	·	·	✓	·
Rank F.E.	·	·	·	·	·	✓
R^2	0.08	0.26	0.35	0.26	0.27	0.27
Observations	26,246,229	26,246,229	26,246,229	26,246,229	26,246,229	26,246,229

Table presents the coefficient of interest $\zeta \times 100$ estimated in (6). $J2J_{it} = 1$ if worker switches establishments or occupations within 90 days of previous employment spell, within a CZ, and wage growth is non-negative. Dependent variable is quarterly growth in wages (column 1) or job fixed effects (column 2 — 6). Job fixed effects estimated in (1). Column 3 includes origin-occupation × destination-occupation fixed effects at the 3-digit level. Column 4 uses job fixed effects estimated with a worker-specific experience slope. Column 5 estimates (6) fully interacted with origin-occupation dummy. Column 6 estimates (6) fully interacted with quartile dummy, where the quartile refers to the rank in the local job fixed effect distribution. Standard errors clustered at the city level.

Table B.2: Parameter estimates

	Parameter	Target	Empirical moment	Simulated moment	Parameter estimate
		A. External calibration			
ρ	Discount factor	Annual interest rate	2%		0.005
		B. Model inversion			
α	Cobb-Douglas preference	Housing exp. share	0.200		0.200
$\boldsymbol{A}$	Amenities	City employment share	·		·
b	Unemployment insurance	Unemployment replacement rate	0.600		0.675
κ	Migration cost	Migration rate	0.454		0.225
δ	Job destruction rate	EU rate	0.021		0.021
ζ	Rel. search efficiency	Job switching rate	0.040		1.009
ξ	Exit rate	Average career length	120.0		0.008
μ	Matching efficiency	Aggregate UE rate	0.210		0.343
ψ	Matching function elasticity	Correlation UE rate - tightness	0.199		0.199
M	Mass employers	Average size	7.521		0.116
γ	Vacancy cost elasticity	Vacancy optimality (53)	2.310		2.310
f	Entry cost	Average profits	1.399		1.399
L^r	Residential housing supply level	Average residential price	0.477		105.2
β^r	Residential housing supply elasticity	Correlation prices - expenditures	0.896		0.896
L^c	Commercial housing supply level	Average commercial price	1.243		0.222
β^c	Commercial housing supply elasticity	Correlation prices - employer demand	0.816		0.816
		C. Indirect inference			
σ	Pareto shape	Wage variance	0.183	0.180	9.438
ϑ	Local costs dispersion	Equation (21)	2.570	2.626	5.266
$\boldsymbol{B}$	Local costs scale	Local market tightness	·	·	·
$\boldsymbol{T}$	Local TFP	Average wage premia	·	·	·
ν	Local TFP spillovers	Correlation TFP - size	0.008	0.008	0.008
χ	Taste shock dispersion	Local labor supply elasticity	2.500	2.500	5.075