Wealth and the Geography of Job Ladders*

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Abstract

Workers' wealth shapes career dynamics by influencing job search and migration decisions. While economic opportunities concentrate in large cities, high living costs often prevent many workers from taking advantage of them. I develop a framework where wealth interacts with spatial search frictions to explain why some individuals remain stuck in low-paying jobs at the bottom of the ladder while others climb to the top. High living costs in productive cities amplify the trade-off between wages and unemployment risk, strengthening precautionary motives that lead low-wealth workers to accept lower-paying jobs. Using French administrative data, I document two facts that highlight the role of wealth. First, the spatial job ladder is steeper for low-wealth workers. Second, financial constraints limit upward mobility by reducing access to high-wage jobs in productive cities. Altogether, the calibrated model accounts for about one-third of the residual wage inequality observed in the data, of which roughly two-thirds is due to local job ladder heterogeneity. Relaxing borrowing constraints increases the share of low-wealth workers in the most productive cities by around 30%. Finally, place-based policies that improve insurance against unemployment risk in high-productivity cities raise welfare by enabling financially constrained workers to access steeper job ladders.

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1 Introduction

Understanding inequality in the labor market has been a central focus for policymakers and researchers over the past few decades. A growing body of research shows that job opportunities vary substantially across local labor markets, with larger cities offering better career prospects through higher wage growth and faster human capital accumulation.[1,2] However, these cities are also the most expensive places to live. Prohibitively high housing costs prevent many workers from accessing these markets and taking advantage of such opportunities. Financial constraints distort both location and job search choices, often forcing low-wealth workers to accept lower-paying jobs or remain in less productive areas. Yet the role of wealth in shaping how workers sort across jobs and locations remains largely overlooked.

This paper contributes to the literature by addressing this gap. First, I propose a model that examines how workers' wealth interacts with local labor market characteristics to shape career dynamics. When living costs are high, unemployment is especially costly for financially constrained workers, who are therefore more likely to accept low-paying jobs and rely on future wage growth along the job ladder. Second, using French administrative data, I document how local job ladders, defined as the hierarchy of jobs ranked by wage levels within a city, vary among workers with different wealth and how financial constraints affect workers' ability to climb the spatial job ladder, defined as the ladder across cities. Third, using the calibrated model, I quantify the contribution of wealth-driven sorting to wage and wealth inequality, with a focus on the role of financial frictions and heterogeneous job ladders. Fourth, I assess the importance of workers' self-insurance by evaluating the consequences of a spatial policy that alters the generosity of local unemployment benefits.

In the first part of the paper, I develop a spatial directed search model in which risk-averse workers differ in both wealth and human capital. Workers search both off- and on-the-job, and can search locally or across labor markets. Within this framework, wealth interacts with spatial search frictions, shaping both job search and migration behavior through two main channels. First, precautionary job search makes low-wealth workers prefer higher job-finding rates over higher wages, leading them to sort into lower-paying jobs at the bottom of the ladder. Second, precautionary location choice leads low-wealth workers to move more frequently. When unemployed, they migrate to cheaper labor markets to save on living costs. When employed, they move to more productive locations to benefit from steeper job ladders.

A key feature of the model is how local living costs shape both location and job search decisions.

[1] See, for instance, Combes et al. (2012), Baum-Snow and Pavan (2012), Davis and Dingel (2019), Eckert et al. (2022a). These papers document both static and dynamic wage premia in large cities. Some recent studies, such as De La Roca and Puga (2017), Eckert et al. (2022b), Martellini (2022), Crews (2023), Duranton and Puga (2023), and Lhuillier (2023), focus on worker interactions and learning in big cities, while others (e.g., Schmutz and Sidibé (2019), Lindenlaub et al. (2022), Lhuillier (2025)) examine spatial differences in gains from job-to-job transitions.

[2] Dynamic gains in big cities are quantitatively relevant: they explain about one-third of the between-city wage inequality. See appendix B.1 for further details.

In more expensive areas, the higher cost of unemployment strengthens precautionary motives. To avoid lengthy unemployment spells, financially constrained workers disproportionately accept lower-paying jobs with higher job-finding probabilities. They are willing to trade off initial wages for higher finding rates, anticipating that future job-to-job transitions will allow them to climb the ladder. In contrast, wealthier workers, who are better insured against income risk, can afford to search longer and target higher-paying matches, regardless of the local housing prices. As a result, in the most productive and expensive labor markets, low-wealth workers initially sort at the very bottom of the ladder and consequently experience relatively higher wage growth from job-to-job transitions.

In this environment, the sorting of workers across local labor markets plays a central role not only in shaping career trajectories but also in determining wealth accumulation. More productive cities offer higher wages and faster human capital accumulation, resulting in steeper job ladders and greater potential for wage growth, which ultimately translates into higher wealth accumulation. Consequently, spatial heterogeneity in dynamic opportunities is essential to understanding both wage and wealth inequality.

In the second part of the paper, I use administrative data from France that combine information on workers' and jobs' characteristics with information on workers' wealth, obtained from their tax records, to provide empirical evidence in support of the theoretical framework and to calibrate it.

First, I document that spatial wealth inequality in France is pervasive. While low-wealth workers are everywhere, high-wealth workers tend to cluster in a few cities. The between-city difference in wealth for workers at the bottom 10th percentile is much smaller relative to wealthier individuals.

Second, I find that heterogeneity across local labor markets is more pronounced among low-wealth workers. In particular, wage growth, whether through job-to-job transitions or learning, is more sensitive to city productivity for financially constrained workers. For instance, when a worker in the bottom 10 percent of the wealth distribution does a job-to-job transition in Paris, his wage increases by approximately 10 percentage points more than that of a worker in the same wealth percentile who changes jobs in Châteaubriant, a city within the bottom 10 percent of the productivity distribution. In contrast, for workers in the top 10 percent of the wealth distribution, there is little difference between a job transition in Paris or any other location.[3] This evidence highlights the existence of search and mobility frictions that disproportionately affect financially constrained workers, which is consistent with the model's prediction that low-wealth workers experience relatively higher gains from local job-to-job transitions in the most productive labor markets.

Finally, I show that low-wealth workers have a lower probability of climbing the spatial job ladder than their wealthier counterparts. In other words, they are less likely to secure a job that pays a higher wage in a more productive location. To demonstrate that the lack of wealth acts as a constraint preventing upward mobility, I analyze the effects of wealth shocks as in Bilal and Rossi-Hansberg (2021). I find that following a positive wealth shock, only low-wealth workers experience

[3] These differences hold both for job-to-job transitions within and between cities.

a higher probability of climbing the spatial job ladder.

In the third part of the paper, I calibrate the model to the French economy to analyze how wealth differences and financial constraints affect workers' career dynamics and how spatial job ladders contribute to broader inequalities. Relaxing the borrowing constraint reveals the central role of financial frictions in shaping access to opportunity. When credit becomes more accessible, financially constrained workers are better able to smooth consumption in expensive cities and thus more likely to move toward high-productivity and high-risk locations. As a result, the share of workers with negative wealth living in the most productive city rises by about 30%, emphasizing how limited access to credit restricts upward mobility and reinforces spatial inequality.

The model, on average, explains around one-third of the residual wage inequality in the data.[4] Wage dispersion is higher in the most productive local labor market, consistently with the data, and arises mainly from three factors: higher productivity naturally results in the availability of higher-paying jobs; higher living costs amplify precautionary motives for financially constrained workers, disproportionately pushing them to the bottom of the local ladder into very low-paying jobs; and larger dynamic gains, in the form of a steeper job ladder.

Local job ladders account for approximately two-thirds of the wage inequality in the model. Low-wealth workers are willing to accept low-paying jobs in highly productive labor markets because they can benefit from substantially faster on-the-job wage growth in those areas.[5] Similarly, low-skill workers are drawn to more productive locations by the prospect of faster human capital accumulation. To assess the importance of these mechanisms, I conduct a counterfactual simulation in which I shut down both on-the-job search and human capital accumulation. In this scenario, wage dispersion declines across all locations, particularly in high-productivity areas. This decline reflects a change in the behavior of low-wealth workers: without dynamic gains, they are no longer willing to accept very low-paying jobs, as the possibility of climbing the local ladder disappears.

In the calibrated model, I find that, on average, skill heterogeneity and human capital accumulation explain a larger share of wage inequality than on-the-job search. Yet in the most productive location, that pattern reverses: there, on-the-job search accounts for the largest share of wage dispersion. The combination of large dynamic gains and limited self-insurance in expensive cities implies that search frictions become a key determinant of local wages, especially for financially constrained workers.

In the final part of the paper, I assess the consequences of spatial policies. Specifically, I study a policy that varies the generosity of unemployment benefits across locations. The focus on such

[4] As argued in Hornstein et al. (2011), standard search and matching models can generate only a small amount of frictional wage dispersion. When allowing for different sources of heterogeneity, several canonical models have explained around 20-50% of residual wage dispersion. The model developed in this paper, which uses only two skill types, heterogeneity in workers' wealth and local productivity, achieves around 30%, suggesting that wealth and spatial job ladders are quantitatively important.

[5] Wage growth for low-wealth workers appears relatively higher because they start on the bottom rungs of the ladder, in very low-paying jobs. As they move up, their wage gains diminish, and they never fully catch up to high-wealth workers who began higher on the ladder.

policy is motivated by the fact that, in the model, workers' ability to insure against earnings risk is a crucial factor influencing the sorting across jobs and locations. Increasing unemployment benefits in more productive locations has two main effects. On the one hand, it improves insurance against unemployment risk. By reducing the downside risk of unemployment, such a policy encourages sorting into productive areas and enables more workers to access steeper job ladders. On the other hand, the resulting in-migration exerts upward pressure on local living costs, partly offsetting the benefits of improved insurance. Overall, the general equilibrium effects remain positive: the policy leads to higher sorting in most productive areas and faster wage growth for low-wealth workers. For instance, when benefits increase by 5% in the most productive locations and decrease by 5% in the least productive, aggregate welfare rises by about 1%, as a larger share of workers can afford to move to the most productive areas and wait for dynamic gains to materialize. In contrast, a policy that raises unemployment benefits in less productive cities while reducing them in high-productivity areas weakens incentives to climb the spatial job ladder and slows wage growth, ultimately lowering aggregate welfare by nearly 0.5%. These findings suggest that place-based policies can enhance welfare by improving the upward mobility of financially constrained workers.

Related Literature. This paper is closely related to the literature studying how workers' wealth influences job search and migration decisions. Specifically, it bridges two strands of research that have so far remained largely separate: one focusing on the interaction between individual wealth and location choices, and the other on the role of wealth in shaping job search strategies.[6]

The first strand of literature explores the relationship between migration and precautionary motives. Bilal and Rossi-Hansberg (2021) develop a theory that examines how financial frictions shape households' optimal location choices. They show that an unexpected negative income shock prompts financially constrained individuals to relocate to cheaper areas to smooth consumption, while wealthier households remain unaffected. Similarly, Giannone et al. (2023) find that low-wealth households are more likely to migrate as a means of mitigating income risks. Their study quantifies migration costs and argues that incorporating wealth accumulation reduces estimated costs, as wealth provides an alternative insurance mechanism. In addition, two papers that belong to this strand of the literature are Greaney (2023) and Luccioletti (2023), both of which focus on the role of home-ownership.

I contribute to this literature by incorporating a job ladder into the analysis, which adds a forward-looking dimension to spatial sorting: workers choose locations not only based on current job opportunities but also on their prospects for future wage growth. Moreover, the interaction of search frictions with wealth magnifies the role of precautionary motives. Workers with different

[6] The interplay of the two is particularly relevant because both migration and job transitions serve as imperfect substitutes for savings. Low-wealth workers may smooth consumption by relocating to more affordable areas, while upward job mobility offers an alternative path to wealth accumulation. As a result, workers with different wealth levels face different incentives to search for jobs, move across locations, and manage income risk. Yet despite these intrinsic links, the existing literature has mainly examined these mechanisms in isolation.

asset holdings sort into jobs offering different wages to self-insure against the risk of unemployment.[7] Finally, this framework also provides a natural setting to evaluate labor market policies that affect workers' ability to insure against income risk, such as spatial differences in unemployment benefit generosity.

This paper also contributes to the growing literature on how workers' wealth shapes job search behavior. Eeckhout and Sepahsalari (2023) show that differences in asset holdings lead to sorting into jobs with varying productivity, as low-wealth workers prioritize job-finding rates over higher wages to mitigate income risk. Building on this, Chaumont and Shi (2022) extends this idea to a framework that incorporates on-the-job search, though with homogeneous firms. Baley et al. (2025) abstract from firm heterogeneity and on-the-job search but allow for skill heterogeneity, focusing instead on skill loss during unemployment and its interaction with occupational mobility. Similarly, Soenarjo (2024) examines how workers' liquidity affects their reallocation across sectors after unemployment. Griffy (2021) develops a life-cycle model with wealth, human capital accumulation, and search frictions, showing that initial wealth is crucial for explaining lifetime earnings inequality. Kaas et al. (2023) endogenize search effort and the interest rate to study the joint dynamics of wages, match quality, and wealth over the life cycle. Finally, Caratelli (2022) and Pellegrini (2025) analyze the risks associated with job switching, showing how these risks shape wealth recovery after recessions and workers' ability to climb the job ladder, respectively. Related work also highlights how access to credit influences job search behavior (e.g., Herkenhoff (2019); Braxton et al. (2024)).[8]

Contributing to this body of work, I introduce multiple locations. In this setting, precautionary job search not only influences the types of jobs workers accept but also the local labor markets in which they choose to search. Differences in local living costs become critical in shaping workers' job search behavior. Additionally, search frictions acquire a spatial dimension, as workers face migration costs and imperfect information that make job search across locations less efficient. These frictions affect workers unequally, with low-wealth individuals disproportionately impacted. Consistent with this, I document empirically that the degree of heterogeneity across local labor markets is significantly larger for low-wealth workers.

Furthermore, this paper connects more broadly with several strands of the geography and macro-labor literature. First, it contributes to research on the sources of spatial agglomeration, the role of learning, and human capital dynamics (De La Roca and Puga (2017); Davis and Dingel (2019); Eckert et al. (2022b); Martellini (2022); Crews (2023); Duranton and Puga (2023); Lhuillier (2023)). While this literature emphasizes the accumulation of human capital as a key driver of wage growth in cities, I emphasize the importance of job transitions as a complementary mechanism. I find that,

[7] In the model proposed by Bilal and Rossi-Hansberg (2021), two workers with identical skills living in the same location receive the same wage, regardless of their wealth. This is not the case anymore in a model with search frictions, where sorting across jobs shapes career trajectories and, in turn, wealth accumulation, thereby reinforcing preexisting disparities.

[8] These papers build on a broader literature examining precautionary savings in the presence of search frictions, including Krusell et al. (2010) and Lise (2013).

in the most productive and expensive cities, the combination of limited self-insurance and dynamic gains makes search friction more relevant than skill dynamics to explain wage dispersion. Second, it relates to studies examining inequality across local labor markets and the role of search frictions (Nanos and Schluter (2018); Gonzalez-Aguado (2021); Heise and Porzio (2022); Bilal (2023); Moretti and Yi (2024); Lhuillier (2025)). Most existing models tend to be static or overlook wealth accumulation. In contrast, my framework incorporates risk-averse workers who decide how much to save and consume over time. This approach enables an analysis of how precautionary motives influence job and location choices, and how these decisions, in turn, contribute to wage and wealth inequality. Additionally, I can study the consequences of place-based policies, taking into account wealth heterogeneity.

This work also connects to job ladder models that analyze earnings inequality and career trajectories. In particular, it is closely related to Borovičková and Macaluso (2024), who study how differences in job-to-job mobility and employer quality shape income inequality over workers' life cycles. While they focus on income dynamics and within-market job ladder heterogeneity, my paper examines how wealth shapes workers' job search behavior across multiple local labor markets. By incorporating wealth accumulation and precautionary motives, my framework shows how financial constraints not only hinder upward mobility but also distort both job and location choices, introducing a spatial dimension to the job ladder.

Outline. The rest of this paper is organized as follows. Section 2 introduces the model. Section 3 turns to the data and presents descriptive evidence on the heterogeneity by wealth that the model can speak to. Section 4 describes the parametrization of the model and quantifies the importance of local job ladders. Section 5 studies the consequences of spatial policies on welfare and inequality. Section 6 concludes.

2 Model

In this section, I develop a spatial directed search model with risk-averse agents to examine how wealth influences the spatial job ladder they climb.[9] The model builds primarily on Chaumont and Shi (2022), extending it to incorporate multiple locations, geographical labor mobility, and human capital accumulation.

[9] Specifically, a job ladder refers to the hierarchy of jobs available within a given local labor market. It captures the idea that workers can move from lower-paying to higher-paying jobs through either job-to-job transitions or human capital accumulation. Importantly, workers can also move across locations and thus switch between different local ladders. A steeper job ladder means that wage gains from job mobility are higher. In contrast, a flatter ladder offers fewer opportunities for wage growth.

2.1 Environment

Time is discrete and infinite. There are L locations, which are exogenously heterogeneous in productivity (y_ℓ), separation rate (δ_ℓ), vacancy cost (κ_ℓ), and human capital accumulation rate (ψ_ℓ). There is a measure one of risk-averse workers who differ in their initial assets, $a \in [\underline{a}, \bar{a}]$, and skills, $x \in \{L, H\}$.[10] Workers consume a tradable good and a local non-tradable good (housing), whose equilibrium price (p_ℓ) varies across locations. Housing acts as a congestion force, preferences are non-homothetic due to a subsistence level of housing consumption $\bar{h}$. Workers can be either employed or unemployed. Unemployed workers receive the unemployment benefit (b) each period and always search for jobs either locally or in other labor markets.[11] High-skill workers, when unemployed, can lose their human capital and become low-skill with probability η, constant across locations. Employed workers, with skills x and assets a, earn the wage $w_\ell(x, a)$ and engage in on-the-job search with probability λ, either within or across local labor markets. Low-skill workers accumulate human capital when employed and become high-skill with probability ψ_ℓ, which increases with local productivity. Searching across local labor markets is less efficient, with search efficiencies $s^u_{\ell,\ell'} < s^e_{\ell,\ell'} < 1$, $\forall\ \ell' \neq \ell$, for unemployed (u) and employed (e) workers, respectively. Unemployed workers can move across locations, incurring a monetary migration cost ($\tau^m > 0$) and a utilitarian cost ($\tau > 0$). Employed workers can only move if they find a new job in a different location, and incur the same costs as the unemployed.

Every period, workers experience idiosyncratic preference shocks. Moving shocks (ϵ^m) affect only unemployed workers and capture their preference for staying in the current location or moving. Search shocks (ϵ^s) influence the preference for searching locally or in a different labor market of both employed and unemployed workers. Both shocks follow a Gumbel distribution with scale parameters ν^m and ν^s, respectively. During the search stage, workers choose where to search by comparing the potential net gains in each submarket within and across locations. This decision is made optimally in two stages: first, workers select the submarket within each location that maximizes their search value; second, they choose the local labor market offering the highest expected net gain from search.

Workers face two key trade-offs: (i) wages versus cost of living, (ii) wages versus unemployment risk.[12] The first trade-off, standard in spatial economics, reflects the fact that more productive

[10] For simplicity, I assume only two skill types: low and high. Consequently, human capital dynamics are simplified. While employed, low-skill workers can acquire skills at a rate that increases with local productivity; while unemployed, high-skill workers risk losing their human capital. This approach captures the idea that more productive cities foster learning, though it contrasts with recent evidence suggesting learning is more beneficial to high-skill workers (e.g., Lhuillier (2023)). Extending the model to allow for richer skill heterogeneity could help reconcile these patterns.

[11] Unemployment benefits are assumed to be uniform across workers and locations. This assumption simplifies the model because there is no need to keep track of workers' last wages before unemployment. In France, unemployment benefits are regulated at the national level, meaning that the rules and eligibility criteria are consistent across all regions, although some may offer additional support.

[12] The unemployment risk in this model arises from two elements. First, the job-finding rate which determines how likely it is for an unemployed worker to become employed. Second, the separation rate, which determines the probability that an employed worker becomes unemployed. Since the separation rate within local labor markets

locations, where wages are higher on average, are also more expensive in equilibrium. The second is a distinctive feature of directed search models, where higher-wage jobs have lower job-finding rates. In both cases, wealth plays a significant role in determining the sorting of workers across jobs and locations. Additionally, the combination of multiple local labor markets, on-the-job search, and human capital accumulation generates a spatial job ladder, which leads workers to trade off the dynamic gains offered by some locations with the associated unemployment risk and living expenses.

Firms are homogeneous and indifferent across locations, posting vacancies in all profitable locations until the value of vacancies is equal across space. I refer to a job as a firm. Competitive entry determines the measure of firms in each local labor market and its tightness θ_ℓ, which is essentially the ratio of vacancies to job seekers.[13] Firms are risk-neutral but share the same discount factor β as workers. The production technology exhibits constant returns to scale, with jobs yielding a constant stream of output proportional to the worker's skill, xy_ℓ. The per-period vacancy cost is $\kappa_\ell > 0$. Existing matches can be destroyed exogenously at a rate $\delta_\ell \in (0, 1)$. Exogenous separation is independent across matches and time but varies by location. Additionally, workers can move to another job at any time. There is no wage bargain, and firms cannot respond to the employees' outside offers. However, firms do not have full commitment. When a firm hires a low-skill worker, it considers the likelihood that the worker will acquire human capital and become high-skill. In this scenario, both the firm's output and the wage paid to the worker adjust accordingly.

Search is frictional and modeled according to the directed search framework. As a consequence, there is a separate submarket for each worker type, which leads workers to direct their search to those contracts, matching probability and wages, that maximize their value. The matching technology exhibits constant returns to scale in the measure of applicants and vacancies. In any submarket with tightness θ_ℓ, the matching probability is $m(\theta_\ell)$ for an applicant and $q(\theta_\ell)$ for a vacancy. Market tightness is endogenously determined by firms' entry decisions and workers' search strategies. Thus, the matching probabilities are an endogenous function of wages, skills, and assets.[14]

The timing of the model is as follows:

1. Output is produced. Employed workers receive their wage (w_ℓ), and unemployed workers receive the unemployment benefit (b).
2. Workers make their consumption and savings decisions.
3. High-skill workers who are unemployed become low-skill at rate η. Low-skill workers who are employed become high-skill at rate ψ_ℓ.

is the same for all jobs, while it varies across locations, when workers search for a job, they trade off the wage offered by a job against its job-finding probability.

[13] Job seekers include both unemployed and employed workers.

[14] As in Chaumont and Shi (2022), the labor market is segmented by wealth and market tightness depends on workers' assets. On-the-job search introduces asset dependence, as the likelihood of an employed worker being matched with another firm and subsequently quitting their current job varies based on their asset holdings. Thus, workers' assets affect the value of a match by influencing its duration and as a consequences markets are also segmented by wealth.

4. Search shocks (ϵ^s) are realized. Workers decide whether to search locally or in a different labor market. Within their chosen location, they select the submarket that maximizes their expected value.

5. New matches are formed. Workers change location if matched with a firm in another labor market.

6. Pre-existing matches are exogenously destroyed with probability δ_ℓ. Workers who lose their jobs become unemployed.

7. Moving shocks (ϵ^m) are realized. Unemployed workers, who did not find a match during the search process or just lost their job, decide whether to move or stay in their current location.

2.2 Workers

Workers have a non-homothetic Cobb-Douglas utility function in the consumption good and housing:[15]

$$u(c,h) = \frac{(c^{\alpha}(h-\bar{h})^{1-\alpha})^{1-\sigma} - 1}{1-\sigma}, \quad \text{with } h > \bar{h} \tag{1}$$

where $\bar{h}$ represents the subsistence level of housing, α determines the share of expenditure on the tradable consumption good, and σ measures the degree of risk aversion. The non-homotheticity in housing preferences implies that the housing expenditure share declines with income and wealth.[16]

Unemployed in Location ℓ. Unemployed workers receive the unemployment benefit b and the returns from their savings in the risk-free asset, $(1+r)a$. They allocate their income between the tradable good and housing, whose price p_ℓ is a general equilibrium object that depends on the location choice of other workers. Unemployed workers also decide how much to save, subject to a borrowing constraint, and choose where to search for a job, in which submarket and location, taking into account the preference shock ϵ^s_ℓ.

The value for a high-skill worker that moved from location k to ℓ at the end of the previous

[15] Finlay and Williams (2022) document that housing is a necessity and estimate a model of non-homothetic housing demand using microdata. Another paper assuming housing non-homotheticity is Ganong and Shoag (2017).

[16] As argued by Gaubert and Robert-Nicoud (2025), housing non-homotheticity leads to sorting of households based on their income. Higher-income workers, who allocate a smaller share of their income to housing, are more willing to pay higher housing costs to live in more productive places.

period is:

$$
\begin{aligned}
V_{k,\ell}^{u}(x=H,a) = \max_{c,h,a'} u(c_\ell^u, h_\ell^u) &+ \beta\eta\mathbb{E}\left[\max_{\ell'}\left\{R_{\ell,\ell'}^{u}(x'=L,a') + \nu^s\epsilon_{\ell'}^{s}\right\}\right] \\
&+ \beta(1-\eta)\mathbb{E}\left[\max_{\ell'}\left\{R_{\ell,\ell'}^{u}(x'=H,a') + \nu^s\epsilon_{\ell'}^{s}\right\}\right] \\
\text{s.t. } & c_\ell^u = b + (1+r)a - a' - p_\ell h_\ell^u - \tau^m \mathbb{1}_{\ell\neq k} \\
& a' \geq \underline{a}
\end{aligned}
$$

Here, $R_{\ell,\ell'}^{u}(x',a')$ is the expected value of searching from location ℓ to location ℓ' for a worker with skills x' and asset holdings a'. Before searching for a job, workers' skills are updated. In particular, high-skill workers can lose their human capital while unemployed. This happens with probability η, which does not depend on the location of residence. The problem of unemployed low-skill workers is the same, except that their human capital does not change. Once workers choose their preferred submarket in each possible location, they select the optimal location by comparing the expected gains from searching in each local labor market, net of moving costs. If workers are not matched with a firm, they decide where to be unemployed by making pairwise comparisons between their value in the current location ℓ and their value in any possible alternative destination ℓ', net of moving costs.[17]

The search problem for an unemployed worker with skills x' and wealth a' is:

$$
\begin{aligned}
R_{\ell,\ell'}^{u}(x',a') = \max_{w}\, & s_{\ell,\ell'}^{u} m(\theta_{\ell'})\left[V_{\ell,\ell'}^{e}(x',w,a') - \tau_{\ell,\ell'}\right] + (1 - s_{\ell,\ell'}^{u} m(\theta_{\ell'}))\bar{V}^{u}(x',a') \\
\text{s.t. } & \theta_{\ell'} = \theta(y_{\ell'}, x', w, a') \\
& \bar{V}^{u}(x',a') = \mathbb{E}\left[\max_{\ell'}\left\{V_{\ell,\ell'}^{u}(x',a') - \tau_{\ell,\ell'} + \nu^m\epsilon_{\ell'}^{m}\right\}\right]
\end{aligned}
$$

Unemployed workers are matched to jobs in location ℓ' with probability $s_{\ell,\ell'}^{u} m(\theta_{\ell'})$, in which case they receive the wage $w_{\ell'}(x',a')$ in the next period. If the new location ℓ' differs from their current one ℓ, they have to pay the utilitarian migration costs $\tau_{\ell,\ell'}$. If no match occurs, the worker remains unemployed and can decide to move somewhere else, again subject to moving costs and the preference shock.

During the search stage, workers face the standard trade-off of directed search models with risk-averse agents: workers who are financially constrained use job search as an insurance mechanism. To exit unemployment as soon as possible, they search for jobs that offer relatively lower wages but higher finding rates. However, now there is a multitude of local labor markets that differ in productivity, search frictions, and the price of the non-tradable good. These additional elements

[17] Compared to models without search frictions, productive locations in this framework offer not only higher wages but also higher job-finding rates—reinforcing the value of moving in and increasing the cost of moving out during unemployment.

affect the intensity of precautionary motives in each local labor market. The high cost of housing in more productive locations makes unemployment more costly and exacerbates the trade-off between wages and job-finding rates for financially constrained workers. Consequently, precautionary motives are strengthened in more productive labor markets, further reinforcing the sorting of low-wealth workers at the bottom of the job ladder, implying that the only way low-wealth workers can benefit from the higher productivity of these locations is through job-to-job transitions or human capital accumulation.[18] Therefore, dynamic gains offered by a particular location are going to be key in determining the sorting of workers across jobs and locations. In contrast, wealthy workers are less impacted by differences in the price of housing, as they can self-insure even in more expensive locations.[19]

Using the properties of the Gumbel distribution, the value function for unemployed workers can be rewritten as:

$$
\begin{aligned}
V^u_{k,\ell}(x=H,a) = \max_{c,h,a'} u(c^u_\ell, h^u_\ell) &+ \eta\nu^s \log\left(\sum_{\ell'}\left(e^{\beta R^u_{\ell,\ell'}(x'=L,a')}\right)^{\frac{1}{\nu^s}}\right) \\
&+ (1-\eta)\nu^s \log\left(\sum_{\ell'}\left(e^{\beta R^u_{\ell,\ell'}(x'=H,a')}\right)^{\frac{1}{\nu^s}}\right) \\
\text{s.t. } & c^u_\ell = b + (1+r)a - a' - p_\ell h^u_\ell - \tau^m \mathbb{1}_{\ell\neq k} \\
& a' \geq \underline{a}
\end{aligned}
$$

and the search problem is:

$$
\begin{aligned}
R^u_{\ell,\ell'}(x',a') = \max_{w}\ & s^u_{\ell,\ell'} m(\theta_{\ell'})\left[V^e_{\ell,\ell'}(x',w,a') - \tau_{\ell,\ell'}\right] + (1 - s^u_{\ell,\ell'} m(\theta_{\ell'}))\nu^m \log\left(\sum_{\ell'}\left(e^{V^u_{\ell,\ell'}(x',a')-\tau_{\ell,\ell'}}\right)^{\frac{1}{\nu^m}}\right) \\
\text{s.t. } & \theta_{\ell'} = \theta(y_{\ell'}, x', w, a')
\end{aligned}
$$

As in standard spatial models, I can use the properties of the Type I Extreme Value distribution to compute the share of unemployed workers, with skills x' and assets a', searching from location ℓ to location ℓ':

$$
\mu^{R^u}_{\ell,\ell'}(x',a') = \frac{\left(e^{\beta R^u_{\ell,\ell'}(x',a')}\right)^{\frac{1}{\nu^s}}}{\sum_{\ell'}\left(e^{\beta R^u_{\ell,\ell'}(x',a')}\right)^{\frac{1}{\nu^s}}} \tag{2}
$$

[18] However, such transitions are less frequent than unemployment-to-employment transitions.

[19] Figure A.1 illustrates the wage policy function for unemployed workers with different levels of wealth, showing how higher housing prices in the most productive locations further distort the job search behavior of low-wealth workers.

and the share of unemployed workers that move from location ℓ to location ℓ' is:

$$\mu^u_{\ell,\ell'}(x',a') = \frac{\left(e^{V^u_{\ell,\ell'}(x',a')-\tau_{\ell,\ell'}}\right)^{\frac{1}{\nu^m}}}{\sum_{\ell'}\left(e^{V^u_{\ell,\ell'}(x',a')-\tau_{\ell,\ell'}}\right)^{\frac{1}{\nu^m}}} \tag{3}$$

Similarly to job search, workers' location choice is also influenced by precautionary motives. As argued in Bilal and Rossi-Hansberg (2021), workers can use their location choice to smooth consumption during unemployment spells by moving to cheaper areas. However, in a model with search frictions and skills' dynamics, this additional insurance mechanism is less efficient as it could imply larger losses. Moving to less productive labor markets could result in longer unemployment spells, since they exhibit lower job-finding rates, lower wages at re-employment, and a lower likelihood of acquiring human capital. Overall, these elements suggest that the effects of negative income shocks on financially constrained workers may be more severe and persistent than models without search frictions and human capital accumulation would predict.

Employed in Location ℓ. The problem for employed workers mirrors that of unemployed workers, with a few key differences. Employed workers earn a wage w_ℓ, can save, and decide whether to search for another job locally or in a different labor market while on the job. Additionally, employed workers can acquire human capital. With probability ψ_ℓ, increasing in location's productivity, a low-skill worker becomes high-skill. The value function for a low-skill employed worker, earning the wage w, and with asset holdings a, that moved from location k to ℓ is:

$$\begin{aligned}
V^e_{k,\ell}(x=L,w,a) = \max_{c,h,a'} u(c^e_\ell,h^e_\ell) &+ \beta\psi_\ell\mathbb{E}\left[\max_{\ell'}\left\{R^e_{\ell,\ell'}(x'=H,w_{x'},a')+\nu^s\epsilon^s_{\ell'}\right\}\right] \\
&+ \beta(1-\psi_\ell)\mathbb{E}\left[\max_{\ell'}\left\{R^e_{\ell,\ell'}(x'=L,w_{x'},a')+\nu^s\epsilon^s_{\ell'}\right\}\right] \\
\text{s.t. } & c^e_\ell = w+(1+r)a-a'-p_\ell h^e_\ell-\tau^m\mathbb{1}_{\ell\neq k} \\
& a' \geq \underline{a}
\end{aligned}$$

When employed, low-skill workers can accumulate human capital, and if this happens, their wage adjusts accordingly to $w_{x'}$. Then, they enter the search stage with new skills, a new wage, and new savings. $R^e_{\ell,\ell'}(x', w, a')$ represents the search problem in location ℓ':

$$
\begin{aligned}
R^e_{\ell,\ell'}(x', w, a') = \max_{w'} \quad & \lambda s^e_{\ell,\ell'} m(\theta_{\ell'})[V^e_{\ell,\ell'}(x', w', a') - \tau_{\ell,\ell'}] \\
& + (1 - \lambda s^e_{\ell,\ell'} m(\theta_{\ell'}))[(1-\delta_\ell)V^e_\ell(x', w_{x'}, a') + \delta_\ell \bar{V}^u(x', a')] \\
\text{s.t. } & \theta_{\ell'} = \theta(y_{\ell'}, x', w', a') \\
& \bar{V}^u(x', a') = \mathbb{E}\left[\max_{\ell'} \left\{ V^u_{\ell,\ell'}(x', a') - \tau_{\ell,\ell'} + \nu^m \epsilon^m_{\ell'} \right\}\right]
\end{aligned}
$$

With probability $\lambda s^e_{\ell,\ell'} m(\theta_{\ell'})$, an employed worker transitions to a new job in location ℓ' with wage w'. If the worker does not find a new job and the current match is not exogenously destroyed, the worker remains employed at the current wage. Otherwise, if the match is destroyed, the worker transitions to unemployment and decides where to go. This choice is subject to the preference shock and migration costs.[20]

Like the unemployed, employed workers use on-the-job search as a form of self-insurance. Those with low wealth and low earnings are more likely to search for jobs offering lower wages but higher job-finding probabilities to build up their asset holdings. In the most productive and expensive locations, low-wealth workers disproportionately sort into the bottom of the job ladder when securing their first job. Thus, as they climb the local ladder, which is steeper compared to less productive areas, the wage gains they achieve through job transitions are relatively larger. In other words, the intensity of precautionary motives makes low-wealth workers gain disproportionately more from job-to-job transitions in the most productive locations.[21]

Using the properties of the Gumbel distribution, the value function for employed workers can be expressed as:

$$
\begin{aligned}
V^e_{k,\ell}(x = L, w, a) = \max_{c,h,a'} \; & u(c^e_\ell, h^e_\ell) + \psi_\ell \nu^s \log\left(\sum_{\ell'} \left(e^{\beta R^e_{\ell,\ell'}(x'=H, w_{x'}, a')}\right)^{\frac{1}{\nu^s}}\right) \\
& + (1-\psi_\ell)\nu^s \log\left(\sum_{\ell'} \left(e^{\beta R^e_{\ell,\ell'}(x'=L, w_{x'}, a')}\right)^{\frac{1}{\nu^s}}\right) \\
\text{s.t. } & c^e_\ell = w + (1+r)a - a' - p_\ell h^e_\ell - \tau^m \mathbb{1}_{\ell \neq k} \\
& a' \geq \underline{a}
\end{aligned}
$$

20 Thus, employed workers can move only if they find a job in another location ($\ell' \neq \ell$) or if they become unemployed and choose to relocate.

21 This is a key prediction of the model that is tested empirically in section 3.3.

and the search problem becomes:

$$
\begin{aligned}
R^e_{\ell,\ell'}(x',w,a') = \max_{w} \lambda s^e_{\ell,\ell'} m(\theta_{\ell'})[V^e_{\ell,\ell'}(x',w',a') - \tau_{\ell,\ell'}] \\
+ (1-\lambda s^e_{\ell,\ell'} m(\theta_{\ell'})) \left((1-\delta_\ell) V^e_{\ell,\ell}(x', w_{x'}, a') + \delta_\ell \nu^m \log \left(\sum_{\ell'} \left(e^{V^u_{\ell,\ell'}(x',a') - \tau_{\ell,\ell'}} \right)^{\frac{1}{\nu^m}} \right) \right) \\
\text{s.t. } \theta_{\ell'} = \theta(y_{\ell'}, x', w, a')
\end{aligned}
$$

The share of employed workers searching from ℓ to ℓ' can also be obtained from the properties of the Type I Extreme-Value distribution. Moreover, it can be approximated as a function of the new wage net of the cost of living, the continuation value of becoming employed at the new wage in the new location, and the search taste shock:

$$
\mu^{R^e}_{\ell,\ell'}(x',w,a') = \frac{e^{\frac{1}{\nu^s}\beta R^e_{\ell,\ell'}(x',w,a')}}{\sum_k e^{\frac{1}{\nu^s}\beta R^e_{\ell,k}(x',w,a')}} \propto \left(\underbrace{w_{\ell'} - p_{\ell'}}_{\text{Static Gains}}, \underbrace{\beta V^e_{\ell,\ell'}(x',w',a')}_{\text{Dynamic Gains}}, \underbrace{\nu^s}_{\text{Taste Shock}} \right) \tag{4}
$$

The value of searching in a location depends primarily on the static gains, that is the wage gains upon a job-to-job transition net of the change in the cost of living ($w_{\ell'} - p_{\ell'}$), and by the dynamic gains that accrue overtime ($\beta V^e_{\ell,\ell'}(x',w',a')$). The latter comes from the possibility of enjoying the local ladder: searching locally is more efficient than searching somewhere else. Furthermore, in more productive locations, the job ladder is steeper, since firms are willing to offer higher wages, and learning is faster.

Workers with different skills, wealth, and wages value these elements differently. Low-skill and low-wealth workers place more value on the dynamic premium.[22] This is because low-skill workers are the only ones who can accumulate human capital, while low-wealth workers typically sort at the bottom of the job ladder and thus place more value on the gains coming from future job-to-job transitions. Low-wealth workers in more productive locations are willing to initially sort at the bottom of the ladder because they expect to climb the ladder through on-the-job search. This feature is key when measuring wage inequality. The existence of job ladders generates a substantial fraction of the wage inequality in more productive places.[23] In contrast, wealthy and skilled workers value more immediate net wage gains rather than future opportunities since, when unemployed, they search for high-wage jobs and sort already at the top of the job ladder, and when employed, they cannot accumulate further human capital.[24]

[22] In my model, human capital accumulation is more valuable for low-skill workers, which may appear contrary to findings from recent studies, such as Lhuillier (2023), which suggest the opposite. However, this difference arises because I am simplifying the analysis by considering only two skill types and assuming that high-skill workers are unable to accumulate any human capital. If I were to include more skill types, it would show that human capital accumulation is also valuable for those who are relatively more skilled in my model.

[23] Further details in section 4.4.

[24] This analysis is mainly a conjecture based on the baseline calibration. It is not a general result of the model.

2.3 Firms

Firms are ex-ante homogeneous and indifferent across locations. The value of a filled job for a firm in location ℓ is determined by the output produced by the match, the wage paid to the worker, and the continuation value of the match. Specifically, the value of a match between a firm and a low-skill worker with wealth a and paid the wage w is:

$$
\begin{aligned}
J_\ell(x = L, w, a) = xy_\ell - w \\
&+ \beta\psi_\ell(1-\delta_\ell)\left(1 - \lambda\sum_{\ell'=1}^{L}\mu^e_{\ell,\ell'}(x' = H, w_{x'}, a')s^e_{\ell,\ell'}m(\theta_{\ell'})\right)J_\ell(x' = H, w_{x'}, a') \\
&+ \beta(1-\psi_\ell)(1-\delta_\ell)\left(1 - \lambda\sum_{\ell'=1}^{L}\mu^e_{\ell,\ell'}(x' = L, w_{x'}, a')s^e_{\ell,\ell'}m(\theta_{\ell'})\right)J_\ell(x' = L, w, a') \\
&+ \beta\left[(1-\delta_\ell)\left(\lambda\sum_{\ell'=1}^{L}\mu^e_{\ell,\ell'}(x', w_{x'}, a')s^e_{\ell,\ell'}m(\theta_{\ell'})\right)V_\ell + \delta_\ell V_\ell\right]
\end{aligned}
\tag{5}
$$

where y_ℓ is the productivity of the match in location ℓ, x are workers' current skills, δ_ℓ is the exogenous separation rate, and $\mu^e_{\ell,\ell'}(w, a')$ represents the share of employed workers searching in location ℓ'.

The continuation value of a filled job depends on the probability that the match is not destroyed. Which, in turn, is influenced by the exogenous separation rate δ_ℓ and the likelihood that the worker finds another job. The latter is an endogenous function of workers' current wage, skills, and assets.[25] Additionally, firms have to take into account the possibility that if they employ a low-skill worker, he may become high-skill in the next period. In this case, they will have to adjust the wage paid to the worker accordingly.[26]

Firms maximize the value of a vacancy by choosing the wage to offer. The value of a vacancy, V_ℓ, is given by:

$$
\begin{aligned}
V_\ell = \max_w -\kappa_\ell + \beta[q(\theta_\ell)J_\ell(x, w, a) + (1 - q(\theta_\ell))V_\ell] \\
\text{s.t. } \theta_\ell = \theta(y_\ell, x, w, a)
\end{aligned}
$$

where κ_ℓ is the cost of posting a vacancy in location ℓ, $q(\theta_\ell)$ is the probability that a vacancy is filled, and θ_ℓ represents market tightness, which depends on local productivity, wages, workers' skills, and

For instance, it does not need to be true if gains from job-to-job transitions were convex.

25 To compute the probability that a worker finds another job, it needs to be taken into account that workers can search in L different local labor markets. Thus, I multiply the share of workers that from location ℓ search in all possible locations ℓ' by the local job finding rate $s^e_{\ell,\ell'}m(\theta_{\ell'})$ and, then, sum it across all possible location L.

26 For simplicity, I am assuming an *ad hoc* rule on the wage setting: the wage is a piece rate in efficiency units proportional to workers' skills.

assets. If a match occurs, the firm obtains the value $J_\ell(x, w, a)$. If no match occurs, the vacancy remains unfilled. Firms discount the future at rate β, just as workers do.

Since firms are homogeneous within each location, the free entry condition in each location ensures that the value of posting a vacancy is zero in steady state: $V_\ell = 0$. This leads to the following condition:

$$\kappa_\ell \leq \beta q(\theta_\ell) J_\ell(x, w, a) \tag{6}$$

This implies that firms create vacancies only in submarkets where the cost of posting a vacancy (κ_ℓ) is less than or equal to the expected benefit from matching with a worker. The vacancy-filling rate must satisfy:

$$q(\theta_\ell) \geq \frac{\kappa_\ell}{\beta J_\ell(x, w, a)} \tag{7}$$

Finally, from equation (7), local market tightness is given by:

$$\theta_\ell(y_\ell, x, w, a) = \begin{cases} q^{-1}\left(\frac{\kappa_\ell}{\beta J_\ell(x,w,a)}\right) & \text{If } J_\ell(x, w, a) \geq \kappa_\ell \\ 0 & \text{Otherwise} \end{cases} \tag{8}$$

Due to the presence of on-the-job search, both the value of a filled job and market tightness depend on workers' asset holdings. Specifically, the probability that a worker-firm match will continue is shaped by the worker's current wage and wealth, as wealth affects the worker's job-finding rate and, consequently, the likelihood of moving to another firm. This framework implies that the labor market is segmented by wealth, and it implicitly assumes that firms observe workers' wealth when posting vacancies. This simplification is essential to deal with the vast heterogeneity of this model, as it implies that firms know the type of worker they attract when posting a vacancy. While this assumption may seem unrealistic, it can be microfounded in different ways. For example, Souchier (2025) develops a model in which firms optimally tailor wage contracts based on workers' access to financial markets and their asset positions, using this information to balance retention incentives, the size of the pass-through of firm-level productivity shocks, and consumption-smoothing motives.[27]

In a one-location framework, as in Chaumont and Shi (2022), firm value increases monotonically with workers' wealth, since wealthier workers are less likely to match with another firm. However, in a multi-location setting, this relationship need not be monotonic. It depends on how likely workers are to search locally versus across labor markets. For instance, if low-wealth workers are more likely to search outside their current labor market, they may have lower effective job-finding rates than wealthier workers, since searching across markets entails lower efficiency. As a result, while financially constrained workers always have higher job-finding rates in single-location models, this is no longer necessarily true in a multi-location setting. The relationship now depends on the

[27] Additionally, Chaumont and Shi (2022) provide a discussion on the role of wealth in the description of submarkets. I refer to their paper for further details.

probability of searching in other locations and the associated loss in search efficiency.[28]

2.4 Housing Sector

Each location ℓ is characterized by a supply function for housing,

$$H_\ell = \mathcal{H} p_\ell^{\phi} \tag{9}$$

where p_ℓ is the housing price, ϕ is the elasticity of housing, $\mathcal{H}$ is a constant, and H_ℓ represents the local housing stock, which is owned by absentee landlords outside the economy.[29]

The price of housing in each location must adjust such that local housing demand equals local housing supply:

$$\underbrace{H_\ell}_{\text{Housing Stock}} = \underbrace{\int \cdots \int_{x,\omega,w,a} \tilde{h}_\ell^{\omega}(x,w,a)}_{\text{Housing Demand}} \tag{10}$$

where $\tilde{h}_\ell^{\omega}(x,w,a)$ represents the housing policy function, for unemployed and employed workers ($\omega = \{u,e\}$), derived from workers' maximization problem. This policy function depends on workers' skills (x), wealth (a), employment status (ω), location (ℓ), and wage (w).

Thus, the housing price in location ℓ is given by:

$$p_\ell = \left[\frac{\int \cdots \int_{x,\omega,w,a} \tilde{h}_\ell^{\omega}(x,w,a)}{\mathcal{H}} \right]^{\frac{1}{\phi}} \tag{11}$$

To compute housing demand, the housing policy function is integrated over the distribution of workers' skills, wealth, employment status, and earnings in each location.

2.5 Equilibrium

The equilibrium in this economy is fully characterized by the optimization decisions of firms and workers, as well as market-clearing conditions in the labor and housing markets.

Definition. An equilibrium consists of a set of value functions for unemployed and employed workers $V_\ell^u(x,a)$ and $V_\ell^e(x,w,a)$, a firm value function $J_\ell(x,w,a)$, a set of policy functions $c^u(x,a)$, $c^e(x,w,a)$, $h^u(x,a)$, $h^e(x,w,a)$, $a'^u(x,a)$, $a'^e(x,w,a)$, $w^u(x,a)$, and $w'^e(x,w,a)$, a market tightness function $\theta_\ell(y_\ell,x,w,a)$, and a price of housing p_ℓ such that:

[28] Figures A.2a and A.2b show that under the baseline calibration, firms still prefer to hire high-wealth workers, consistent with Chaumont and Shi (2022).

[29] Following Lhuillier (2023), the elasticity of housing is assumed to be constant across locations. However, this assumption is not crucial and can be relaxed.

(i) The value function of workers, $V_\ell^u(x,a)$ and $V_\ell^e(x,w,a)$, solve unemployed and employed workers maximization problem respectively. The corresponding optimal consumption of the tradable and non-tradable good and savings yield the policy functions $c^u(x,a)$, $c^e(x,w,a)$, $h^u(x,a)$, $h^e(x,w,a)$, $a'^u(x,a)$, $a'^e(x,w,a)$, and the optimal search decisions yield the policy functions $w^u(x,a)$ and $w'^e(x,w,a)$.

(ii) The firm value function $J_\ell(x,w,a)$ satisfies equation (5). The value of a vacancy is zero in each location and submarket, $V_\ell = 0$, and w is the associated policy function.

(iii) Market tightness, $\theta_\ell(y_\ell,x,w,a)$, satisfies equation (8), for all submarkets (y_ℓ,x,w,a).

(iv) The housing market clears at the price p_ℓ, that is it satisfies equation (11).

In this model, the distribution of workers affects the price of housing in each location. However, the equilibrium is still block recursive, as defined by Shi (2009) and Menzio and Shi (2010), for any given housing price. This property arises from the directed nature of search and the competitive entry of vacancies in each location and submarket. It ensures that the individual state (workers' skills, wealth, location, employment status, and wage) is sufficient to determine the optimal decisions of firms and workers across locations. Workers take the price of housing and the labor market tightness in each location as given when making their decisions. Workers self-select into the submarkets and locations that maximize their expected gains from search, trading off job-finding probabilities with the net value of transitioning to a new job or location. Specifically, low-wealth workers tend to search in submarkets with higher job-finding rates and lower wages, while high-wealth workers tend to do the opposite.

Consequently, firms know the type of workers they will meet in each submarket and location, and that their job offers will not be rejected. As a result, the value of meeting a worker in a particular submarket is independent of the distribution of workers across the economy, as are the tightness and matching probabilities.

Block recursivity significantly reduces the computational burden, as the optimal decisions of firms and workers depend only on the individual state, which has a lower dimensionality. The distribution of workers across space, skills, wealth, and jobs does not enter the state space directly.[30]

3 Descriptive Evidence

As highlighted in the previous section, workers with identical characteristics except for their wealth may end up on different spatial job ladders. In this section, I present empirical evidence on how

[30] To determine the equilibrium housing price in each location, I still need to compute the invariant distribution of workers across locations. Starting with an initial guess for housing prices, I update them based on the distribution of workers over skills, wealth, wages, employment status, and locations, which is determined by their optimal decisions. Exploiting block recursivity, I iterate on the local living cost p_ℓ.

wealth shapes workers' transitions across jobs and local labor markets. This evidence serves as motivation for the theoretical model and provides inputs for its estimation. First, I describe the dataset used throughout the analysis. Next, I examine the distribution of wealth across commuting zones and the heterogeneity in local job ladders for workers with different wealth levels. Finally, I document how a positive wealth shock affects workers' probability of climbing the spatial job ladder.

3.1 Data

The main data sources are the *Base tous salariés* (BTS) and the *Données Sociales et Fiscales* from the *Echantillon Demographique Permanent* (EDP). Both datasets are administrative tax records provided by the French Statistical Institute (INSEE) and the Ministry of Finance.[31]

The BTS is a matched employer-employee dataset covering the universe of French workers. It replaces the older *Déclaration de Données Sociales* (DADS). I use the BTS job position data (BTS-Postes), which includes detailed information on workers' characteristics, job positions, and employer data from the Register of Enterprises and Establishments. Each record corresponds to a workstation, defined as the consolidation of an employee's work periods within the same establishment. I use this data to compute some statistics at the commuting zone level.

The EDP dataset contains income tax returns for French households sampled from the BTS, starting in 2008. It includes individuals born in October of even years (approximately 8% of the BTS sample) as well as individuals born in January 2-5, April 1-4, July 1-4, and October 1-4. This sampling strategy ensures a representative sample of the population over time. I use this data to study the role of workers' wealth in shaping career dynamics.

For the analysis, I focus on mainland France, which consists of 96 districts (*Départements*), 36,552 municipalities (*Communes*), and around 300 commuting zones. I define a city as a commuting zone, as it best captures the concept of a local labor market. For simplicity, I use the terms commuting zones and cities interchangeably. Additionally, as in Lhuillier (2025), I construct ten population-weighted deciles of cities based on productivity, measured as the average annual wage earnings in each commuting zone.[32]

Following Bilal and Rossi-Hansberg (2021), I measure workers' wealth as the sum of lifetime rents, net housing income, nontaxable financial income, and taxable financial income. Importantly, I do not observe the stock of wealth directly but instead infer it by dividing the flow of income from financial and housing assets by a fixed interest rate of 5%.[33] This measure primarily reflects liquid wealth, as I lack data on the value of owner-occupied houses without outstanding mortgages. Since housing constitutes a significant share of French households' portfolios, I control for home ownership through all the analyses.

31 Additional data sources are described in Appendix B.2.

32 For reference, the tenth decile includes only Paris.

33 In Figure B.2, I compare the wealth distribution derived from my data with the World Inequality Database, showing strong alignment.

A job is defined as a unique pair of establishment and occupation, where occupations are at the two-digit level. Job-to-job transitions are defined as transitions between two jobs occurring within a quarter. Workers' wages are measured as real annual labor earnings, net of payroll taxes.[34]

Because the data come from tax records rather than surveys, they are particularly reliable. However, this also means I lack direct information on workers' education. To approximate workers' skills, I follow Bilal (2023) and estimate a Mincer regression, controlling for occupation, age, year, and city fixed effects. I then define workers' skills as the average occupation and age premium.[35]

Finally, I restrict the sample to heads of households who are in their working age, between 21 and 60 years old, remain in the dataset for at least two consecutive years, and work full-time. I exclude individuals working fewer than 30 days per year, less than 2 or more than 12 hours per day on average, those with seasonal or temporary contracts, and those working in industries that take place mostly outside of cities (agriculture and the extraction industry), as well as the public sector.[36]

3.2 Spatial Wealth Inequality

I start by looking at the spatial distribution of wealth in France and at the heterogeneity in living costs. Altogether, figure 1 shows that more productive labor markets are more unequal and more expensive.

Figure 1a plots the 10th and 90th percentiles of the local wealth distribution across commuting zones, ordered by the difference between the 90th and 10th percentiles. Cities on the far right of the x-axis exhibit greater wealth inequality. What emerges is that wealth is not uniformly distributed across space but is instead concentrated in specific cities. Low-wealth workers are more evenly distributed across space, while high-wealth workers are significantly more spatially concentrated. The between-city difference in wealth is much smaller for workers at the 10th percentile of the wealth distribution than for those at the 90th percentile.[37]

The spatial distribution of wealth is influenced by two main factors: (i) the evolution of workers' income in different locations, and (ii) workers' mobility decisions. At the same time, workers' wealth also affects their location choices and job search behavior. In the following sections, I explore how wealth influences workers' sorting across local labor markets and how location affects workers' wage growth.

Figure 1b plots the average rent price per m^2 across French commuting zones ranked by their productivity. There is a clear positive correlation between cities' productivity and living costs.

[34] The data contains information on hours, but it usually refers to the legal number of hours and therefore does not represent the actual number of hours worked. For this reason, in my main specification, I do not adjust for it. However, in the appendix, I run some robustness checks with hourly wages.

[35] Further details on the estimation of workers' skills are provided in Appendix B.4.

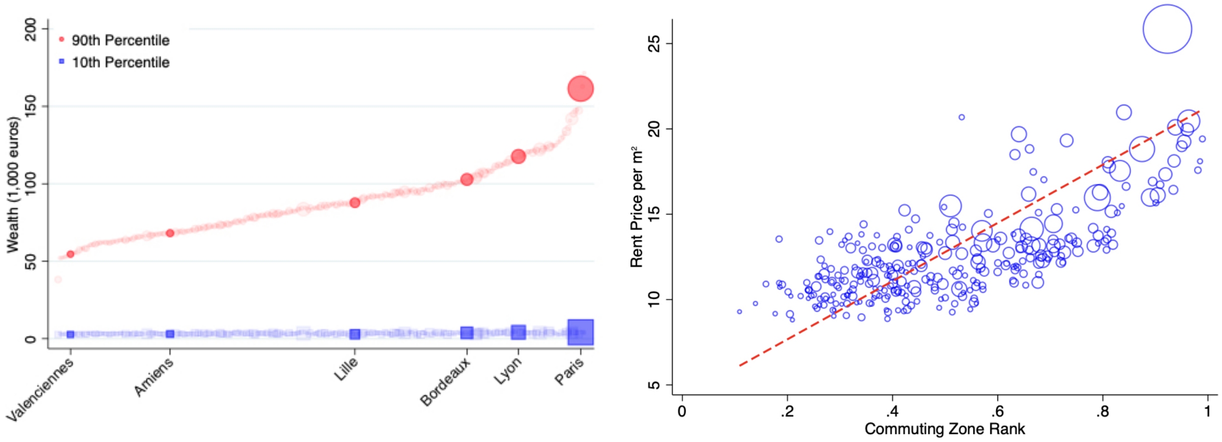
[36] Table B.1 provides some summary statistics.

[37] Figure B.3 plots also the median wealth across commuting zones and wealth in logs.

Figure 1: Local Wealth Distribution & Cost of Living by City

(a) Wealth held by the top and bottom 10%

(b) Rent Price and Location Ranking



Note: Panel (a) shows the average wealth held (in thousands of euros) by different percentiles of the wealth distribution across French commuting zones in the data. The blue line represents the average wealth of workers in the bottom 10 percent of the distribution, while the red line corresponds to the top 10 percent. Panel (b) plots the average rent per square meter for a standard $40m^2$ apartment across the same commuting zones ranked by their productivity. Marker sizes are proportional to city size.

3.3 Wealth and the Spatial Job Ladder

How does wage growth vary by location and workers' wealth? To answer this question, I use a specification similar to that in Lhuillier (2025):

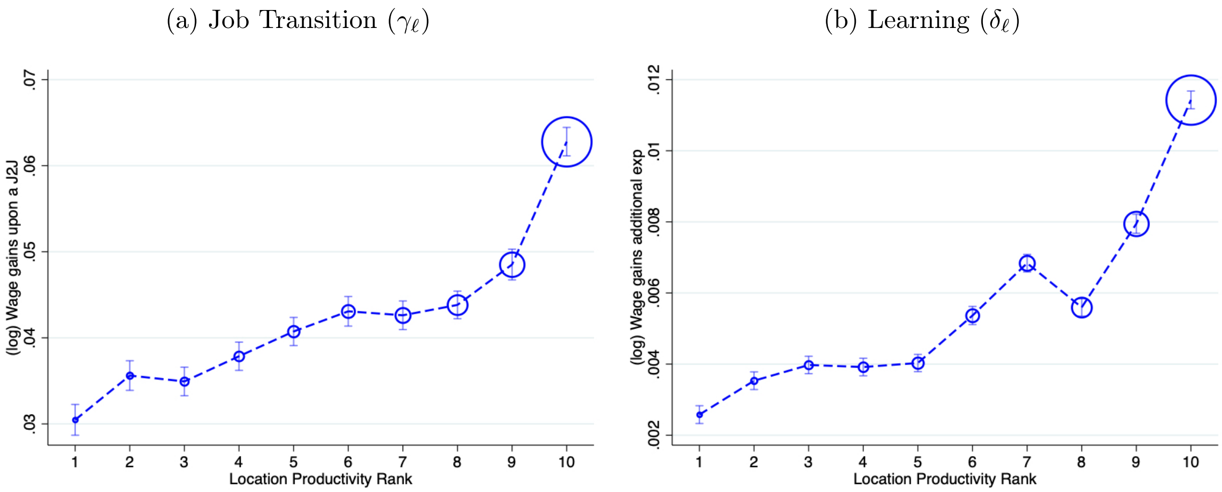
$$\log w_{i\ell t} = \alpha_\ell + \sum_{\ell=1}^{L} \gamma_\ell \sum_{\tau=\underline{t}}^{t} J2J_{i\ell\tau} + \sum_{\ell=1}^{L} \delta_\ell exp_{i\ell t} + \beta_X X_{i\ell t} + \varepsilon_{i\ell t} \tag{12}$$

Here, I measure the extent to which job-to-job transitions and learning, defined as additional experience in the labor market, affect workers' wages. In particular, I regress the log wage of individual i in location ℓ at time t, $w_{i\ell t}$, on a dummy variable $J2J_{i\ell\tau}$ which is equal to 1 whenever individual i experienced a job-to-job transition at time τ in location ℓ, and on a variable, $exp_{i\ell t}$ that represents i's experience at time t. I control, in $X_{i\ell t}$, for a variety of individual characteristics like age, sex, home-ownership, and year fixed effects. Also, I include city fixed effect, α_ℓ. The coefficients of interest are γ_ℓ, which capture the heterogeneity in the returns to job-to-job transitions across local labor markets, and δ_ℓ, which capture the heterogeneity in the returns to experience.[38]

Figure 2 confirms the finding in Lhuillier (2025). Wage gains from job-to-job transitions and additional experience are higher in more productive cities. Figure 2a plots the wage gains from job-to-job transitions in each decile of the city productivity distribution. A worker transitioning to another job in Paris experiences a wage gain of around 6%, while a worker doing a similar transition

[38] As in De La Roca and Puga (2017), experience is allowed to vary depending on the local labor market where it is acquired.

Figure 2: Wage Growth by City



Note: Panel (a) shows the log wage growth associated with job-to-job transitions across ten location bins in the data. Panel (b) shows the log wage growth due to human capital accumulation across ten location bins in the data. Marker sizes are proportional to city size.

in a city ranked at the bottom of the productivity distribution experiences only a 3% gain. Figure 2b shows a similar picture for the gains coming from learning. An additional year of experience in Paris is around 4 times more valuable than in a city at the bottom of the productivity distribution.

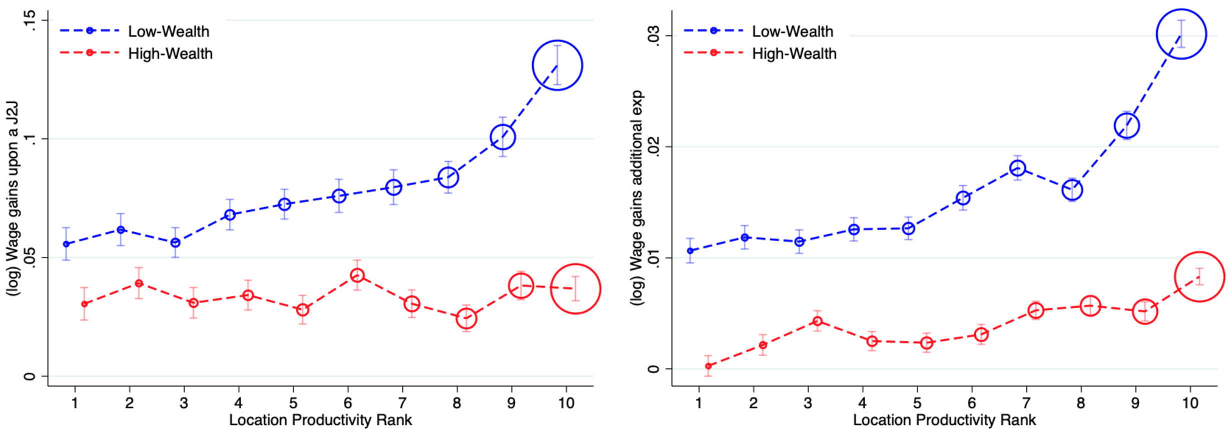
To examine the heterogeneity across local labor markets for workers with different wealth, I run the same specification in (12) but splitting the sample into low-wealth and high-wealth workers. To define these two groups, I use the bottom 10 percent and the top 10 percent of the wealth distribution.[39] What emerges from figures 3a and 3b is that wage growth for low-wealth workers is more sensitive to cities' productivity. In other words, the spatial heterogeneity in gains from job-to-job transitions is concentrated among workers who are financially constrained. Low-wealth workers appear to climb different job ladders compared to their wealthier counterparts. Financially constrained workers often begin their careers at the bottom of the job ladder, irrespective of location, while wealthier workers start with better jobs. Consequently, wage gains from job-to-job transitions are relatively higher for low-wealth workers as they climb rungs that wealthier workers have already climbed.[40] This effect is particularly pronounced in more productive cities, where opportunities for wage growth through job transitions and learning are more abundant. If a worker in the bottom 10 percent of the wealth distribution does a job-to-job transition in Paris, his wage increases by around 10 percentage points more than the wage of a worker in the same percentile of the wealth

[39] This result is also robust to alternative definitions of low- and high-wealth workers (e.g., using quintiles or quartiles of the wealth distribution).

[40] The coefficients for workers with different wealth are obtained by splitting the sample. Thus, they have to be interpreted as relative to workers with the same wealth who did not change jobs. The coefficients of high- and low-wealth workers are not directly comparable.

Figure 3: Wage Growth by City & Wealth

(a) Job Transition (γ_ℓ) (b) Learning (δ_ℓ)



Note: Panel (a) shows the log wage growth associated with job-to-job transitions across ten city bins in the data. Panel (b) shows the log wage growth due to human capital accumulation across ten location bins in the data. In both panels, the blue line represents low-wealth workers (those in the bottom 10 percent of the wealth distribution), and the red line represents high-wealth workers (those in the top 10 percent). Marker sizes are proportional to city size.

distribution who changes jobs in a city in the bottom 10 percent of the productivity distribution. Meanwhile, there is no difference for workers in the top 10 percent of the wealth distribution. This evidence supports the idea that search and mobility frictions exist and are stronger for financially constrained workers. It is also consistent with the model's prediction that low-wealth workers experience relatively higher gains from job-to-job transitions in the most productive labor markets. Regarding gains from learning, a similar pattern holds even if the difference between the two wealth groups is less pronounced.[41]

The relative steepness of the spatial job ladder for low-wealth workers suggests that city productivity has a larger impact on their wage gains compared to high-wealth workers, for whom the spatial job ladder is flatter.[42] The fact that wage growth for low-wealth workers is more sensitive to cities' productivity suggests that search frictions are stronger for workers who are financially constrained. Moreover, the more pronounced heterogeneity in job-to-job wage gains across cities for low-wealth workers suggests the existence of barriers to spatial arbitrage. Financial constraints may prevent these workers from moving toward opportunities and equalizing returns across space, as more productive locations are also the most expensive. To better understand this, I examine the direction of movements on the spatial job ladder in the next section, focusing on the role played by wealth.

41 Further decomposition of the heterogeneity by wealth and skills shows that dynamic gains from productive cities are concentrated among low-wealth workers who are high-skill rather than low-skill.

42 This result is consistent with the finding in Lhuillier (2025) that spatial heterogeneity in local gains from job switching is higher for workers at the bottom of the wage distribution.

Robustness. In appendix B.7, I provide some robustness exercises. First, I run the same regression in (12) but using the local wealth distribution to split the sample, instead of the aggregate wealth distribution, and restricting the sample to non-migrants only, to capture solely gains from movements on the local ladder. Results are shown in figure B.4 and B.5 respectively. In both cases, a similar picture holds. Second, I check to what degree the heterogeneity by wealth is captured by differences in workers' skills and age. Figure B.6 shows a different picture when workers are distinguished by their skills, suggesting that the observed difference by wealth cannot be fully explained by differences in workers' skills. While figure B.7 shows that heterogeneity by wealth is preserved even when I restrict the sample to young workers only. Finally, I use hourly wage instead of annual earnings as the dependent variable of regression (12). Figure B.8 also shows that a similar picture holds.[43]

3.4 Movements on the Spatial Job Ladder and Wealth Shocks

In this section, I focus on workers who change jobs and location to study how workers with different wealth levels move on the spatial job ladder. In particular, I estimate a linear probability model where the dependent variable is the probability of moving up, defined as moving to a better-paying job in a higher-ranked location, or down, defined as moving to a lower-paying job in a worse-ranked location. Controls include individual characteristics such as age, sex, skills, labor income, commuting distance, the total number of transitions, and home ownership. I also allow for year times city, and occupation times industry fixed effects.

As shown in Figure 4, low-wealth workers are significantly less likely to move up and more likely to move down on the spatial job ladder compared to high-wealth workers. For instance, the probability of moving to a better-paying job in a higher-ranked location is approximately 27% for low-wealth workers, nearly 10 percentage points lower than for high-wealth workers.[44]

To explore whether the lack of wealth constrains upward mobility, I examine the effect of positive wealth shocks (e.g., inheritances or donations) on the probability of moving up the spatial job ladder. A positive wealth shock is defined as an increase in wealth of at least 50,000€.[45] I estimate the following specification, similar to Bilal and Rossi-Hansberg (2021):

$$Pr\left[MoveUp_{it}\right] = \sum_{q=1}^{5}\sum_{s=0}^{1} \alpha_{qs} \mathbb{1}_{Q_{it}=q} \times \mathbb{1}_{S_{it}=s} + \beta_X X_{it} + \varepsilon_{it} \tag{13}$$

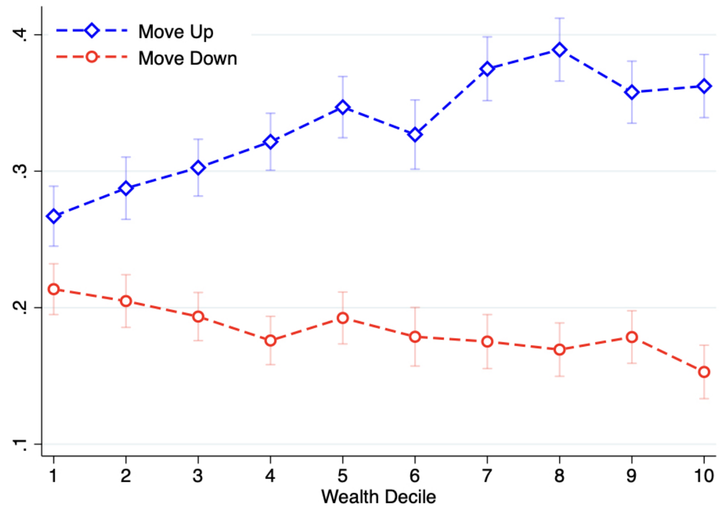
where $\mathbb{1}_{Q_{it}=q}$ indicates whether individual i belongs to wealth quintile q before the shock, and $\mathbb{1}_{S_{it}=s}$

43 Additionally, these results are robust also when I use a measure of *local* real wages and *local* real wealth, computed as nominal wages and wealth deflated by a citywide Cobb-Douglas price index with a housing expenditure share of 0.3.

44 The probabilities of moving up and down do not sum to 1 due to the presence of mixed outcomes, as shown in Figure B.9.

45 Table B.2, provides some summary statistics on the wealth shock.

Figure 4: Probability Moving on the Spatial Job Ladder by Wealth



Note: The figure shows the probability that workers from different percentiles of the wealth distribution change both job and location. These probabilities are computed for the sub-sample of those who change jobs and location. The blue line represents the probability of moving to a job with a higher wage in a more productive location. The red line represents the probability of moving to a job with a lower wage in a less productive location.

indicates whether the individual received a wealth shock. Controls include individual characteristics, as well as year-city and occupation-industry fixed effects.

Table 1 shows that a positive wealth shock significantly increases the probability of moving up the spatial job ladder, but only for workers in the bottom quintile of the wealth distribution. For workers who are financially constrained, a wealth shock raises the probability of moving up by 8 percentage points. The effect is robust to controls and fixed effects, and pre-trends show no significant differences before the shock between workers that receive the shock and those that do not.[46]

These findings suggest that the lack of wealth acts as a constraint, limiting workers' ability to move toward better-paying jobs and more productive locations.

4 Quantitative Analysis

In this section, I first calibrate the model developed in section 2 using French administrative data. Then, I use it to quantify how differences in local job ladders shape spatial wage and wealth inequality.

[46] I also examine the effects of negative wealth shocks and the probability of moving down, but find no significant results. Additionally, in table B.3 I report the results for different sub-samples.

Table 1: Effects of a Positive Wealth Shock

	(1)	(2)	(3) Pre-Shock
Shock × Q1	0.0968**	0.0800*	0.0609
	(0.0417)	(0.0426)	(0.0497)
Shock × Q2	0.0162	0.0301	-0.0813
	(0.0576)	(0.0587)	(0.0543)
Shock × Q3	-0.0028	0.0018	-0.0210
	(0.0531)	(0.0540)	(0.0537)
Shock × Q4	0.0020	-0.0095	-0.0716
	(0.0457)	(0.0464)	(0.0493)
Shock	-0.0067	-0.0220	0.0402
	(0.0276)	(0.0281)	(0.0361)
Controls			
Age, Sex, Skills, Income, Home-ownership,			
Commuting distance, Transitions	✓	✓	✓
Fixed effects			
Year × City	✓	✓	✓
Occupation × Industry	·	✓	✓
Observations	15,106	14,932	12,254
R^2	0.380	0.424	0.443

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The sample includes all workers who change both job and location, in addition to the previously described restrictions. The shock dummy equals 1 whenever an individual's wealth increases by at least 50,000€ between two periods. Occupations and industry are measured at the two-digit level.

4.1 Calibration

The model period is set to one month to match the flow rates observed in the French labor market. I calibrate the model using a mixed strategy. Some parameters are externally set to standard values commonly used in the literature, others are estimated directly from French microdata, and the remaining ones are internally calibrated to match key empirical moments. Table 2 summarizes all parameter values and their corresponding targets. In what follows, I describe the parameter and the particular moment of interest they heuristically identify.[47]

Matching Function. Following Menzio and Shi (2011), I adopt a Constant Elasticity of Substitution (CES) matching function:

$$m(\theta) = \theta(1+\theta^{\gamma})^{-\frac{1}{\gamma}} \qquad\qquad q(\theta) = (1+\theta^{\gamma})^{-\frac{1}{\gamma}}$$

The elasticity of the matching function, γ, is set to match the average job-finding probability, unemployment-to-employment rate, of 29%, observed in the data.

[47] Figure A.6 illustrates how some of the targeted moments vary with changes in model parameters. Overall, the targeted moments respond most strongly to the parameters they are intended to identify.

Table 2: Parameters

Parameter	Description	Value	Source / Moment	Data	Model
		A. Externally calibrated			
σ	Risk Aversion	2	*Standard*	.	.
r	Interest Rate	0.003	*Standard*	.	.
α	Non-housing consumption share	0.8	Lhuillier (2023)	.	.
$\bar{h}$	Housing subsistence level	0.25	Ganong and Shoag (2017)	.	.
		B. Directly calibrated			
y_ℓ/y_1	Location Productivity Gap	$[1, 1.71]$	Wage gap between ℓ & $\ell = 1$	See A.3	See A.3
δ_ℓ	Destruction Rate	$[0.0067, 0.0082]$	E2U rate	See A.4	See A.4
$x_H - x_L$	Skill Productivity Gap	0.24	(log) Wage gap between H & L	0.24	0.2
ϕ	Housing supply elasticity	5.014	Model inversion	See 5b	See 5b
$\mathcal{H}$	House price intercept	186.394	Model inversion	See 5b	See 5b
		C. Internally calibrated			
β	Discount Factor	0.992	Median Wealth-to-Income Ratio	0.6	0.6
b	Unemployment Benefit	0.6	Average $\frac{b}{w}$	0.48	0.47
γ	Matching Elasticity	0.28	U2E rate	0.29	0.3
κ_ℓ	Vacancies Cost	$[0.18, 1.57]$	Unemployment rate	$[0.14, 0.18]$	$[0.15, 0.18]$
λ	On-the-job Search Efficiency	0.85	E2E rate	0.18	0.17
$s^e_{\ell,\ell'}$	Abroad Search Efficiency Employed	0.1	Share of E2E associated with migration	0.09	0.07
$s^u_{\ell,\ell'}$	Abroad Search Efficiency Unemployed	0.35	Share of U2E associated with migration	0.12	0.04
$\tau_{\ell,\ell'}$	Migration Cost	12	Migration rate	0.08	0.08
ν^m	Migration taste shock	3.2	Fraction of unemployed that migrate	0.22	0.12
ν^s	Search taste shock	2.5	Wage premium migrants	0.3	0.24
η, ψ_ℓ	Skill change	$0.02,\ 0.007 \times y_\ell$	Share of Low Skill	0.29	0.27
$\underline{a}$	Minimum Wealth	-2	Share of workers with negative wealth	0.02	0.08

Note: The table describes the parameter used in the quantitative model. The first two columns describe the parameter, and the third column presents the value of the parameter. The fourth column describes the source or the moment used to calibrate the parameter. The fifth and sixth columns show the value of that moment in the data and in the model. Flow rates in the French labor market (U2E, E2U, E2E) are computed using the Continuous Labor Force Survey. While the other moments are computed using the main dataset described in the previous section.

Firms' Specific Parameters. Firms are homogeneous within each local labor market but differ in productivity across locations. I calibrate productivity differences across cities to match the observed log wage gap across the ten city bins. In the model, productivity in the least productive location is normalized to one. In the data, the average wage in Paris is approximately 70% higher than in cities at the bottom of the productivity distribution.[48]

The vacancy posting cost, κ_ℓ, is calibrated to reproduce the average unemployment rate in each city decile, which ranges from 14% to 18% across commuting zones. The job destruction rate, δ_ℓ, is set to match monthly employment-to-unemployment transitions, varying from 0.67% in low-productivity areas to 0.82% in Paris.[49]

Workers' Specific Parameters. Standard values are assigned to the coefficient of relative risk aversion, $\sigma = 2$, and the monthly interest rate, $r = 0.3\%$.

The discount factor, β, is calibrated to match a median wealth-to-income ratio of 0.6, consistent with the data. While this may appear relatively low, the measure of wealth used in both the model and the data excludes housing wealth, which constitutes a substantial share of household assets in

48 See Figure A.3 for details.
49 See Figure A.4 for details.

France.[50]

The unemployment benefit, b, is assumed to be constant across locations and is set so that it equals approximately 50% of the average wage in equilibrium, in line with the data.[51]

The parameter governing on-the-job search efficiency, λ, is calibrated to match the observed employment-to-employment transition rate. Spatial search frictions, $s^e_{\ell,\ell'}$ and $s^u_{\ell,\ell'}$, are chosen to reproduce the share of employment-to-employment and unemployment-to-employment transitions that involve a change of commuting zone.

Migration decisions are governed by a combination of migration costs $(\tau_{\ell,\ell'})$[52] and Gumbel taste shock scale parameters (ν^m, ν^s). These parameters are jointly calibrated to match three empirical targets: the annual migration rate, the share of movers who were unemployed in their origin location at the time of the move, and the relative wage growth of workers who change location during a job-to-job transition compared to those who switch jobs without relocating.[53]

The productivity gap between low- and high-skill workers is calibrated to match the observed log wage gap across skill groups, which equals 0.24 in the data. The human capital accumulation parameters, $(\eta,\ \psi_\ell)$, are set to replicate the average share of low-skill workers in the economy.

The borrowing constraint, $\underline{a}$, is set such that the fraction of the workers with negative liquid wealth is 8%, slightly above the 2% in the data.[54]

Housing. Following Lhuillier (2023), I estimate the housing supply elasticity (ϕ) and the housing price constant $(\mathcal{H})$ by inverting the model. The market-clearing condition for the housing sector links local housing prices to housing demand through:

$$\log p_\ell = \left(\frac{1}{1+\phi}\right)\log Y_\ell + \left(\frac{1}{1+\phi}\right)\log\left(\frac{1-\alpha}{\mathcal{H}}\right),$$

where $Y_\ell = u_\ell b + e_\ell \mathbb{E}[w_\ell]$. In the data, wages refer to the monthly wage, normalized by the average wage in the first location bin of the productivity ranking. Rent prices correspond to the average monthly rent per square meter for a $40m^2$ apartment at the municipal level. To ensure consistency with the model, I compute the average rent within each of the ten location bins, residualize it with respect to worker fixed effects, and normalize it. The housing consumption share $(1-\alpha)$ is set to 0.2, as in Lhuillier (2023). Estimating the above equation by OLS identifies ϕ and $\mathcal{H}$. Finally, the housing subsistence level $(\bar{h})$ is calibrated using estimates from Ganong and Shoag (2017).

[50] Figure A.5b plots the wealth-to-income ratio in the data and in the model across ten percentiles of the wealth distribution.

[51] In France, unemployment benefits are governed at the national level. However, there can be regional differences in implementation and additional support services. For simplicity, I assume it to be the same across space. In the policy exercise, I will allow the unemployment benefit to vary across space.

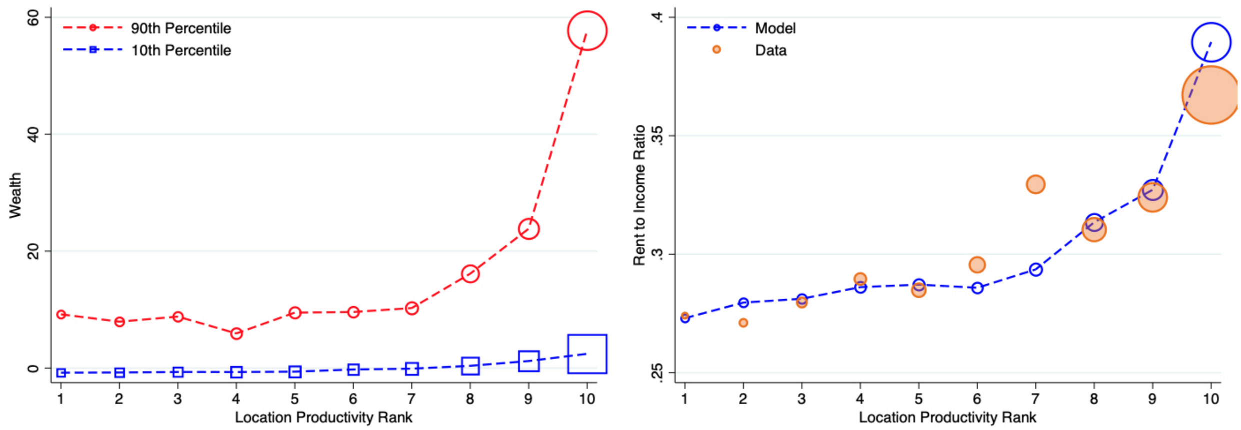
[52] In the baseline model, I allow for both monetary and utilitarian migration costs. For quantification, I retain only the utilitarian cost to better identify it. Including both has little effect on the results.

[53] The wage premium associated with relocation reflects the strength of workers' location preferences.

[54] Figure A.5a plots the wealth distribution obtained in the model.

Figure 5: Local Wealth Distribution & Cost of Living - Simulated Data

(a) Spatial Wealth Distribution (b) Rent-to-Income Ratio



Note: Panel (a) shows the average wealth held by different percentiles of the wealth distribution across ten location bins in the simulated data from the model. The blue line represents the average wealth of workers in the bottom 10 percent of the distribution, while the red line corresponds to the top 10 percent. Panel (b) plots the average rent-to-income ratio across the same location bins in the simulated data from the model. Rent is measured as the average monthly price per square meter for a standard $40m^2$ apartment, and income refers to monthly wages. The blue line shows those implied by the model, while the orange dots represent data. Marker sizes are proportional to city size.

4.2 Model Fit

In this section, I show that the model fits some important moments that were not targeted in the calibration. First, the model can account for the concentration of high-wealth workers in the most productive labor market. In figure 5a, I plot the 10th and the 90th percentiles of the wealth distribution by locations in the model. As in the data, high-wealth workers are concentrated in more productive locations, while low-wealth workers are more evenly distributed. Second, figure 5b shows that the model also matches pretty well the average rent-to-income ratio across the cities' productivity distribution.

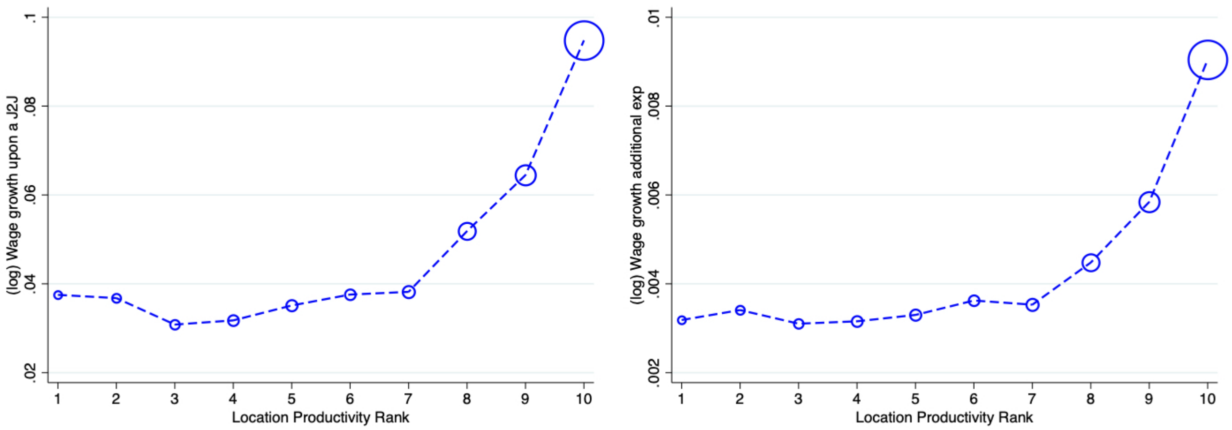
Then, I look at the wage growth across space and for workers with different levels of wealth in the model. Figure 6 shows that, as in the data, wage growth is higher in big and more productive cities. In figure 6a, I plot the gains from job-to-job transitions. Workers who change jobs in the most productive location obtain, on average, more than a 10% wage increase, while workers who do the same transition in an unproductive city obtain only a 4% wage increase. A similar picture holds for learning. Figure 6b shows that human capital accumulation is more valuable as cities' productivity increases.

Finally, the model is also capable of replicating the gains for workers with different wealth. Figure 7 shows that wage gains from job-to-job transitions and learning are concentrated among low-wealth workers in the most productive locations. Moreover, the heterogeneity across space is much more pronounced for workers who are financially constrained. The reason for this result is that low-wealth workers are heavily affected by differences in local housing prices. In particular,

Figure 6: Wage Growth by City - Simulated Data

(a) Job Transition

(b) Learning



Note: Panel (a) shows the log wage growth associated with job-to-job transitions across ten location bins in the simulated data from the model. Panel (b) shows the log wage growth due to human capital accumulation across ten location bins in the simulated data from the model. Marker sizes are proportional to city size.

the high housing price in the most productive locations strengthens precautionary motives, leading low-wealth workers to initially sort at the bottom of the ladder and thus experiencing higher gains from subsequent job-to-job transitions.[55] Also, crucial for this result is the existence of dynamic gains, which are valued differently by workers with different asset holdings. Furthermore, it is worth noting that gains from job-to-job transitions are higher when they are associated with migration, and since low-wealth workers move relatively more, this could potentially drive part of the wealth heterogeneity. However, as shown in figure A.7 in the appendix, a very similar picture can be obtained when migration is shut down.

It's noteworthy that the model can capture some wealth-related moments, even though I target only the median wealth-to-income ratio and the share of workers with negative wealth. This result mainly follows from the presence of dynamic gains and heterogeneity in housing prices. Then, I now turn to examine how the various channels present in the model influence spatial wage and wealth inequality.

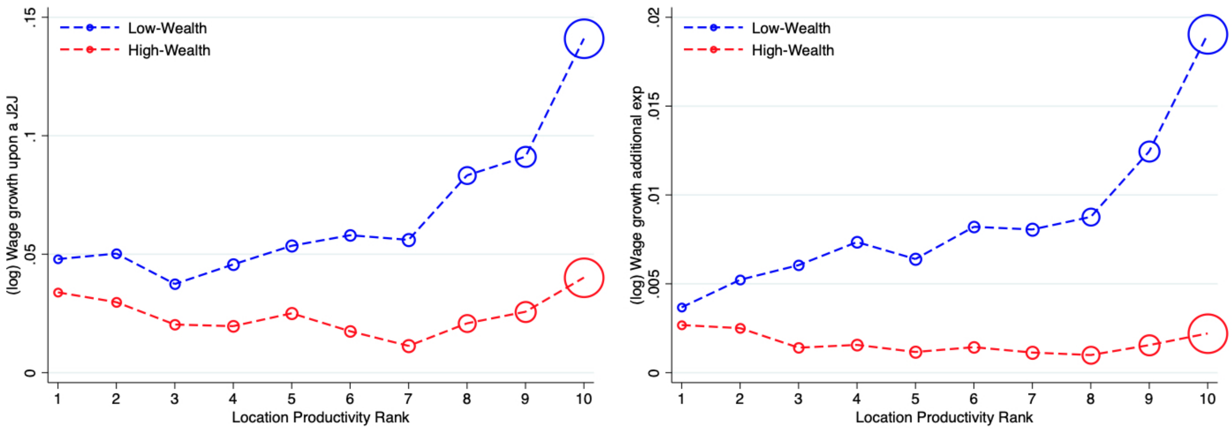
4.3 The Role of Financial Frictions

Borrowing constraints play a central role in determining which workers can access high-return opportunities. I assess their importance by comparing the baseline equilibrium with a counterfactual

[55] Figure A.1 plots the wage policy across different labor markets for unemployed workers with different wealth. The sorting of low-wealth workers into jobs that pay low wages is exacerbated in more productive but expensive locations.

Figure 7: Wage Growth by City & Wealth - Simulated Data

(a) Job Transition (b) Learning



Note: Panel (a) shows the log wage growth associated with job-to-job transitions across ten location bins in the simulated data from the model. Panel (b) shows the log wage growth due to human capital accumulation across ten location bins in the simulated data from the model. In both panels, the blue line represents low-wealth workers (those in the bottom 10 percent of the wealth distribution), and the red line represents high-wealth workers (those in the top 10 percent). Marker sizes are proportional to city size.

economy in which credit access is expanded.[56] In this environment, financially constrained workers can better smooth consumption and absorb the higher costs and risks associated with living in productive cities.

Figures 8a and 8b plot the distribution of all workers and of those with negative wealth across locations in the baseline and in the relaxed-borrowing scenarios. When credit access expands, the most productive and expensive city becomes more accessible, and a larger share of workers relocate there. Specifically, the share of the population residing in the most productive location rises from 52.3% to 54.9%, an increase of 2.6 percentage points (about 5%).

The benefits of a relaxed borrowing constraint concentrate among low-wealth workers. Among those with negative wealth, the share living in the most productive city rises from 28.2% to 36.7%, an 8.5 percentage point (30%) increase. This result shows that easing borrowing constraints allows financially constrained workers to relocate to places where job ladders are steeper and dynamic wage gains are larger, as their insurance against unemployment risk improves.

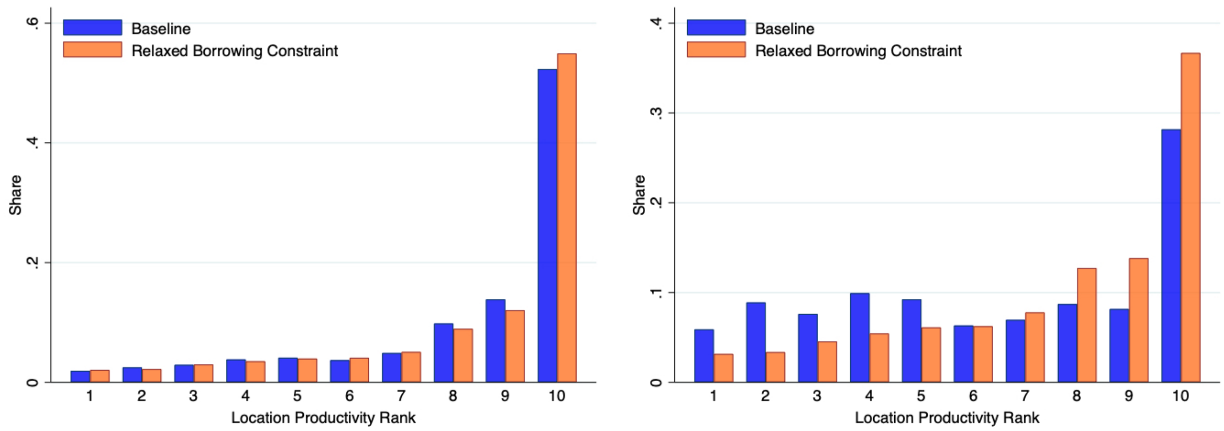
Together, these results show that financial frictions act as a key barrier to spatial mobility and, consequently, to upward career mobility. Alleviating these frictions, through improved access to credit or stronger insurance against unemployment risk, can therefore enhance both efficiency and equity by enabling more workers to benefit from the dynamic gains available in high-productivity labor markets.

The following section turns to the model's central mechanism: how job ladders shape the evo-

[56] The borrowing limit is five times larger in the counterfactual: -2 in the baseline and -10 in the counterfactual. Under this scenario, virtually no workers hit the borrowing constraint.

Figure 8: Access to Opportunities and the Role of Financial Constraints

(a) All Workers (b) Constrained Workers



Note: Panel (a) shows the share of workers across cities in the baseline model (blue) and in the counterfactual economy with a relaxed borrowing constraint (orange). Panel (b) shows the share of workers with negative wealth across cities in the baseline model (blue) and in the counterfactual economy with a relaxed borrowing constraint (orange).

lution of workers' wages and wealth.

4.4 The Role of Job Ladders

This section investigates how job ladders contribute to wage and wealth inequality across space. I compare the baseline equilibrium with a counterfactual economy without job ladders. This exercise isolates the dynamic gains that arise from job-to-job transitions and human capital accumulation and quantifies their contribution to wage and wealth inequality.[57]

Figure 9a plots spatial wage inequality across French commuting zones, grouped into ten bins by productivity.[58] The figure compares three cases: the data (orange), the baseline model (blue), and the counterfactual without on-the-job search and skill heterogeneity (red). On average, the baseline model accounts for about one-third of the residual wage inequality observed in the data, ranging from 30% in the least productive markets to around 40% in the most productive.[59]

The model captures a key empirical pattern: wage inequality is higher in more productive labor

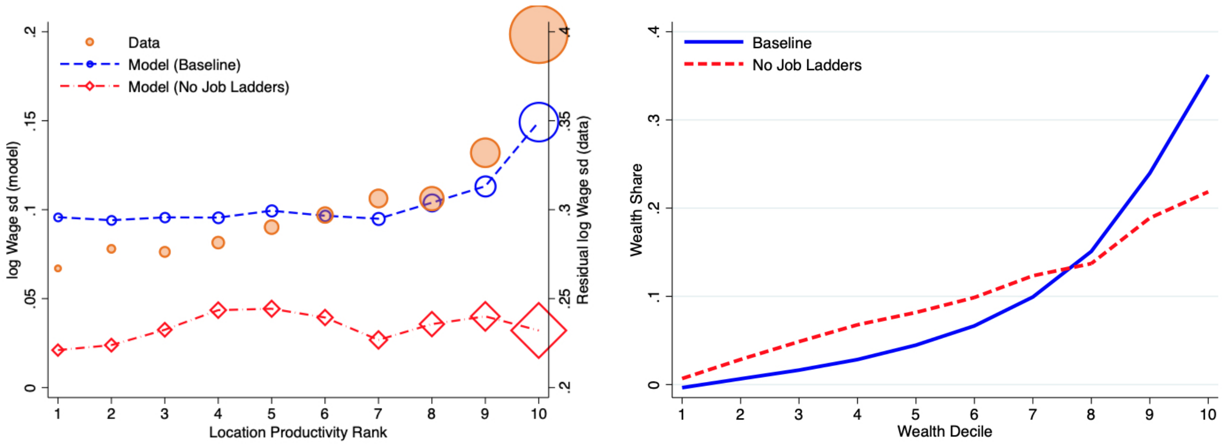
[57] In this counterfactual, removing human capital dynamics is implemented by collapsing the two skill types into one. In the baseline model, skill heterogeneity serves to capture human capital appreciation while employed (a wage increase from w_L to w_H) and depreciation while unemployed (a wage loss from w_H to w_L). Since transitions between skill types have limited direct effects beyond these wage changes, considering one skill type effectively shuts down both human capital accumulation and depreciation.

[58] Wage inequality in both the data and the model is measured using the standard deviation of log wages.

[59] In appendix A.8, I also compute the mean-min wage ratio to measure wage dispersion. It ranges from less than 1.1 in unproductive locations to nearly 1.8 in the most productive ones. Hornstein et al. (2011) show that the mean-min wage ratio does not exceed 1.04 in various search models, while Chaumont and Shi (2022) report a ratio of 1.728. Their model features only one location and temporary unemployment benefits, which increases the pressure to accept low-wage jobs. In contrast, my model allows for permanent unemployment benefits and incorporates spatial heterogeneity in living costs.

Figure 9: Inequality and the Role of Job Ladders

(a) Spatial Wage Inequality (b) Wealth Inequality



Note: Panel (a) shows the standard deviation of log monthly wages across ten location bins. Values from the model are reported on the left axis; values from the data are on the right axis. The blue line represents the baseline model, the red line corresponds to the counterfactual economy without job ladders, and the orange dots show the data. Marker sizes are proportional to city size. Panel (b) displays the share of total wealth held across the wealth distribution in the model. The blue solid line corresponds to the baseline model, while the red dashed line shows the counterfactual with no dynamic gains.

markets. This result arises from the coexistence of both very low- and very high-paying jobs in these locations. On one hand, firms in productive cities offer higher wages, both because they are more productive and because they must compensate workers for higher living costs. This results in steeper job ladders. On the other hand, high living costs intensify the precautionary motives of low-wealth workers, making them more willing to accept low-paying jobs at the bottom of the ladder in exchange for the opportunity to climb it over time. Similarly, low-skill workers are more likely to sort into these labor markets due to the faster pace of human capital accumulation. The interaction between heterogeneous job ladders, local housing prices, and workers' wealth is thus central to understanding spatial inequality.

In the counterfactual economy without on-the-job search and human capital dynamics, wage inequality declines substantially, especially in the most productive locations.[60] Without job ladders, workers no longer accept low-wage jobs as stepping stones, since they have no opportunity to climb the ladder once employed. Figure A.9a shows that this change is primarily driven by low-wealth workers: in the absence of dynamic gains, they are no longer willing to accept low-paying jobs at the bottom of the ladder. In contrast, the search behavior of high-wealth workers remains largely unchanged.[61] As a result, high-productivity cities with high living costs become less attractive to workers who would otherwise sort into the bottom rungs of the local ladder. Overall, job ladders account for roughly two-thirds of the wage inequality generated by the model, with their contribution

[60] For the counterfactual exercise, the model is recalibrated to match key moments in the data.

[61] Figure A.9b further illustrates that removing job ladders substantially flattens the wage–wealth premium, especially in high-productivity areas.

ranging from 50% in less productive areas to about 80% in the most productive ones.

Decomposing the contributions of on-the-job search and human capital accumulation, I find that the latter plays a larger role on average. Removing skill heterogeneity and human capital accumulation reduces wage inequality by roughly 60%, while removing on-the-job search lowers it by just around 40%. Notably, on-the-job search is essential for explaining inequality in the most productive labor markets: it accounts for 55% of wage dispersion in these areas, compared to 45% attributable to human capital. This pattern reverses in the least productive locations, where skill heterogeneity is the primary driver of inequality.[62]

The presence of heterogeneous job ladders across space affects not only wage inequality but also wealth inequality. Steeper ladders substantially improve workers' ability to accumulate wealth. In this sense, wealth is both a determinant and a consequence of job search and location choices. Workers who sort into more productive areas and successfully climb local ladders accumulate more wealth over time. By contrast, those who remain stuck in less productive markets with flatter ladders have a lower wealth accumulation rate.

Figure 9b shows the share of wealth held across percentiles of the wealth distribution in the baseline model (blue) and the counterfactual without job ladders (red). In both cases, wealth is heavily concentrated at the top: the top 10% of workers hold between 22% and 34% of total wealth.

In the counterfactual without dynamic gains, workers accumulate less wealth overall, resulting in a more equal wealth distribution. When job ladders are present, however, the sorting of workers across jobs and locations amplifies wealth differences: those who reach higher rungs accumulate disproportionately more, reinforcing wealth inequality. Specifically, wealth concentration, measured as the ratio between the wealth held by the top 10 percent and the bottom 50 percent, declines by almost 60% when job ladders are shut down. Thus, job ladders not only contribute to wage inequality but also play a critical role in shaping the wealth distribution. By enabling steeper earnings trajectories, particularly in high-productivity areas, they amplify the initial wealth differences.

This section, therefore, suggests that guaranteeing access to steep job ladders is key to addressing wage and wealth inequality. I conclude this paper by quantifying the consequences of place-based policies that affect workers' ability to insure against unemployment risk.

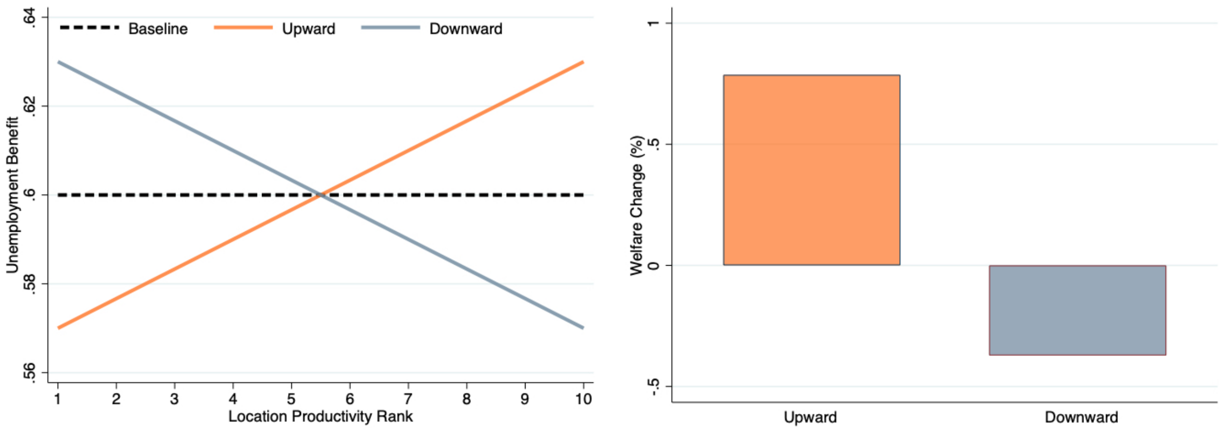
5 Policy Exercise

In this section, I study the consequences of spatial policies in an environment where workers rely on multiple forms of self-insurance against earnings risk. Specifically, the policy experiment consists of varying the generosity of local unemployment benefits. Similar policies have been implemented in several countries to face the recent affordability crisis. One relevant example is Germany, where the Hartz IV Reform adjusted the unemployment benefit to cover the costs of rent and heating, which

[62] Details in appendix A.10.

Figure 10: The Consequences of Spatial UI

(a) Spatial UI (b) Aggregate Welfare



Note: Panel (a) shows the two policy scenarios. The black dashed line represents the baseline economy. The orange line depicts the *upward* policy, which increases benefits in the most productive locations. While the gray line shows the *downward* policy, which does the reverse. Panel (b) shows the percentage change in aggregate welfare under each policy relative to the baseline. The aggregate effect is computed as the average of the local welfare gains in equation (14).

vary across different areas. [63]

A central feature of the model is that unemployment is more costly in high-productivity locations due to their higher living expenses. As a result, spatial differences in benefit generosity alter the risk–return trade-off across locations. These differences in the cost of unemployment can, in turn, have sizable effects on workers' sorting behavior, job search strategies, and overall welfare. In this setting, this is especially true for low-wealth workers for whom unemployment is more costly. Therefore, although this policy affects everyone, it is implicitly targeting low-wealth workers. Here, I focus on the steady-state effects of each policy.

5.1 Welfare Effects

Following Chaumont and Shi (2022), I measure the welfare effects of each policy in terms of the percentage change in lifetime consumption. Let $\bar{\mu}_\ell$ denote the aggregate welfare gain in location ℓ, defined by:

$$\int_0^1 \sum_{t=0}^{\infty} \beta^t u\left(c^0_{i\ell t}(1+\bar{\mu}_\ell), h^0_{i\ell t}(1+\bar{\mu}_\ell)\right) di = \int_0^1 \sum_{t=0}^{\infty} \beta^t u\left(c^1_{i\ell t}, h^1_{i\ell t}\right) di \tag{14}$$

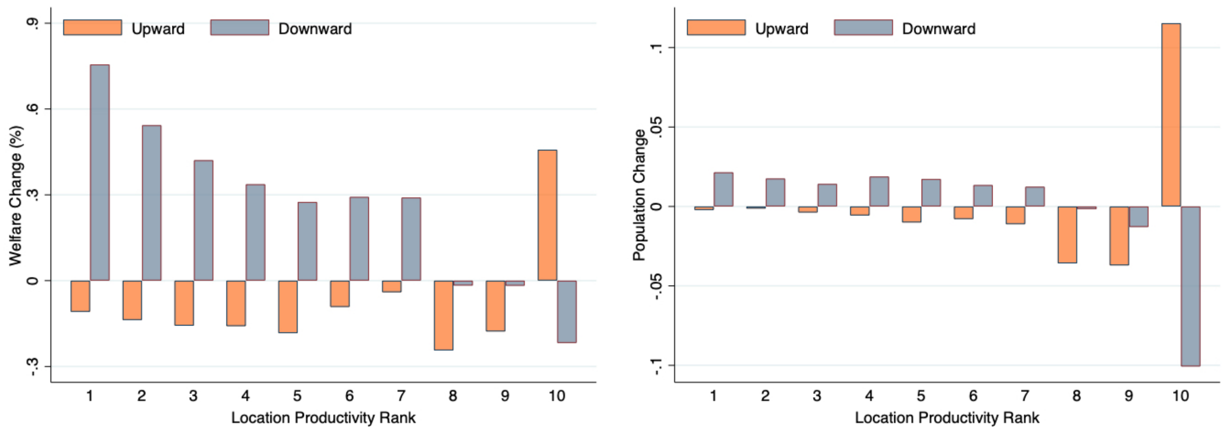
Where $c^0_{i\ell t}$ and $c^1_{i\ell t}$ denote the consumption of individual i in location ℓ at time t in the baseline and policy counterfactual, respectively. Accordingly, $\bar{\mu}_\ell$ can also be interpreted as the percentage change in consumption that makes workers indifferent between the two scenarios.

The policy is financed by a proportional tax τ_w on wages, such that the government maintains

[63] See Wiegand (2025) for more details on the spatial consequences of this policy.

Figure 11: The Local Consequences of Spatial UI

(a) Local Welfare (b) Population Change



Note: Panel (a) shows the percentage change in welfare across locations for each policy relative to the baseline, computed from equation (14). Panel (b) reports the change in the population share in each location under each policy.

a balanced budget:

$$\bar{e}_\ell \tau_w \int \cdots \int_{x,a} w_\ell(x,a) = \bar{u}_\ell b_\ell$$

Where $\bar{e}_\ell$ and $\bar{u}_\ell$ are the shares of employed and unemployed workers in location ℓ, respectively. The tax τ_w is assumed to be uniform across space, and thus does not distort the spatial allocation of economic activity.

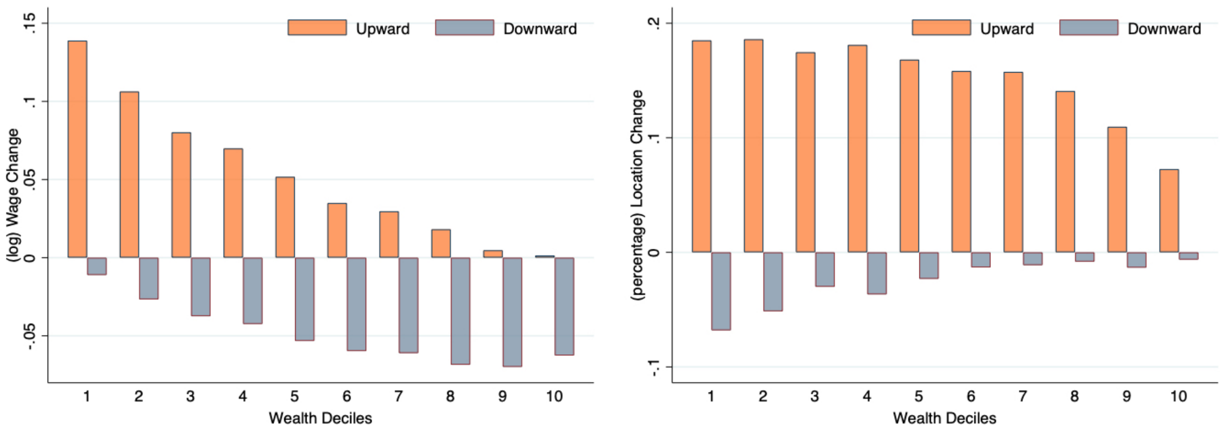
Figure 10a illustrates the two policy scenarios.[64] Each policy varies in the generosity of the unemployment benefit across locations. I label *upward* the policy that raises benefits in the most productive cities and reduces them elsewhere, while *downward* is the policy that does the opposite. Figure 10b displays the aggregate welfare effects. The upward policy yields positive welfare gains. Increasing benefits by 5% in the most productive location and decreasing them by 5% in the least productive location raises aggregate welfare by almost 1% relative to the baseline economy. By contrast, the downward policy results in a welfare loss of just under 0.5%.

To better understand these effects, I break down the welfare gains by location. Figure 11a illustrates the percentage change in welfare across different areas. The gains from the upward policy are concentrated in the most productive location, where more generous benefits improve insurance against unemployment risk. As a result, this area has become more appealing to low-wealth workers, allowing them to better smooth their consumption during periods of unemployment, despite higher living costs. This change is also evident in the increase of the local population share, as shown in

[64] Figure A.11 plots the real unemployment benefit deflated by a citywide Cobb-Douglas price index with a housing expenditure share of 0.2. In the baseline scenario, the real unemployment benefit is lower in the most productive locations, as they are the most expensive. Under the upward policy, the real unemployment benefit becomes higher in the most productive areas.

Figure 12: The Consequences of Spatial UI by Wealth

(a) Change in Wage by Wealth (b) Change in Location by Wealth



Note: Panel (a) shows the log change in the average wage across the wealth distribution for each policy relative to the baseline economy. Panel (b) reports the change in the location across the wealth distribution.

figure 11b. The opposite pattern emerges under the downward policy.

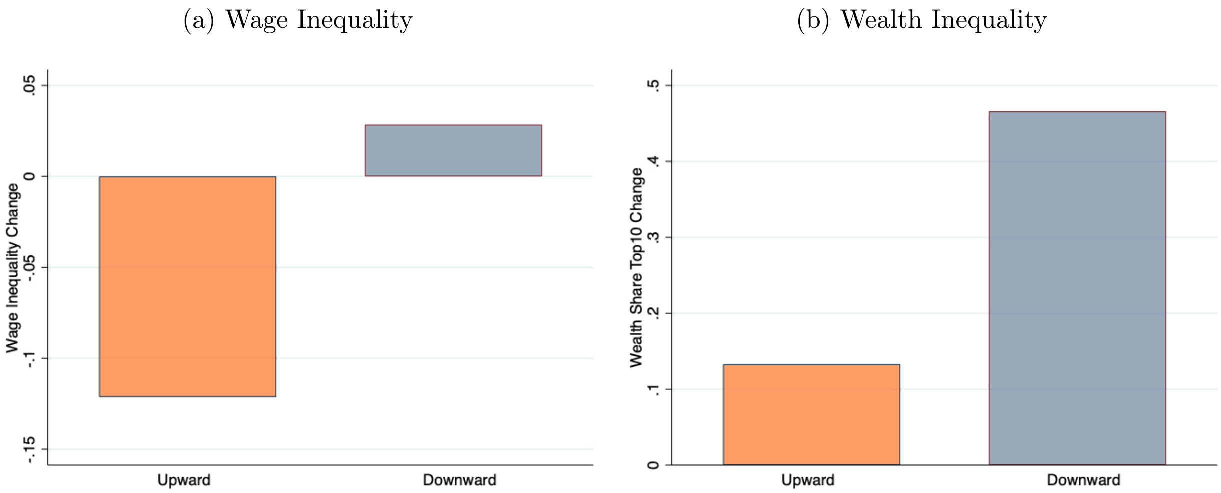
The upward policy, which makes the most productive location more attractive, has the side effect of increasing local living costs as more workers relocate there. However, this adverse effect is more than offset by the fact that a larger share of workers, particularly those who are financially constrained, can now access and benefit from the dynamic wage gains available in high-productivity labor markets. By improving insurance against unemployment risk, this policy relaxes the barriers that previously limited upward mobility, allowing more workers to sort into locations where job ladders are steeper and long-term wage growth is higher.[65]

Figures 12a and 12b illustrate the effects of spatial unemployment insurance policies across the wealth distribution. Under the upward policy, wage gains are concentrated among low-wealth workers because relaxed precautionary motives enable them to sort more easily into productive but expensive locations. As a result, the average wage of workers at the bottom of the wealth distribution rises by about 15%, while it remains nearly unchanged for wealthier workers. These policies also increase the likelihood that financially constrained workers upgrade their location of residence.[66] By contrast, the downward policy disproportionately reduces the average wage of high-wealth workers, as they are more concentrated in areas where benefits decline. In this case, low-wealth workers are

[65] Despite the higher unemployment benefits in locations 6, 7, 8, and 9 under the upward policy, these locations experience welfare losses. This occurs because sustaining the policy requires a higher wage tax, while workers in these locations would prefer to pay less tax and rely on self-insurance mechanisms. Location 10 is an exception: the local job ladder is steep enough that low-wealth workers who relocate there benefit significantly from the policy, more than offsetting the higher tax burden.

[66] This policy effectively targets low-wealth workers, who are most affected by spatial differences in unemployment benefits. Since it induces relocation, it is comparable to moving voucher policies, which are often debated for their limited effectiveness.

Figure 13: The Consequences of Spatial UI on Inequality



Note: Panel (a) shows the percentage change in wage inequality for each policy relative to the baseline. Panel (b) shows the percentage change in the share of wealth held by the top 10 percent of the wealth distribution for each policy relative to the baseline.

more likely to downgrade their location because unemployment in productive cities becomes too costly.

5.2 Consequences on Inequality

Finally, I examine how these spatial policies affect wage and wealth inequality. Figure 13a shows that increasing the generosity of unemployment benefits in more productive locations reduces overall wage inequality. In contrast, decreasing benefits in productive areas while increasing them in less productive labor markets leads to higher wage inequality. This result reflects a core mechanism of the model: the interaction between workers' wealth and local search frictions. When benefits are more generous in high-productivity cities, financially constrained workers are better insured against unemployment risk and can smooth consumption more effectively. As a result, their job search decisions become less sensitive to high local living costs, allowing them to access higher-paying opportunities from the beginning. Therefore, the very low-paying jobs in most productive locations disappear, as financially constrained workers no longer need to sort at the very bottom of the local ladder. This, in turn, reduces overall wage inequality. The opposite occurs when benefits are relatively more generous in low-productivity areas and less so in more productive locations, further deterring constrained workers from moving to or remaining in more expensive cities and strengthening their precautionary motives.

Figure 13b focuses on the effects of these policies on wealth inequality, measured by the share of total wealth held by the top 10 percent of the distribution. Under both scenarios, wealth inequality increases, but for different reasons. The upward policy leads to lower dis-saving during unemployment in productive locations, which in turn boosts wealth accumulation for those who successfully climb the spatial job ladder. Under the downward policy, fewer low-wealth workers are willing or able to move to high-productivity areas, resulting in higher wealth inequality.

Summing up, place-based policies that affect workers' ability to insure against unemployment risk can enhance aggregate welfare by improving access to wage growth opportunities, but their effectiveness hinges on targeting financially constrained workers in high-productivity cities, where the cost of unemployment is relatively higher.

6 Conclusion

This paper studies how workers' wealth affects career trajectories by shaping job search and migration decisions. Spatial differences in wage growth opportunities and living costs make wealth a key determinant of workers' sorting behavior. I developed a model that integrates these features. Workers face trade-offs between wages, unemployment risk, and local living costs. The combination of these elements with the heterogeneity in local job ladders generates precautionary motives, whose intensity varies across space. In expensive cities, the high cost of unemployment leads low-wealth workers to disproportionately sort into lower-paying jobs at the bottom of the ladder. Consequently, this implies that they gain relatively more from job-to-job transitions in big cities. Empirically, I document that wage growth for low-wealth workers is more sensitive to local labor market productivity, resulting in a steeper spatial job ladder, and that financial constraints significantly reduce their upward mobility along the ladder. Quantitatively, the model replicates these patterns and shows that the interaction between financial frictions, spatial differences in dynamic gains, and living costs contributes substantially to wage and wealth inequality.

These findings suggest that addressing labor market inequality may require policies that alleviate financial constraints and broaden access to high-productivity labor markets. Interventions that ease liquidity constraints, improve mobility, or expand high-quality job opportunities in less productive areas could help low-wealth workers overcome these barriers, ultimately fostering greater mobility and reducing spatial inequality. In line with this, I evaluate a policy that increases unemployment benefits in high-productivity locations. By lowering the cost of unemployment in the most productive labor markets, the policy allows financially constrained workers to access steeper job ladders and raises aggregate welfare.

The housing affordability crisis is one of the main challenges of our time. Its impact varies widely across space and among households. A natural extension of this research agenda is to explore how changes in housing costs interact with broader labor market trends, such as the long-run decline in job mobility and dynamism. Moreover, the framework developed in this paper is well-suited to study spatial policies that affect workers' self-insurance. One policy that has received relatively little attention from a spatial perspective, yet may have relevant implications in this setting, is the minimum wage.

References

Baley, I., Figueiredo, A., Mantovani, C., and Sepahsalari, A. (2025). Self-insurance in turbulent labor markets. Technical report, Working Paper.

Baum-Snow, N. and Pavan, R. (2012). Understanding the city size wage gap. *The Review of economic studies*, 79(1):88–127.

Bilal, A. (2023). The geography of unemployment. *The Quarterly Journal of Economics*, 138(3):1507–1576.

Bilal, A. and Rossi-Hansberg, E. (2021). Location as an asset. *Econometrica*, 89(5):2459–2495.

Borovičková, K. and Macaluso, C. (2024). Heterogenous job ladder.

Braxton, J. C., Herkenhoff, K., and M. Phillips, G. (2024). Can the unemployed borrow? implications for public insurance. *Journal of Political Economy*, 132(9):3025–3076.

Caratelli, D. (2022). Labor market recoveries across the wealth distribution. Technical report, working paper.

Chaumont, G. and Shi, S. (2022). Wealth accumulation, on-the-job search and inequality. *Journal of Monetary Economics*, 128:51–71.

Combes, P.-P., Duranton, G., Gobillon, L., Puga, D., and Roux, S. (2012). The productivity advantages of large cities: Distinguishing agglomeration from firm selection. *Econometrica*, 80(6):2543–2594.

Crews, L. G. (2023). A dynamic spatial knowledge economy.

Davis, D. R. and Dingel, J. I. (2019). A spatial knowledge economy. *American Economic Review*, 109(1):153–170.

De La Roca, J. and Puga, D. (2017). Learning by working in big cities. *The Review of Economic Studies*, 84(1):106–142.

Duranton, G. and Puga, D. (2023). Urban growth and its aggregate implications. *Econometrica*, 91(6):2219–2259.

Eckert, F., Ganapati, S., and Walsh, C. (2022a). Urban-biased growth: a macroeconomic analysis. Technical report, National Bureau of Economic Research.

Eckert, F., Hejlesen, M., and Walsh, C. (2022b). The return to big-city experience: Evidence from refugees in denmark. *Journal of Urban Economics*, 130:103454.

Eeckhout, J. and Sepahsalari, A. (2023). The effect of wealth on worker productivity. *Review of Economic Studies*, forthcoming.

Finlay, J. and Williams, T. (2022). Housing demand, inequality, and spatial sorting. *Inequality, and Spatial Sorting (April 28, 2022)*.

Ganong, P. and Shoag, D. (2017). Why has regional income convergence in the us declined? *Journal of Urban Economics*, 102:76–90.

Gaubert, C. and Robert-Nicoud, F. (2025). Sorting to expensive cities. Working Paper 33652, National Bureau of Economic Research.

Giannone, E., Li, Q., Paixao, N., and Pang, X. (2023). Unpacking moving: A quantitative spatial equilibrium model with wealth. Technical report, Bank of Canada.

Gonzalez-Aguado, E. (2021). Labor mobility over the business cycle.

Greaney, B. (2023). Homeownership and the distributional effects of uneven regional growth. *Available at SSRN 4406024*.

Griffy, B. S. (2021). Search and the sources of life-cycle inequality. *International Economic Review*, 62(4):1321–1362.

Heise, S. and Porzio, T. (2022). Labor misallocation across firms and regions. Technical report, National Bureau of Economic Research.

Herkenhoff, K. F. (2019). The impact of consumer credit access on unemployment. *The Review of Economic Studies*, 86(6):2605–2642.

Hornstein, A., Krusell, P., and Violante, G. L. (2011). Frictional wage dispersion in search models: A quantitative assessment. *American Economic Review*, 101(7):2873–2898.

Kaas, L., Lalé, E., and Siassi, N. (2023). Job ladder and wealth dynamics in general equilibrium.

Krusell, P., Mukoyama, T., and Şahin, A. (2010). Labour-market matching with precautionary savings and aggregate fluctuations. *The Review of Economic Studies*, 77(4):1477–1507.

Lhuillier, H. (2023). Should i stay or should i grow?

Lhuillier, H. (2025). The local root of wage inequality. *University of Chicago, Becker Friedman Institute for Economics Working Paper*, (2025-78).

Lindenlaub, I., Oh, R., and Peters, M. (2022). Firm sorting and spatial inequality. Technical report, National Bureau of Economic Research.

Lise, J. (2013). On-the-job search and precautionary savings. *Review of economic studies*, 80(3):1086–1113.

Luccioletti, C. (2023). Should governments subsidize homeownership? a quantitative analysis of spatial housing policies. Technical report, Working Paper.

Martellini, P. (2022). Local labor markets and aggregate productivity. Technical report, Working Paper.

Menzio, G. and Shi, S. (2010). Block recursive equilibria for stochastic models of search on the job. *Journal of Economic Theory*, 145(4):1453–1494.

Menzio, G. and Shi, S. (2011). Efficient search on the job and the business cycle. *Journal of Political Economy*, 119(3):468–510.

Moretti, E. and Yi, M. (2024). Size matters: Matching externalities and the advantages of large labor markets. Technical report, National Bureau of Economic Research.

Nanos, P. and Schluter, C. (2018). Search across local labour markets. Technical report, Working Paper, Aix-Marseille School of Economics and University of Sheffield.

Pellegrini, E. (2025). Wealth inequality and labor mobility: The job trap.

Schmutz, B. and Sidibé, M. (2019). Frictional labour mobility. *The Review of Economic Studies*, 86(4):1779–1826.

Shi, S. (2009). Directed search for equilibrium wage–tenure contracts. *Econometrica*, 77(2):561–584.

Soenarjo, A. (2024). Liquidity and labor reallocation in an uneven economy. Technical report.

Souchier, M. (2025). Insurance inside and outside the firm. *Available at SSRN 5137109*.

Wiegand, M. (2025). Cities with benefits.

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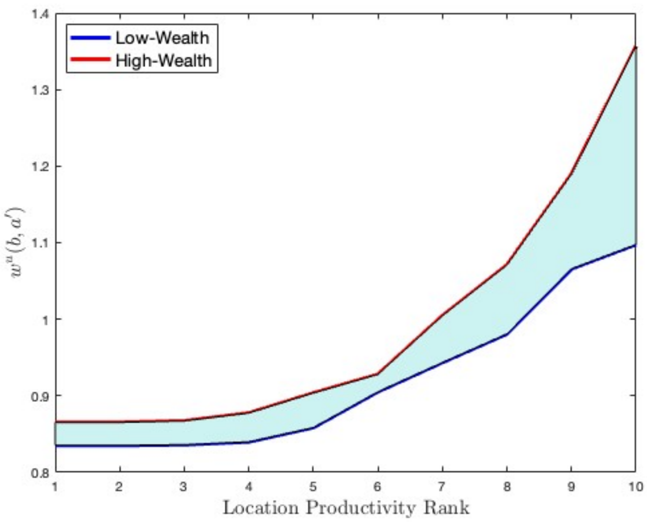
A Model

A.1 Wage Policy across Locations

Figure A.1 shows the wage policy for unemployed workers with different wealth in ten locations, which differ in their productivity and cost of living. For simplicity, to obtain this graph, I solve a version of the model where workers cannot move across locations and the price of the non-tradable good is exogenous.[67] As the productivity of a local labor market increases, the wages that unemployed workers search for increase too. This is because in more productive labor markets, firms are willing to offer higher wages.

Figure A.1: Wage Policy Unemployed Workers by Wealth and Location



Note: The figure displays the wage policy for unemployed workers with different wealth levels across ten location bins. The blue line represents the policy for low-wealth workers, while the red line corresponds to high-wealth workers. The light-blue area highlights the distortion in the optimal search strategy caused by precautionary motives. The figure is based on a simplified version of the model that excludes migration and is calibrated solely to match differences in rent prices and productivity across French commuting zones.

Low-wealth workers, who are all else equal to wealthier agents, always search for lower wages because of the precautionary job search motive that makes them want to exit unemployment as soon as possible and so search for jobs with a higher finding rate, those that offer lower wages. The difference between workers with different wealth, the light-blue area in the graph, increases as the productivity of locations increases. The reason is that more productive locations are, in equilibrium, more expensive. Thus, an unemployment period is relatively more costly in the most productive location compared to the least productive. This makes the precautionary job search motive stronger in more productive locations, which, in turn, distorts further low-wealth workers' optimal search

[67] These restrictions are just to make the interpretation of the wage policy function straightforward. A similar picture can be obtained from the full quantitative model.

strategy.

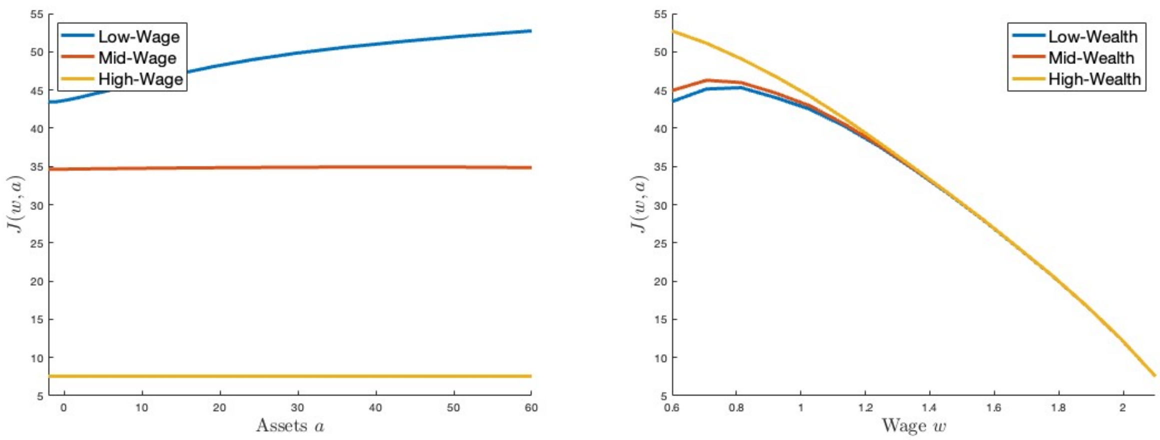
A.2 The Value of Firms, Workers' Wealth and Wages

In this section, I illustrate how a firm's value of a filled job varies with worker wealth and wages. Figure A.2a shows that, consistent with Chaumont and Shi (2022), firms prefer to hire workers with higher wealth, as these matches tend to last longer due to lower job-switching probabilities. Figure A.2b displays the relationship between firm value and wages. As expected, firms prefer to offer lower wages and, again, favor high-wealth workers, who are less likely to leave.

Figure A.2: Firm's Value by Wealth and Wages

(a) Firm's Value and Wealth

(b) Firm's Value and Wages



Note: Panel (a) shows the relationship between firm value and worker wealth for different wage levels. Panel (b) shows the relationship between firm value and wages for different levels of worker wealth. Both plots are based on firms in the most productive location, where the full range of wage offers is observed.

A.3 Average Wage in the Data and Model

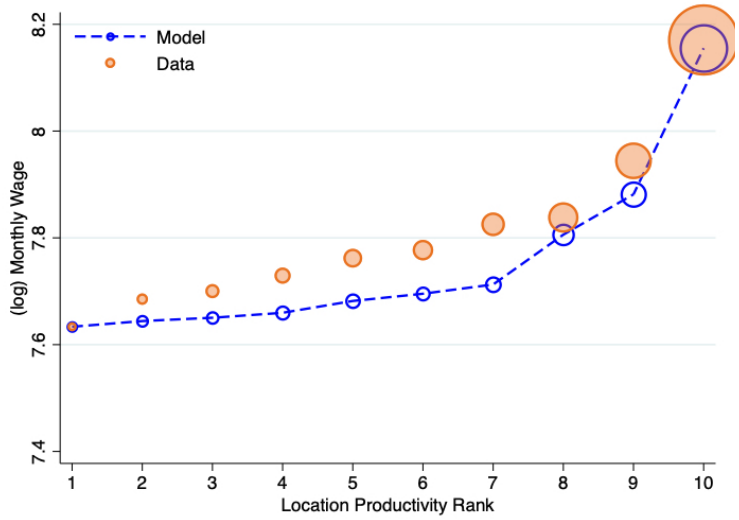
Figure A.3 plots the average log monthly wage in the data and in the model, accounting for the normalization, across the ten location bins.

Average wages are higher in more productive locations. This reflects both the higher value of matches in those areas—leading firms to offer higher wages—and the large differences in living costs. Given the relatively modest variation in job-finding rates across space, firms in the most expensive locations must raise wages to attract and retain workers.

A.4 Average Separation Rate in the Data and Model

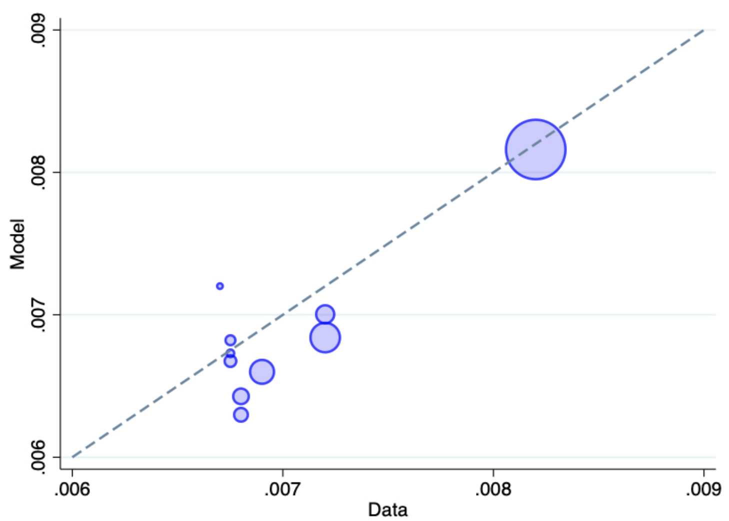
Figure A.4 plots the average monthly employment-to-unemployment rate in the data and in the model across the ten location bins.

Figure A.3: Average Wage by Location



Note: The figure plots the average log monthly wage across location bins in the model (blue line) and in the data (orange circles). Wages in the model reflect the normalization of productivity to one in the first location bin. Marker sizes are proportional to city size.

Figure A.4: Average Separation Rate by Location



Note: The figure plots the average monthly employment-to-unemployment rate across location bins in the model (y-axis) and in the data (x-axis). The dashed line represents the 45 degree line. Marker sizes are proportional to city size.

A.5 Wealth Distribution

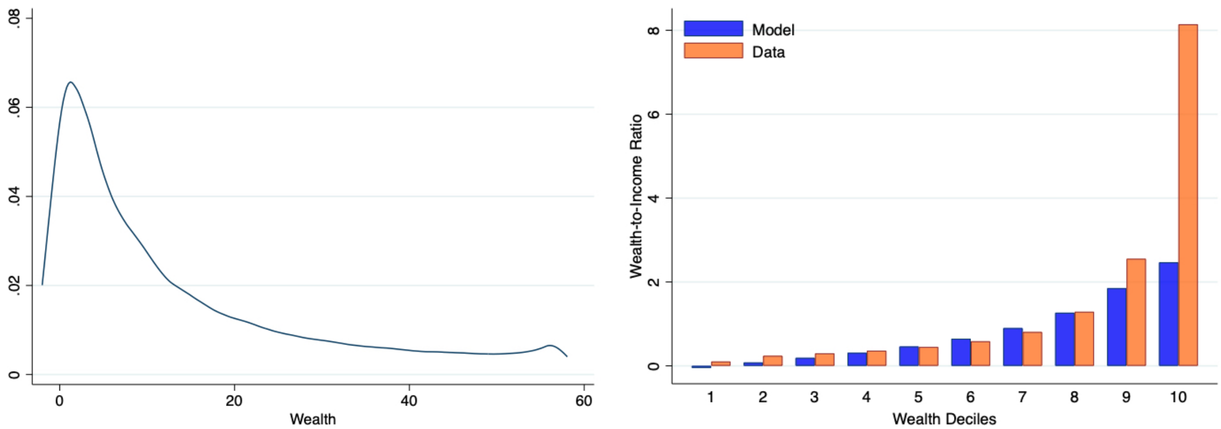
Figure A.5a presents the model-implied wealth distribution, while Figure A.5b compares the model's wealth-to-income ratio to that observed in the data. The model closely matches the wealth-to-income ratio across most of the asset distribution, but underestimates asset holdings in the top decile.

One potential explanation is the model's assumption of a single asset, which rules out heterogeneity in returns to wealth, a feature widely recognized as crucial for replicating the concentration of wealth at the top of the distribution.

Figure A.5: Wealth Distribution

(a) Wealth Distribution - Model

(b) Wealth-to-Income Ratio



Note: Panel (a) displays the wealth distribution in the model. Panel (b) plots the wealth-to-income ratio in the model (blue line) and in the data (orange line) across percentiles of the wealth distribution.

A.6 Sensitivity Analysis

A.7 Gains from Local Job-to-Job Transitions

Figure A.7 presents a counterfactual in which migration is shut down. Even when focusing only on local transitions—that is, job-to-job moves within the same labor market—gains from job-to-job transitions remain concentrated among low-wealth workers.

On average, these gains are smaller compared to the baseline model that includes migration. This is consistent with the presence of a migration premium in the data and reflects the fact that migration entails costs, requiring workers to receive additional compensation to make such a transition worthwhile.

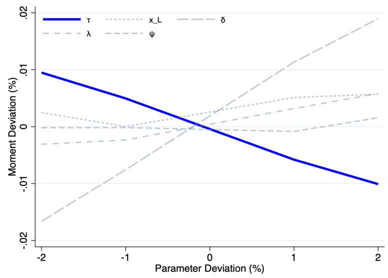
A.8 Mean-min Ratio

I also measure wage dispersion using the mean-min wage ratio—the ratio of the average wage earned by employed workers to the lowest wage in equilibrium—as proposed by Hornstein et al. (2011). This measure, also used by Chaumont and Shi (2022), captures the extent of wage dispersion in frictional labor markets.

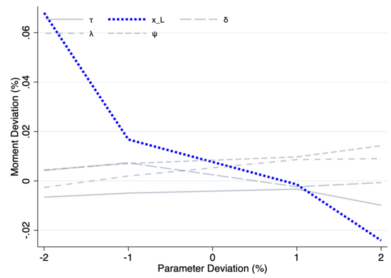
In the model, the average mean-min ratio is 1.5, slightly below the 1.8 reported in Chaumont and Shi (2022). This difference stems from the assumption about unemployment benefits: while

Figure A.6: Sensitivity of targeted moments to parameters

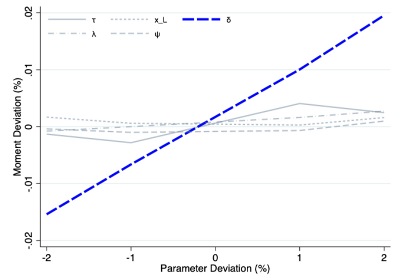
(a) Migration Rate



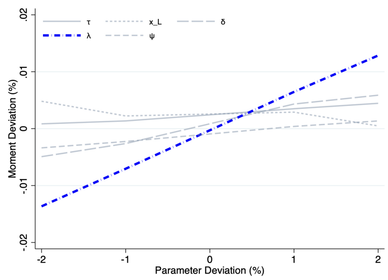
(b) Wage Gap by Skill



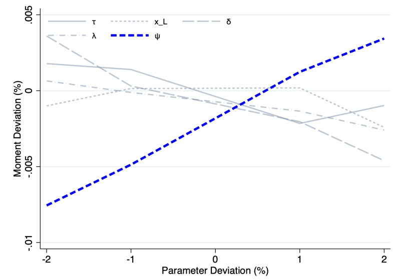
(c) E2U Rate



(d) J2J Rate

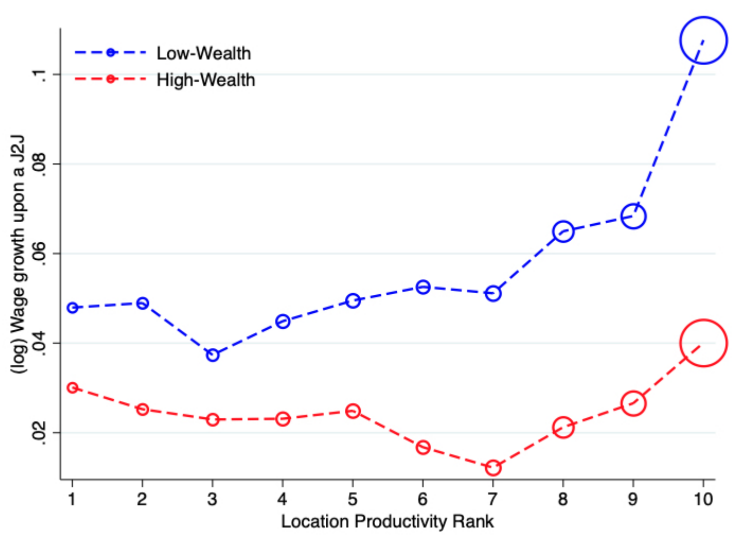


(e) Share High Skill



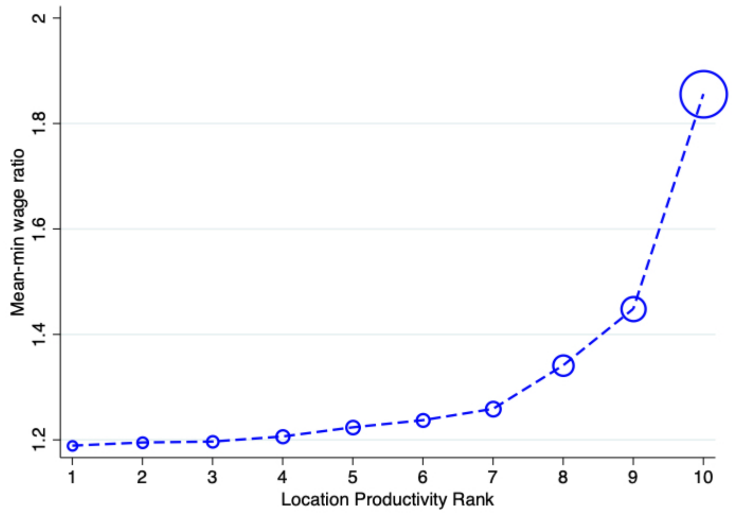
Note: each panel is a targeted moment in the calibration procedure. Each line represents how a parameter affects the moment of interest. The blue lines highlight the parameter that are heuristically identified by the particular moment of interest. The x-axis represents deviations around the calibrated parameters of 2% in each direction. The y-axis represents the percentage change in the parameter of interest.

Figure A.7: Wage Gains upon Local J2J - Simulated Data



Note: The figure plots log wage gains from job-to-job transitions for workers who remain in the same location. The blue line represents low-wealth workers, while the red line represents high-wealth workers. Marker sizes are proportional to city size.

Figure A.8: Mean-min Wage Ratio by Location - Simulated Data



Note: The figure plots the mean-min wage ratio across ten location bins using simulated data from the model. Marker sizes are proportional to city size.

their model features temporary benefits that eventually compel workers to accept very low-wage jobs, my framework assumes benefits last indefinitely, allowing workers to remain unemployed longer and avoid the lowest-paying matches.

Beyond aggregate inequality, the model also captures local wage dispersion. Figure A.8 plots the mean-min ratio across ten local labor markets. The ratio ranges from approximately 1.2 in the least productive locations to nearly 1.8 in the most productive ones.

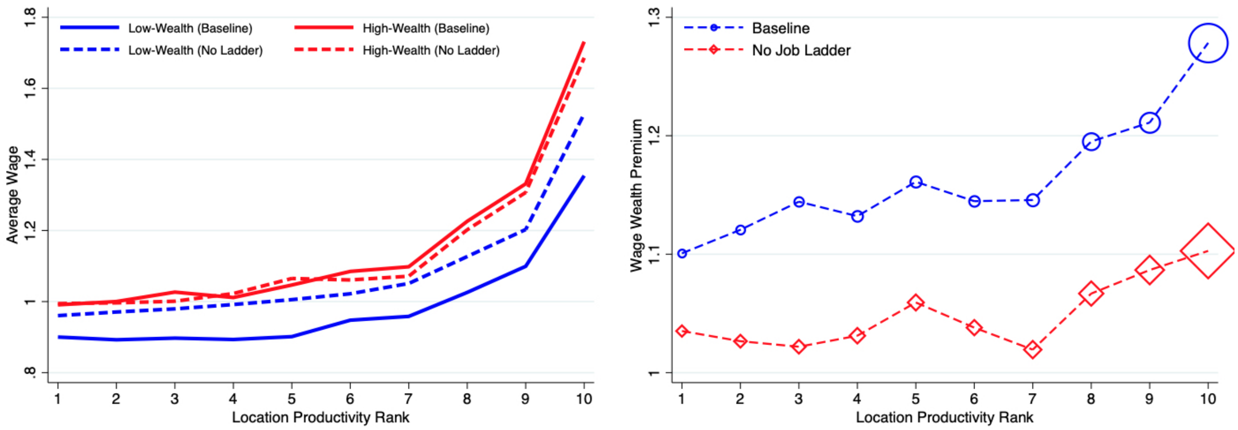
A.9 Search Policy and Wage Wealth Premium

To illustrate how the removal of job ladders affects inequality, I examine how it alters the sorting behavior of workers with different wealth levels. Figure A.9a shows that the decline in inequality is primarily driven by a change in low-wealth workers' search strategy. In the absence of job ladders, they are not willing to accept low-paying jobs at the bottom of the ladder, especially in cities with high living costs. In contrast, the search behavior of high-wealth workers remains largely unchanged.

Figure A.9b plots the wage wealth premium across locations in both the baseline model and the counterfactual without job ladders. The premium—defined as the ratio between the wage of high-wealth and low-wealth workers—increases with local productivity: for example, in the most productive locations, high-wealth workers earn about 30% more than their low-wealth counterparts upon reemployment. This premium arises from the precautionary job search motive, which leads low-wealth workers to prefer jobs with higher finding probabilities over higher wages. When dynamic gains are removed, the wealth premium declines across all locations, with the largest drop observed in the most productive labor markets.

Figure A.9: Search Policy and Wage Wealth Premium

(a) Wage upon U2E (b) Wage Wealth Premium



Note: Panel (a) shows the wage accepted by unemployed workers upon reemployment. The blue solid line corresponds to low-wealth workers in the baseline model, the red solid line to high-wealth workers, and dashed lines to their counterparts in the counterfactual economy without job ladders. Panel (b) displays the wage–wealth premium in the baseline model (blue) and in the counterfactual (red). The premium is defined as the ratio of wages for high-wealth to low-wealth workers across locations.

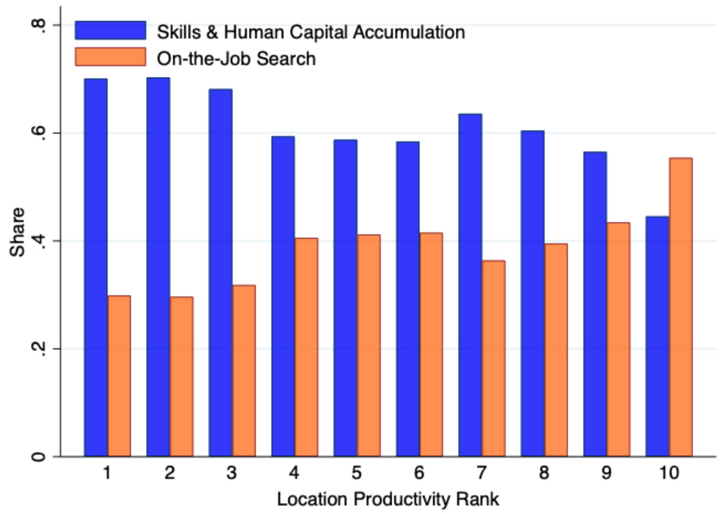
Together, these figures highlight the importance of job ladders in explaining why low-wealth workers accept lower initial wages in high-productivity cities. In the baseline economy, they are willing to trade off current earnings for future wage growth through on-the-job search. Once dynamic gains are removed, this strategy is no longer optimal, flattening the wage–wealth gradient, reducing sorting into low-paying jobs, and ultimately dampening wage inequality.

A.10 Wage Inequality Decomposition

Figure A.10 shows the contribution of skill heterogeneity and human capital accumulation, and on-the-job search to the level of wage inequality in each local labor market in the model. These contributions are computed using counterfactual simulations in which each channel is shut down individually, and the resulting decline in wage inequality is measured. To shut down human capital dynamics, I remove skill heterogeneity by collapsing the two skill types into one. In the baseline model, skill heterogeneity captures the possibility that workers' human capital appreciates while employed and depreciates during unemployment. Removing it therefore eliminates both mechanisms. To shut down on-the-job search I simply set the parameter governing on-the-job search efficiency, λ, to zero.

Across most locations, skill heterogeneity and human capital accumulation explain the largest share of wage dispersion. However, in the most productive area, on-the-job search becomes the dominant driver, accounting for 55% of local wage inequality. This result highlights the importance of search frictions. The combination of high living costs, financial constraints, and the existence of a job ladder makes search frictions outweigh human capital in determining local wage inequality.

Figure A.10: Job Ladder Decomposition



Note: The figure shows the share of wage inequality in the model attributable to skill heterogeneity and human capital accumulation (blue) and to on-the-job search (orange) across the location productivity rank.

Table A.1 focuses on the role of job ladders and wealth heterogeneity. Dynamic gains—arising from human capital accumulation and job-to-job transitions—account for approximately 67% of the wage inequality generated in the model, with the remaining 33% attributable to wealth differences. Dynamic gains are especially important in the most productive location, where job ladders are relatively steeper.

Table A.1: Wealth Heterogeneity & Job Ladders

Location	Wealth	Skills & Human Capital Accumulation	On-the-job Search
1	0.220	0.547	0.233
2	0.254	0.524	0.222
3	0.340	0.450	0.210
4	0.456	0.323	0.221
5	0.446	0.326	0.229
6	0.408	0.346	0.246
7	0.282	0.455	0.262
8	0.343	0.397	0.260
9	0.354	0.366	0.281
10	0.215	0.350	0.435
Total	0.332	0.408	0.260

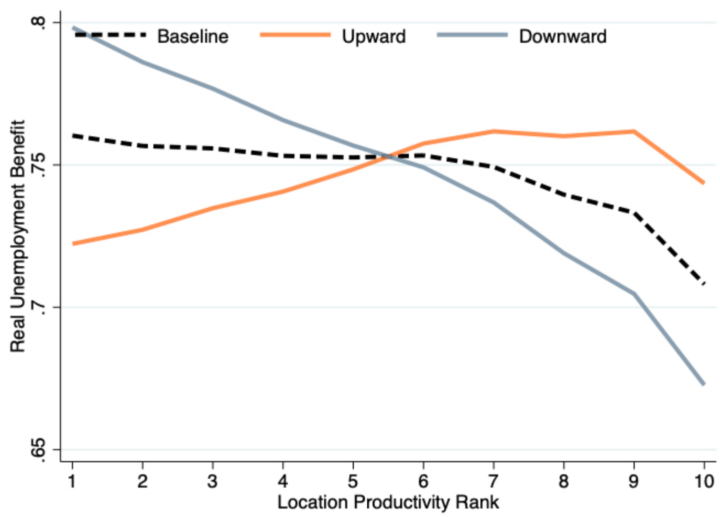
Note: The table reports the share of wage inequality in the model attributable to wealth heterogeneity (column 2), to skills and human capital accumulation (column 3), and to on-the-job search (column 4) across the ten locations ranked by productivity.

These findings underscore the importance of job ladders—both through job-to-job transitions and human capital accumulation—for understanding spatial wage inequality. While skills account for the largest share of wage dispersion in most locations, the contribution of on-the-job search rises substantially in high-productivity areas, where local ladders are steeper and dynamic opportunities more abundant. In contrast, in less productive labor markets, wage inequality is primarily driven by differences in skill endowments and asset holdings.

A.11 Real Unemployment Benefit

Figure A.11 replicates 10a deflating the unemployment benefit by the local living cost. In particular, I use a citywide Cobb-Douglas price index with a housing expenditure share of 0.2. In the baseline scenario, the real unemployment benefit is lower in the most productive locations, as they are the most expensive. Under the upward policy, the real unemployment benefit becomes higher in the most productive areas. Even if it is still relatively low in location 10, where housing costs are the highest. Under the downward policy, the spatial difference is higher as unemployment benefits are now lower in the most productive and expensive locations.

Figure A.11: Real Unemployment Benefit



Note: The figure shows the two policy scenarios deflated by the local living cost. The black dashed line represents the baseline economy. The orange line depicts the upward policy, which increases benefits in the most productive locations. While the gray line shows the downward policy, which does the reverse.

B Data

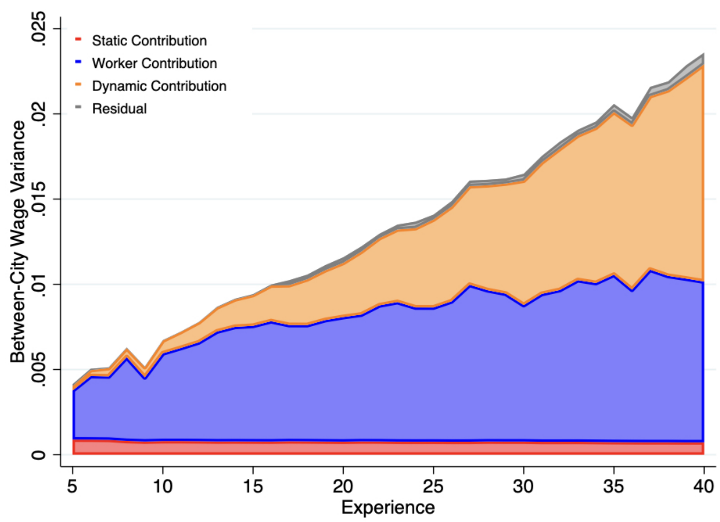
B.1 Between-City Wage Inequality Decomposition

Wages are higher in big cities due to a static and a dynamic premium. To understand the importance of each component, I follow Lhuillier (2025) and estimate the following equation:

$$\log w_{i\ell t} = \underbrace{\alpha_\ell}_{\text{City FE}} + \underbrace{\beta_i}_{\text{Worker FE}} + \underbrace{\gamma_\ell \sum_{\tau=\underline{t}}^{t} J2J_{i\ell\tau} + \delta_\ell exp_{i\ell t}}_{\text{Dynamic Gains}} + \underbrace{\varepsilon_{i\ell t}}_{\text{Residual}}$$

Using the coefficients obtained from this regression, I compute the mean conditional on city and workers' experience, and finally take the variance across cities by experience. In this specification, dynamic gains are measured by wage gains from job-to-job transitions and learning. Both depend on the location where they happen. In particular, as in De La Roca and Puga (2017) I allow for spatially differentiated learning.

Figure B.1: Between-City Wage Variance Decomposition by Experience



Note: The figure decomposes the between-city variance in wages by years of labor market experience into four components: productivity differences (red), worker sorting and observable characteristics (blue), job ladder effects (orange), and an unexplained residual (gray).

Figure B.1 plots the between-city variance decomposition. As expected, the importance of the dynamic component grows with workers' experience, while the static component remains constant. On average, around 30% of the between-city wage inequality is explained by dynamic gains. Overall, the largest fraction is explained by workers' fixed effects, which captures workers' observable and unobservable characteristics and their sorting across space. Additionally, Lhuillier (2025) decomposes the sources of wage growth and finds that the reallocation of workers across jobs explains around

70% of the between-city wage difference and that workers' experience accounts for the remaining 30%.

B.2 Additional Data

I complement my main dataset with three additional sources.

Continuous Labor Force Survey. It is a quarterly survey collected continuously throughout the year that provides a measure of the concepts of activity, unemployment, employment, and inactivity as defined by the International Labor Office (ILO). I use this dataset to compute some of the moments used to take my model to the data.

Official Postal Code Base. To measure migration and commuting distance, measured as the distance between each residence-workplace municipality pair, I also obtain data on the centroids of each municipality in France from a database publicly available from the French government at the following link.

Survey on Rents and Charges. To have a proxy for the local cost of living, I obtain data on rents per m^2 in France communes, from the following source: link.

World Inequality Database. Further, to validate the measure of financial wealth I use in the empirical analysis, I obtain data on the wealth distribution in France from another source.

B.3 Wealth Distribution in the Data

To validate the measure of wealth I obtain from the EDP sample I compare its distribution with the one computed from the World Inequality Database (WID)[68]. I plot the average wealth for 10 percentiles of the wealth distribution in figure B.2, and the two align fairly well.

The average wealth at the top and the bottom of the distribution is a bit off. The reason is probably because at the top, the wealth of the top 5% is not perfectly captured in my data, while in the WID, they can even look at the wealth for the top 0.1%. Regarding the bottom, in the EDP, I include the net income from housing, and this is why the average wealth for the bottom 10% is slightly negative. While in the WID, no debts are subtracted.

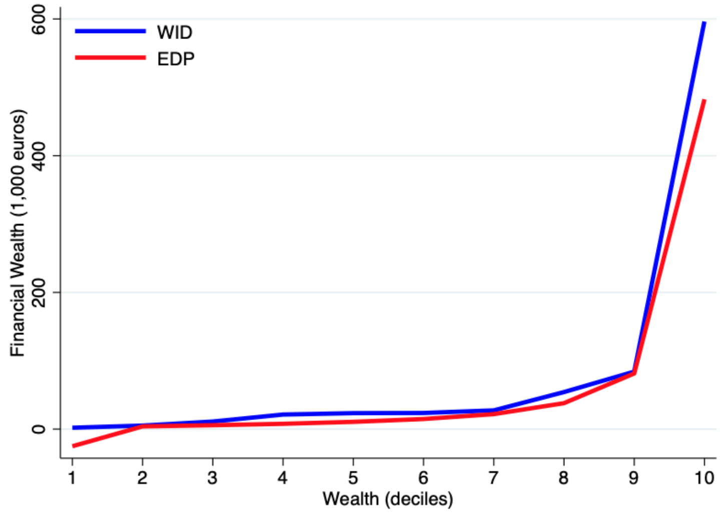
B.4 Measure of Workers' Skills

Following Bilal (2023), I run the following Mincer regression:

$$\log w_{it} = \underbrace{\alpha_{O(it)}}_{\text{Occupation}} + \underbrace{\alpha_{Y(it)}}_{\text{Year}} + \underbrace{\alpha_{C(it)}}_{\text{City}} + \underbrace{\alpha_{A(it)}}_{\text{Age Bin}} + \varepsilon_{it}$$

68 The measure of wealth taken from the WID is *personal financial assets*, which includes bank deposits, bonds, stocks (held directly or indirectly), pension funds, and life insurance held by households. No debts are subtracted.

Figure B.2: Wealth Distribution from the EDP and the WID



Note: The figure shows the average financial wealth across the wealth distribution in the Échantillon Démographique Permanent (red line), which is used in the empirical analysis, alongside the corresponding data from the World Inequality Database (blue line).

Then, define skills as the average occupation and age premium:

$$\hat{S}_i = \frac{1}{N_{i,O}} \sum_{k=1}^{N_{i,O}} (\hat{\alpha}_{O(it),k} + \hat{\alpha}_{A(it)})$$

B.5 Summary Statistics

In table B.1, I report some summary statistics for job-to-job transitions, wage growth, and migration in aggregate and for workers with different wealth, those at the top 10 percent of the wealth distribution, and those at the bottom 10 percent of the wealth distribution.

Almost 20% of the sample face a job-to-job transition, almost 2/3 of them are associated with a wage increase, and about 8% are associated with a change in the commuting zone of residence. Wage growth is higher for job switchers, more for low wealth than high wealth, while it is the reverse for those who remain in the same job across two years. Wage growth within a job is higher for wealthier workers. Finally, as in Bilal and Rossi-Hansberg (2021), migration is decreasing in wealth.

B.6 Wealth Distribution across French Commuting Zones

Figure B.3 displays the wealth and log wealth held by the top 10%, bottom 10%, and 50% of the wealth distribution across French commuting zones ranked by the top-bottom difference.

Table B.1: Summary Statistics

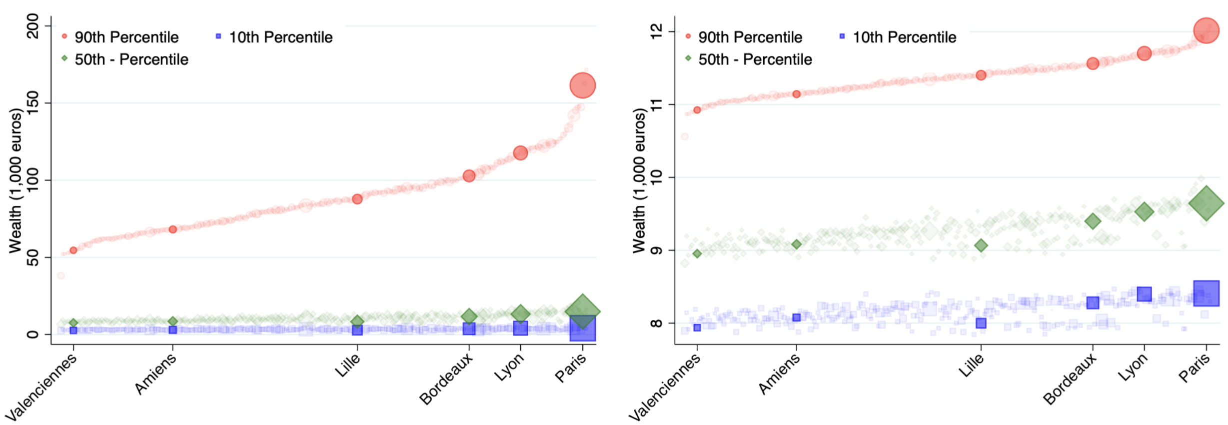
	France			US		
	Aggregate	Wealth Deciles		Aggregate	Wealth Deciles	
		D1	D10		D1	D10
Job-to-Job Transitions (%)	19.5	20.3	20	27.9	31.1	25.6
Associated with Wage Gains	63.9	63.1	61.9	55.9	56.9	54.4
Associated with Migration	8.1	10.2	6.9	7.6	8.9	8.4
Wage Growth (log)	0.016	-0.008	0.015	0.023	0.028	0.031
Job Switchers	0.077	0.11	0.069	0.157	0.163	0.175
Job Stayers	0.011	0.002	0.012	0.041	0.065	0.02
Migration across Municipalities (%)	7.7	9.7	6.1	7.9	10.1	6.9
Migration across Commuting Zones (%)	2.9	3.7	2.6	5.7	7.7	6

The table reports summary statistics for France and the United States. U.S. statistics are computed using data from the 1997 National Longitudinal Survey. In the U.S. context, municipalities correspond to counties, and commuting zones correspond to states.

Figure B.3: Wealth Distribution across French Commuting Zones

(a) Wealth

(b) log Wealth



Note: Panel (a) displays the wealth held by the top 10%, bottom 10%, and 50% of the wealth distribution across French commuting zones ranked by the top-bottom difference. Panel (b) plots the same graph but in logs.

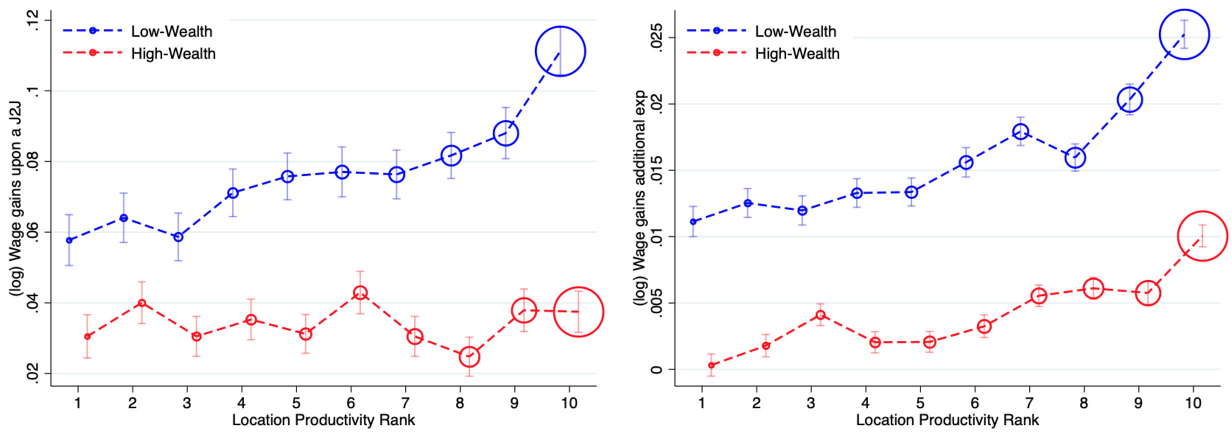
B.7 Wealth and the Spatial Job Ladder - Robustness

Local Wealth and the Spatial Job Ladder. Figure B.4 shows the results of regression (12) when the local wealth distribution is used to define wealth types. The picture obtained is similar to the one in figure 3.

Local Job-to-Job Transitions. Figure B.5 shows the results of regression (12) when the sample is restricted to those workers who change job within a local labor market, that is, all transitions

Figure B.4: Wage Gains upon J2J and Learning by City & Local Wealth

(a) Job Transition (γ_ℓ) (b) Learning (δ_ℓ)

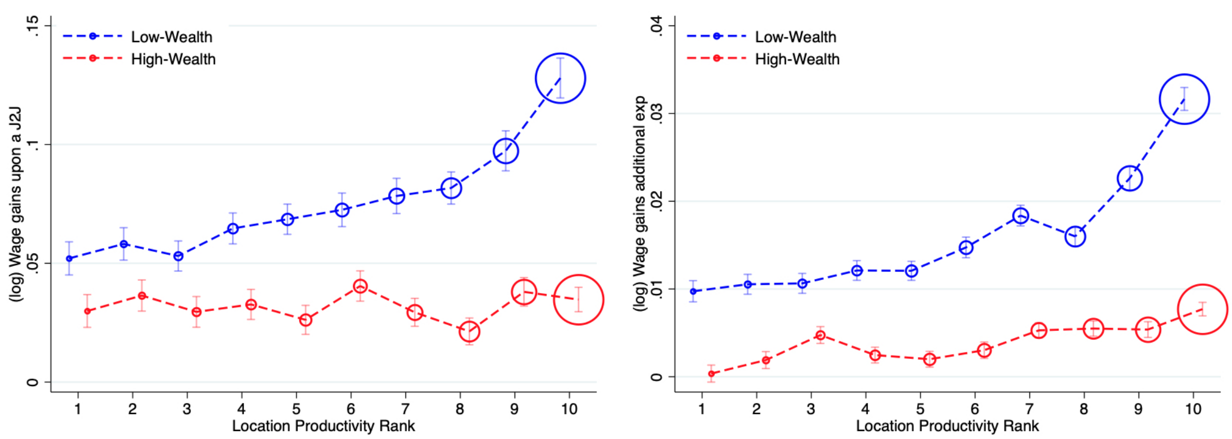


Note: This figure corresponds to Figure 3, with the key difference that the wealth distribution is constructed at the local level.

that involve migration are excluded. The picture obtained is similar to the one in figure 3.

Figure B.5: Wage Gains upon J2J and Learning by City & Wealth - Non-Migrants

(a) Job Transition (γ_ℓ) (b) Learning (δ_ℓ)

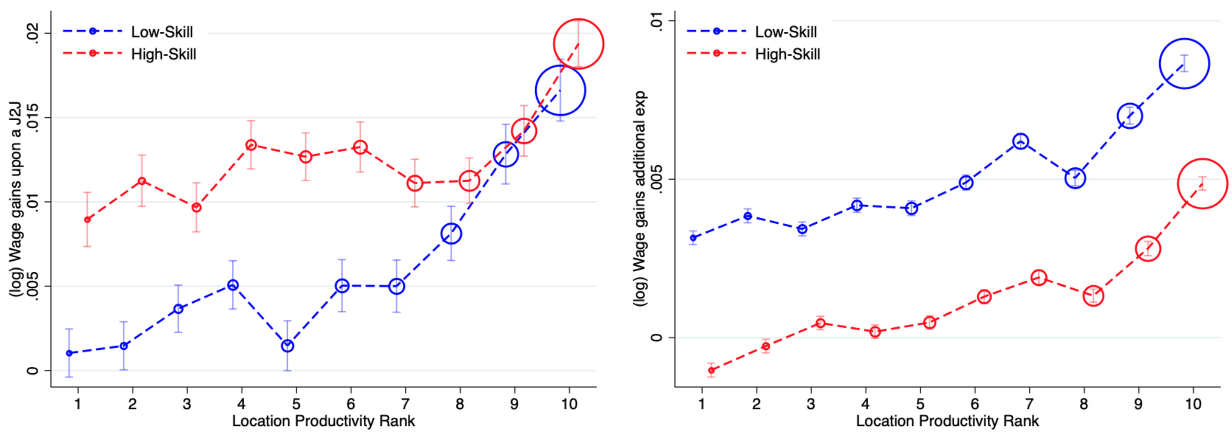


Note: This figure corresponds to Figure 3, with the key difference that here the sample is restricted to non-migrants only.

Skills and the Spatial Job Ladder. Figure B.6 shows the results of regression (12) when the sample is split into low and high-skill workers. In this case, what emerges is a very different picture from the one obtained by using wealth. Figure B.6a shows that, on average, high-skill workers tend to gain more from job-to-job transitions. Most importantly, it shows that for both types, it is more beneficial to change jobs in Paris rather than in a city at the bottom of the productivity distribution.

Figure B.6: Wage Gains upon J2J and Learning by City & Skills

(a) Job Transition (γ_ℓ) (b) Learning (δ_ℓ)



Note: This figure corresponds to Figure 3, with the key difference that here the distinction is made between low- and high-skill workers, rather than low- and high-wealth workers. Skills are proxied by the age and occupational premium estimated from a Mincer regression.

Figure B.6b shows that the spatial heterogeneity in the gains from learning is more pronounced among the high-skill workers.[69] This result is consistent with the findings of other papers that study the role of learning and interactions among workers, such as De La Roca and Puga (2017). In particular, these papers conclude that learning is complementary to workers' skills.

Young Workers and the Spatial Job Ladder. Figure B.7 shows the results of regression (12) when the sample is restricted to young workers who are under 35. Even in this case, the heterogeneity by wealth is preserved.

Figure B.7a confirms that the spatial heterogeneity in gains from job transitions is concentrated among low-wealth workers. While the difference in learning by wealth is less evident, as shown in figure B.7b, with high-wealth workers who seem to gain disproportionately more in Paris.

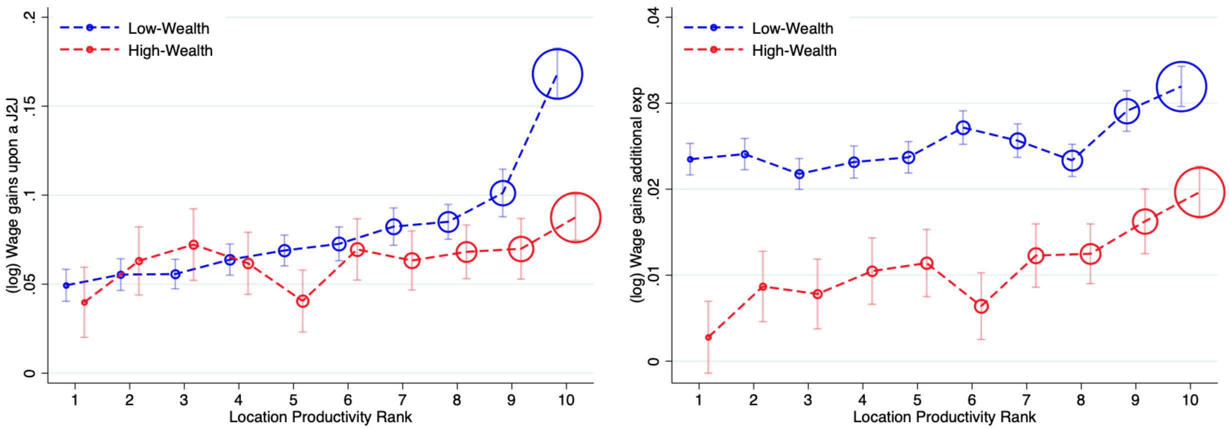
Hourly Wage. Figure B.8 shows the results of regression (12) when the dependent variable is hourly wage instead of annual earnings. The picture obtained is similar to the one in figure 3.

Hourly wage is computed by dividing annual earnings by the total number of hours worked in a year. However, the amount of hours reported in the dataset is contractual hours, which may differ from the actual number of hours worked since they exclude, for instance, extra hours. For this reason, in my main specification, I use annual earnings.

69 The red line is steeper than the blue line. The difference between the gains from one additional year of experience in Paris compared to a city at the bottom of the ranking is much higher for high-skill workers.

Figure B.7: Wage Gains upon J2J and Learning by City - Young Workers

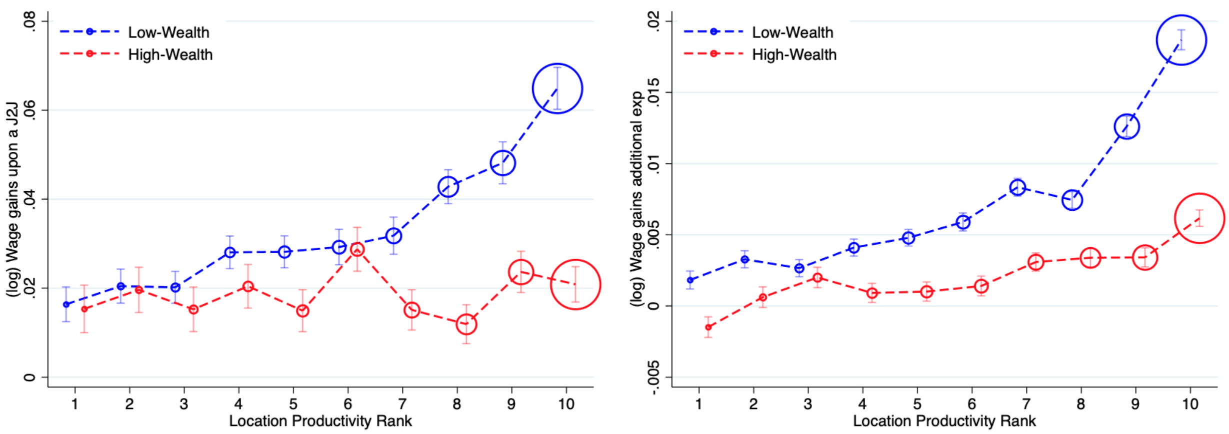
(a) Job Transition (γ_ℓ) (b) Learning (δ_ℓ)



Note: This figure corresponds to Figure 3, with the key difference that here the focus is on workers under 35 only.

Figure B.8: Hourly Wage Gains upon J2J and Learning by City & Wealth

(a) Job Transition (γ_ℓ) (b) Learning (δ_ℓ)



Note: This figure corresponds to Figure 3, with the key difference that here log wage growth is measured using the hourly wage instead of the monthly wage.

B.8 Wealth Shock Summary Statistics

Table B.2 reports summary statistics related to the wealth shock. It distinguishes between workers who received a wealth shock at some point in their life and those who never did.

B.9 Wealth Shock Regression - Full Sample

Table B.3 presents the regression results examining the effect of a wealth shock on the probability of climbing the spatial job ladder across different sub-samples. Column (1) reports the results for the

Table B.2: Wealth Shock Summary Statistics

	Aggregate	Ever Received Shock	
		Yes	No
Positive Wealth Shock (%)	5	·	·
Average Wealth Shock (€)	218,531	·	·
Homeowners	224,348	·	·
Non-homeowners	194,268	·	·
Median Wealth Shock (€)	102,220	·	·
Homeowners	104,360	·	·
Non-homeowners	94,970	·	·
Age	42.5	43.1	42.5
Education	4.1	5.5	4
Labor Income (€)	27,399	36,253	26,728
Wealth Percentile			
Q1 (%)	20.6	17.2	20.9
Q2 (%)	22.4	10	23.3
Q3 (%)	22.6	15	23.2
Q4 (%)	22	24.3	21.8
Q5 (%)	12.4	33.8	10.8

Note: The table reports summary statistics on the magnitude of the wealth shock, comparing workers who experience the shock with those who never face it.

full sample of workers. Column (2) restricts the sample to job switchers, while column (3) focuses on geographic movers. Column (4), which corresponds to Table 1 in the main text, considers the intersection of the two: individuals who both switch jobs and move across locations.

Table B.3: Effects of a Positive Wealth Shock - Full Sample

	(1) Full Sample	(2) Job Switchers	(3) Movers	(4) Switchers & Movers
Shock × Q1	0.00535***	0.0219***	0.0439**	0.0800*
	(0.000486)	(0.00286)	(0.0177)	(0.0426)
Shock × Q2	0.0084***	0.0415***	0.0154	0.0301
	(0.000878)	(0.00505)	(0.0233)	(0.0587)
Shock × Q3	0.00271***	0.00984***	0.0172	0.00177
	(0.000704)	(0.00407)	(0.0219)	(0.0540)
Shock × Q4	0.00174***	0.00940***	0.0137	-0.00950
	(0.000537)	(0.00318)	(0.0191)	(0.0464)
Shock	0.00055**	0.00206	-0.00479	-0.0220
	(0.000277)	(0.00163)	(0.0116)	(0.0281)
Observations	2,475,707	383,028	47,019	14,932
R^2	0.042	0.167	0.320	0.424

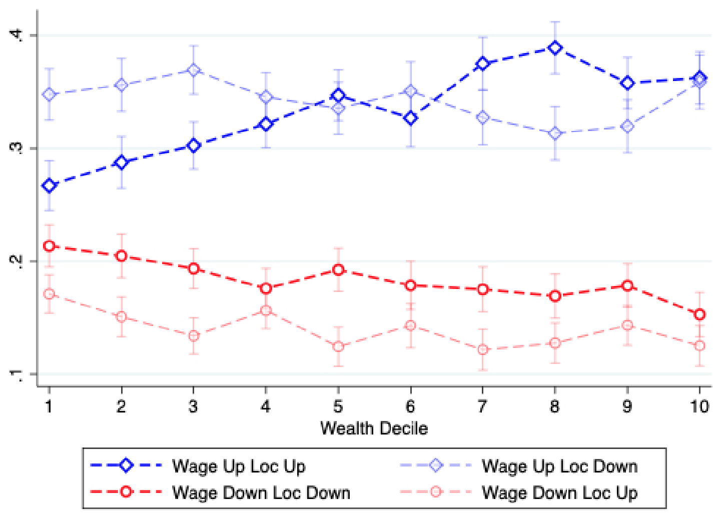
Note: This table reports the estimated effect of a wealth shock on the probability of moving to a job that pays a higher wage in a more productive location, across different wealth groups and sub-samples. Column (1) uses the full sample; column (2) restricts to job switchers; column (3) to geographic movers; and column (4), as in Table 1, to individuals who both switch jobs and move. Controls include age, sex, education, income, wealth, commuting distance, home-ownership, and total transitions. All regressions include year × municipality and occupation × industry fixed effects. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.10 Movements on the Spatial Job Ladder

Workers that change job and location can move in four possible directions: to a job that pays a higher wage in a more productive location, to a job that pays a higher wage in a less productive location, to a job that pays a lower wage in a more productive location, and to a job that pays a lower wage in a less productive location. Figure B.9 shows the probability of moving in all possible directions.

What emerges from the graph is that the probability of a mixed outcome occurring is less heterogeneous by wealth.

Figure B.9: Probability Moving on the Spatial Job Ladder



Note: This figure corresponds to Figure 4, with the key difference that here all the possible outcomes are considered.